

Case No. \_\_\_\_\_

UNITED STATES COURT OF APPEALS  
FOR THE NINTH CIRCUIT

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IN RE HIGH-TECH EMPLOYEE ANTITRUST LITIGATION

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Petition for permission to appeal from the United States District Court  
Northern District of California  
The Honorable Lucy H. Koh, Presiding  
Case No. 5:11-2509-LHK

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**DEFENDANT-PETITIONERS' EXCERPTS OF RECORD  
VOLUME II OF VIII**

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**UNITED STATES DISTRICT COURT  
NORTHERN DISTRICT OF CALIFORNIA  
SAN JOSE DIVISION**

IN RE HIGH-TECH EMPLOYEE  
ANTITRUST LITIGATION

THIS DOCUMENT RELATES TO:  
  
ALL ACTIONS

**Master Docket No. 11-CV-2509-LHK**

EXPERT REPORT OF  
PROFESSOR KEVIN M. MURPHY

Date: January 17, 2013  
Time: 1:30 p.m.  
Courtroom: 8, 4th Floor  
Judge: Honorable Lucy H. Koh

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## I. CREDENTIALS

1. My name is Kevin M. Murphy. I am the George J. Stigler Distinguished Service Professor of Economics in the Booth School of Business and the Department of Economics at the University of Chicago, where I have taught since 1983.
2. I earned a doctorate degree in economics from the University of Chicago in 1986. I received my bachelor's degree, also in economics, from the University of California, Los Angeles, in 1981.
3. At the University of Chicago, I teach economics in both the Booth School of Business and the Department of Economics. I teach graduate level courses in microeconomics, price theory, empirical labor economics, and the economics of public policy issues. In these courses, I cover a wide range of topics, including the incentives that motivate firms and individuals, the operation of markets, the determinants of market prices, and the impacts of regulation and the legal system. Most of my teaching focuses on two things: how to use the tools of economics to understand the behavior of individuals, firms and markets; and how to apply economic analysis to data. My focus in both research and teaching has been on integrating economic principles and empirical analysis.
4. Of particular relevance to the issues in this matter, I have published extensively on labor markets and the determinants of wages and compensation. My work in labor economics has addressed the market determinants of wage by skill level as well as the determination of relative wages across industries and occupations. Several of my papers have focused on the determinants of the wage structure by age, education and gender. My work on wage determination also has addressed the links between wages and labor mobility. I teach PhD-level courses on empirical labor economics with a focus on the wage structure and the determinants of relative wages across groups differentiated by age, education and skill.
5. I have authored or co-authored more than sixty-five articles in a variety of areas in economics. Those articles have been published in leading scholarly and professional journals, including the *American Economic Review*, the *Journal of Law and Economics*, and the *Journal of Political Economy*.

6. I am a Fellow of the Econometric Society and a member of the American Academy of Arts and Sciences. In 1997, I was awarded the John Bates Clark Medal, which the American Economic Association awarded once every two years to an outstanding American economist under the age of forty.<sup>1</sup> In 2005, I was named a MacArthur Fellow, an award that provides a five-year fellowship to individuals who show exceptional merit and promise for continued and enhanced creative work.

7. In addition to my position at the University of Chicago, I am also a Principal at Navigant Economics, a consulting firm that specializes in the application of economics to law and regulatory matters. I have consulted on a variety of antitrust, intellectual property and other matters involving economic and legal issues such as mergers, class certification, damages, labor practices, joint ventures, and allegations of anticompetitive exclusionary access, tying, price fixing, and price discrimination.

8. I have submitted testimony in Federal Court, the U.S. Senate and to state regulatory bodies, and I have submitted expert reports in numerous cases. I have testified on behalf of the U.S. Federal Trade Commission and I have consulted for the U.S. Department of Justice. A list of the reports I have filed and the testimony I have given over the past four years is provided in my CV, attached as Appendix A. Navigant Economics is being compensated at a rate of \$1,250 per hour for my work on this matter.

## **II. ASSIGNMENT AND SUMMARY OF CONCLUSIONS**

9. I have been asked by Counsel for Adobe Systems Inc., (“Adobe”), Apple Inc. (“Apple”), Google Inc. (“Google”), Intel Corporation (“Intel”), Intuit Inc. (“Intuit”), Lucasfilm Ltd. (“Lucasfilm”) and Pixar (collectively “Defendants”) to provide an economic analysis of claims by “individual and representative plaintiffs”<sup>2</sup> (“Plaintiffs”) that an alleged “conspiracy among

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<sup>1</sup> The John Bates Clark Medal was awarded biennially until 2009, but it now is awarded annually. See, [http://www.aeaweb.org/honors\\_awards/clark\\_medal.php](http://www.aeaweb.org/honors_awards/clark_medal.php).

<sup>2</sup> In Re: High-Tech Employee Antitrust Litigation, Plaintiffs’ Notice of Motion and Motion for Class Certification, and Memorandum of Law in Support (“Motion”), October 1, 2012, p. 1.

Defendants to fix and suppress the compensation of their employees”<sup>3</sup> would have a class-wide impact and would be susceptible to class-wide proof. Plaintiffs have asked the Court to certify a class of “[a]ll natural persons employed on a salaried basis in the United States by one or more” of the Defendants during part or all of the period from January 2005 through December 2009 (the “Class” or “All-Salaried Employee Class”).<sup>4</sup> As an alternative, Plaintiffs have asked the Court to certify a “Technical Class” defined as “[a]ll natural persons who work in the technical, creative, and/or research and development fields that are employed on a salaried basis in the United States by one or more of the” Defendants during the same time periods and with the same excluded categories as identified for the All-Salaried Employee Class. In support of their claims, Plaintiffs offer the *Expert Report of Edward E. Leamer, Ph.D.* (“Leamer Report”).<sup>5</sup> The arguments and evidence provided by Plaintiffs and Dr. Leamer typically do not distinguish between the two alternative class definitions, and in my report I also distinguish between the two potential classes only when I present evidence specific to one or the other.

10. Plaintiffs claim that there was a conspiracy among the Defendants to refrain from “cold calling” each other’s employees; that cold calling “is a particularly effective recruiting method;”<sup>6</sup> that “cold calling has a significant impact on employee compensation in a variety of ways;”<sup>7</sup> and, essential to their claim of antitrust impact, that “the compensation effects of cold calling are not limited to the particular individuals who receive cold calls.”<sup>8</sup> Plaintiffs claim that, due to the

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<sup>3</sup> Consolidated Amended Complaint in Re: High-Tech Employee Antitrust Litigation (“*Complaint*”) ¶1.

<sup>4</sup> Plaintiffs define the All-Salaried Employee Class as “All natural persons employed on a salaried basis in the United States by one or more of the following: (a) Apple from March 2005 through December 2009; (b) Adobe from May 2005 through December 2009; (c) Google from March 2005 through December 2009; (d) Intel from March 2005 through December 2009; (e) Intuit from June 2007 through December 2009; (f) Lucasfilm from January 2005 through December 2009; or (g) Pixar from January 2005 through December 2009. Excluded from the Class are: retail employees; corporate officers, members of the boards of directors, and senior executives of all Defendants” (*Motion*, p. 1).

<sup>5</sup> Expert Report of Edward E. Leamer, Ph.D., October 1, 2012.

<sup>6</sup> *Complaint* ¶42.

<sup>7</sup> *Complaint* ¶46.

<sup>8</sup> *Complaint* ¶50. According to Dr. Leamer, “Cold-Calling” refers to communicating directly in any manner (including orally, in writing, telephonically, or electronically) with another firm’s employee who has not otherwise applied for a job opening” (Leamer Report Footnote 3, adopting essentially the same definition as in

alleged conspiracy, the resulting “elimination of competition and suppression of compensation and mobility had a cumulative effect on *all* Class members,”<sup>9</sup> resulting in “lower compensation from Defendants than they otherwise would have received.”<sup>10</sup>

11. Plaintiffs acknowledge that the alleged “conspiracy” among the seven Defendants consisted of a small number of bilateral agreements (which I refer to in my report as the “challenged agreements” or “do not cold call” (“DNCC”) agreements) between certain pairs of Defendants to not cold-call each other’s employees.<sup>11</sup> Despite the limited nature of the alleged conspiracy, Plaintiffs claim that the small number of bilateral agreements had a class-wide impact on a class that includes virtually all U.S. salaried employees at all seven Defendants during the periods identified. Plaintiffs claim that the reduction in cold calls between pairs of Defendants reduced the information available to employees about their “value.”<sup>12</sup> According to Plaintiffs, the reduced flow of information allegedly not only affected the compensation received by employees who did not receive cold calls that they might otherwise have received, but also reduced the compensation of all other salaried employees of the Defendant firms as well – from engineers to cafeteria workers. Plaintiffs claim that all or almost all employees in their proposed

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Plaintiffs’ Complaint ¶41). This definition would include conduct that was not prohibited by the challenged agreements, such as responding to inquiries by potential applicants about a particular job opening, or potential job openings in general, if those potential applicants simply were gathering information before filing an application. My understanding of the do-not cold call restrictions at issue in this case is that they generally were intended to prevent a Defendant from calling (or emailing) employees at a firm with which it had an agreement if those employees had expressed no interest in exploring employment with the Defendant or in exploring potential new employment opportunities in general – in other words, if they were a totally passive candidate.

<sup>9</sup> *Complaint* ¶110 (emphasis added).

<sup>10</sup> *Complaint* ¶123.

<sup>11</sup> Dr. Leamer says that he “understand[s] that Defendants entered into several additional agreements” (Leamer Report ¶22).

<sup>12</sup> According to Plaintiffs, “by restricting “cold-calling” (i.e., outreach to solicit applications from candidates who are not actively seeking employment) and other active competition for employees, the agreements depressed compensation by impairing information flow about compensation and job offers, reducing negotiating leverage of employees, and minimizing movement of employees between firms” (*Motion*, p. 3). Plaintiffs claim that “Dr. Leamer describes abundant evidence common to all Class members capable of showing that the Defendants’ agreements would tend to suppress employee compensation generally, by preventing class members from discovering the true value of their work” (*Motion*, p. 16).

classes were affected by an amount that can be measured on a class-wide basis using conventional methods and common evidence.

12. In his report, Dr. Leamer addresses two questions: (1) whether there is “proof common to each proposed class capable of showing that the Non-Compete Agreements artificially reduced the competition [*sic*: compensation] of its members;”<sup>13</sup> and (2) whether there is a “reliable Class-wide or formulaic method capable of quantifying the amount of suppressed compensation suffered by each class.”<sup>14</sup> Dr. Leamer concludes that the answer to both questions is “yes,” and that “all or nearly all” members of both classes “had their compensation suppressed” by an aggregate amount that can be quantified reliably using “standard economic methods.”<sup>15</sup>

13. Dr. Leamer’s analysis has three essential steps. First, the challenged agreements must materially reduce the information available to Defendants’ employees. Second, that reduction in information must cause the salaries of individual employees to be reduced. Third, the “somewhat rigid” compensation structures of the Defendants must cause the reductions in the compensation of some employees to reduce compensation on a class-wide basis. Economic theory and empirical evidence demonstrate that his analysis of each of these essential steps is critically flawed. First, the labor markets from which Defendants hire are enormous and diverse, and the recruiting practices of a small number of employers that would directly affect only a small number of employees would not meaningfully affect the information levels of employees at any Defendant. This would break the chain at the first step. Second, any effects would be highly individualized and would not be common across members of the proposed class. In particular, the same conduct that reduced the information provided to one employee likely would increase the information provided to others. This would stop the chain at the second step, since the impact on individual compensation would not be common. Finally, if the compensation structures of the Defendants are not rigid, then an impact on one individual’s compensation

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<sup>13</sup> Leamer Report ¶10; *see*, Leamer Depo. at 21:5-7.

<sup>14</sup> *Ibid.*

<sup>15</sup> Leamer Report ¶11.

would not increase compensation for other members of the class. This would stop the chain at the third step. None of the required links in the chain hold, let alone all three.

14. Thus, based on my analysis, I conclude that Plaintiffs' claims and Dr. Leamer's opinions are both inconsistent with economic theory and contradicted by documentary and empirical evidence. Given the lack of economic logic to their allegations, it is not surprising that Plaintiffs' claims are not supported by empirical evidence. The following are my core opinions regarding Plaintiffs' allegations, which I explain in detail in this report:

**Opinion 1: The high level of hiring by Defendants during the class period demonstrates the implausibility of Dr. Leamer's claim that average compensation at these firms was suppressed as Dr. Leamer and Plaintiffs claim.**

Collectively, between 2005 and 2009, Defendants hired an average of over 8,000 new workers per year – equal to 11 percent of their combined workforces. And their actual hiring was dwarfed by the number of applications they received. It is implausible that, for five years, these firms consistently undercompensated their employees by the large amount estimated by Dr. Leamer (see Part V.B.1, below).

**Opinion 2: Empirical evidence of Defendants' hiring activities demonstrates that the challenged conduct had no economically significant class-wide impact on the information about labor market opportunities and compensation available to Defendants' employees.**

- a) Employee movements to or from other Defendants – whether resulting from cold calling or another recruiting method – accounted for only about *one percent* of Defendants' employee turnover (hires and separations) over the period 2001 to 2011. Employee movements between Defendants that had DNCC agreements was even lower. Using turnover as a proxy for underlying recruiting activity, this means that, during this period, about 99 percent of potential recruiting activity was unaffected by the challenged agreements.<sup>16</sup> See Table 1 below (and see Exhibits 1A and 1B for details).<sup>17,18</sup> Given the

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<sup>16</sup> Given that forms of recruiting of other than cold calling were still available and used during the class period to recruit employees of Defendants subject to a DNCC agreement, the fraction of turnover accounted for by the movements to and from other Defendants will tend to overstate the actual importance of the challenged agreements.

relative unimportance of employee movement between Defendants both within and outside the class period, any restriction in that movement would not have a material effect on compensation. Moreover, during the class period, Defendants' collective hires from other Defendants ("cross hires") represented just 1.1 percent of Defendants' total hires (cross hires and separations represented 1.2 percent of their total hires and separations), a share that is not materially different than the corresponding shares from before and after the class period. The data in Table 1 clearly demonstrate that employee movements between the Defendants account for a minute fraction of the labor market activity for employees of these firms. As such, changes in those flows would have no substantial effect on the information available to Defendants' employees even if (counterfactually) those flows and the associated recruiting activity represented the only source of information available to employees.

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<sup>17</sup> For purpose of this discussion, I use the period from 2005 to 2009 to approximate the "class period." According to Plaintiffs, agreements involving four out of the seven Defendant companies (Adobe, Apple, Google, Intel) began in 2005. Together these four companies accounted for about 92 percent of total average annual employment at the Defendants from 2001 to 2011.

<sup>18</sup> This analysis uses one-year windows to identify hires (looking back one year between the separation date at the previous employer and the hire date at the new employer) and separations (looking ahead one year). For hires and separations between Defendants in a given year, the numbers of hires and separations may differ slightly due to the two different windows used.

**Table 1**  
**Summary of Hires and Separations at Defendant Companies**

	<b>Annual Average</b>			
	<u>2001-</u> <u>2004</u>	<u>2005-</u> <u>2009</u>	<u>2010-</u> <u>2011</u>	<u>2001-</u> <u>2011</u>
<b>Overall Hires</b>	5,795	8,814	11,435	8,193
From Other Defendant Companies	35	95	159	85
From Other DNCC Defendant Companies	28	69	123	64
<b>% From Other Defendant Companies</b>	<u><b>0.6%</b></u>	<u><b>1.1%</b></u>	<u><b>1.4%</b></u>	<u><b>1.0%</b></u>
<b>% From Other DNCC Defendant Companies</b>	<u><b>0.5%</b></u>	<u><b>0.8%</b></u>	<u><b>1.1%</b></u>	<u><b>0.8%</b></u>
<b>Overall Hires and Separations</b>	12,182	15,985	16,525	14,700
From/To Other Defendant Companies	71	191	305	168
From Other DNCC Defendant Companies	57	139	239	127
<b>% From/To Other Defendant Companies</b>	<u><b>0.6%</b></u>	<u><b>1.2%</b></u>	<u><b>1.8%</b></u>	<u><b>1.1%</b></u>
<b>% From Other DNCC Defendant Companies</b>	<u><b>0.5%</b></u>	<u><b>0.9%</b></u>	<u><b>1.4%</b></u>	<u><b>0.9%</b></u>

Source: Based on analysis in Exhibit 1A and 1B.

- b) There were many sources of labor market information available to Defendants' employees other than cold calling, including Defendants' hires and employees leaving Defendants to go to non-Defendants. During the class period, total workforce at Defendants averaged about 78,000 employees a year (see Exhibit 1A). Therefore new hires (roughly 8,800 a year based on Table 1) averaged about 11.3 percent of Defendants' total workforce during the year, while separations (roughly 7,200 a year based on Table 1) averaged about 9.2 percent of Defendants' total workforce during the year. This suggests that about 20 percent of Defendants' employees had direct contact with the labor market and the associated labor market information in a typical year. Other sources of labor market information include information from co-workers (some of whom may have been actively looking for work), friends working at other firms, dedicated internet sites such as job boards, and media and internet-based advertising, as well as cold calling from the very large number of non-Defendant employers and from Defendants where no DNCC agreement was in place. Under Plaintiffs' theory of the spread of information,



information from these other sources (which vastly exceeds any reduction in information resulting from the challenged agreements) would have been widely disseminated among Defendants' employees, even if there were no cold calling between pairs of Defendants.

- c) Year-to-year fluctuations in Defendants' hiring activity vastly exceed any hiring changes that might have resulted from the challenged agreements. Over the class period, hiring by Defendants varied widely, from a high of 12,700 in 2005 to a low of 4,100 in 2009, a difference of over 8,500 hires. These aggregate changes dwarf any changes in the roughly one percent of total hires accounted for by Defendants that would be caused by the hypothesized reduction in cold calling due to the challenged agreements. Such large fluctuations in overall hiring activity are inconsistent with economically significant effects of the challenged conduct on class-wide compensation (see Part V.B.1, below).
- d) There was no reduction in cross hires between Defendants during the class period. The percentage of Defendants' hiring from either (a) all other Defendants or (b) Defendants with DNCC agreements was essentially the same during 2005-2009 as during the 2001-2011 period as a whole. Thus, the data are inconsistent with Dr. Leamer's central premise that the agreements reduced information flows and consequently employee movements between Defendants.

**Opinion 3: A reduction in inter-Defendant cold calling would not result in class-wide harm because there are many channels by which Defendants recruit employees**

- a) Market price (including the price employers pay for labor and thus the compensation earned by members of the proposed class) is determined by supply and demand for labor. The alleged agreements affected neither the supply of nor the demand for labor – in other words, they affected neither the number of available jobs nor the number of employees available to fill those jobs. Therefore, there is no reason why they would affect market compensation, or compensation of the class generally (see Part IV.B, below).
- b) As a matter of economic theory, the alleged conspiracy to restrict a small number of employers from using a single recruiting tool when approaching employees at one or a few other firms would not lower compensation on a class-wide basis. The challenged agreements were not commitments to reduce salaries or restrict employment and would

not have changed the supply of or demand for labor overall or the number of job positions Defendants had to fill. The alleged agreements only affected recruiting of certain employees through a particular method (cold calling). Even if the agreements reduced recruiting of certain employees from particular employers and potentially affected certain individuals as a result, the impact would be to increase recruiting through other unrestricted channels, which would benefit those hired by Defendants through those channels. For example, if, as a result of an alleged agreement with Adobe, Apple recruited a new employee for an open position from a non-Defendant, such as Microsoft, rather than from Adobe, the person hired from Microsoft (a member of the proposed class) benefitted (see Part IV.C, below).

- c) As a matter of economics, reduced cold calling (to the extent it has an effect) could raise, rather than reduce, average compensation. If less cold calling reduced the number of potential candidates contacted by Defendants, it would reduce the pool of potential hires for those Defendants. This reduction could increase the amount of compensation that the Defendants had to offer to attract employees from the smaller resulting labor pool. Under Plaintiffs' theory of information flow, this would increase compensation of other employees as well, which is the opposite of the effect hypothesized by Plaintiffs. The fact that a reduction in cold calling affects the options available to both sides of the market (firms and workers) means that any overall impact on compensation is ambiguous (it could be positive or negative). Moreover, the fact that the reduction in cold-calling would increase demand for some individuals and reduce demand for others implies that the impact on wages would not be common across members of the proposed class (see Part IV.B, below).

**Opinion 4: Defendants' compensation structures are not rigid.**

- a) Defendants had (and exercised) substantial flexibility in setting compensation of individual employees. Dr. Leamer's own model implies that employee compensation was highly individualized, with large variations even within particular job categories and between observationally similar individuals (see Part IV.D, below). As I demonstrate below, in every year and for each Defendant, there is substantial dispersion in employee compensation unexplained by Dr. Leamer's model. Dr. Leamer has shown that different

jobs have different average compensation, but not that increases in an individual's compensation resulting from a cold call results in higher compensation for other employees.

- b) Dr. Leamer's premise is also flawed. A rigid wage structure, even if one existed, would not imply that a change in compensation for one or more employees would shift the entire structure, because the cost of increasing compensation for one employee would be enormous (an increase for all employees), and would be resisted. Thus, Dr. Leamer's theory makes no economic sense.
- c) Finally, Dr. Leamer's analysis cannot distinguish the impact he hypothesizes from an alternative hypothesis that compensation of Defendants' employees is broadly determined by competition in a vast labor market, and that adjustments for individual employee's unique circumstances (such as an attractive outside offer) are highly individualized (see Part V.D.3, below).

**Opinion 5: Dr. Leamer's conduct regressions suffer from severe conceptual and methodological flaws and are completely unreliable and thus uninformative. His regression methodology provides evidence that is inconsistent with his conclusion of class-wide impact and damages.**

- a) Given the nature of Plaintiffs' allegations, the question whether the impact of the challenged conduct was common across Defendants is critical to understanding whether there is class-wide impact, and whether the impact can be measured on a class-wide basis. Data analyzed by Dr. Leamer fail to demonstrate that compensation changes during the conduct period were common across Defendants. Indeed, application of his methodology suggests that the changes were not common. Specifically, the estimated values of his so-called "conduct effects" vary substantially across Defendants, and for some of the Defendants the "effect" is actually positive (see Part V.E.2, below). Thus, Dr. Leamer's own regression specification and statistical methods (which I critique further below) show substantial variation across Defendants in the estimated impact, with some employees "overcompensated" as the result of the challenged conduct.

- b) Dr. Leamer's estimated impact of the challenged agreements on compensation is highly "statistically significant" only because he ignores a critical and obvious feature of his data – that his observations are correlated, not independent. This is not only contrary to his own theory of how an individual's compensation is determined, but also a major error in statistical inference. When properly estimated, Dr. Leamer's conduct regression provides no meaningful evidence that the challenged agreements reduced compensation of members of the proposed class (see Part V.E.3, below).
- c) In his conduct regression analysis, Dr. Leamer fails to account for important determinants of firm-level compensation. The existence of these factors invalidates his statistical analysis and shows that his claimed "conduct effects" are unreliable (see Part V.E.5, below). Dr. Leamer's estimated effects also are highly unstable, reflecting the imprecision with which they are estimated. For example, limiting his regression analysis to the conduct and post-conduct periods should not change his findings if Plaintiffs' theory is correct. Yet doing so completely changes his estimated "conduct effect"—the estimated "effect" is *positive* (implying overcompensation of class members) for all Defendants (see Part V.E.4, below). Similarly, simply controlling for changes in overall economic conditions and financial market performance (as measured by changes in the S&P 500 stock index) yields substantially smaller "undercompensation" or even overcompensation estimates (see Part V.E.5, below).

15. My report is organized as follows. In Part III, I provide background information on the Defendants and their recruiting, hiring and compensation practices that is relevant to my economic analysis. In Part IV, I show that there is neither economic logic nor empirical evidence to support Plaintiffs' claims that the challenged conduct would have a common impact on members of the class overall. Cold calling is only one of many recruiting tools, and other Defendants are not an important source of hires for any Defendant. These facts together refute Plaintiffs' claim that the challenged agreements would reduce compensation on a class-wide basis. Moreover, these same facts imply that some members of the proposed class will have benefitted from the same conduct that Plaintiffs allege harmed other employees, which means there is no economic basis to certify a class. Part V critiques Dr. Leamer's analysis and explains that he fails to support the economic requirements for class certification.

16. The information that I relied upon in forming my opinions includes documents and data produced by the parties in this litigation, deposition transcripts of the named Plaintiffs and of Defendants' employees, interviews that my staff and I conducted with Defendants' compensation and recruiting executives, economic literature, and other materials listed in Appendix B.

### III. BACKGROUND ON THE DEFENDANTS

17. Defendants are seven companies headquartered in California. As Dr. Leamer describes in his report, the firms generally focus in different business areas.<sup>19</sup> While product market and labor market competition can differ, evidence that Defendants engage in different types of businesses suggests that each will need labor market skills that are not uniquely similar to the types of skills required by other Defendants.<sup>20</sup>

18. The Defendants also differ in their labor market needs during the class period. Exhibits 2A and 2B show that some firms (including Intel and Intuit) had a fairly constant number of salaried employees, both total and technical employees (as defined by the Plaintiffs), while others (including Apple and Adobe) had substantial growth and Google had extremely rapid growth.

19. Compensation philosophies and practices of the recruiting and hiring strategies used by the Defendants have certain common features, but also differ in certain ways.<sup>21</sup> First, the

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<sup>19</sup> Leamer Report ¶¶13-19.

<sup>20</sup> Dr. Leamer does not claim to have evaluated the labor market in which any of the Defendants competes for employees (Leamer Depo. at pp. 433:5-19, 454:1-15). However, he acknowledges that each Defendant competes for employees with many non-Defendant companies (Leamer Depo. at 74:4-11, 79:3-10). See Declaration of Tina M. Evangelista in Support of Opposition to Class Certification p. 2 ("Declaration of Tina Evangelista") (

\_\_\_\_\_) See also Declaration of Frank Wagner in Support of Defendants' Opposition to Plaintiffs' Motion for Class Certification p. 10 ("Declaration of Frank Wagner") ("Between 2004 and 2011, Google aggressively recruited and hired from hundreds of employers. Among the top 20 employers that Google most often recruited new hires from during the period from 2005 to 2009 were: \_\_\_\_\_").

<sup>21</sup> The discussion in the remaining paragraphs of this section is based on my review of the Declarations filed by Defendants, interviews I conducted with compensation and recruiting managers at each Defendant, and my review of Defendants' data and documents.

companies subscribe to and use information obtained from third-party marketplace surveys as an input in determining compensation levels. The most commonly used source of market data is Radford. Although a subscriber can request a custom report from Radford that limits the data to particular labor market competitors or a limited geographic area, Defendants also often obtain reports that summarize responses from a broad selection of companies across the United States.<sup>22</sup> The Defendants use information from Radford and other market benchmarking studies, in some case targeted more closely to their particular geography or type of business,<sup>23</sup> as an input in making annual compensation adjustments.

20. Second, Defendants differ in how they incorporate third-party market data into their compensation decisions. [REDACTED]

[REDACTED]

Others used the Radford and other benchmarking data more informally, but all relied on the survey information in understanding whether their compensation was appropriate and how compensation should change annually to remain competitive in the labor markets in which they compete.<sup>25</sup>

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<sup>22</sup> For example, Intel obtains from Radford a survey report that covers responses from more than 800 U.S. technology companies outside the Silicon Valley. *See* Declaration of Danny McKell in Support of Defendant's Opposition to Plaintiff's Motion for Class Certification p. 4 ("Declaration of Danny McKell").

<sup>23</sup> For example, both Pixar and Lucasfilm rely heavily on third-party compensation surveys of animators, surveys in which none of the other Defendants participate or have any reason to find relevant for their compensation and hiring activities. In their declarations, Pixar and Lucasfilm both say they use Radford and Croner survey data. Croner is specific to certain "creative" positions that are not found in other Defendant companies. Lucasfilm states that no other Defendants were present in the Croner Games survey. *See* Declaration of Michelle Maupin in Support of Defendants' Opposition to Plaintiffs' Motion for Class Certification pp. 4-5 ("Declaration of Michelle Maupin"), p. 5.

<sup>24</sup> Adobe and Lucasfilm use survey data to develop midpoints within salary ranges. *See* Declaration of Donna Morris of Adobe Systems Inc. in Support of Defendants' Opposition to Plaintiffs' Motion for Class Certification ("Declaration of Donna Morris") p. 6 and Declaration of Michelle Maupin, pp. 6-7. Google uses survey data to set Market Reference Points (MRPs). *See* Declaration of Frank Wagner p. 3 ("[REDACTED]").

<sup>25</sup> *See* Declaration of Mason Stubblefield, p. 7, Declaration of Lori McAdams in Support of Defendants' Opposition to Plaintiffs' Motion for Class Certification ("Declaration of Lori McAdams") p. 3, and

21. Third, the companies use a large variety of channels for recruiting employees. They tend to rely heavily on employee referrals.<sup>26</sup> Many have formal referral programs that provide a bonus to current employees who refer individuals who ultimately are hired by the firm. Other important channels are new university graduates,<sup>27</sup> unsolicited applications to the company's job applicant website, job boards (such as monster.com), professional networking sites (such as LinkedIn and dice.com), and job fairs.<sup>28</sup> The importance of these different channels may have changed over time (LinkedIn, for example, increased in importance since the mid-2000s), but the use of many different channels has characterized the recruiting practices of these firms throughout the past decade and more.

22. From an economic standpoint, the use by Defendants of many different recruiting channels is important. It implies that a reduction in the use of one channel can and will be compensated for by increased use of (or at least reliance on) other channels. This has two critical implications. First, it implies that both employers and employees have alternative sources of information on hiring and compensation. Second, it implies that individuals (including class members) that utilize these other channels will have expanded opportunities as a result of the reduced cold calling.

**IV. ECONOMIC THEORY AND EMPIRICAL EVIDENCE SHOW THAT INDIVIDUAL FACTORS PREDOMINATE OVER ANY COMMON FACTORS IN DETERMINING WHETHER AND BY HOW MUCH ANY MEMBER OF THE PROPOSED CLASS WAS INJURED BY THE CHALLENGED CONDUCT**

23. The allegations in this matter concern the impact of the challenged agreements between pairs of Defendants to eliminate cold calling on compensation received by the Defendants'

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Declaration of Steven Burmeister in Support of Defendants' Opposition to Plaintiffs' Motion for Class Certification p. 3.

<sup>26</sup> For example, employee referral is the most important recruiting method for Adobe, accounting for about 35-40 percent of new hires. *See* Declaration of Jeff Vjungco of Adobe Systems Inc. in Support of Defendants' Opposition to Plaintiffs' Motion for Class Certification ("Declaration of Jeff Vjungco"), p. 2.

<sup>27</sup> Fichtner Depo. at 177:2-10. *See also* Declaration of Tina Evangelista, p. 1-2.

<sup>28</sup> *See* Declaration of Jeff Vjungco pp. 2-3, Declaration of Frank Wagner p. 10, Declaration of Chris Galy p. 2, and Declaration of Tina Evangelista p. 3.

salaried employees. The challenged agreements did not restrict other recruiting channels, prohibit hiring employees of other Defendants, limit how many employees could be hired, or fix wages or any other element of compensation.<sup>29</sup>

24. The five individual plaintiffs named in this lawsuit claim to represent virtually all persons who were salaried employees (or in the alternative salaried “technical” employees) of the seven Defendants at any time between 2005 and 2009. I understand that, in order to have such a class certified, Plaintiffs must demonstrate, among other things, both that common issues predominate over individual issues in determining whether class members have been injured by the alleged conspiracy, and that there is a reasonable way of quantifying the amount of damages owed to each class member without relying on individualized analyses. An economic analysis can support Plaintiffs’ claims only if that analysis explains how agreements that 1) do not reference or relate directly to compensation; 2) do not affect direct determinants of an employee’s compensation such as promotions or performance evaluations, and 3) do not restrict Defendants’ hiring nevertheless cause class-wide changes in compensation. Thus, the relevant economic issue is whether, given how labor markets operate, an agreement that potentially limited one of many recruiting methods by which employees at one Defendant might have been made aware of specific employment opportunities at another Defendant would reduce compensation received by all members of the proposed class.

25. Dr. Leamer’s theory has three essential elements. In particular, under his theory, in order for the alleged agreements to affect compensation received by members of the proposed class, 1) those agreements must materially reduce the level of information possessed by Defendants’ employees; 2) that reduction in information must lead to a reduction in compensation for those individuals relative to what they would have received absent the challenged agreements; and 3) the “rigid” nature of the compensation structures at the defendant firms must then generate a class-wide reduction in compensation through the pressure for internal equity. This sequence,

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<sup>29</sup> Pixar had a “gentlemen’s agreement” with Lucasfilm that it would not counter if Lucasfilm made an offer to a Pixar employee, and that Pixar would notify Lucasfilm if it (Pixar) made an offer to a Lucasfilm employee (see, McAdams Depo. (August 2, 2012) at 123:16-126:15, 134:23-135:6, 148:3-5).



which underlies Dr. Leamer's "price discovery" and "internal equity" frameworks, is speculative and inconsistent with economics and empirical evidence, as I show below.

**A. The Challenged Agreements Would Not Meaningfully Reduce the Supply of Information**

26. As a matter of economic theory, the impact of eliminating supply to the market from one source will depend on the size of the supply restriction and the elasticity of market supply – or the extent to which supply to the market from other sources increases when supply from one source is reduced. Here, it is the supply of "information" that allegedly was reduced by the challenged agreements. In Dr. Leamer's model, the reduction in the information that cold calling provides leads to less price discovery and lower compensation for all (or almost all) class members.<sup>30</sup> In effect, Plaintiffs and Dr. Leamer equate recruiting activity with information flow, and claim that reduced cold calling results in less information available to employees.

27. Class-wide impact of the challenged agreements on information possessed by employees at Defendant A would depend on the combined impact of (1) the importance of cold calling relative to other recruiting channels<sup>31</sup> and (2) the importance of other Defendants with which Defendant A has a DNCC agreement as a source of potential recruiting.<sup>32</sup> If (outside the class period) cold calling accounts for 25 percent of Defendant A's hires, while employees of other Defendants with which Defendant A has DNCC agreements account for one percent of Defendant A's hires, then the share of Defendant A's hiring potentially affected directly by the

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<sup>30</sup> Dr. Leamer assumes that *all* price discovery raises, rather than reduces, compensation, an assumption he neither acknowledges nor explains. It is possible that information gained by cold calling could reveal to recruiters (or employees) that current compensation is either above or below market.

<sup>31</sup> Cold calling is not clearly identified in the Defendants' data, and their recruiting managers explain in their declarations (and in my discussions with them) that this generally is not tracked. Therefore, I do not have available any specific measures of the importance of cold calling relative to other recruiting channels, other than information provided in declarations and interviews that cold calling generally does not account for a very large fraction of recruiting and the evidence from the Defendants' recruiting data that many employees were recruited through other channels such as employee referrals.

<sup>32</sup> Dr. Leamer does not disagree with this, but he simply claims that his conduct regression provides the "proof in the pudding" that there was an impact, which means that this combined effect must be large (Leamer Depo. at 40:4-25; 183:2-23; 413:21-414:7). However, as I explain below, his conduct regression is so flawed that it does not demonstrate impact.

agreements during the class period is only 0.25 percent (assuming that cold calling is as important in hiring from the Defendants with which Defendant A has DNCC agreement(s) as from firms in general). Even this likely would overestimate the effect, because it assumes that Defendant A did not expand its recruiting efforts by utilizing other recruiting channels more heavily. As explained below, the impact if Defendant A avoids cold calling employees of Defendants with which it has DNCC agreements is to make it more likely that another company's employee was hired (either someone from a Defendant with which Defendant A did not have a no cold call agreement, a non-Defendant, or even one of the Defendants with which Defendant A had a cold call agreement if that employee was recruited without a cold call), a process by which "lost" information is replaced.

**1. Evidence Shows that Employees of Other Defendants are not an Important Source of Recruits and Hires**

28. The likelihood that the challenged agreements affected employee compensation by reducing information depends on the relative importance of other Defendants' employees in a Defendant's recruiting efforts. Using Defendants' data, I summarized the former employer of Defendant's new hires.<sup>33</sup> The loss of cold-call opportunities from an agreement between Defendants A and B could not have a meaningful impact on the information available to and compensation earned by employees of either company if cross hires between Defendant A and Defendant B would have accounted for a very small fraction of their total hiring anyway.

29. Exhibit 3 shows the top 20 previous employers of new hires at each of the Defendants (based on recruiting data provided by Defendant).<sup>34</sup> A striking observation from this exhibit is that no single firm (not just the Defendant firms) accounts for more than six percent of hires at any Defendant, and that the top 20 firms combined typically account for less than 20 percent of

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<sup>33</sup> Despite the availability of this information (which I understand was provided by the Defendants in response to *Plaintiffs' First Set of Requests for Document Production*, October 3, 2011), Dr. Leamer claimed during his deposition that he had no way to quantify the importance of other Defendants as the former employer of new hires by a Defendant. *See Leamer Depo.* at 45:18-48:25.

<sup>34</sup> My staff standardized employer names in the recruiting databases to the extent possible (the prior employer field in the Defendants' data typically was self-reported by the applicant and was entered as free-form text).

total hires. Other Defendants account for at most three of the top 20 former employers at any Defendant, and collectively other Defendants typically accounted for less than three percent of total hires. Thus, even a policy that eliminated all hiring from other Defendants – which is much stronger than the limitation on a single recruiting channel from certain Defendants during certain periods that Plaintiffs challenge here – would not meaningfully affect the flow of information to class members. In fact, measured over all Defendants, hiring from other Defendants accounts for only about one percent of total hires.

30. Theoretically, these aggregate numbers could mask a narrower time period or narrower group of employees where other Defendants accounted for a substantial share of hires (and thus particular employees that might have been affected by the alleged conduct). But the extremely low level of hiring by one Defendant of employees of other Defendants (even outside the class period) implies that any reduction in cold calling because of the challenged agreements would not have any significant class-wide economic effect on the proposed class. Thus, even if there were an effect for individual employees or small groups of employees, an individualized analysis of the importance of other Defendants and of cold calling as a recruiting channel would be needed to identify those individuals, and quantify any damages they suffered.

31. The number of Defendant-to-Defendant labor market transitions that might have been initiated by cold calls as a fraction of all employee transitions to and from Defendants provides a way to summarize the amount of “information” and potential price discovery that could conceivably be lost by restrictions on cold calling among Defendants. Exhibit 4A shows the total number of hires and separations as a percentage of total employees at the seven Defendants, broken out by movements between Defendants versus between Defendants and other firms. Exhibit 4B shows these same figures for the Technical, Creative, and R&D class. As can be seen from these exhibits, the total movement of employees in and out of the Defendant firms is large and highly variable from year to year. At the same time, movements between the defendants are miniscule by comparison regardless if one looks before, during or after the class period. If hiring by one Defendant of employees from another Defendant were economically important in the price-discovery process, then employee movement between Defendants should account for a

substantial part of the overall movement of workers.<sup>35</sup> The exhibit shows that exactly the opposite is true. Even if *all* hires and separations to and from Defendants were initiated by cold calls, the amount of information lost and the potential impact on compensation received by members of the proposed class would be extremely limited both in terms of its magnitude and relative to other market level fluctuations, even before taking into account the incentive for recruiters to compensate by using other recruiting channels more intensively.

**B. Restrictions on Recruiting Methods Would Not Affect Market Compensation**

32. Market price (including the price employers pay for labor and thus the compensation earned by members of the proposed class) is determined by supply and demand for labor. The alleged agreements affected neither the supply of nor the demand for labor – in other words, they affected neither the number of available jobs nor the number of employees available to fill those jobs. Therefore, there is no reason why they would affect market compensation, or compensation of the class generally.

33. Even if, contrary to the evidence presented above, the decline in cold calling was sufficient to cause a meaningful decline in overall recruiting efforts, that effect would not necessarily reduce overall compensation and certainly would not reduce compensation on a class-wide basis. While a reduction in cold calling would reduce the number of firms contacting some employees, that same reduction in recruiting reduces the pool of potential hires for those firms by that same amount. The reduction in potential hires would raise the level of recruiting of other individuals and the level of compensation required to fill the open positions, which would put *upward* pressure on compensation at Defendants, the opposite of the effect hypothesized by Plaintiffs. The fact that the reduction in cold calling affects the options available to both employers and employees makes the overall impact on compensation ambiguous, even if it were material. Moreover, in this scenario, the fact that there would be more demand for some

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<sup>35</sup> Hiring should be a reasonable proxy for the price discovery process given that information on compensation is most commonly provided to candidates only at the later stages of the recruiting process (once the number of candidates has been reduced to a small group that then is interviewed for a job or job opening). Both Adobe and Intuit clearly state that they do not discuss compensation until the later stages of the recruiting process. *See* Declaration of Jeff Vijungco pp. 5-6 and Declaration of Chris Galy pp. 3-4.

individuals and less demand for others implies that the impact on compensation would not be common across members of the proposed class. Workers who remain in the pool of potential hires would stand to benefit, while those who are left out potentially would be harmed.

34. One job category common to all Defendants (and a large portion of both proposed classes) is software engineers. Employment opportunities for software engineers (and other types of employees) are widespread geographically and across industries, with any single employer, or even the seven Defendants collectively, accounting for only a small fraction of employment. As shown in Exhibit 5, Defendants accounted for two percent or less of employment of software engineers in the United States, and only about 10 percent of employment of software engineers in the industries in which the Defendants operate.<sup>36</sup>

35. The economics of labor mobility provides an additional reason why compensation of Defendants' employees will not be influenced meaningfully by changes in Defendants' recruiting and hiring practices. Employees are more willing to change jobs and to relocate geographically when they are young,<sup>37</sup> and the labor forces of several Defendants are very young. For example, as shown in Exhibit 6, ██████████ percent of employees hired at Google, Intel and Pixar were ██████████, and ██████████.

36. Exhibits 1A and 1B show that turnover of employees at Defendants (i.e., employees leaving or joining) is substantial.<sup>38</sup> During the class period, annual new hires at Defendants represented about 11.3 percent of the Defendants' average number of workers during a year, while annual separations (i.e., workers leaving Defendants) averaged 9.2 percent of the average number of workers employed during a year. This means that, on average, about 20 percent of Defendants' combined workforces were active participants in the job market in a typical year (in

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<sup>36</sup> I performed this comparison for software engineers and limited the analysis to industries in which Defendants compete (based on CapIQ information for the Defendants) simply to show that even this conservative calculation (focusing on software engineers because that is the profession of the named Plaintiffs and restricting total employment to firms engaged in businesses of the type (in a general sense) in which Defendants engage) demonstrates that Defendants account for only a small share of job opportunities.

<sup>37</sup> Robert H. Topel and Michael P. Ward, "Job Mobility and the Careers of Young Men," 107 *The Quarterly Journal of Economics* 2 (1992), p. 440.

<sup>38</sup> Details by Defendant are shown in Appendices 1A through 2D.

the sense that they had sought out a new job or been recruited by another employer, and thereby obtained information about compensation. This extensive employee turnover provides a natural source of information on market compensation to both employees and employers. The exhibit also shows that employee movements (or cross hires) between Defendants accounted for an extremely small fraction of total hires and separations of employees at Defendants.

37. Thus, data show that Defendants compete for employees against a large number of other companies. The competition may be more immediate with some firms than others, but the tendency is for compensation of employees with the same skills and experience to equalize across employers, because the labor markets in which these firms recruit and hire is broad and employees are mobile. The movement of employees into and out of Defendants and other firms means that Defendants' employees have access to a vast flow of information about market opportunities and compensation.

**C. The Alleged Conspiracy Would Benefit Some Members of the Proposed Class Even if it Harmed Others**

38. Even if the alleged conspiracy reduced the compensation received by some members of the proposed class because they did not receive information or a job opportunity because of a lost cold call, the necessary corollary is that it increased compensation of other members of the proposed class by opening up opportunities that they otherwise would not have received or, under Plaintiffs' theory, providing them with information that they otherwise would not have obtained. Thus, Plaintiffs' and Dr. Leamer's own arguments imply that the impact is neither uniform across class members, nor even harmful to all, but rather a mix of benefits to some caused by the same conduct that could, at least in principle, have injured others.

39. Defendants generally follow the same process for filling open jobs.<sup>39</sup> A manager with an open position reaches out to the company's recruiting department – to a “talent manager” or

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<sup>39</sup> Adobe, Intuit and Intel all describe the roles of managers, sourcers and recruiters as key to their recruiting processes. *See* Declaration of Jeff Vjungco p. 3, Declaration of Chris Galy p. 2, and Declaration of Tina Evangelista p. 2. Nearly all defendants use multiple sources to find potential candidates. *See* Declaration of Jeff Vjungco pp. 2-3, Declaration of Frank Wagner p. 10, Declaration of Chris Galy p. 2, and Declaration of Tina Evangelista p. 3.

recruiter who will assist with the search for candidates. The job opening is posted internally, either before or at the same time that it is posted on the company's jobs website and on third-party websites such as monster.com and LinkedIn.com. An important way of finding candidates is through employee referrals, which may not require any recruiter efforts (an employee makes a friend aware of an employment opportunity, and the friend then submits an application). To add to the pool of internal applicants and candidates referred by current employees, the recruiter may pursue a variety of avenues to identify additional candidates, including marketing, networking on websites such as LinkedIn, and attending and sponsoring job fairs. In order to fill some open positions (typically those that are more difficult to fill), some Defendants also use a "sourcer" who is responsible for making more active efforts to identify and initiate contact with potential candidates, including through cold calling.<sup>40</sup> Recruiters then generally use phone interviews and other screening methods to eliminate applicants that are unqualified, uninterested or inappropriate for the position, and to obtain a small group of promising candidates for in-person interviews. The manager ultimately decides who to hire.

40. Understanding the recruiter's role and incentives is important in evaluating whether Plaintiffs' claims make economic sense, and whether the impact that Dr. Leamer claims to estimate has a logical magnitude given the relevant institutional framework. The decision whether there is a job to fill and selection of who to hire generally is made by the manager, and the decision how to fill that job is led by the recruiter. The alleged agreements challenged by Plaintiffs affected only the methods used to find qualified job candidates. Since the role of a recruiter is to identify candidates to fill open positions, recruiters would find candidates through other channels if they were constrained from cold calling employees at certain companies by the alleged agreements (including by cold calling employees at other companies, such as Defendants with which there was no DNCC agreement, or recruiting employees at firms with which they have DNCC agreements through other channels). The net effect of the challenged agreements would be to *increase* the likelihood that candidates would be recruited, interviewed, offered a job, or hired through channels other than cold calling employees of a DNCC Defendant

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<sup>40</sup> See Bates Document 76550DOC000014.

(including cold calls or other channels directed at non-DNCC Defendants). Through that process, these other individuals would obtain the “information” about their value allegedly denied to the employees who did not receive the cold call (and possibly the benefit of a better job with one of the Defendants). The pool of such potential hires is vast; Adobe, for example, receives 100,000 inquiries a month on its adobe.com career site (the portal through which all applications begin),<sup>41</sup> while it is reported that Google received two million resumes in 2011.<sup>42</sup>

41. The consequence is that there could not be class-wide harm. Instead, some members of the class would benefit even if some were harmed, and distinguishing the two could not be done with common evidence such as that offered by Dr. Leamer. The class member who gets hired has benefited, according to the Plaintiffs’ logic, from the conduct that Plaintiffs claim harmed the class member who did not receive the cold call. The class member who is hired might be an internal hire (someone already working for the company who switches jobs and potentially receives a higher salary by doing so). Or the new hire might be a different external candidate, someone who was employed at one of the hundreds or thousands of firms that employs software engineers, hardware engineers, accountants, human resource professionals, etc., including Defendant firms where recruiters do not cold call but where employees have access to all the other methods (employee referrals, LinkedIn, monster.com, job fairs etc.) that recruiters use.<sup>43</sup>

42. The probability that one of those other candidates is called or hired increases with any reduction in potential hires through cold calls to a Defendant’s employees. The fact that the person hired (wherever he previously worked) accepted the job means that he was made better off by doing so. If he was previously employed by a non-Defendant, that person becomes a member of the class and (thus according to Plaintiffs’ claims) has been injured, even though he was able to obtain a better position *only because of the challenged conduct*.<sup>44</sup> Thus, under the

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<sup>41</sup> Declaration of Jeff Vijungco, p. 3.

<sup>42</sup> See <http://online.wsj.com/article/SB10001424052970203750404577173031991814896.html>.

<sup>43</sup> Fichtner Depo. at 144:5-21; 147:12-19.

<sup>44</sup> In Plaintiffs’ but-for world, this person would not have been hired; for him, it is irrelevant whether compensation for the position that he would not have received would have been higher.



very theory put forward by Plaintiffs, the challenged conduct would benefit some class members even if it harmed others. There is no class-wide harm, even if some individuals are injured.

**D. Employee Compensation is Highly Individualized and Therefore Determining Which (if any) Employees were Injured and By How Much Would Require Individualized Analysis**

**1. There is Tremendous Variation in Compensation Paid to Individual Employees**

43. The tremendous variation in annual compensation for members of the proposed classes at each Defendant shown in Exhibits 7A and 7B is at odds with a central tenet of Plaintiffs' theory – that a rigid compensation structure necessitates that changes in compensation for individual employees resulting from cold calls would be transmitted across the class.<sup>45,46</sup> In each year, the range of total compensation changes differs substantially across Defendants.

[REDACTED]

44. Thus, compensation does not move in lock step across the Defendants.<sup>48</sup> In any year during the alleged conspiracy period, some employees at a particular Defendant received a 10 percent raise, while others received no raise. This implies that, under Plaintiffs' theory, the

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<sup>45</sup> The data presented by Dr. Leamer supports this same conclusion. As I point out in my critique of Dr. Leamer's analysis below, his data show substantial differences in compensation even for individuals in one of the over 4,000 narrow job categories he analyzes. Even this understates the level of pay variation, since there is no reason individuals cannot be moved *across* job classifications in response to external pressure (e.g., promoted from Software Engineer 2 to Software Engineer 3).

<sup>46</sup> As I discuss below (and show in Exhibits 14A and 14B), this variation is not explained by individual characteristics – age, job tenure, sex – that Dr. Leamer takes into account in his regression analyses.

<sup>47</sup> Changes in base salaries also show very large variations (see Appendix 3A and Appendix 3B). I also show in Appendix 4A through 4D the distribution of compensation levels, which also show substantial variations.

<sup>48</sup> Company-specific performance also affects changes in employee compensation at a particular Defendant; for example, Pixar's bonuses are tied to the success of individual films (see, McAdams Depo. at 42:2-43:3).

propensity for salary changes for an individual employee to be propagated across his or her coworkers would vary substantially across members of the proposed class. In Dr. Leamer's terms, these data show that the requirement of "internal equity" and the degree to which employees received similar percentage compensation increases annually differ substantially across Defendants. His theory would have to be tested and evaluated for each Defendant separately to understand the source of the variation. In order to understand whether a cold call would have affected any employee's compensation and, if so, by how much, it is necessary to understand first why one employee received a much larger raise than the other.

## **2. The Composition of Total Compensation Differs Across Employers and Employees**

45. Exhibits 8A and 8B summarize the composition of compensation received by employees at the Defendants. These exhibits show that Defendants differ in their relative reliance on three components of employee compensation: base salary, bonus and equity (or options). For example, during the alleged conspiracy period, a [REDACTED]

[REDACTED] Since the degree to which compensation is individualized likely varies across the three types of compensation, the degree to which Plaintiffs' "internal equity" and rigid compensation structure theories apply would vary across Defendants as well.<sup>49</sup> This implies that the validity of the Plaintiffs' theory would have to be evaluated separately for each of the Defendants.

46. The composition of compensation also varies substantially across job titles within each Defendant. Exhibits 9A and 9B show the composition of total compensation for the jobs at Apple and Google that Dr. Leamer analyzes in his Figures 15 through 17.<sup>50</sup> [REDACTED]

[REDACTED]

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<sup>49</sup> Leamer Depo. at 278:25-282:22.

<sup>50</sup> Corresponding exhibits for other Defendants are in Appendices 5A through 5E.

[REDACTED]  
[REDACTED]. This variation implies that the validity of Plaintiffs theories would need to be established separately for each group of employees. Plaintiffs and Dr. Leamer have failed to do so.

47. The impact of differences in the composition of total compensation extends to the individual level as well. The difference in the share of compensation provided in base salary, bonus and equity means that the value to an employee of a cold call and any potential resulting job offer will depend on his preference for receiving compensation in different forms. A highly risk-averse employee or one who expects to change employers frequently may place little value on stock options, and may value expected bonus much less than a corresponding amount of base salary. Thus, an offer of substantially greater expected total compensation may be worth less to him if it consists of a large expected bonus and stock options than lower compensation from another company that provides almost all its compensation in base salary. These same factors will affect how an employer might respond when an employee receives an outside offer that he asks his employer to match; if the outside offer is heavily weighted toward stock options, then “matching” that offer might require only a small increase in base compensation.

48. The reliance on stock options by some Defendants creates another individualized inquiry, because the impact of the challenged agreements will depend on how soon an employee’s options will vest, and how many options he holds. All else equal, the same outside compensation offered to an employee without stock options at his current employer that would vest (allowing them to be exercised) in the near future will be more likely to interest a potential hire than when the same compensation is offered to an employee that holds substantial options that are unvested.<sup>51</sup> Consequently, the response by the employee’s current employer (if the employer wants to match the outside offer) also will likely differ.

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<sup>51</sup> For example, Plaintiff Siddharth Hariharan testified that, while employed by Zynga, he turned down an offer of employment elsewhere “[b]ecause I was still vesting at Zynga. I was not looking to work for another company where the equity was growing again, and I would have to start all over again” (Hariharan Depo. at 273:1-4).

**V. DR. LEAMER PROVIDES NO ECONOMIC SUPPORT FOR PLAINTIFFS' CLASS CERTIFICATION REQUEST**

49. Plaintiffs support their class certification motion with the Leamer Report, which they claim demonstrates that the challenged agreements suppressed the compensation of all or nearly all Class members<sup>52</sup> and so provides the required support for class certification. However, Dr. Leamer's analysis and the evidence he offers demonstrate neither that there was an average or "generalized" reduction in compensation of class members nor that "all or nearly all" members of the proposed class were undercompensated.<sup>53</sup> Dr. Leamer has not provided a class-wide method for proving impact or the amount of damages.

**A. Summary of Dr. Leamer's Opinions**

50. Dr. Leamer divides his analysis into three parts. First, he argues that "class-wide evidence is capable of showing that the non-compete agreements suppressed compensation generally,"<sup>54</sup> by which he appears to mean that, *on average*, members of the proposed class received lower compensation because of the challenged conduct. In support, he offers three types of evidence: (1) economic theory, which he says is supported by economic literature, of a link between (a) the amount of cold calling and (b) information flows about compensation and job opportunities, employees' "negotiating leverage," and movement of employees between firms; (2) Defendants' internal documents, which he claims demonstrate their concern about the impact of cold calling on compensation; and (3) empirical evidence that job "movers" receive higher compensation than "stayers," which he claims supports his conclusions that cold calling leads to "price discovery" that raises compensation. He explained at his deposition that he also

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<sup>52</sup> *Motion* p. 2-3.

<sup>53</sup> In his report, Dr. Leamer does not provide a clear definition of what he means by "all or nearly all." When asked at his deposition "[i]n your expert opinion, Dr. Leamer, what percentage are you confident class members were undercompensated?" he replied that "my opinion is that most members of each class were undercompensated," and when asked "what percentage is most" and asked to provide a "range," he responded "Greater than 50 percent" (Leamer Depo. 32:20-33:10).

<sup>54</sup> Leamer Report ¶65(heading IV.A, emphasis added).

regards his conduct regression as supporting his claim that the impact of the challenged agreements was to suppress compensation generally.<sup>55</sup>

51. Second, Dr. Leamer claims that “class-wide evidence is capable of showing that the non-compete agreements suppressed the compensation of *all or nearly all members* of the all-salaried employee class and technical class,”<sup>56</sup> which I interpret as an opinion that the “average” impact that he claims to establish through his first set of analyses reflects undercompensation of “all or nearly all” individual members of the proposed class, and not just harm to some members. To support this part of his argument, he again offers three types of evidence: (1) “economic theory” that, he claims, demonstrates that concerns with “internal equity” results in “somewhat rigid salary structures;” (2) Defendants’ internal documents, which he claims confirm concern with internal equity and “more specifically demonstrat[e] the broad effects on compensation of the Non-Compete Agreements;”<sup>57</sup> and (3) multiple regression analysis that, he claims, shows that compensation earned by individual class members is determined “largely by common factors and that Defendants maintained rigid salary structures such that one would expect Non-Compete Agreements to have widespread effects on compensation.”<sup>58</sup>

52. Finally, Dr. Leamer opines that “standard forms of econometric analysis are capable of computing the *aggregate* amount of compensation suppression” to members of the proposed

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<sup>55</sup> Leamer Depo. at 80:7-25 (“Q. How much information was suppressed between Apple and Adobe? A. Well, that would require a data set that I don't have. I already indicated, I don't have the cold calling agreements. I don't have the – I don't have the information on all the cold calling that was made and all the cold calling that was not made as a consequence of the agreement. And secondly, to translate that into some measure of information is going to be very difficult. It's no simple thing that you can do. So you need to carry out an econometric exercise to answer that question. And I haven't had a database that would allow me to do it. But I have indirectly done it through that damage model because I tell you that before or after, during comparisons, that tells you the impact of these agreements. Q. Your regression analysis? A. The regression, yeah.”). *See also* Leamer Depo. at 97:19-100:12.

<sup>56</sup> Leamer Report ¶100(heading IV.B, emphasis added).

<sup>57</sup> Leamer Report ¶101.

<sup>58</sup> Leamer Report ¶101.

class “caused by the Non-Compete Agreements.”<sup>59</sup> In other words, he claims to provide a statistical model for calculating aggregate damages and demonstrating causality.<sup>60</sup>

53. As I now explain, none of Dr. Leamer’s opinions are supported by proper economic analysis. Empirical evidence, including evidence he ignores as well as proper analysis and interpretation of evidence that he offers, contradicts his opinions and demonstrates that class members have not been injured “generally” and that there has been no harm to “all or nearly all” members of the proposed class.

**B. Economic Analysis Does not Support Dr. Leamer’s Claim that the Challenged Agreements would Reduce Information Flows, Limit “Price Discovery” or Affect Compensation “Generally”**

54. Dr. Leamer’s economic “theory” does not fit the facts of the labor market at issue here – one that is characterized by many ways of recruiting employees, a vast amount of information available to employees on available jobs and market compensation, mobile employees, and tremendous density of employers and employees in small geographic areas (where Defendants account for only a small fraction of employment and employee movement). In order to be useful, an economic model must fit the key characteristics of the industry or market that is being modeled, and Dr. Leamer has not attempted to match his “price discovery” framework and theory of compensation impact to available evidence on the amount of available information and the competitive nature of the environment in which Defendants and their employees operate.

**I. Evidence Shows that the Flow of Information and thus “Price Discovery” Would Not be Reduced by the Challenged Agreements**

55. Dr. Leamer relies on economic theory to link the challenged agreements to the widespread effect on compensation claimed by Plaintiffs. He claims that “[t]here are three economic frameworks that are particularly useful” in evaluating the impact of the agreements, and that these frameworks “explain various mechanisms by which anti-Cold-Calling agreements can suppress worker compensation generally.” He focuses primarily on the “market price

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<sup>59</sup> Leamer Report ¶135 (emphasis added).

<sup>60</sup> Leamer Depo. at 24:8-25:16.

discovery” framework, arguing that labor markets can have “very sluggish price discovery,” and that the “expensive and time-consuming task of uncovering and valuing the unique features of workers slows down the price discovery process.”<sup>61</sup> Consequently, Dr. Leamer claims, “many transactions ... occur at prices far from equilibrium levels.”<sup>62</sup> According to Dr. Leamer, “Cold-Calling is an important channel of information about outside opportunities” and “[a]bsent Cold-Calling, many labor contracts are negotiated in unequal bargains between informed and uninformed employees.”<sup>63</sup> The consequence, he concludes, is that the challenged agreements restrict price discovery by members of the proposed class and cause employees to be undercompensated. However, Dr. Leamer’s argument about “price discovery” is invalid, and the “logic” that he claims supports a link between reduced cold calling and class-wide reduced compensation is inconsistent with assertions that he makes to support that link.

**a. Dr. Leamer Exaggerates the Loss of “Information” from the Challenged Conduct**

56. Dr. Leamer provides no evidence of, and concedes he has not studied and does not know, how much information might have been lost to Defendants’ employees and potential employees from the challenged agreements.<sup>64</sup> Despite the central role that he claims cold calling by other Defendants plays in the price-discovery process, he provides, and concedes he has done, no analysis of Defendants’ recruiting and hiring flows – data that can be used to evaluate the impact that restrictions on cold calling among the Defendants would have on the amount of information available and thus (by his logic) on compensation of members of the proposed Class.<sup>65</sup>

57. Exhibits 4A and 4B, which I discussed above in Part IV.A.1, showed that movements between Defendants accounted for a very small fraction (roughly one percent) of the overall employee flows at Defendants, including during the periods before and after the challenged

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<sup>61</sup> Leamer Report ¶73.

<sup>62</sup> *Ibid.*

<sup>63</sup> Leamer Report ¶75.

<sup>64</sup> Leamer Depo. at 80:4-23.

<sup>65</sup> Leamer Depo. at 47:2-48:14.

conduct. Thus, any reduction in information flow from the challenged agreements would be extremely small relative to the level of the overall flow of information or to the natural year-to-year fluctuation in the flow of employees.

58. Plaintiffs and Dr. Leamer allege that the information flow that was lost to members of the proposed class occurs as a part of the hiring and recruiting process. The number of cross-Defendant hires is a good indicator of the importance of such reduced information flows, and data show that these were extremely small. This does not mean that, under certain circumstances, an employee could not benefit from additional information and opportunities obtained through a cold call. Some employees may have below-market compensation, may become aware of this only because of a cold call, and may then use the information gained to obtain greater compensation. However, even if the loss of cold calls resulted in lower compensation for some employees, it would not create class-wide harm. Indeed, under Plaintiffs' theory, that same conduct would benefit some members of the proposed class as I explained above.

59. Dr. Leamer also ignores the incentive of both employers (and their recruiters) and employees to compensate for restrictions in information flowing through one channel by increasing the information flow through other channels. As a matter of economics, the restriction on cold calling *among* the Defendants need not even reduce the total use of cold calling in their recruiting processes. For example, if recruiters at Intel did not cold-call employees at Google during certain periods, they likely increased cold calling to employees at the vast number of other firms from which Intel recruits (including other Defendants). They would also use other channels (e.g., job boards) more intensively if the restriction on cold calling employees at Google meaningfully restricted their ability to hire good candidates. Other firms, including both Defendants and non-Defendants, also would be expected to change their behavior and make additional cold-calls to the would-have-been targeted employees.

60. Exhibit 5 shows that the Defendants accounted for two percent or less of employment of software engineers in the United States, and only about 10 percent of employment of software engineers in the industries in which the Defendants operate (so many other employers had candidates with skills suitable for the Defendants). Consistent with results established above, these exhibits demonstrate that the reduced information flow through a limited channel would



not have a meaningful impact on the total flow of labor market information available to employees of the Defendants. Indeed, employees still would have access to the recruiting opportunities provided by firms other than the Defendants, as well as to Defendants' recruiting efforts through other channels.

61. A simple exercise illustrates the realities of this marketplace. As shown in Table 1 and Exhibit 1A, hiring from and movements to other Defendants accounted for roughly one percent of total hires over the class period. A conservative calculation to help understand how much information potentially could have been reduced by the challenged agreements could use the higher post-period (2010-2011) rate of 1.4 percent as a base of comparison, and measure the "lost" hires as the difference between the cross hire level in the post and class periods.<sup>66</sup> Inter-Defendant cross hires were lower by only about 0.3 percent of total hires during the class period, an annual difference in the number of cross hires of roughly 30 employees per year compared with total hires of about 8,800 per year and total departures of about 7,200 per year at Defendants, or less than two-tenths of one percent of Defendants' total labor turnover. In other words, if each of the 30 additional employees who moved from one Defendant to another provided "information" to both the firm that employee left and the firm to which it moved, there would be 60 additional "bits" of information annually to add to the total bits of information provided by employee movements of 16,000 bits of information ( $=8,800+7,200$ ), or an increase of 0.38 percent in the bits of information available to Defendants' employees.<sup>67</sup> Since employees obtain information on market conditions through other channels (such as new hires, co-workers actively seeking work elsewhere, internet sources, friends, etc.), the actual percentage reduction in information from all sources would be even smaller. Such a small difference would have no material economic effect on overall compensation

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<sup>66</sup> This calculation is conservative because, as I discuss above, using both the pre-class and post-class periods as a benchmark, there is no change in aggregate cross-hiring among Defendants during the class period. The slightly higher cross hiring in the post-class period may reflect the growth of Defendants and thus their increased share of employment overall.

<sup>67</sup> Even this percentage is much too large, because it assumes all information acquisition comes through employee movement and ignores information obtained by employees in other ways.

62. This change also is *de minimis* compared with year-to-year fluctuations in hiring and recruiting activity. Over the class period, hiring by Defendants varied from a high of almost 12,700 in 2005 to a low of roughly 4,100 in 2009, a range of roughly 8,500 employees per year. That range is more than 200 times the variation implied by the calculations above (roughly 30 employees per year) of what would be caused by the hypothesized reduction in cold calling due to the challenged agreements. Given the degree of fluctuation in hiring due to other forces, Dr. Leamer's claims that the impact of the challenged conduct was economically significant (implying effects as large as 20 percent of total compensation based on his Figures 22 and 24) imply a sensitivity to incremental information flows that is simply untenable given the marketplace realities.

63. Dr. Leamer provides no evidence of the importance of the information allegedly lost because of the agreements, the evidence presented above demonstrates that any such effect would be vanishingly small. His theory and empirical analysis ignore and are inconsistent with the nature of the relevant labor market, and his claim of class-wide impact is not grounded in consideration of the specific dynamics of information discovery that apply to the proposed class.

**b. Plaintiffs and Defendants Have Vast Amounts of Available "Information"**

64. Even if there were some groups of employees in some markets with limited access to information about appropriate compensation, so that incremental cold calling might affect employee compensation, Plaintiffs do not represent such a group. In particular, members of the proposed "Technical Employee" (and at least a large portion of the All-Salaried Employee) class are poster children for an informed labor force. The labor market in which they participate is characterized by extensive use of internet and other channels by both employees and employers to facilitate mobility and information flows, many publicly available data sources on salaries and opportunities, such as monster.com, dice.com, salary.com, etc.) and networking among both current employees and university graduates who are recruited by technology firms and maintain friendships and contacts with fellow students and colleagues.<sup>68</sup>

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<sup>68</sup> Fichtner Depo. at 45:9-46:4.

65. Dr. Leamer implies that the labor market from which Defendants hire (and where Defendants' employees obtain information that they can use when they negotiate their compensation) consists of hapless and poorly informed employees who "rely mostly on 'water-cooler talk' perhaps supplemented by Internet sources"<sup>69</sup> to obtain scraps of information, which they then use to bargaining weakly with employers who "often hire private consulting firms to provide aggregated information about 'market compensation'."<sup>70</sup> But this characterization lacks credibility. The agglomeration of Defendants and a large and constantly changing number of other employers of technical and other employees located in Silicon Valley and other geographic technology centers contradicts Dr. Leamer's (unsupported) implication that members of the proposed class are employed in jobs that "involve high costs for transactions [involving labor services] including time, money and *personal dislocation*."<sup>71</sup> The high rates of employee turnover (hiring and separations) at Defendants shown in Exhibits 4A and 4B, with the sum of annual hires and separations as a fraction of average annual employment between 10 and 25 percent during the conduct period, demonstrates the substantial flow of information of the type that Dr. Leamer claims was restricted into and out of these firms and contradicts Dr. Leamer's claims that these employees were immobile.

**c. "Lost" Information will not have Class-wide Impact if it is "Unique" to Individual Employees**

66. According to Dr. Leamer, the "expensive and time-consuming task of uncovering and valuing the *unique* features of workers slows down the price discovery process."<sup>72</sup> But his claim that cold calling helps uncover "unique" features of potential employees is inconsistent with his claim that there would be class-wide impact from reduced cold calling through the price discovery process. Indeed, he stated at his deposition that employers, including the Defendants,

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<sup>69</sup> Leamer Report ¶75.

<sup>70</sup> Leamer Report ¶75.

<sup>71</sup> Leamer Report ¶74.

<sup>72</sup> Leamer Report ¶73 (emphasis added).

often differentiate compensation across employees to account for such “unique” features.<sup>73</sup> The lost “information” would relate to the unique features of the worker who was not cold-called, and would not have any impact on employees without those “unique” features. To the extent that the price-discovery process is employee specific, then the effect of reducing cold calling also will be employee specific. There would be no class-wide impact.

**d. Dr. Leamer’s Claims about “Lost Information” and “Price Discovery” are not Supported by the Economic Literature**

67. Finally, Dr. Leamer claims that his information flow and price-discovery framework is “well-accepted in the economics literature.”<sup>74</sup> Neither the cited literature nor the broader economic literature provides support for his claims. One paper he cites (by Joseph Stiglitz) argues that the full-information neoclassical model has limitations for understanding many markets, including the labor market, but that paper does not by itself show or claim that economic models that acknowledge and incorporate information imperfections demonstrate that employees are “undercompensated” as a result of information limitations.<sup>75</sup> The other three economic papers he cites all involve the so-called “rockets and feathers” phenomenon, according to which prices might rise faster than they fall in markets with imperfect information.<sup>76</sup> Dr. Leamer cites these in support of his claim that restriction of information in the labor market leads to lower wages, but the “rockets and feathers” model does not imply that a *restriction* of information in the labor market would cause a reduction in wages. Rather, these models explain only why prices rise quickly in response to *positive* information but fall slowly in response to *unfavorable* information.

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<sup>73</sup> Leamer Depo. at 316:16-317:17. (“Q. Don’t internal promotions result in the price discovery process? ... A: I don’t know that it would be relevant. Because I’m thinking these internal promotions, the big bumps up that occur are – are compensation for people who turned out to be extraordinarily good ...”)

<sup>74</sup> Leamer Report ¶66.

<sup>75</sup> Joseph Stiglitz, “Information and the Change in the Paradigm in Economics,” 92 *American Economic Review* 460 (June 2002).

<sup>76</sup> The cited paper by Green et al. (2010) is an empirical paper documenting asymmetric price adjustment in a major over-the-counter financial market, not a labor market. The cited papers by Tappata (2006) and Yang and Ye (2006) develop theoretical models explaining asymmetric price responses.

68. The economic literature on bargaining with asymmetric information corresponds more closely to the mechanism by which Dr. Leamer hypothesizes that reduced cold calling affects negotiations and in turn results in under-compensation of members of the proposed class. Samuelson made an early contribution to this literature, showing that some mutually beneficial trades are foregone when parties have asymmetric information.<sup>77</sup> However, Samuelson's model does not establish that the resulting price is more favorable to the informed party than the price that would prevail with full information. Rather, he explains that an uninformed party who knows that the informed party has superior information will take this into account when formulating his strategy.<sup>78</sup> Similarly, more recent economic literature does not generally establish that the price that prevails with asymmetric information is more favorable to the informed party than the price that would prevail with full information, but instead demonstrates that some mutually beneficial trades are forgone when there is asymmetric information.<sup>79</sup> Indeed, Dr. Leamer asserts in his report that lack of information would disadvantage both employers and employees.<sup>80</sup>

69. Thus, the available evidence shows that the challenged agreements would not meaningfully affect information flows. Dr. Leamer's price discovery "framework" is not supported by the economic literature or by empirical evidence of Defendants' recruiting and hiring practices. Further, his argument that cold calling uncovers "unique" features of individual employees contradicts his claim that the challenged agreements had a class-wide impact.<sup>81</sup>

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<sup>77</sup> William Samuelson, "Bargaining Under Asymmetric Information," *Econometrica* 52 (July 1984).

<sup>78</sup> In a similar vein, Grossman and Perry (1986) study a sequential bargaining game with asymmetric information, and obtain similar results. *Ibid.* ("In order to calculate correctly his payoff, the uninformed player must anticipate and draw the proper inferences from the behavior of his informed opponent." p. 1004.) And see Grossman, Sanford J. and Motty Perry, "Sequential Bargaining under Asymmetric Information," Academic Press, revised February 2, 1986.

<sup>79</sup> Ausubel, Lawrence M., Peter Cramton, and Raymond J. Deneckere, "Bargaining with Incomplete Information," *Handbook of Game Theory*, Aumann, Robert J. and Sergiu Hart, eds., Vol. 3, Amsterdam: Elsevier Science B.V., chapter 50, 2002.

<sup>80</sup> Leamer Report ¶68-70.

<sup>81</sup> Leamer Report ¶73.

**2. Dr. Leamer Wrongly Claims that His Empirical Analysis of Defendants' Compensation Data Shows that Restricting Cold Calling Impedes the Price Discovery Process**

70. In addition to (wrongly) claiming that “economic theory” and economic literature show that reduced cold calling limited information flows and price discovery and thereby “suppress[ed] employee compensation on a widespread basis,”<sup>82</sup> Dr. Leamer provides empirical analysis that he characterizes as “additional *common* evidence capable of showing that restricting Cold-Calling would artificially suppress employee compensation by impeding the price discovery process.”<sup>83</sup> However, his data show instead that there is no common evidence of suppressed employee compensation.

71. Dr. Leamer claims that “a symptom of price discovery at work would be better compensation packages for those who moved between Defendants than for those who stayed.”<sup>84</sup> He says that his Figures 6 and 7, which compare the median base and total compensation, respectively, of employees that “move” between Defendants and employees that “stay” at a Defendant<sup>85</sup> in each year between 2001 and 2011, demonstrate this process.<sup>86</sup> However, even if this comparison were meaningful, it does not support his conclusion that the challenged agreements impaired information flows and price discovery.

72. First, the economics literature on between-employer mobility shows that job changers generally receive atypically large wage increases, so the pattern shown by Dr. Leamer would occur generally and is not evidence of disequilibrium.<sup>87</sup> Economic theory and evidence imply

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<sup>82</sup> Leamer Report ¶80.

<sup>83</sup> Leamer Report ¶89 (emphasis added).

<sup>84</sup> Leamer Report ¶91.

<sup>85</sup> Dr. Leamer describes “stayers” as “those who stayed” at a Defendant (¶91), but his “stayers” category also includes new hires. His “stayers” category only excludes from the Defendants’ total employees the individuals who moved between Defendants.

<sup>86</sup> There are very few “movers” in his data (only between 26 to 178 movers in a year) compared with tens of thousands of “stayers.” Dr. Leamer has not controlled for potential differences in mix between the few movers and the many stayers.

<sup>87</sup> Topel, Robert H. and Michael P. Ward, “Job Mobility and the Careers of Young Men,” *The Quarterly Journal of Economics*, May 1992. Bartel, Ann P. and George J. Borjas, “Middle-Age Job Mobility: Its

that an employee who moves likely will obtain a larger increase in compensation than observably similar incumbent employees for two reasons. First, as Dr. Leamer recognizes, employers must compensate employees for the cost of moving. Dr. Leamer acknowledges that the relevant disparity for evaluating whether compensation is “suppressed” must net out movers’ “moving costs.” However, he provides no evidence about the magnitude of such moving costs, and what portion of their higher compensation compensates for this, rather than reflects a disequilibrium in earnings. Second, the process by which “movers” are selected means that, *ex ante*, “movers” and “stayers” are not equivalent.<sup>88</sup> Employees who move on average will be “uniquely” attractive to the hiring firm (movers are, in effect, getting “promoted” and were chosen because they are desirable to another firm, perhaps because of their “unique” features (as Dr. Leamer says)), but their movement does not affect compensation generally because it reveals nothing about appropriate compensation for “stayers” and is not evidence that stayers would have received the same compensation increase if they had moved. In other words, compensation increases of “movers” do not increase the compensation of stayers. The vast economic literature on employee-firm matching supports exactly this conclusion but does not rely on disequilibrium or undercompensation.

73. Second, and critically, evidence that movers earn more than stayers is not evidence that their movement affects the compensation of stayers. Dr. Leamer’s comparison is static – it compares the compensation of movers and stayers in a particular year, but provides no evidence that the compensation of movers *affects* compensation of stayers. Yet, his price-discovery argument requires that the change in compensation for movers also changes the compensation of stayers. Without this unproven link (which he wrongly claims is closed by “internal equity” concerns that converts one person’s raise into raises for all employees), there is no support for

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Determinants and Consequences,” Working Paper No. 161, NBER Working Paper Series, January 1977. Borjas, George J. “Job Mobility and Earnings Over the Life Cycle,” Working paper No. 233, NBER Working Paper Series, February 1978.

<sup>88</sup> Topel, Robert H. and Michael P. Ward, “Job Mobility and the Careers of Young Men,” *The Quarterly Journal of Economics*, May 1992. Bartel, Ann P. and George J. Borjas, “Middle-Age Job Mobility: Its Determinants and Consequences,” Working Paper No. 161, NBER Working Paper Series, January 1977.

his claim that a restriction on information that would have been obtained through cold calls to employees of other Defendants affected compensation of class members generally.

74. Thus, Dr. Leamer's Figures 6 and 7 reflect the normal operation of labor markets and do not support his claim that "price discovery" was impaired by the alleged conduct or that the alleged conduct prevented compensation from reaching "equilibrium."

**3. Data do not Support Dr. Leamer's Claim that the Timing of the "Non-Compete" Agreements Prevented Increased Compensation to Members of the Proposed Class that Otherwise Would Have Accompanied Economic Expansion**

75. According to Dr. Leamer, "[i]t's not a surprise why these agreements were put in place in 2005"<sup>89</sup> because "the timing of the agreements coincided with periods of expansion that would otherwise have caused compensation of class members to rise."<sup>90</sup> He claims that this "expansion" period began in 2004, and that subsequently members of the proposed class received less equity compensation than would be expected absent the challenged agreements "if we use 2010 and 2011 as the relevant 'after expansion' period" (referencing his Figure 8).<sup>91</sup> Then, in his Figure 9, he uses data from Apple to support his claim that the timing of the agreements was motivated by Defendants' desire to avoid sharing improved profits during the expansion with employees. He claims that Apple data show that the "Apple Non-Compete Agreements went into effect when Apple revenues surged, and when the risk of sharing the gains with the workforce was a threat to the firms' high levels of profits," and that the comparison of average per-employee revenue at Apple with average per-employee compensation in his Figure 9 provides support for this conclusion. Dr. Leamer appears to view the timing of the challenged agreements as evidence that the Defendants' incentive to reduce information flows (equivalently, that the cost to them of informed employees) increased when their profits increased, so their incentive to enter into information-restricting DNCC agreements also increased at that time.

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<sup>89</sup> Leamer Depo. at 434:17-18.

<sup>90</sup> Leamer Report ¶94.

<sup>91</sup> Leamer Report ¶98.



76. However, data in Dr. Leamer's Figure 9 demonstrate the exact opposite trend from the one he claims. [REDACTED]

[REDACTED]

Exhibit 10 also shows that, for other Defendants as well, there is no evidence that the percentage of revenue accounted for by employee compensation declined during the conduct period, or that there was any change in trend consistent with Dr. Leamer's unfounded allegation about the Defendants' motivation or the challenged conduct's effects.

77. Dr. Leamer also implies that the challenged agreements caused a decline in equity compensation relative to what it would have been otherwise, claiming that the "market ...continued to improve in 2005 equity compensation fell, coincident with the initialization of the non-compete agreements."<sup>93</sup> But implying a causal connection between the decline in equity compensation and timing of the challenged conduct makes no sense for at least two reasons. First, many of the equity grants *received* in 2005 were made before the challenged agreements went into effect, so the decline in equity compensation in 2005 cannot result from the challenged

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<sup>92</sup> In his report, Dr. Leamer says that "[REDACTED]" while "Apple revenues per worker doubled from around \$500,000 in 2001 around \$1,000,000 in 2005," but this preceded the proposed class period rather than occurring during a period that Dr. Leamer uses in his regression analysis as a competitive benchmark (Leamer Report ¶99).

<sup>93</sup> Leamer Report ¶98. At his deposition, Dr. Leamer characterize the information in Figure 8 as "compatible with this notion that the 2005 agreements suppressed equity compensation" (Leamer Depo. at 438:13-14).

conduct.<sup>94</sup> Second, only the 90<sup>th</sup> percentile shows the effect that Dr. Leamer claims is evident – the mean and median lines for equity compensation as a percentage of compensation had declined from 2001-2003, but were virtually flat from 2003-2008 before rising in 2009 and then declining after the conduct period was over (according to Dr. Leamer’s argument) in 2010.<sup>95</sup> In addition, the decline in equity values in earlier years may have made options and stock grants less attractive to employees than other, more certain, forms of compensation.<sup>96</sup>

**C. Google’s “Big Bang” Does Not Support Plaintiffs’ and Dr. Leamer’s Claim of Class-Wide Evidence**

78. Dr. Leamer argues that Defendants’ “internal documents” constitute a form of “common proof” capable of demonstrating the class-wide impact of challenged agreements.<sup>97</sup> His discussion, however, centers around a single “interesting example of the impact Cold-Calling can have on compensation firm-wide,” namely Google’s compensation change in 2011 (the “Big Bang”).<sup>98</sup> Plaintiffs and Dr. Leamer imply that the timing of the Big Bang (“approximately two months after the DOJ’s antitrust investigation was made public”) was a direct result of the ending of the alleged agreements.<sup>99</sup> [REDACTED]

[REDACTED]

[REDACTED]

[REDACTED]

<sup>94</sup> Moreover, any impact of the challenged conduct would not be immediate. Employees would not suddenly forget any information on outside opportunities they had accumulated prior to the implementation of the challenged DNCC agreements.

<sup>95</sup> In addition, he dates the “Alleged Collusive Agreements” to “Before 2000” in his Figure 1 (*See* Leamer Report ¶21), yet here he claims that the conduct began in 2005.

<sup>96</sup> Indeed, the 2010 Google “Big Bang” compensation adjustment that Dr. Leamer points to as evidence of the common impact of the challenged agreements [REDACTED]

[REDACTED] *See* Part V.C below. I discuss the flaws in Dr. Leamer’s analysis of the Big Bang adjustment later in my report.

<sup>97</sup> Leamer Report, Section IV.B.1.

<sup>98</sup> Leamer Report at 107, 110.

<sup>99</sup> Leamer Report at 110.

<sup>100</sup> *See* Frank Wagner Declaration.

[REDACTED]

[REDACTED]

[REDACTED]

[REDACTED]

[REDACTED]

79. The fact that Google responded to a unique challenge from Facebook by instituting a change in compensation supports the view that compensation outcomes at Defendants were heavily influenced by factors that were specific to different Defendants at specific points in time. Thus, Dr. Leamer's discussion of Big Bang not only fails to demonstrate "common evidence," but in fact highlights the uncommon nature of evidence related to factors such as Facebook.

**D. Economic Theory and Empirical Evidence Refute Dr. Leamer's Claim that Defendants have "Rigid Compensation Structures"**

80. The second essential element of Dr. Leamer's analysis in support of Plaintiffs' class certification motion is evidence that, he claims, demonstrates "that the artificial suppression of employee compensation would have been widespread, *extending to all or nearly all members of the All-Employee Class.*"<sup>102</sup> To supplement evidence (which I discussed above) that he claimed showed the link between the challenged agreements and suppressed compensation generally, he offers three additional types of analysis that he says support his claim of wide-spread impact on class members:

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<sup>101</sup> See, for example, a November 2007 online article "Facebook Stealing Googlers At An Alarming Rate" (<http://techcrunch.com/2007/11/21/facebook-stealing-googlers-at-an-alarming-rate/>), a May 2008 online article "Google Finds That Perks Can't Keep Some Employees From Leaving" (<http://www.dailytech.com/Google+Finds+That+Perks+Cant+Keep+Some+Employees+From+Leaving/article11794.htm> "President of global communications and public affairs Elliot Schrage jumped ship to work at Facebook this last week. Just two months prior Sheryl Sandberg had left to become the number two executive at Facebook."), and a May 2009 Wall Street Journal online article "Google Searches for Staffing Answers" (<http://online.wsj.com/article/SB124269038041932531.html> "Concerns about a talent exodus have revived in recent weeks amid the departures of top executives, including advertising sales boss Tim Armstrong and display-advertising chief David Rosenblatt. Meanwhile, midlevel employees like lead designer Doug Bowman, engineering director Steve Horowitz and search-quality chief Santosh Jayaram continue to decamp to hot start-ups like Facebook Inc. and Twitter Inc.")

<sup>102</sup> Leamer Report ¶101 (emphasis added).

- Economic theory “implicating firm incentives to maintain worker loyalty by adhering to principles of internal equity through a rigid salary structure;”<sup>103</sup>
- Defendants’ internal documents that, he says, reflect adherence to internal equity principles and the impact of the challenged agreements on compensation;<sup>104</sup>
- Multiple regression analysis.

As I now explain, both economic theory and empirical evidence are inconsistent with Dr. Leamer’s claim that common evidence demonstrates a widespread impact on compensation of members of the proposed class through a rigid compensation structure.

### **1. Economic Theory Does not Support a Rigid Salary Structure**

81. According to Dr. Leamer, firms have incentives to maintain worker loyalty by maintaining a “somewhat rigid” salary structure to assure internal equity. However, he does not discuss the strength of this incentive relative to other compensation goals,<sup>105</sup> or circumstances in which a rigid salary structure promotes greater worker loyalty than would a more flexible compensation structure that emphasizes and rewards individual contributions. There is considerable difference between unionized workforces that employ seniority and other “objective” characteristics of workers in setting compensation, on the one hand, and the compensation systems of the Defendants that rely on individual performance and other individual characteristics to determine compensation and compensation changes.<sup>106</sup> Based on my interviews with compensation managers at each Defendant and my review of declarations

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<sup>103</sup> Leamer Report ¶101.

<sup>104</sup> I do not address the sparse evidence offered by Dr. Leamer in support of this claim in detail. However, I note that documents he cites relate to Google’s concern about cold-calling of its employees by Facebook, and not by another Defendant. This is evidence of the broad labor market for members of the proposed class, with new employers such as Facebook hiring rapidly at various times, and the unimportance of cold calling among Defendants in contributing to information flows and the “price discovery” process.

<sup>105</sup> For example, in their work, Terpstra and Honoree (2003) find that procedural equity is more important than internal equity to the university faculty in their sample.

<sup>106</sup> Freeman, Richard B. and James L. Medoff. *What Do Unions Do?* New York: Basic Books, 1984. p. 135. Hirsch, Barry T. “Sluggish Institutions in a Dynamic World: Can Unions and Industrial Competition Coexist?,” *Journal of Economic Perspectives*, vol. 22(1), Winter 2008. pp. 153-176.

filed in this matter, I conclude that there is substantial flexibility delegated to individual managers to determine employees' annual and periodic compensation adjustments, with individual merit (and relative ranking), and not just "internal equity," important in explaining compensation adjustments. Indeed, many Defendants encourage managers to draw such distinctions by requiring them to identify over- and underperformers and compensate them accordingly.<sup>107</sup> Moreover, Defendants differ in their compensation philosophies; for example, Intuit rejects internal equity as a goal and instead emphasizes "pay for performance" and differential compensation.<sup>108</sup> This implies that any impact working through a somewhat rigid wage structure would require employer-specific analyses that Dr. Leamer does not conduct.

82. According to Dr. Leamer, "a secure long-term relationship can come either from commitment (emotional or financial) to the mission of the organization, or from jointly owned firm-specific assets."<sup>109</sup> He cites a speech by economist Gary Becker to support this argument,<sup>110</sup> but in that speech Professor Becker discusses commitment only in the context of the family, and not in the very different context of long-term employment relationships. In any event, Dr. Leamer does not provide evidence that commitment to "the mission of an organization" results from internal equity.

83. Dr. Leamer also asserts that "equitable" compensation practices spread wage increases or reductions across broad categories of workers, but he makes no attempt to establish the

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<sup>107</sup> [REDACTED]

[REDACTED] See Declaration of Donna Morris p. 4, Declaration of Frank Wagner p. 4, and Declaration of Danny McKell p. 3.

<sup>108</sup> Intuit clearly state that it does not use internal equity. See Declaration of Mason Stubblefield pp. 3-4 and Declaration of Donna Morris pp. 3-4; 8-9. Adobe, Pixar and Intel also say that if the compensation of one employee changes, it does not affect the salary of other employees. See Declaration of Donna Morris pp. 3-4; 8-9; Declaration of Lori McAdams ("If an individual employee received greater compensation in response to an offer from another company, it would not have affected compensation throughout the company, or even within the employee's business unit, job family or salary range.") See also Declaration of Danny McKell p. 4 ("If an individual employee received greater compensation in response to an offer from another company, it would not have affected compensation throughout the company, or even within the employee's business unit, job family or grade level").

<sup>109</sup> Leamer Report ¶102.

<sup>110</sup> Leamer Report Footnote 123, referring to Gary Becker, "Nobel Lecture: The Economic Way of Looking at Behavior," 101 *Journal of Political Economy* 385 (June 1993).

importance of this effect, or even that it is present in this context. He cites an article by Alexandre Mas<sup>111</sup> to support his argument, but Mas does not consider changes in the dispersion of wages within an employer. Rather, he examines the effect on police union members' job performance of *across-the-board* wage cuts, a very different labor market and different event than the one at issue here. Dr. Leamer also cites an article by Albert Rees, "who describes the role of demand and the impact of market forces on salary structures of university faculty,"<sup>112</sup> but this article simply emphasizes the uncertainty inherent in how higher compensation received by a new or incumbent employee translates (if at all) into compensation adjustments for other employees to preserve "fairness," which does not support Dr. Leamer's claims.

84. Finally, Dr. Leamer ignores the fact that, if new hires transmit the information that results in adjustments to compensation of incumbent employees to maintain internal equity, there was no reduction in this source of information and thus no decline in any (hypothesized) pressures to adjust compensation to maintain internal equity. Plaintiffs do not claim that employment or hiring was reduced by the challenged agreements, but simply that Defendants agreed not to cold call employees of certain other Defendants for certain periods of time, resulting (according to their theory) in less employee movement between Defendants with DNCC agreements than would have occurred if those challenged agreements were not in place. However, if Apple did not cold call employees at Adobe, but instead cold called or otherwise recruited new hires from Microsoft, Yahoo! or any of the hundreds of other companies from which it obtained employees, then the same information was transmitted to Apple, and the same adjustments to maintain "internal equity" would have had to be made. Since Dr. Leamer has not shown – and indeed has not explicitly considered or analyzed – whether the challenged agreements resulted in any loss of information,<sup>113</sup> and the available evidence demonstrates that there was not, it is irrelevant

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<sup>111</sup> Leamer Report Footnote 126, referring to Alexandre Mas, "Pay, Reference Points, and Police Performance," 121 *Quarterly Journal of Economics* 783 (2006).

<sup>112</sup> Leamer Report Footnote 126. *See*, Albert Rees, "The Role of Fairness in Wage Determination," 11 *Journal of Labor Economics* 243 (1993).

<sup>113</sup> Leamer Depo. at 87:101-18; 4132-20.

whether principles of “internal equity,” merit or a combination govern compensation setting at individual Defendants.

**2. Compensation Adjustment Practices at Several Defendants Necessitate that in Some Circumstances Increased Compensation of Some Employees Results in Reduced Compensation of Others**

85. Based on my review of the compensation structure and practices of Defendants, I find no evidence of a rigid compensation system that would link together compensation changes within a Defendant, let alone at all Defendants. First, Defendants differ in the flexibility they offer managers to provide targeted compensation adjustments when an employee has an employment offer from another firm.<sup>114</sup> Second, none of the Defendants has a formulaic compensation system that links one employee’s compensation to another’s (the type of system that might be provided under a union contract, for example). Rather, all classify jobs by title, typically provide for a range of possible base salaries for employees with the same job title, and determine the employee’s position in the range based on individual characteristics, such as experience and, importantly, performance. Nothing in the compensation adjustment procedures causes salaries of everyone in a particular position to increase if a new employee is offered a higher salary than others receive; and nothing in the compensation adjustment procedures provides that an employee’s coworkers receive a salary increase if the employer increases one employee’s compensation in response to an outside offer. Further, the Defendants’ compensation practices would not prevent them from promoting a worker and changing his job classifications in response to external information that demonstrated the individual’s unique talents.

86. The common practice used by Defendants to make annual compensation adjustments is to use input from the third-party benchmark studies, such as Radford, as an important part of the

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<sup>114</sup> [REDACTED] sis (Declaration of Lori McAdams p. 6, Declaration of Danny McKell p. 4, Declaration of Michelle Maupin p. 10). Adobe, Google, Lucasfilm say that counteroffers rarely occur. *See* Declaration of Donna Morris p. 8, Declaration of Frank Wagner p. 10 and Declaration of Michelle Maupin 11. Adobe has specific guidelines about what can constitute a counteroffer. Adobe usually offered a one-time cash bonus and typically did not undertake salary adjustments. *See* Declaration of Donna Morris p. 9. Intuit typically does not make counteroffers, and when it does it usually uses restricted stock units for retention. Declaration of Mason Stubblefield, p. 6-8.

information considered in setting an overall budget for salary increases for the companies' employees. For example, in 2004, Intel budgeted a four percent change in employee salaries overall. Each manager then decided how to allocate her pro rata share of that budget in salary increases to her staff, guided in some cases by company policies. In 2005, Intel's guidelines for distributing the aggregate budgeted salary increase across employees were that employees who received the poorest performance ratings should get no salary increase, while those who received the top performance rating averaged over 10 percent salary increase.<sup>115</sup>

87. Given this system, a manager would have only limited ability to increase the compensation for a group of employees when one of those employees received a cold call.<sup>116</sup> Assume a manager at one Defendant learns that one of his engineers received a cold call from another Defendant, and that the engineer received a job offer with a 20 percent salary increase. Assume that the manager wants to match that salary increase, both for the individual who received the job offer and for other engineers with similar skills and responsibilities. This is an implication of Dr. Leamer's claim that cold calls provide information not only that the individual receiving a job offer is "undercompensated," but that "market" compensation generally is too low. If the manager's salary increase budget that year is five percent, he manages 25 employees, and he wants to give five of his employees a 20 percent "market adjustment," then his other 20 employees will receive much smaller increases than five percent (the exact amount depends on the salary distribution among those 20 employees). Thus, the budgeting process that drives compensation changes at Defendants essentially creates a system where granting above average salary increases to some employees may require that other employees receive below average increases, rather than the above average increases implied by Dr. Leamer's theory.

88. Dr. Leamer ignores the fact that the total amount budgeted for salary increases generally is based heavily on data from the compensation surveys performed by third-party companies like

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<sup>115</sup> Intel compensation data. 76583DOC001487.pptx

<sup>116</sup> Based on my discussion with compensation managers at the Defendants and my review of Declarations filed in this matter, I understand that Defendants infrequently counter outside offers because they consider an employee's willingness to pursue outside opportunities as evidence that the employee is disaffected for other reasons, and would remain so even if he received an increase in pay.



Radford, and not on idiosyncratic information obtained from new hires and separated employees.<sup>117</sup> The information each Defendant receives from Radford and similar firms is derived from data on salaries paid in a marketplace much broader than the Defendant firms and that information is specific to types of jobs at the Defendant, which then are matched with the same positions at the firms against which the Defendant benchmark employee compensation. An individual employee might be able to obtain a raise by threatening to move to another Defendant, but his ability to do so will not provide a basis on which the Defendant would decide to ignore market intelligence in favor of increasing salaries throughout the company. Due to the fixed budgeting process, it may even lead to smaller compensation increases for other employees, at least in the short run.

**3. Dr. Leamer's Analysis Wrongly Assumes that if Individuals' Compensation is Affected by *Some Common Factors* then *Only Common Factors* Potentially Affect Compensation**

89. Dr. Leamer claims that changes in compensation of a small number of employees (those who would have received a cold call from another Defendant but-for the challenged conduct) would have class-wide impact – that “Cold-Calling and related practices would be expected to increase compensation across the board rather than be narrowly focused on the skills that are most in demand at any point in time.”<sup>118</sup> To support this claim, he provides an empirical “common factors” analysis to show that compensation paid by Defendants to individual employees can be explained in part by common factors, such as experience, job title, and education. However, his analysis does not demonstrate that changes in compensation of a subset of (let alone a small number of ) individuals because they received a cold call would affect compensation class-wide. His analysis cannot distinguish the impact he hypothesizes from an alternative hypothesis that the level of compensation of Defendant’s employees is broadly

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<sup>117</sup> Indeed, Plaintiff Hariharan testified that he did not share compensation information with prospective or current employers when considering a new job (Hariharan Depo. at 104:105:18; 136:24- 137:12; 184:5-185:16).

<sup>118</sup> Leamer Report ¶120.

determined by competition in a vast labor market for similar employees and that adjustments for unique circumstances of particular employees are highly individualized.

90. Dr. Leamer's claim to be able to demonstrate that generally "the compensation of class members tended to move together over time"<sup>119</sup> is neither surprising nor informative about his claim of class-wide impact. Such movement is the hallmark of a competitive marketplace. As I explained above, the labor market in which Defendants compete for employees and in which members of the proposed class seek employment is broad and characterized by rapid and extensive flow of information through a variety of channels and high employee mobility. Thus, it is not surprising that "common" factors explain much of the variation in average compensation across employers and jobs. An employer who offered compensation that is not competitive with the market would have difficulty attracting and keeping good employees. At the same time, compensation varies across employees because each possesses unique characteristics that makes that individual more or less attractive to any given employer. Dr. Leamer never even examines pay variation within these job categories. If he had, he would have discovered that both the level and rate of growth of compensation vary greatly across individuals within his job categories (see Exhibits 11A and 11B).<sup>120,121</sup>

91. Dr. Leamer claims that "Defendants had highly structured compensation systems built on a two dimensional matrix with several grades and many titles,"<sup>122</sup> and that "high level management established ranges of salaries for grades and titles which left relatively little scope for individual variation."<sup>123</sup> He provides a regression analysis that he claims shows that "about

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<sup>119</sup> Leamer Report ¶130.

<sup>120</sup> The degree of variation with job categories will understate the ability of employers to differentiate pay across individuals, since it ignores the ability of employers to move individuals across job categories in response to "cold calls" or other events.

<sup>121</sup> Exhibits 11A and 11B show the distribution of annual changes in total compensation for the Apple and Google jobs that Dr. Leamer analyzes in his Figures 15 through 17. Appendix 6A through 6E show the distribution of annual changes in total compensation for the "major" jobs at the other five Defendants. I identify the major at these companies using the same algorithm that Dr. Leamer uses to identify the top ten jobs at Apple and Google.

<sup>122</sup> Leamer Report ¶121.

<sup>123</sup> Leamer Report ¶122.

90 percent of the variability in a class member's compensation can be explained" in each year by age, tenure, gender, location, job title, and employer.<sup>124</sup> Based on his regression results, Dr. Leamer concludes that "almost the entire variation in salaries within each firm at each point in time can be explained by a common set of employee characteristics."<sup>125</sup> The statistic on which he bases this conclusion is the "R-squared," a statistic that measures the fraction of the variance in the dependent variable that is explained by the independent variables and that lies between zero (no explanatory power) and one (perfect explanatory power). As used by Dr. Leamer, an R-squared of 0.9 or so means that the regression equation has a good "fit" and the independent variables (an individual's job title (which is employer specific), age, tenure, gender and location) do a good job of explaining the person's compensation.

92. Exhibit 12 compares R-squareds reported in Dr. Leamer's Figures 11 and 13 with the values when only the employer-specific job title variables are included, but not the employee-specific factors of age, tenure, gender and location. The exhibit shows that the "fit" of the regression is almost the same with or without the employee-specific variables. Dr. Leamer has not demonstrated, as he claims, that he has "controlled" for important employee-specific factors that even he would acknowledge affect an employee's compensation, but only that variation in compensation among employees is largely explained by employer-specific job titles, because employees with different employer-specific job titles have different levels of average compensation and there is wide variation in average pay across job categories.<sup>126</sup> However, the fact that job titles explain a large fraction of the firm-wide variation in compensation does not mean that there is not substantial variation in compensation within job titles in addition to the

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<sup>124</sup> Regression analysis is a statistical tool to measure the impact on a "dependent" variable (here, a class member's annual compensation) of changes in one or more "independent" or "control" variables (here, age, tenure, etc.), identifying the impact of the independent variables on the dependent variables by using data for many different individuals with different characteristics and/or different time periods with different values for the variables. For example, regression analysis can be used to understand the relationship between the amount of rainfall, sunshine and fertilizer (the independent variables) and crop yields (the dependent variables).

<sup>125</sup> Leamer Report ¶129.

<sup>126</sup> The wide variation in pay across job categories is a consequence of the broad definitions of the Plaintiffs' proposed classes. Hence, Dr. Leamer's finding of a high R-squared to a large extent reflects the heterogeneity of the Plaintiffs' class rather than any homogeneity.

variation across titles. In fact, the data used in Dr. Leamer's regression analysis show exactly the opposite.

93. A simple test of the ability of Dr. Leamer's regressions to explain compensation of individual employees is shown in Exhibits 13A and 13B. I use regression estimates from his Figures 12 and 14 to predict the compensation that would have been earned by each named Plaintiff in each year that he was employed by one of the Defendants. Two conclusions can be drawn from this table. First, for the most part, the named Plaintiffs were *overcompensated* relative to their predicted compensation based on Dr. Leamer's models – Brandon Marshall, for example, received 17.4 percent greater compensation in 2006 than the “rigid compensation schedule” asserted by Dr. Leamer predicts, while Daniel Stover received 15.4 and 1.7 percent less compensation than predicted in 2006 and 2007 respectively, and 37.9 and 8.4 percent more compensation than predicted in 2008 and 2009 respectively. Second, there is considerable variation across years and individuals in the difference between their predicted and actual compensation, which is inconsistent with a rigid compensation system.

94. The difference between predicted and actual compensation of named Plaintiffs resulting from Dr. Leamer's common factors regression analysis shows that, while an individual's job title and employer helps to explain his compensation, wide dispersion remains in the portion of his compensation that remains unexplained (even after accounting for employee-specific factors). This is illustrated in Exhibits 14A, which shows the distribution (based on the results in Dr. Leamer's Figure 12) of the difference between an individual's actual compensation and the compensation that Dr. Leamer's regression model predicts.<sup>127</sup> In each year and for each Defendant, there is substantial dispersion in the unexplained portion of compensation. For example, in 2007 – in the middle of his conduct period – the percentage difference between actual and predicted compensation was about plus or minus 10 percent (or more) for half of Adobe's employees, and plus or minus 15, 13, 5, 11, 5, and 9 percent for Apple, Google, Intel, Intuit, Lucasfilm and Pixar, respectively. In the same year, the percentage difference between actual and predicted compensation was about plus or minus 25 percent or more for 10 percent of

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<sup>127</sup> Exhibit 14B shows the distribution of differences based on Dr. Leamer's Figure 14.

Adobe's employees, and plus or minus 44, 40, 14, 29, 22, and 30 percent for Apple, Google, Intel, Intuit, Lucasfilm and Pixar, respectively.<sup>128</sup> Based on the 5<sup>th</sup> and 95<sup>th</sup> percentile salaries, his regression estimates imply that 10 percent of Google's employees in 2007 (accounting for approximately 900 classmembers) earned less than 40 percent or more than 40 percent of the "average" compensation predicted by his regression, which demonstrates that there was wide scope to differentiate pay across employees, even within the narrow job classifications he studies.<sup>129</sup> Therefore, contrary to Dr. Leamer's claims of a relatively rigid compensation structure, his regression model demonstrates that there is substantial variation in compensation earned by employees who have the identical values of the characteristics (including being in one of over 4,000 specific job titles in a typical year) included in Dr. Leamer's regression model.<sup>130</sup> This evidence shows that the Defendants did not have the type of formulaic compensation structure that would support Plaintiffs' claim that there would be class-wide impact from the challenged conduct.<sup>131</sup>

95. Even within a given job title, there is large variation in the amount of compensation unexplained by Dr. Leamer's regression model. Exhibits 15A and 15B show the distribution (based on Dr. Leamer's Figure 12 regression model) of the differences between the actual compensation and the compensation that Dr. Leamer's regression model predicts for the top ten Apple and Google jobs.<sup>132</sup> In 2007, ten percent of Software Developer Engineer 3 employees at Apple (which was the top ranking Apple job based on the algorithm Dr. Leamer used in his

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<sup>128</sup> The regression "fits" Intel data better simply because observations from Intel's employees constitute such a large portion (about 60 percent) of the regression data.

<sup>129</sup> This, of course, ignores the firm's ability to differentiate compensation across employees by moving high-performing and otherwise potentially "undercompensated" employees into new jobs with higher average compensation.

<sup>130</sup> According Dr. Leamer's data, between 2005 and 2009, the proposed All-Salaried Employee Class includes over 100,000 employees in about 7,000 different job titles, and the proposed Technical Class includes over 60,000 employees in about 2,400 job titles.

<sup>131</sup> As I noted above, even these figures understate the flexibility that the Defendants had to differentiate compensation in response to external pressure, because they ignore Defendants' ability to move individuals across job titles.

<sup>132</sup> The distributions of the of differences in actual and predicted compensation for the other five defendants are shown in Appendices 7A through 7E.

Figures 15 through 17) earned approximately 42 percent more or less than the compensation predicted by Dr. Leamer's model. Similarly for Software Engineer III employees at Google (again, the top ranking job), ■■■ percent of the employees earned plus or minus ■■■ percent of the compensation predicted by Dr. Leamer's model in 2007.

96. Together, the evidence on compensation means that individualized analysis would be necessary to determine the extent to which any individual was under- or overcompensated (relative to the assumed rigid wage structure) because of the challenged conduct rather than because of other factors, and to avoid paying damages to members of the proposed class who were not harmed by (and indeed could have benefited from) the challenged agreements.

#### **4. Dr. Leamer's Model Does not Demonstrate his Hypothesized Price Discovery Process Because it Cannot Explain Compensation Changes**

97. In Section V.D of my report, I discuss in detail the regression analysis (which I refer to as his "conduct regression") that Dr. Leamer offers as evidence that the challenged conduct affected aggregate compensation of members of the proposed class and that he uses to estimate the amount of undercompensation and damages allegedly suffered by the Class. That analysis, and the conclusions that Dr. Leamer draws from it, are inconsistent with his claim that there is a rigid compensation structure that allows him to infer that the (assumed) loss of information and reduced price discovery, combined with Defendants' commitment to "internal equity," causes localized price discovery to affect all members of the proposed class in a common way. Using his conduct regression estimates, I simulate the change in compensation over time of otherwise identical individuals based on the empirical distribution of "unexplained" compensation in each year for each Defendant.<sup>133</sup> The result shows how dramatically compensation can diverge over

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<sup>133</sup> I perform the following experiment. Assume that there are two individuals who are comparable in all characteristics in 2004. I randomly draw residuals (or the unexplained portion of their compensation) for each person, so that the only difference in their 2005 compensation is the difference in their residuals. I do the same in subsequent years and thereby predict the difference in their compensation in each subsequent year taking into account the persistence effects from the prior two years (based on Dr. Leamer's model) and the new randomly drawn residuals. I performed the same experiment 50,000 times to obtain a distribution of resulting compensation for individuals who were identical in 2004. The resulting distributions show how compensation of otherwise similar people (identical in all characteristics that Dr. Leamer claims explain an individual's compensation) can diverge over time.

time for otherwise comparable individuals due to the portion of an individual's compensation that remains unexplained by Dr. Leamer's conduct regression each year, the effect of which cumulates over time.

98. Compare, for example, two employees who, as of 2004, are identical in every characteristic controlled for by Dr. Leamer in his conduct regression (age, gender, company tenure, and location as well as current (i.e., 2004) and prior (i.e., 2003) compensation). By 2006, Dr. Leamer's conduct model implies that these two employees would, on average, have salaries that differed by 24 percent. By 2009, the difference between the compensation of the two individuals would be around 37 percent.<sup>134</sup> Such results, shown in Exhibits 16 and 17, demonstrate that otherwise identical employees can rapidly end up with tremendously different compensation. Thus, Dr. Leamer's conduct regression model contradicts his claim of a rigid compensation schedule. His own model estimates imply that he has no basis to conclude that individual changes in compensation would translate to class-wide effects through his claimed "somewhat rigid" wage structure. Empirical evidence shows wide variation in both the levels and rates of growth of employee compensation, even within job categories. As such, Dr. Leamer's results provide no support for Plaintiffs' claims that the amount of harm to members of the proposed class could be determined on a class-wide basis.

##### **5. Dr. Leamer's "Constant Attribute Compensation Ranking" Analysis is Misleading**

99. Exhibits 18A and 18B show that Dr. Leamer's evidence of "relatively stable" compensation trends within and across job titles masks substantial variation. I have converted his Figures 15-17 into annual changes in compensation, and expanded the analysis to include the

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<sup>134</sup> I excluded Lucasfilm and Pixar because of missing data for those two firms. Exhibit 16 shows the mean and the 90<sup>th</sup> percentile differences both by firm and overall. The 90<sup>th</sup> percentile figures indicate that ten percent of the pairs of employees would have compensation that differed by at least 56 percent after two years and by at least 86 percent after five years. Exhibit 17 shows the entire distribution of differences in each year from 2005 through 2010. In both exhibits, the numbers assume the two employees have the same job title in each year. If the two identically situated employees were promoted at different rates, then the compensation differences would likely be even larger.

top 25 job titles for each Defendant, rather than just the top 10 job titles for Apple and Google.<sup>135</sup> Dr. Leamer's claim that his Figures 15-17 imply that compensation increased in a "parallel" fashion across groups is highly misleading. The fact that the ordering of compensation across job titles is relatively "stable" over time does not imply that changes in compensation are in any way linked across job categories through concerns about internal equity or other forces. Indeed, Dr. Leamer admitted at his deposition that such evidence would be consistent with a wage structure that was not rigid.<sup>136</sup> Moreover, the maintenance of a roughly stable ordering does not even mean that changes in compensation are correlated, let alone causally related across groups.

100. Exhibits 18A and 18B examine the limited claim that changes in compensation are similar for the different job categories (which, even if true, would not be sufficient to establish a causal link of the form required by Dr. Leamer's theory). Changes in compensation are more relevant than compensation levels, because they more closely proxy Dr. Leamer's claims that changes in compensation for one group drive changes in compensation for others. If Dr. Leamer were correct that compensation across job titles was relatively stable, then one would expect that changes in average compensation for different job titles also would be similar in a given year. But Exhibits 18A and 18B show substantial variation across Defendants, and across job titles within Defendants, in "constant attribute compensation" changes, with large positive and negative changes in compensation across titles in a year and from year to year. The scale of his figures and the overall upward trend in compensation (which would be driven by market forces independent of any internal equity concerns) mask this variation.

**6. One Cannot Conclude that Because Some Defendants had Policies and Even Formulas for Annual Compensation Adjustments that a Limited Number of Additional Cold Calls Would Move the Structure**

101. Dr. Leamer's logic implies that a small number of "movers" hired at a compensation level that substantially exceeds that of current employees (e.g., 20 or 30 percent higher according to his Figure 7) ripples through the rigid compensation structures of Defendants to cause an

<sup>135</sup> I show charts for the top 10 jobs in Appendices 8A and 8B.

<sup>136</sup> "Q. Could a nonrigid wage structure, as you've defined it, lead to parallel lines? A. Yes, it could" (Leamer Depo. 283:23-25).



equivalent (or similar) increase in compensation of current employees. But, it is economically unreasonable to expect this to occur. A firm considering whether to offer employment to a candidate identified through a cold call who demands 25 percent greater compensation than earned by a “constant attribute” current employee would not make the hire if it required increasing compensation of *all* salaried employees by 25 percent (or even by a substantially lesser amount). In effect, hiring the cold-called employee would cost the firm not only 25 percent more than was earned by the person who previously performed the job, but higher compensation for *all* employees in the proposed class. An employer would be willing to offer a mover a substantial compensation increase (compared with current employees) only if any impact were limited to similar employees, or to only employees who directly gain information from the new hire, and not if it required a substantial increase in compensation of all employees.

102. One way in which an employer can respond when a valued employee receives an outside offer of higher compensation is by countering with a promotion to a position that provides higher total compensation. Because Dr. Leamer’s regression focuses on compensation *within* a job title, it would not be able to identify this type of effect, which occurs even if the firm’s wage structure is “rigid.” To explain, assume a firm has only two job titles: a junior software engineer position that pays \$75,000 and a senior software engineer position that pays \$125,000, and a junior software engineer receives an outside offer (as the result of a cold call) with compensation of \$110,000. The firm can respond by promoting the junior software engineer to senior software engineer with \$125,000 in compensation, without causing a “ripple” effect on compensation of other junior software engineers. Using data such as this, Dr. Leamer’s regression would show a perfectly rigid compensation structure (his R-squared would be 1), yet there is no ripple effect and the rigid structure reflected in the fixed relationship between compensation of junior and senior software engineers provides no information about whether the challenged conduct had any impact, let alone a class-wide impact.

**E. Dr. Leamer’s Econometric Model of “Undercompensation” Fails to Show Common Impact Because it is Flawed Both Conceptually and in its Implementation**

103. The third issue addressed by Dr. Leamer is whether “standard econometric analysis” can be used to demonstrate that the challenged agreements “generally” suppressed the compensation of members of the proposed class. He first presents a simple analysis of the change in total

compensation for Defendants – an analysis he later described as a “warm-up” exercise. He claims that this is “suggestive” evidence that there was undercompensation during the class period.

104. Dr. Leamer then performs a “conduct regression” to attempt to quantify the aggregate undercompensation from the alleged agreements. He indicated at his deposition that his “conduct regression” also had a central role in making up for the lack of direct supporting evidence for other parts of his theory. In particular, he said that even though he lacked evidence to evaluate and quantify the amount of “information” that was lost because of the challenged agreements, he did not need this evidence, because his conduct regression would show undercompensation during the conduct period *if* the amount of information lost was substantial enough to affect the price discovery process.<sup>137</sup>

105. Thus, Dr. Leamer’s conduct regression is not only offered to demonstrate that “standard forms of econometric analysis are capable of computing the aggregate amount of compensation suppression to the All-Employee Class and Technical Employee Class caused by the Non-Compete Agreements,”<sup>138</sup> and to measure aggregate damages,<sup>139</sup> but also as empirical support for his “conceptual framework” of information reduction and price discovery for which he has no other independent empirical evidence. His conduct regression is the lynchpin in his chain of logic; it links the “possibility” that the challenged agreements reduced cold calling and information and thereby hampered “price discovery” to a measurable impact on compensation both on average for the proposed class and, through his claimed “somewhat rigid” compensation structure, to each (or almost each) member of the proposed class.

106. However, Dr. Leamer’s conduct regression is also flawed in multiple ways. First, his implementation masks the fact that he has no evidence of common impact, but rather that the “undercompensation” effect he estimates is not common to all Defendants. When disaggregated

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<sup>137</sup> Leamer Depo. at 413:21-414:7 (acknowledging that he does not have evidence on whether the amount of cold calling declined during the conduct period, but stating that the regression will decide whether the effect identified in his (price discovery) framework is actually there).

<sup>138</sup> Leamer Report ¶135.

<sup>139</sup> Leamer Depo. at 24:8-25:36.

by Defendant, his own conduct regression model would show that some Defendants *overcompensated* their employees during the conduct period. Second, Dr. Leamer's statistical assumptions regarding his model are demonstrably false. In particular, his analysis assumes that compensation received by each of a Defendant's employees is determined independently, which is inconsistent with his claim of a "somewhat rigid" compensation structure. The lack of independence implies that his model estimates are highly imprecise, and are not reliable estimates or proof of class-wide impact. Third, Dr. Leamer's regression model is "fragile," and fails simple sensitivity tests. For these reasons, Dr. Leamer's conduct regression provides no support for Plaintiffs' claims that "class-wide methods and evidence are capable of showing that ... suppression of compensation affected all or virtually all Class Members."<sup>140</sup>

### **1. Dr. Leamer's "Warm-up" Exercise Demonstrates No Common Impact**

107. Before presenting his proposed "standard econometric analysis," Dr. Leamer provides in his Figure 19 "[a]n estimate of the effect of the Non-Compete Agreements on employee compensation [calculated by] contrasting compensation during the periods when the Agreements were in effect with compensation before and after the Non-Compete Agreements."<sup>141</sup> At his deposition, he referred to this analysis as a "warm-up to the regression analysis,"<sup>142</sup> a way of "illustrating how the before and after works."<sup>143</sup> Based on his review of "growth cycle periods for the U.S. economy" between 2001 and 2011 (summarized in his Figure 18), he concludes that he can illustrate the "before and after" methodology for measuring damages (which he also employs in his regression model) by comparing the average change in compensation at the Defendants (pooled together as if they were a single company) during the conduct period with "what was happening in relevant periods before and after."<sup>144</sup> He selects 2004 and 2011 as the relevant non-conduct periods, because he concludes that these years "reveal the kind of

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<sup>140</sup> *Motion* p. 3.

<sup>141</sup> Leamer Report ¶136.

<sup>142</sup> Leamer Depo. at 379:9-10.

<sup>143</sup> Leamer Depo. at 380: 21.

<sup>144</sup> Leamer Report ¶140.

compensation increases that occur in expansion periods that were similar to 2005-2007.”<sup>145</sup> Based on this comparison, he calculates “estimated underpayment” percentages for 2005-2009 for all Defendants as a whole.<sup>146</sup>

108. While Dr. Leamer uses Figure 19 as a “warm-up,” a fundamental problem with his regression analysis can be illustrated by an expanded version of his Figure 19 analysis. In Exhibit 19, I perform the same “before and after” comparisons as Dr. Leamer did in his Figure 19. The only change is that I perform the analysis for each Defendant individually rather than simply pooling them together. Dr. Leamer’s theory – and his claim that he “examined [his regression model] defendant by defendant” and then “made the judgment that it was better to pool across firms in order to create a more coherent, more efficient model”<sup>147</sup> because the “firms are sufficiently similar”<sup>148</sup> – implies that the same type of effect (namely, undercompensation during the conduct period) should be found for each Defendant individually. Plaintiffs’ claim of “common impact” implies, at a minimum, suppression of compensation at each individual Defendant that allegedly participated in the conspiracy.

109. However, as shown in Exhibit 19, Dr. Leamer’s Figure 19 methodology masks substantial underlying differences in estimated “undercompensation” at each Defendant. Indeed, according to his methodology, Intel and Google are the only two companies that “undercompensated” their employees during the conduct period, while the other five Defendants “overcompensated” their employees. Apple employees, for example, were “overcompensated” by more than 27 percent and Pixar’s employees by more than 70 percent. This suggests that Dr. Leamer’s Figure 19 shows an overall average result that *blends together opposite effects* at individual Defendants – he estimates an average negative effect only because two out of seven

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<sup>145</sup> Leamer Report ¶140.

<sup>146</sup> Dr. Leamer assumes that there would have been no change in compensation in 2008 and 2009 because of the weak economy.

<sup>147</sup> Leamer Depo. at 364:24-365:16.

<sup>148</sup> Leamer Depo. at 364:20-365:7.

Defendants show a negative impact, and one of the two Defendants (Intel) accounts for about 60 percent of the employees in the All-Salaried Employee Class.<sup>149</sup>

110. This “warm up” exercise (when disaggregated by company) should have raised a red flag for Dr. Leamer and caused him to consider whether his regression is capable of determining whether there is “common impact.” The large magnitudes of the effects also should have given him pause about the ability of his methodology to identify the effects of the challenged conduct, rather than reflecting the impact of other factors that differ between the conduct and non-conduct periods.

## **2. Dr. Leamer’s Common Impact across Defendants is Assumed, Not Demonstrated, in his Regression**

111. After using Figure 19 as an illustration, Dr. Leamer presents his “conduct regression” analysis, which he says “is a better approach because ... it allows for differences among defendants as well as for employees.”<sup>150</sup> He constructs a regression model that attempts to explain total annual compensation of individual employees (his Figures 20 and 23).<sup>151</sup> Using this model, he calculates annual “undercompensation percentages” by Defendant and year (his Figures 22 and 24).

112. As suggested by his Figure 19 analysis, the approach underlying Dr. Leamer’s regression analysis is fundamentally flawed because it *assumes* rather than establishes or demonstrates that the challenged conduct had common impact (lower compensation) at all Defendants (and for all or virtually all employees of the Defendants). Once disaggregated by Defendant, Dr. Leamer’s regression analysis completely fails to demonstrate common impact and implies instead that the alleged impact is not common across Defendants.

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<sup>149</sup> See Dr. Leamer’s Figure 3.

<sup>150</sup> Leamer Report ¶141.

<sup>151</sup> Dr. Leamer said at his deposition that total compensation is the relevant variable for analysis. Leamer Depo. at 121:8-21.

**a. Summary of Dr. Leamer's Model of Compensation**

113. Dr. Leamer's regression model uses real annual compensation of each employee in each year as the dependent variable, and includes the following independent variables:

- An indicator variable for when the challenged agreements were in effect (the "conduct variable"). This variable is essentially a dummy (or zero-one) variable that is turned "on" for a particular Defendant during the period when that Defendant allegedly participated in any of the challenged agreements.<sup>152</sup> Dr. Leamer also includes variables that represent the interaction<sup>153</sup> between the conduct variable and employee age (and age squared) and the hiring rate at a given Defendant;<sup>154</sup>
- "Persistence" (or lagged compensation) effects, which he claims reflect "how the effects linger over time;"
- Employee characteristics, industry characteristics, a time trend, and employer indicator variables. He includes these to control for "normal" variation in compensation across employees, within the industry over time, and across Defendants.<sup>155</sup>

114. Dr. Leamer's claims that his conduct variable alone and interacted with age and hiring rate together identify the immediate undercompensation caused by the challenged agreements. He uses the coefficient estimates on these variables (along with average employee age and hiring rate at a given company) to calculate "initial" annual undercompensation by company. Since his persistence variables purport to measure the extent to which undercompensation in one year remains in subsequent years, Dr. Leamer then combines his initial undercompensation estimates

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<sup>152</sup> Because 2005 and 2009 were not full "conduct" years, he assigns a value of 0.5 and 0.25 to the conduct variable in those two years, respectively.

<sup>153</sup> In a regression model, an "interaction" of two explanatory variables measures the multiplicative, or "joint" effect of the two variables on the independent variable.

<sup>154</sup> The hiring-rate variable is measured as the log of the ratio of new hires to the number of employees at the firm in the previous year.

<sup>155</sup> Leamer Report ¶ 142.

and the persistence effects to calculate total annual undercompensation by company (his Figures 22 and 24).<sup>156</sup>

115. At his deposition, Dr. Leamer acknowledged that the conduct variable in his model measures the *average* impact of the conduct across all Defendants, but claimed that the regression allowed for Defendant-specific measurement of the impact because he interacted his conduct variable with variables measuring the age of employees and hiring rate at each Defendant. Thus, he claims that, to the extent that employees at one Defendant are younger or their employer has a slower hiring rate than at another Defendant, the aggregate impact of alleged conduct will differ at the two Defendants. However, it is important to note that any commonality of the effect across firms is still assumed rather than demonstrated by his model, since his model forces the impact to be the same for two individuals of the same age as long as the hire rate is the same, even if those individuals are employed by different Defendants. He makes no provision for a Defendant's unique characteristics to affect the potential impact of the challenged conduct, even though his theory says that he should.

**b. Once Disaggregated, Dr. Leamer's Regression Does Not Show  
"Undercompensation" for All Defendants**

116. Given the nature of Plaintiffs' allegations, the question whether the impact of the challenged conduct was common across Defendants is critical to understanding whether there is class-wide impact and whether the impact can be measured on a class-wide basis. Thus, I have used the regression framework offered by Dr. Leamer to address this question. One way to do so would be to estimate the regression separately for each Defendant (which Dr. Leamer claims to have done);<sup>157</sup> however, as Dr. Leamer acknowledged in his deposition, despite the large number of individual observations for a particular Defendant (annual data for all employees who fit the criteria for belonging to the class), some of his coefficients are estimated only because he can

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<sup>156</sup> Figure 22 presents his results for the all-salaried employee class while Figure 24 presents his results for the technical employee class. I will focus my analysis on his results for that putative class (his exhibits Figures 20 and 22). The central conclusions are the same for the technical employee class though some of the individual results differ.

<sup>157</sup> Leamer Depo. at 365:8-16.

combine data across Defendants.<sup>158</sup> Therefore, in order to test whether the effect of the challenged conduct was similar across Defendants, I use a version of his regression that includes separate conduct variables for each Defendant (and also includes separate Defendant-specific interactions with age and hiring rate). By nature of the regression analysis, Dr. Leamer's estimate of the aggregate conduct effect reflects a combination of these disaggregated Defendant-specific estimates.

117. In Exhibit 20, I show results from the disaggregated model and compare them with Dr. Leamer's Figures 22 and 24 results.<sup>159</sup> In stark contrast to Dr. Leamer's "undercompensation" estimates (negative percentages) for all Defendants in every year between 2005 and 2009, the disaggregated analysis does not suggest common impact from the alleged conduct. In fact, for both the All-Salaried Employee Class and Technical Class, two Defendants (Lucasfilm and Pixar) show no "undercompensation" but instead "overcompensation" estimates (positive percentages) throughout the period. Google shows "overcompensation" for most years, while two other companies (Adobe and Intel) also show "overcompensation" for one or two years during the period. The "undercompensation" estimates for Apple – the "hub" of the network of agreements according to Plaintiffs and Dr. Leamer – generally are much smaller than Dr. Leamer's results. Thus, once disaggregated by Defendant, results from the conduct regression not only differ substantially from Dr. Leamer's reported "undercompensation" results in both magnitude and the *sign* of the estimated impact, but also vary greatly across companies and over time.<sup>160</sup>

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<sup>158</sup> Dr. Leamer's conduct regression includes many variables that only vary by year (for example, change in IT sector employment in San Jose) or by company by year (for example, the new hire ratio variable). As a result, the model becomes "overspecified" when estimated using annual data from a single company for the nine-year period (2003-2011) over which the regression is estimated.

<sup>159</sup> Detailed regression outputs from the disaggregated model are provided in Appendices 9A and 9B. In order to estimate a Pixar-specific conduct effect, I have included in my regression Pixar's revenue data after 2005 which were unavailable to Dr. Leamer. See "Pixar revenues 2005 - 2011.xlsx". Pixar was acquired by Disney in 2006. As a result its 2006 revenue was reported for only nine months. I annualized the 2006 number by multiplying the reported number by 12/9.

<sup>160</sup> Results of disaggregating by Defendant can also be illustrated using a simplified version of Dr. Leamer's regression. In Appendices 10A to 10C, I provide regression details and "undercompensation" estimates from an "aggregated" regression specification that includes a single conduct variable, and excludes interactions



118. Dr. Leamer should not be surprised by the finding of “uncommon” impact across Defendants if, as he believes, the challenged agreements had an actual impact (and was not just spurious or unrelated to those agreements). At his deposition, Dr. Leamer acknowledged differences across Defendants that would translate into different conduct effects even under his theory. These include the fact that the magnitude of the impact would depend on the level of the firm’s demand for internal equity, and the fact that demand for internal equity varies across firms; that “outside pressure” will affect the general wage structure at a firm and that pressure depends on the situation each firm faces; and that the extent to which information was reduced differed across firms.<sup>161</sup>

119. At his deposition, Dr. Leamer said that he did not provide results disaggregated by Defendant because efficiency (i.e., the ability of the data to identify and quantify the hypothesized impact of the challenged agreements) would have been reduced if he had done so.<sup>162</sup> He claimed to have “examined the models defendant by defendant “ and decided that the efficiency gain from pooling (combining) data for all Defendants was reasonable.<sup>163</sup> However, Dr. Leamer offered no specifics (other than acknowledging differences in results across Defendants), and no explanation how he weighed the importance of the efficiency gain from pooling against the potential for reaching the wrong conclusion about the impact of the challenged agreements. When the gain in “efficiency” is at the expense of the ability to analyze

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between conduct and age and hiring rate. Comparison with Dr. Leamer’s Figures 22 and 24 shows that the results are very similar for the All-Salaried Employee Class. While the results differ somewhat from Dr. Leamer’s for the Technical Class, the simplified version still shows “undercompensation” for all Defendants throughout the period. This suggests that results using the simplified specification will be informative as to the impact of disaggregation. In Appendices 11A to 11C, I provide regression details and “undercompensation” estimates from the simplified model, except that I now disaggregate the model by interacting company indicators with the single conduct variable (so now there are seven Defendant-specific conduct variables). As shown in Appendix 11C, there is large variation in the size and even the *sign* of the estimated effects. Three of the seven Defendants (Pixar, Lucasfilm, and Adobe) had no undercompensation, but rather the estimated impact of the challenged agreements was to *increase* compensation. The estimated negative impacts at the other four Defendants vary greatly in magnitude and differ substantially from Dr. Leamer’s undercompensation percentages.

<sup>161</sup> Leamer Depo. at 257:8-14.

<sup>162</sup> Leamer Depo. at 364:8-365:1.

<sup>163</sup> Leamer Depo. at 365:3-366:2.

the question at issue – namely, whether or not there is common impact, or indeed any impact consistent with the economic theory of how failure to cold call a few employees at a few companies translates into class-wide harm – it is senseless to claim (as he did) that the efficiency gain from pooling data is appropriate. Doing so simply allowed Dr. Leamer to conclude that his estimates were more “precise,” even though his estimates were not meaningful.

120. Thus, Dr. Leamer’s own regression specification and statistical methods (which I critique further below) show substantial variation across Defendants in the estimated impact, with some employees “overcompensated” as the result of the challenged conduct.<sup>164</sup>

### **3. The Statistical Framework Underlying Dr. Leamer’s Analysis is Improper**

121. In his Figures 20 and 22, Dr. Leamer reports standard errors and t-values to test the statistical significance of his estimated coefficients (and thus to test his hypothesis that the conduct reduced employee compensation). In calculating these values, Dr. Leamer assumes that the compensation of each individual employee is independent of those of other employees. However, the estimated impact of the challenged agreements on compensation are highly “statistically significant” only because Dr. Leamer ignores a critical and obvious feature of his data – that his observations are correlated, not independent, especially under his own theory of how an individual’s compensation is determined. This is a major error in statistical inference.

122. All else equal, a regression model provides more statistically reliable estimates the larger the amount of data with which the coefficients are estimated. However, if the data, although voluminous, largely reflect a common impact, then the number of individual observations (in this case, the number of employee-years for the Defendants) is a highly misleading measure of the ability to evaluate statistically whether the regression is identifying an underlying relationship

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<sup>164</sup> Even the disaggregation by Defendant is insufficient to capture variation in the impact of the challenged agreements (if there were any impact), because that effect would differ by job type. Analyses disaggregated across Defendants are informative only under the (unsubstantiated and wrong) assumption of a rigid compensation system that imposes formulaic adjustments across all types of jobs, locations, etc. within a firm, an assumption that is not consistent with the evidence.

between the variables. This problem is widely recognized in the econometrics literature generally and the labor empirical labor economics literature in particular.<sup>165,166</sup>

123. Dr. Leamer's regression suffers from a severe version of this problem. Dr. Leamer's sample contains over 500,000 individual observations, but fewer than 60 unique combinations of employer and year (and thus effectively fewer than 60 observations from which to estimate his conduct variable).<sup>167</sup> This means that Dr. Leamer has almost 10,000 observations per group (per employer-year), so his statistical analysis greatly overstates the effective sample size and the resulting precision of his estimates.

124. Dr. Leamer treats each Defendant's employees as if he or she provides completely independent information about the underlying structure by which compensation is determined at an employer. But the supposed rigid compensation structure (and thus lack of independence) is a critical feature of the economic framework on which he relies for his conclusion that the challenged agreements to reduce cold calling reduced price discovery, which rippled through the compensation of all members of the proposed class because of the Defendants' rigid compensation system. He failed to take into account when performing his statistical test that, aside from the challenged agreements, employees at a firm are affected by common factors that influence their compensation – e.g., a highly successful movie at Pixar can result in large and unusual bonuses for all Pixar employees, or a short-term reduction in the demand for PCs and the

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<sup>165</sup> This problem is well known in the econometric literature. In their econometrics textbook, Russell Davidson and James MacKinnon describe the potential error of ignoring the correlation between across observations within a given dataset: "If it is thought that the within group correlation  $\rho$  is small, it may be tempting to ignore it and use OLS estimation, with the usual OLS covariance matrix. This can be a serious mistake unless  $\rho$  is actually zero, since the OLS standard errors can be drastic underestimates even with small values of  $\rho$  ... The problem is particularly severe when the number of observations per group is large.... The correlation of the error terms within groups means that the effective sample size is much smaller than the actual sample size when there are many observations per group" Davidson, Russell and James G. MacKinnon. *Econometric Theory and Methods*. Oxford University Press, Inc. 2004, p. 305.

<sup>166</sup> Greene, William H. *Econometric Analysis*: 6th Edition, Chapter 9.3.3 New Jersey: Pearson Prentice Hall, 2008. Angrist, Joshua D. and Jörn-Steffen Pischke, *Mostly Harmless Econometrics*, Chapter 8.2. New Jersey: Princeton University Press, 2009.

<sup>167</sup> Dr. Leamer's conduct regression includes data for seven companies over nine years (2003-2011). However because he lacks revenue data for Lucasfilm and Pixar for some years, his regression includes only 55 employer-years.

microprocessors that power them can cause a decline in Intel's revenue and profitability and lead Intel to impose a wage freeze such as occurred in 2009.

125. Dr. Leamer's independence assumption is inconsistent with his claims of a rigid compensation structure and with Plaintiffs' claim that compensation of all members of the proposed class would move together. According to Plaintiffs and Dr. Leamer, a "shock" such as an increase in information about compensation obtained through cold calling would affect compensation generally, and the impact would not be limited to only the employee who receives the cold call. Statistically, this means that compensation of individual employees – within a Defendant and within a year – are related or correlated in a way that must be accounted for in making statistical inferences. Put differently, although Dr. Leamer's regression estimates are based on over 500,000 individual observations on employee compensation, the information that is informing his estimates is much more limited, and any statistical inference from the regression estimates must take this into account.

126. A generally accepted method to take into account the fact that observations used to estimate a regression contains "groups" of observations that are affected by certain common factors (such as those affecting a particular company or present in a single year) is commonly referred to as "clustering" the standard errors. Dr. Leamer not only failed to implement this (or any other) methodology to address the underlying nature of his data, but he did not even acknowledge in his report that his reported standard errors and resulting t-statistics (used for testing whether the estimated impacts of variables hypothesized to affect compensation were statistically significant, and unlikely to result from chance) were not meaningful. It is as if Dr. Leamer had estimated a regression to explain the price of milk per ounce by state using data on the price per ounce of pints, quarts, half gallons and gallons sold at grocery stores in each state and treating the various package sizes at a store as if they provided completely independent information. A proper analysis would have to recognize that a store that sells high priced gallons likely sells high priced pints as well, and if the price of gallons rises at that store (say, because it is far from the dairy and there is a spike in the cost of gasoline needed to deliver the milk to the store), then the price of all package sizes will increase. The "power" of the regression to identify the impact of gasoline price, distance from a dairy, store quality, etc. is not enhanced by

including individual observations on prices of four different package sizes at a particular store, because all reflect the same underlying information.

127. Dr. Leamer recognizes that it is improper to rely on the independence assumption in cases such as this.<sup>168</sup> When asked at his deposition about whether his failure to cluster his standard errors was equivalent to “counting your wealth in small change” Dr. Leamer admitted that it “seems like appropriate use of that language” to describe “having lots of individuals but only having one experiment at a firm.”<sup>169</sup>

128. “Clustering” standard errors is commonly used in studies of labor markets and widely accepted as necessary in analyses such as this.<sup>170</sup> In Exhibits 21A and 21B, I show coefficient estimates and other details from Dr. Leamer’s Figure 20 and 23 regressions, except that the standard errors are now clustered on employer-year. The conduct variable (line 4 in the table) is not statistically significant under these proper standard errors. In Exhibits 22A and 22B, I further show t-statistics and p-values (which are used to determine statistical significance) calculated for Dr. Leamer’s “undercompensation” estimates in his Figures 22 and 24.<sup>171</sup> This exhibit shows that *none* of Dr. Leamer’s “undercompensation” estimates for any employer or year is statistically significant at conventional levels under the properly computed standard errors. The p-values imply that Dr. Leamer’s estimates are completely consistent with there being no true effect of the desired conduct and his estimates resulting entirely from random factors unrelated to that conduct. Thus, once properly analyzed, Dr. Leamer’s conduct regression provides no meaningful evidence that the challenged agreements reduced compensation of members of the proposed class.

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<sup>168</sup> Leamer Depo. 374:6-18.

<sup>169</sup> Leamer Depo. at 375:19-376:5.

<sup>170</sup> Angrist, Joshua D. and Jörn-Steffen Pischke. *Mostly Harmless Econometrics*, Chapter 8.2. New Jersey: Princeton University Press, 2009 pp. 308-315 and Greene, William H. *Econometric Analysis: 6th Edition*, Chapter 9.3.3 New Jersey: Pearson Prentice Hall, 2008, p. 188.

<sup>171</sup> Standard errors for the annual “undercompensation” estimates are calculated using a bootstrap method..

**4. Dr. Leamer Does not Report any Sensitivity Tests from which to Evaluate Whether his Results are Robust or Fragile**

129. Dr. Leamer wrote many years ago that “[t]he econometric art as it is practiced at the computer terminal involves fitting many, perhaps thousands, of statistical models. One or several that the researcher finds pleasing are selected for reporting purposes.” As a consequence, he wrote, “[i]t is . . . much more efficient for individual researchers to perform their own sensitivity analyses, and we ought to be demanding much more complete and more honest reporting of the fragility of claimed inferences.”<sup>172</sup>

130. Consistent with this view, Dr. Leamer responded at his deposition as follows:

Q. Would you agree, Dr. Leamer, that someone who is evaluating the conduct regression analysis would have to reserve judgment on its reliability until that evaluator saw sensitivity analyses related to the regression?

A. I would think that the sensitivity analysis would help to determine reliability.

Q. And how sensitive is your regression analysis?

A. First, you need to know, I did not carry out a complete sensitivity analysis. I have a record of econometrics that discusses how this should be carried out, and this isn't something I've done. But I have estimated more than one model, more than one that you see in the document, and there is some dimensions in which it's not sensitive and it's sturdy, but there's some dimensions of variability in which the changes can be substantial.<sup>173</sup>

He testified further that “there are some variability – some directions of variability in which the conclusions with change substantially. And I made econometric and economic judgments about the coherence of the models that are produced, the accuracy of the estimates that are implied by the model, and selected . . . this one as my suggested model . . . that demonstrates the method by which damages can be computed.”<sup>174</sup>

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<sup>172</sup> Edward E. Leamer, “Let’s Take the Con Out of Econometrics,” 73 *The American Economic Review* 1 (1983).

<sup>173</sup> Leamer Depo. at 356:1-20.

<sup>174</sup> Leamer Depo. at 358:8-18.

131. Dr. Leamer's report (and the backup data, documentation and computer programs he provided) contain no evidence of any sensitivity analyses.<sup>175</sup> Thus, it is unclear what alternative models Dr. Leamer tried to fit to the data. He acknowledged a specification "which has to do with disaggregation with data by a defendant,"<sup>176</sup> and "examin[ing] the models [ ] defendant by defendant."<sup>177</sup> He also said that "I've carried out an extensive sensitive [sic] analysis in several different directions, not a complete one, but it's substantial,"<sup>178</sup> but he did not describe any of those other directions. Thus, it is unclear what alternative models Dr. Leamer tried to fit to the data.

132. The results I provided above – allowing the impact of the conduct to differ across Defendants – clearly show the fragility of the single regression specification that Dr. Leamer reported. Another common way of testing the robustness of a regression specification, and of the conclusions that can be drawn, is to verify that the results are robust to changes in the time period for which the regression is estimated. Dr. Leamer bases his conclusion that the challenged agreements reduced compensation on a regression that compares compensation during the class period (essentially 2005-2009) to the combined periods before (effectively, 2003 and 2004) and after (2010 and 2011). An alternative specification to test robustness is to use only the before period, or only the after period, as the "control" or benchmark period in the regression and test whether the challenged agreements affected compensation of members of the proposed class.

133. Exhibit 23 shows that Dr. Leamer's model fails a test of whether it is robust to differences in the estimation period.<sup>179</sup> Using only the pre-period as the benchmark, Dr. Leamer's conduct regression implies generally substantial, but very different, estimated undercompensation percentages than reported in his Figures 22 and 24 – almost twice as large

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<sup>175</sup> Leamer Depo. at 359:6.

<sup>176</sup> Leamer Depo. at 360:16-18.

<sup>177</sup> Leamer Depo. at 365:15-16.

<sup>178</sup> Leamer Depo. at 366:7-9.

<sup>179</sup> Detailed regression outputs are provided in Appendices 12A to 12D.

for several Defendants but substantially lower for Intel. Using only the post-period as the benchmark, Dr. Leamer's conduct regression implies virtually no undercompensation, but instead overcompensation of roughly the same magnitude (though opposite in sign) from the effects he reports in Figures 22 and 24.

134. Another sensitivity test of Dr. Leamer's model is to first estimate his conduct regression using data outside his conduct periods, and then use the coefficient estimates to predict compensation during the conduct period. If Dr. Leamer's model is robust, one would expect the predicted compensation to be generally higher than actual compensation during the conduct period. However, as Exhibit 24 shows, the predicted compensation levels are in fact lower than actual compensation (and therefore implying "overcompensation") at two Defendants in all years, and five Defendants in at least some of the years.<sup>180</sup> Dr. Leamer's model again fails the sensitivity test.

#### **5. Dr. Leamer's Regression Model Does Not Explain Changes in Compensation Over Time**

135. The analysis presented above showed that the statistical conclusions that can be drawn from Dr. Leamer's regression model are fundamentally different once we account for the correlated nature of his data. That correlation implies that there are important factors that drive firm-level compensation that are not accounted for in his model. Given that his methodology relies on comparison of the actual level of compensation to the level that his model would predict, obtaining a reliable prediction of compensation absent the challenged agreements is critical to estimating the impact (if any) of those agreements.

136. Exhibits 25A and 25B show that the factors that Dr. Leamer does not account for are quantitatively important. I plot the difference, by company and year, between the average compensation earned by a firm's employees and the average level of compensation predicted by Dr. Leamer's conduct regression (Figures 20 and 23). The exhibit shows that these prediction

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<sup>180</sup> Detailed regression outputs are provided in Appendices 13A and 13B.



errors are substantial (in Dr. Leamer's terms, economically significant<sup>181</sup>) and are not evenly distributed across years and Defendants (as would be expected if the model were capturing virtually all the factors that explain an individual's compensation – one of which, according to Dr. Leamer, is whether the Defendant had a challenged agreement with another Defendant). Rather, the model predicts very poorly in some years for some companies, which means that important factors that are unique to compensation outcomes at different Defendant companies in different years have been left out of the regression. Large average differences between employees' actual and predicted compensation are evident, with the most extreme examples being Google in 2003 and 2004 and Pixar in 2004.

137. I performed a standard statistical test for whether there are important factors explaining firm-level compensation that are omitted from Dr. Leamer's regression model. This test essentially examines the average residuals from his regression by company and year (the variation in compensation not explained by his model) and asks whether those average residuals are too large to be explained solely by sampling error. The test resoundingly rejects the hypothesis that there are no such omitted firm-specific factors, and establishes the need to use "clustered" standard errors (or correct for that correlation in other ways).<sup>182</sup> Critically, the average residuals are economically, not just statistically, significant, which implies that, contrary to his claims, Dr. Leamer has not controlled for important factors that determine compensation at the Defendants over time.

138. A consequence of omitting important determinants of firm-level compensation is that Dr. Leamer's estimated conduct effects will capture the impact of variables (other than the

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<sup>181</sup> Dr. Leamer used the term "economically significant" numerous times in his deposition and stated that in evaluating results one should focus on economic significance and not just statistical significance. The average residuals in his All Salaried Employee Class model (Figure 20) are economically significant. Actual real total compensation ranges from 39 percent below the value predicted by Dr. Leamer's regression to 49 percent above the value predicted by his regression. A model that predicts overall compensation so poorly cannot provide accurate estimates of the impact of his conduct variable. The root mean square error of the average residual in his model is 16.5 percent, indicating that his model measures average compensation at the company year level at roughly plus or minus 33 percent (using a 95 percent confidence level).

<sup>182</sup> The test (F-test) results are  $F(39, 504771)=1319.6$  for Dr. Leamer's Figure 20 regression, and  $F(39,292367)=832.09$  for his Figure 23 regression. P-values for both tests are virtually zero.

challenged agreements) that differ systematically between the conduct and non-conduct periods. To illustrate the potential problem, I considered what would happen if I simply add a variable measuring the performance of the stock market from his regression, which potentially would measure general economic and financial performance in the economy that Dr. Leamer acknowledges likely affect compensation (see his Figure 8 and related discussion).<sup>183</sup> Exhibit 26 shows the results from adding the change in the S&P 500 index as an explanatory variable in his conduct regression.<sup>184</sup> In contrast to Dr. Leamer's Figure 22 and 24 "undercompensation" results, the addition of this variable yields much smaller "undercompensation" estimates for the All-Salaried Employee Class, and "overcompensation" for all Defendants (except Google) for the Technical Class throughout 2005-2009. Thus, the existence of economically significant factors not captured by his model causes Dr. Leamer's Figure 20 and 23 regression estimates to be unreliable measures of damages and unreliable as a method of demonstrating common class-wide impact.

#### **6. Dr. Leamer's Conduct Variable Cannot Capture the Impact of the Challenged Agreements**

139. Dr. Leamer's conduct variable reflects challenged agreements between pairs of Defendants to avoid cold calling each other's employees for a period of time. Although Dr. Leamer refers to these throughout his report as "non-compete" agreements, I understand that Plaintiffs do not claim (in their Complaint or in their Motion for Class Certification) that these agreements prevented a Defendant from hiring applicants from another Defendant,<sup>185</sup> as long as that applicant was not identified or recruited through a cold call. Evidence I presented above

<sup>183</sup> Leamer Report ¶98.

<sup>184</sup> Appendices 14A and 14B show detailed regression outputs. The coefficient estimate on the change in S&P 500 shows the expected positive sign, and is statistically significant under Dr. Leamer's assumption (independent observations).

<sup>185</sup> See Declaration of Jeff Vijungco on p. 6 ("Adobe and Apple continued to recruit and hire from each other during the Class Period. I am unaware of any requisitions that went unfilled because of the no-cold call agreement with Apple.") See also Declaration of Chris Galy pp. 4-5 ("I understand that plaintiffs in this case allege Intuit has agreed to not cold call employees at Google. To my knowledge, no such agreement exists. I have never been instructed to refrain from making cold calls to Google employees and have never given any such instruction to anyone else at Intuit. To the contrary, I have made cold calls to Google employees on the same basis as any other company and am aware that other recruiters at Intuit have also done so.")

(and that underlies Dr. Leamer's analysis of compensation earned by "movers" in his Figure 7) demonstrates that, during the period of the challenged agreements, Defendants hired employees of other Defendants even when they had agreed not to cold call those employees, and that the amount of hiring from other Defendants did not decline during the conduct period as would have occurred if cold calling were an important way of recruiting from other Defendants (leading to hiring from other Defendants) and cold calling activity were eliminated or substantially reduced by the challenged agreements.

140. Dr. Leamer can identify and measure the impact of the challenged agreements only if the variable in his regression that represents the impact of those agreements properly represents the conduct that he is trying to evaluate. His conduct variable cannot do so for several reasons. First, evidence I reviewed (some of which Dr. Leamer cites to support his Figure 1) shows that cold-call restrictions typically were not limited to the other Defendant identified in Figure 1, but extended to other firms as well.<sup>186</sup> In part, this reflects the fact that the motivation for these agreements generally does not appear to be holding down compensation of (or "undercompensating") a firm's employees, but instead arose from concerns about conflicts-of-interest (potential or perceived) from membership on one company's Board of Directors of senior executives of another, commercial arrangements, or concerns about the impact of cold calling on the willingness of partners to collaborate.<sup>187</sup> If unchallenged DNCC agreements or unilateral policies involving a non-Defendant existed during the same period as the challenged agreements, but not during the non-conduct periods, then the effect estimated by Dr. Leamer would include the impact of those other policies, biasing his estimated effect upwards. If (as Dr. Leamer claims) DNCC agreements between firms lead to undercompensation, he can measure the impact of the challenged agreements only if he can separate their impacts from the corresponding impact of unchallenged policies.

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<sup>186</sup> For example, Google had restrictions on hiring from Genentech, Yahoo, EBay, PayPal and Bizrate. See Geshuri Exhibits 176, 177, 178, 179, 182, 183.

<sup>187</sup> See, e.g., 231APPLE041662; Bentley Depo. 61:21-62:2, 25:16-18; Lambert Depo. 21:7-8.

141. The Consent Decrees that the Defendants signed with the U.S. Department of Justice made clear that restrictions on recruiting other companies' employees are legal under certain circumstances, including when they are "the function of a legitimate collaboration agreement, such as joint development, technology integration, joint ventures, joint projects (including teaming agreements), and the shared use of facilities."<sup>188</sup> The Consent Decrees state further that "[n]othing in Section IV shall prohibit a Defendant from unilaterally deciding to adopt a policy not to consider applications from employees of another person, or to solicit, cold call, recruit or hire employees of another person, provided that Defendants are prohibited from requesting that any other person adopt, enforce, or maintain such a policy, and are prohibited from pressuring any other person to adopt, enforce, or maintain such a policy."<sup>189</sup>

142. Under the Plaintiffs' theory of how compensation is determined, any less-restrictive and legal alternative to the challenged agreements (e.g., limiting cold calling and hiring prohibitions only to employees involved in actual collaborations) still would have affected opportunities and compensation of employees involved in those collaborations. Thus, the but-for world for purposes of measuring impact and loss has some employees affected (by legal restrictions) and others not, requiring an individual determination of which employees were involved in collaborations where restrictions on recruiting the other Defendant's employees would have been permissible as, on balance, procompetitive.<sup>190</sup> This requires individualized analysis to understand what collaborations existed during the class period, which employees were involved, the likelihood that there would have been legal restrictions on cold calling, etc.

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<sup>188</sup> *Final Judgment* in United States of America v. Adobe Systems Inc. et al, 3/17/2011, p. 6 and *[Proposed] Final Judgment* in United States of America v. Lucasfilm Ltd., 5/9/2011, p. 5.

<sup>189</sup> *Final Judgment* in United States of America v. Adobe Systems Inc. et al, 3/17/2011, p. 7 and *[Proposed] Final Judgment* in United States of America v. Lucasfilm Ltd., 5/9/2011, p. 6.

<sup>190</sup> Similarly, nothing prevents an employer from implementing a unilateral policy to avoid cold calling another Defendant's employees (for example, when a member of the Board of Directors is CEO of a competitor). If there were unilateral policies at Defendants during the Class period to not cold call employees of non-Defendants, then, under Dr. Leamer's theory, the price discovery process would have been affected in the same way it was affected by the challenged agreements, and the impact and loss from the challenged agreements would only be the incremental amount above that caused by legal agreements.

143. Second, Dr. Leamer's conduct variable cannot measure the intensity of restrictions on cold calling, but treats any agreement between pairs of Defendants as having the same impact as multiple agreements between a Defendant and other Defendants. For example, Adobe and Apple were assigned the same conduct values every year, but Adobe engaged in a single challenged agreement with one Defendant (Apple), while (according to Plaintiffs and Dr. Leamer) Apple participated in challenged agreements with several other Defendants simultaneously. Dr. Leamer's price-discovery framework does not imply that the amount of information that is restricted is irrelevant to the process of price discovery. Rather, such models would show (where they apply) that more information results in better and more rapid price discovery than less information, and thus that multiple agreements should have a larger impact than a single agreement.

**7. Estimated Persistence Effects are Inconsistent with Dr. Leamer's Price-Discovery Model and his Claim that Defendants had Rigid Compensation Structures**

144. Dr. Leamer describes his persistence estimates as follows:

The persistence variables are the levels of total compensation in the previous year and the year before that, two for each employer. The fact that these numbers sum to around 90 percent indicates very persistent effects, meaning when a worker gets a bump up in compensation in some year that makes him or her better off than comparable coworkers, that effect lingers on for many years.<sup>191</sup>

145. However, this finding is inconsistent with the price-discovery and internal equity frameworks on which he relies as the theoretical basis for why the challenged agreements and resulting reduced flow of information to employees would cause a significant and wide-spread impact on all or virtually all class members. Dr. Leamer claims that economic theory combined with Defendants' rigid compensation structures shows that new information on appropriate compensation levels gained by one Defendant's employees from cold calls from another Defendant affects all employees' compensation. If this were true, however, then there should be only a weak "persistence" between past compensation levels and current ones; a "mover" who is

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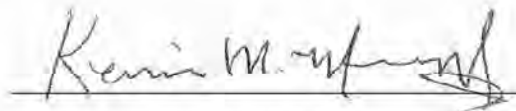
<sup>191</sup> Leamer Report ¶144.

induced to move to Defendant A from Defendant B by a cold call from Defendant A and receives a 30 percent increase in compensation should cause a change in all Defendant A's employees' compensation irrespective of those other employees' previous compensation. Yet, Dr. Leamer's regression rules out such an impact by demonstrating that an individual's compensation is determined in any year largely by his previous two-years' compensation, and that any increase in an individual's compensation relative to others in the firm generates a highly persistent increase in that individual's compensation.

146. Dr. Leamer's model and his estimates of damages imply that any effect of the reduced information flow persists strongly for an extended time, even after employees have obtained more information. Yet, he provides no reason why aggregate compensation of members of the proposed class would remain depressed so long after the information flow has been fully resumed. Indeed, his model implies that, even five years after the flow of information is restored, more than 95 percent of the impact of reduced information on compensation would remain for Adobe, Apple and Pixar employees, while more than 60 percent of the effect would remain for Google employees (Google has the lowest estimated persistence level). The flow of information in Dr. Leamer's model is not just slow, it is glacial. Such slow adjustment is hard to reconcile with the [REDACTED] rates of hiring at these firms (averaging over [REDACTED] percent of average employment per year), as well as with his own price discovery theory.

## 8. Summary

147. Dr. Leamer's regression model of undercompensation and his derived estimates of annual undercompensation percentages by company and year are invalid. When necessary corrections are made to permit a test of his theory, there is no evidence of common impact from the challenged conduct, no evidence of average impact across members of the proposed class, and no basis for his estimates of undercompensation.



Kevin M. Murphy

November 12, 2012

## Exhibit 1A

### Hires and Separations at Defendant Companies - From/To Other Defendants vs. Overall

	Hires	Separations	Hires + Separations
<b>Year</b>			
2001			
2002			
2003			
2004			
2005			
2006			
2007			
2008			
2009			
2010			
2011			
<b>2001-2004 Avg</b>			
<b>2005-2009 Avg</b>			
<b>2010-2011 Avg</b>			
<b>2001-2011 Avg</b>			
<b>2001-2004 Total</b>			
<b>2005-2009 Total</b>			
<b>2010-2011 Total</b>			
<b>2001-2011 Total</b>			

Notes: This analysis excludes hires indicated as acquisitions, hires showing the same defendant company as their immediate previous employer within one year of the hiring, and separations that appear as immediately rehired by the same defendant company within one year. Number of employees is calculated as average employment in each year.

Source: Dr. Leamer's employee data.

## Exhibit 1B

### Hires and Separations at Defendant Companies - From/To Other DNCC Defendants vs. Overall

	Hires	Separations	Hires + Separations
<b>Year</b>			
2001			
2002			
2003			
2004			
2005			
2006			
2007			
2008			
2009			
2010			
2011			
<b>2001-2004 Avg</b>			
<b>2005-2009 Avg</b>			
<b>2010-2011 Avg</b>			
<b>2001-2011 Avg</b>			
<b>2001-2004 Total</b>			
<b>2005-2009 Total</b>			
<b>2010-2011 Total</b>			
<b>2001-2011 Total</b>			

Notes: This analysis excludes hires indicated as acquisitions, hires showing the same defendant company as their immediate previous employer within one year of the hiring, and separations that appear as immediately rehired by the same defendant company within one year. Number of employees is calculated as average employment in each year.

Source: Dr. Leamer's employee data.



**Exhibit 2A**  
**Number of Employees by Defendant and Year**  
**All Salaried Employee Class**

	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	All Defendants
2001	2,503	5,096	210	████	3,169	██	██	66,242
2002	2,226	5,255	542	████	3,982	██	██	63,569
2003	2,291	5,424	1,329	████	4,311	██	██	62,439
2004	2,508	5,684	2,346	████	4,247	██	██	64,172
2005	3,791	6,474	4,117	████	4,418	██	██	73,556
2006	3,663	6,993	6,873	████	4,498	██	██	74,045
2007	3,951	7,951	8,768	████	5,069	██	██	73,247
2008	4,203	9,135	10,983	████	5,081	██	████	75,205
2009	4,928	10,005	11,175	████	4,683	██	████	75,166
2010	5,010	11,655	13,988	████	4,605	██	████	80,193
2011	5,385	13,226	18,179	████	4,770	██	████	90,070

Source: Dr. Leamer's backup data and materials.

**Exhibit 2B**  
**Number of Employees by Defendant and Year**  
**Technical, Creative, and R&D Class**

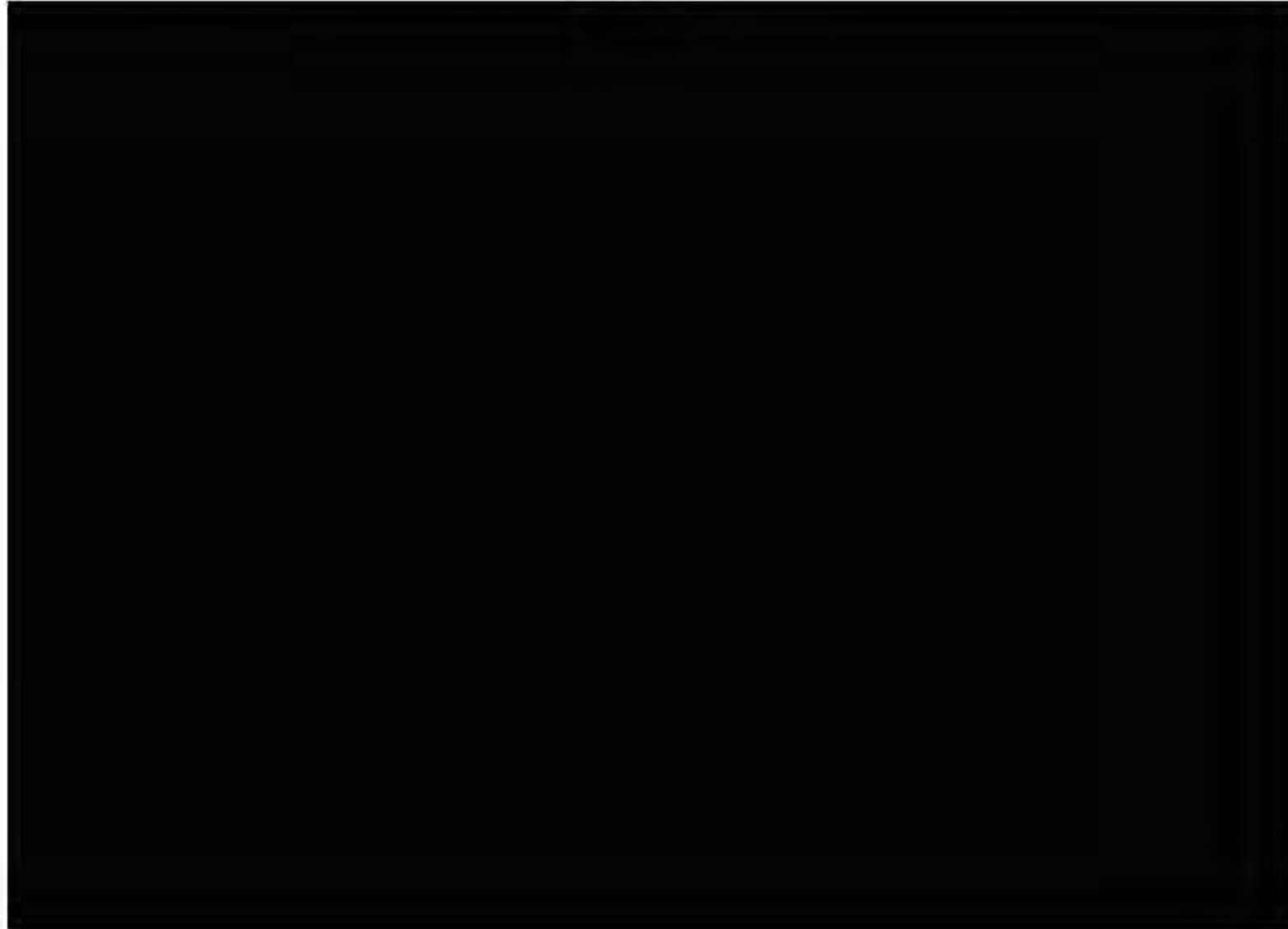
	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	All Defendants
2001	1,582	2,670	101	████	1,557	██	██	34,484
2002	1,441	2,866	207	████	1,977	██	██	33,881
2003	1,450	2,954	509	████	1,907	██	██	33,517
2004	1,579	2,942	1,026	████	1,829	██	██	33,592
2005	2,205	3,358	2,258	████	1,814	██	██	40,479
2006	2,218	3,677	3,776	████	1,863	██	██	41,216
2007	2,277	4,248	5,290	████	2,244	██	██	42,550
2008	2,400	4,950	6,388	████	2,349	██	██	44,243
2009	2,552	5,589	6,825	████	2,237	██	██	45,453
2010	2,489	6,663	8,693	████	2,308	██	██	48,994
2011	2,639	7,582	11,139	████	2,457	██	██	55,338

Source: Dr. Leamer's backup data and materials.

## Exhibit 3

### Top 20 Previous Employers of Hires by Defendant Companies

#### Adobe

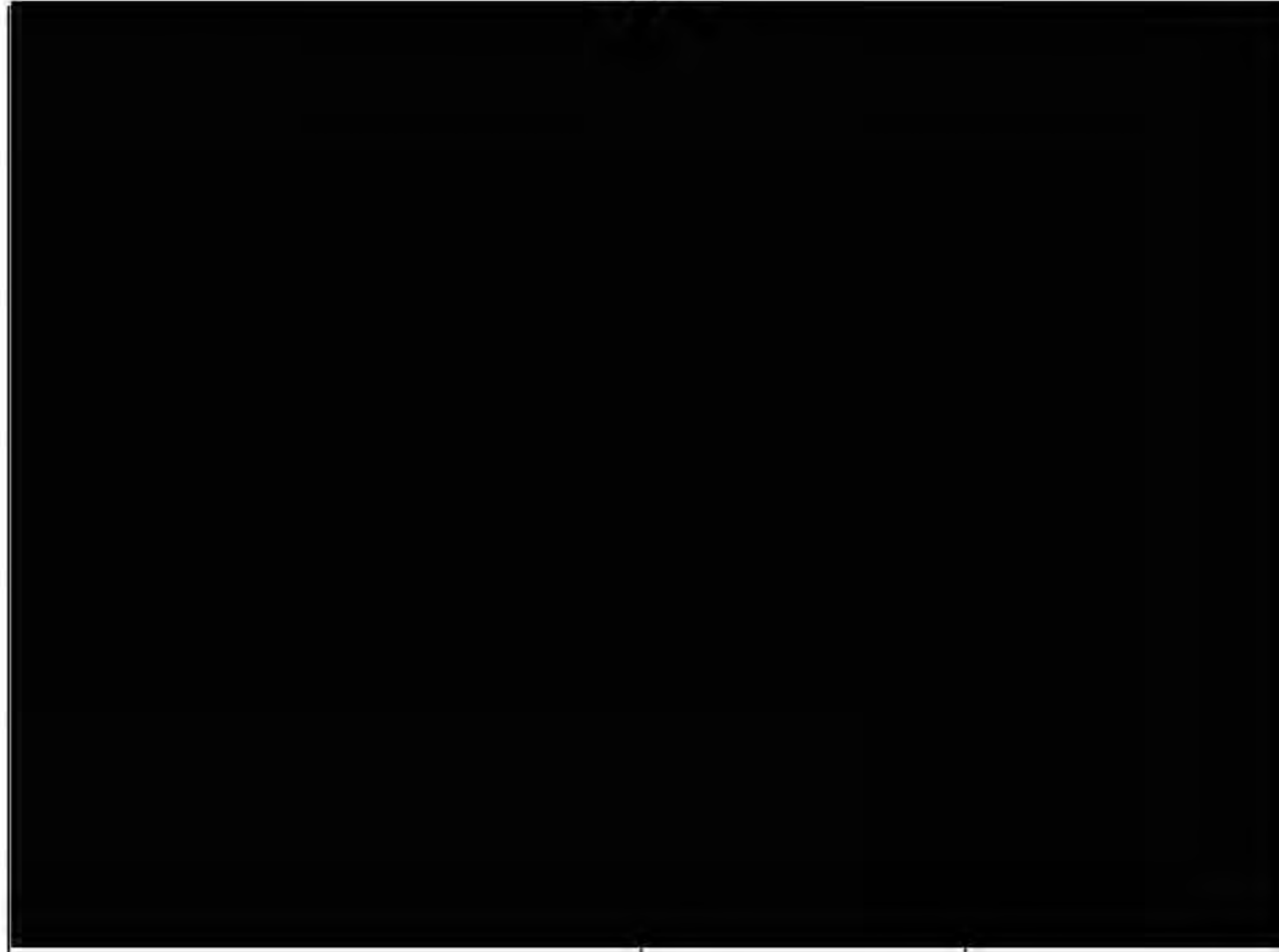


Note: Hires through acquisitions are excluded. This analysis uses Adobe's compensation data and may not include all internal transfers.

## Exhibit 3

### Top 20 Previous Employers of Hires by Defendant Companies

#### Apple



Note: Analysis restricted to hires for job codes provided in the compensation data.

## Exhibit 3

### Top 20 Previous Employers of Hires by Defendant Companies

Google



### **Exhibit 3**

#### **Top 20 Previous Employers of Hires by Defendant Companies**

Intel



## Exhibit 3

### Top 20 Previous Employers of Hires by Defendant Companies

Intuit



## Exhibit 3

### Top 20 Previous Employers of Hires by Defendant Companies

#### Lucasfilm

Rank	Previous Employer	Number of Hires 2008Q2-2012Q1	Percentage of Total Hires 2008Q2-2012Q1
	LUCASFILM	26	7.1%
1	ELECTRONIC ARTS	20	5.5%
2	IMAGEMOVERS DIGITAL	8	2.2%
3	WALT DISNEY	6	1.6%
4	ACTIVISION	5	1.4%
5	ORPHANAGE INC	5	1.4%
6	2K GAMES	4	1.1%
7	CBS	4	1.1%
8	DIGITAL DOMAIN	4	1.1%
9	PDI	4	1.1%
10	SONY	4	1.1%
11	APPLE	3	0.8%
12	DOUBLE FINE PRODUCTIONS	3	0.8%
13	DREAMWORKS	3	0.8%
14	MICROSOFT	3	0.8%
15	PIXAR	3	0.8%
16	ZYNGA	3	0.8%
17	CRYSTAL DYNAMICS	2	0.5%
18	MUNKYFUN INC	2	0.5%
19	ADOBE	1	0.3%
20	EBAY	1	0.3%
	Self Employed/Unemployed	3	0.8%
	Unknown	61	16.7%
	Other (Non-Defendants)	187	51.2%
	Other Defendants	0	0.0%
	<b>All Defendants excluding Lucasfilm</b>	<b>7</b>	<b>1.9%</b>
	<b>Lucasfilm Total</b>	<b>365</b>	<b>100%</b>



## Exhibit 3

### Top 20 Previous Employers of Hires by Defendant Companies

#### Pixar

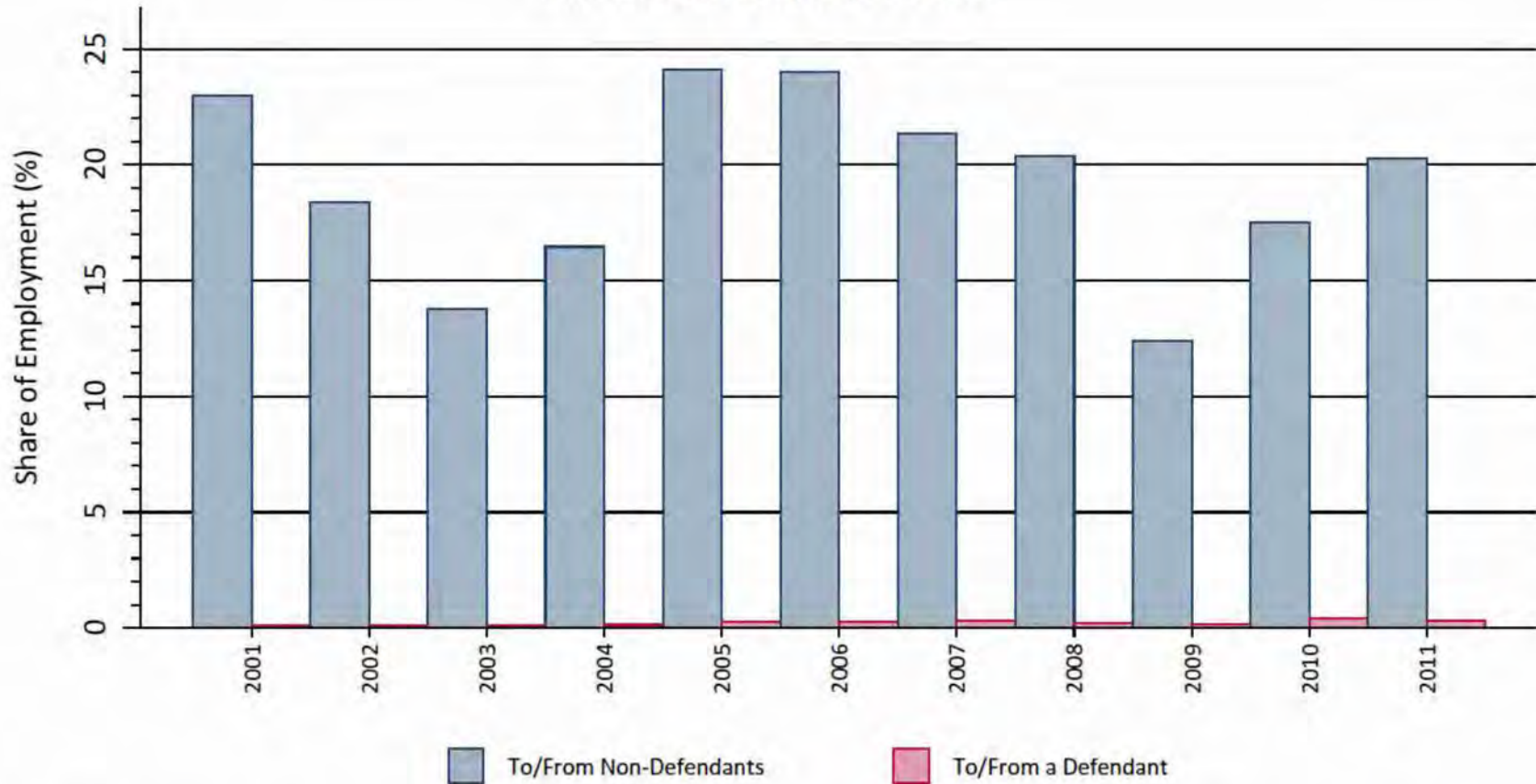
Rank	Previous Employer	Number of Hires 2001-2012Q2	Percentage of Total Hires 2001-2012Q2
	PIXAR	5	0.6%
1	LUCASFILM	22	2.5%
2	BLUE SKY STUDIO	18	2.1%
3	WALT DISNEY	16	1.8%
4	PDI	10	1.1%
5	TIPPETT	10	1.1%
6	APPLE	8	0.9%
7	DREAMWORKS	6	0.7%
8	RHYTHM & HUES	6	0.7%
9	UC BERKELEY	5	0.6%
10	WDFB	5	0.6%
11	ELECTRONIC ARTS	4	0.5%
12	ESC ENTERTAINMENT	4	0.5%
13	MICROSOFT	4	0.5%
14	SONY	4	0.5%
15	BRIGHAM YOUNG UNIV	3	0.3%
16	FRAMESTORE	3	0.3%
17	GOOGLE	3	0.3%
18	TAMU	3	0.3%
19	WARNER BRO	3	0.3%
20	ACTIVISION	2	0.2%
	Self Employed/Unemployed	7	0.8%
	Unknown	420	48.2%
	Other (Non-Defendants)	294	33.7%
	Other Defendants	7	0.8%
	<b>All Defendants excluding Pixar</b>	<b>40</b>	<b>4.6%</b>
	<b>Pixar Total</b>	<b>872</b>	<b>100%</b>

Note: The lengths of the periods analyzed vary by company based on data availability.

Sources: Recruiting data from Apple, Google, Intel, Intuit, Lucasfilm, and Pixar. Compensation data from Adobe and Apple.

**Exhibit 4A**

**Annual Hires and Separations as a Share of Defendants' Average Total Employment**  
**All Salaried Employee Class**

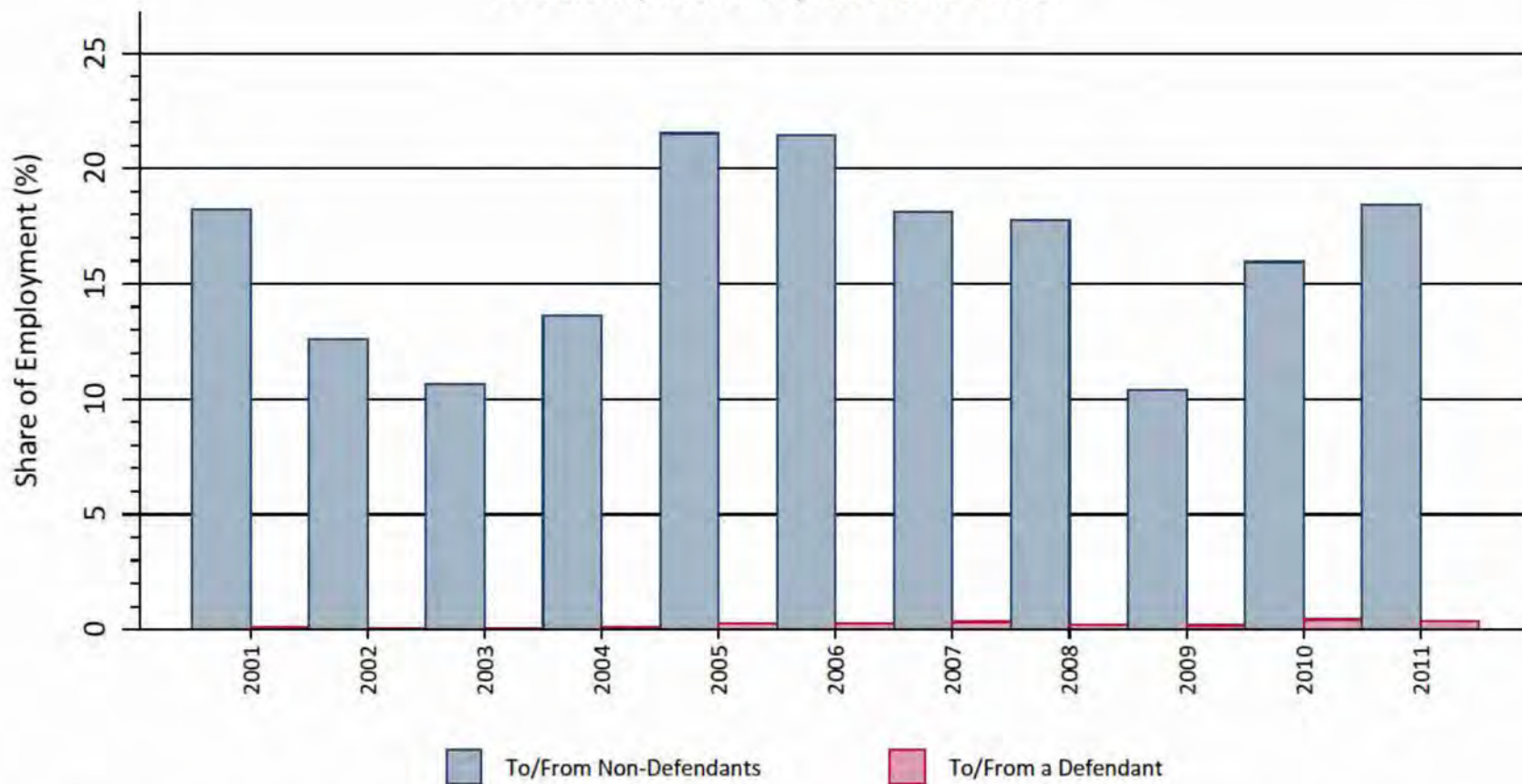
**Notes:**

- [1] An employee is classified as "To/From a Defendant" if he/she is employed by one Defendant within 12 months of separating from a different Defendant.  
 [2] Employees who are rehired by the same Defendant within one year of separating are excluded from the counts of hires and separations.

Source: Dr. Leamer's backup data and materials.

**Exhibit 4B**

### Annual Hires and Separations as a Share of Defendants' Average Total Employment Technical, Creative, and R&D Class

**Notes:**

- [1] An employee is classified as "To/From a Defendant" if he/she is employed by one Defendant within 12 months of separating from a different Defendant.  
 [2] Employees who are rehired by the same Defendant within one year of separating are excluded from the counts of hires and separations.

Source: Dr. Leamer's backup data and materials.

## Exhibit 5

### Employment of Software Engineers

Year								% of Industries of Defendant Companies							Defendant Companies		
	Adobe	Apple	Google	Intel	Intuit	LucasFilm	Pixar	Defendant Companies	Industries of Defendant Companies	Adobe	Apple	Google	Intel	Intuit		LucasFilm	Pixar
2002	1,165	█	█	█	1,263	█	█	8,065	79,910	1.5%	█	█	█	1.6%	█	█	10.1%
2003	1,167	█	█	█	1,228	█	█	7,811	101,470	1.2%	█	█	█	1.2%	█	█	7.7%
2004	1,258	█	█	█	1,207	█	█	8,317	105,160	1.2%	█	█	█	1.1%	█	█	7.9%
2005	1,694	█	█	█	1,336	█	█	10,656	106,890	1.6%	█	█	█	1.2%	█	█	10.0%
2006	1,728	█	█	█	1,333	█	█	11,742	96,440	1.8%	█	█	█	1.4%	█	█	12.2%
2007	1,880	█	█	█	1,411	█	█	13,907	108,650	1.7%	█	█	█	1.3%	█	█	12.8%
2008	1,958	█	█	█	1,425	█	█	15,404	122,130	1.6%	█	█	█	1.2%	█	█	12.6%
2009	1,984	█	█	█	1,282	█	█	16,301	127,860	1.6%	█	█	█	1.0%	█	█	12.7%
2010	1,865	█	█	█	1,361	█	█	18,728	124,910	1.5%	█	█	█	1.1%	█	█	15.0%
2011	1,939	█	█	█	1,475	█	█	22,318	134,150	1.4%	█	█	█	1.1%	█	█	16.6%

2002-2004 Average: 8.6%  
2005-2009 Average: 12.1%  
2010-2011 Average: 15.8%

All Industries	% of All Industries							Defendant Companies
	Adobe	Apple	Google	Intel	Intuit	LucasFilm	Pixar	
584,020	0.2%	█	█	█	0.2%	█	█	1.4%
651,740	0.2%	█	█	█	0.2%	█	█	1.2%
717,420	0.2%	█	█	█	0.2%	█	█	1.2%
758,050	0.2%	█	█	█	0.2%	█	█	1.4%
764,430	0.2%	█	█	█	0.2%	█	█	1.5%
834,850	0.2%	█	█	█	0.2%	█	█	1.7%
851,850	0.2%	█	█	█	0.2%	█	█	1.8%
852,670	0.2%	█	█	█	0.2%	█	█	1.9%
868,210	0.2%	█	█	█	0.2%	█	█	2.2%
921,500	0.2%	█	█	█	0.2%	█	█	2.4%

2002-2004 Average: 1.2%  
2005-2009 Average: 1.7%  
2010-2011 Average: 2.3%

Source: Defendant employment numbers are based on Dr. Leamer's employee data as well as classification of software engineers performed by my staff. Employment of industries of Defendant companies based on BLS OES National Industry Specific Data for the following NAICS codes (based on CapIQ company information):

334100 Computer and Peripheral Equipment Manufacturing  
519100 Other Information Services  
334400 Semiconductor and Other Electronic Component Manufacturing  
511200 Software Publishers  
512100 Motion Picture and Video Industries

**Exhibit 6**  
**Age Distribution of New Hires**  
 2001 through 2011

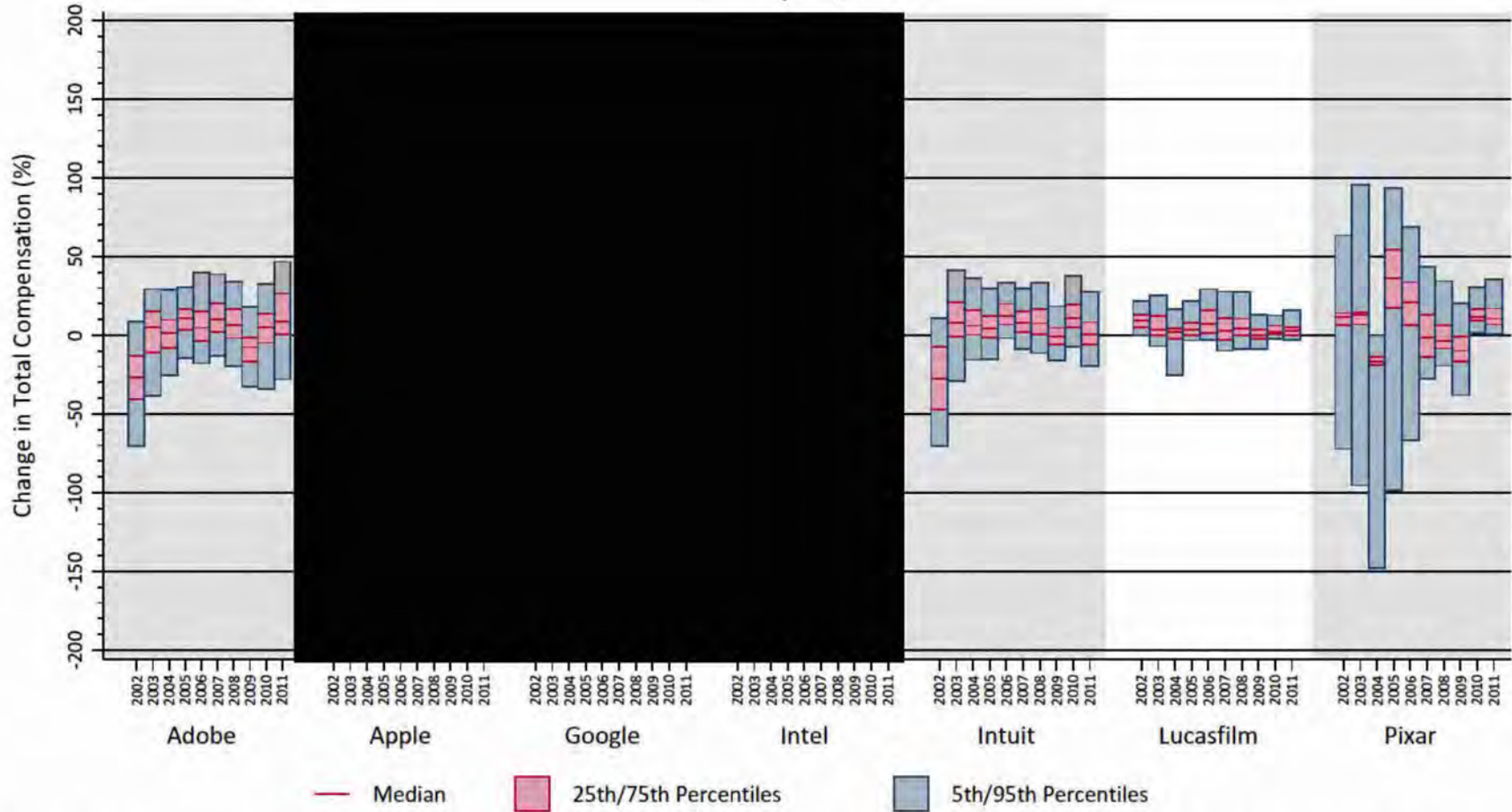
	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar
<b><u>All Salaried Employee Class</u></b>							
25 and under	7%	■	■	■	7%	6%	19%
26 to 30	19%	■	■	■	17%	24%	30%
31 to 35	24%	■	■	■	24%	30%	24%
36 to 40	22%	■	■	■	22%	22%	14%
41 and over	28%	■	■	■	30%	17%	13%
<b><u>Technical, Creative, and R&amp;D Class</u></b>							
25 and under	8%	■	■	■	6%	7%	18%
26 to 30	20%	■	■	■	17%	27%	32%
31 to 35	24%	■	■	■	26%	33%	24%
36 to 40	21%	■	■	■	22%	21%	15%
41 and over	27%	■	■	■	29%	12%	10%

Source: Dr. Leamer's backup data and materials.

### Exhibit 7A

## Distributions of Annual Changes in Total Compensation

### All Salaried Employee Class



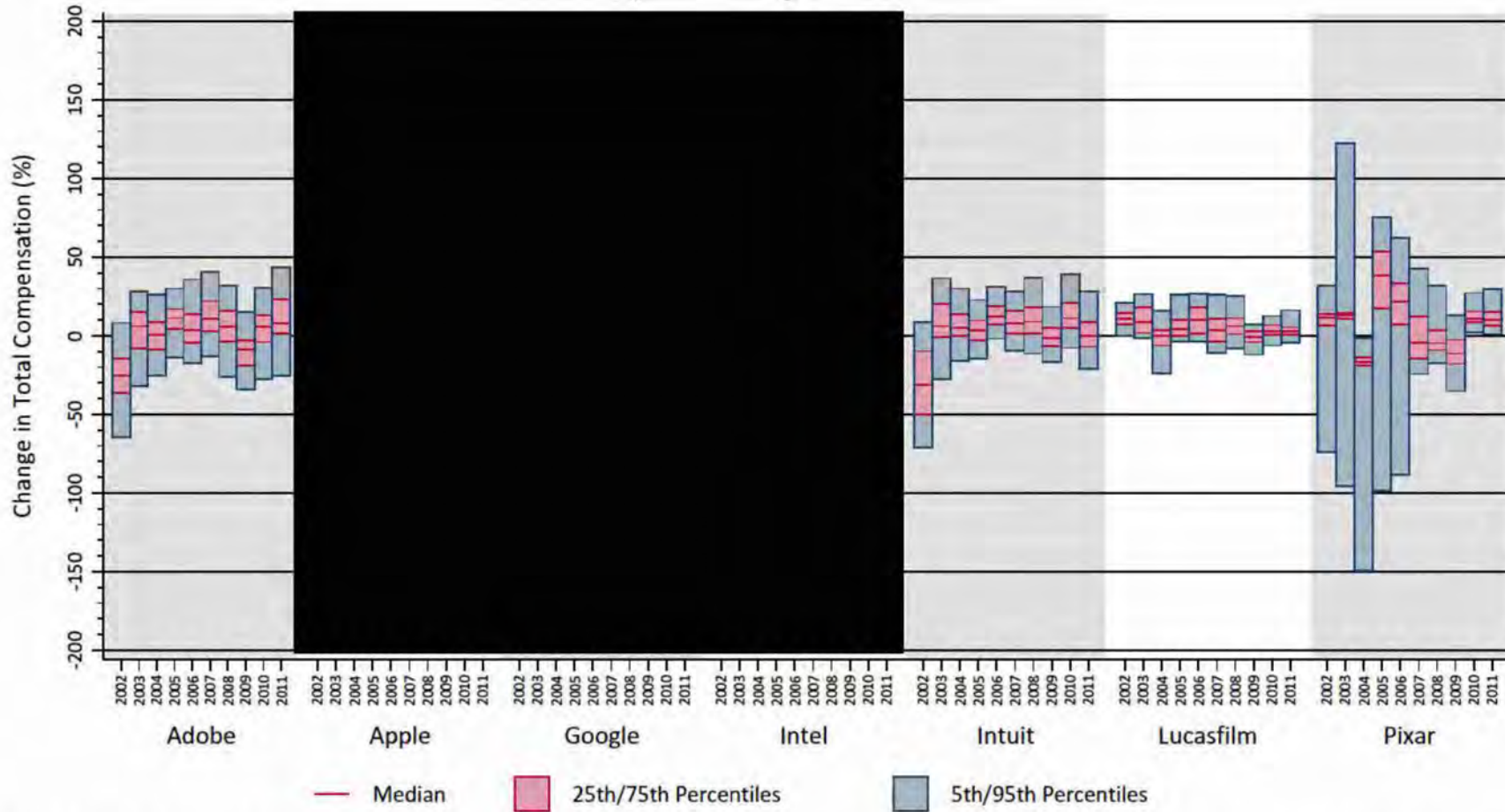
Note: Percent changes in total compensation are defined as the log of the current year's total compensation minus the log of the previous year's total compensation multiplied by 100.

Source: Dr. Leamer's backup data and materials.

### Exhibit 7B

## Distributions of Annual Changes in Total Compensation

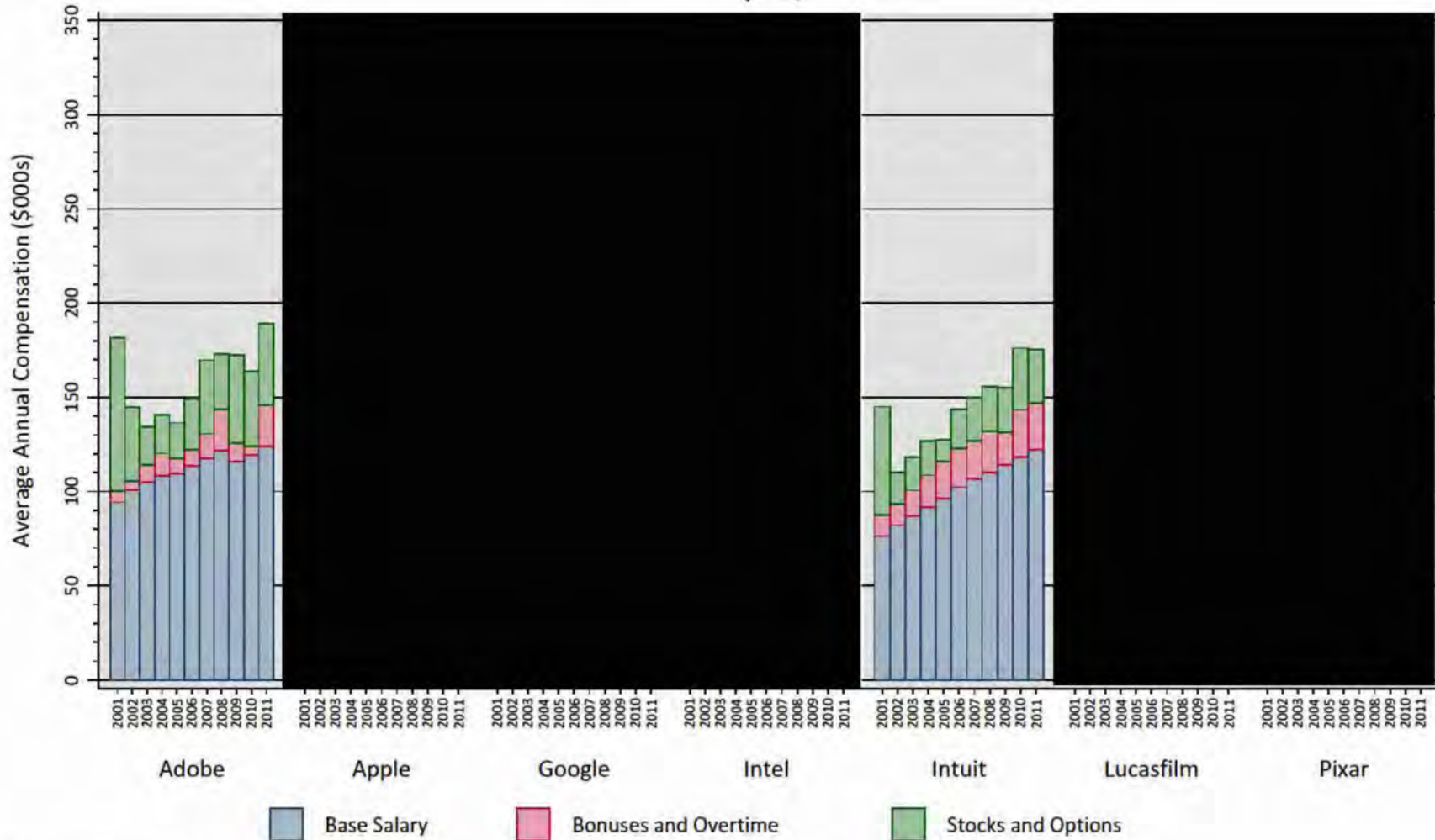
### Technical, Creative, and R&D Class



Note: Percent changes in total compensation are defined as the log of the current year's total compensation minus the log of the previous year's total compensation multiplied by 100.

Source: Dr. Leamer's backup data and materials.

### Exhibit 8A Composition of Total Compensation All Salaried Employee Class

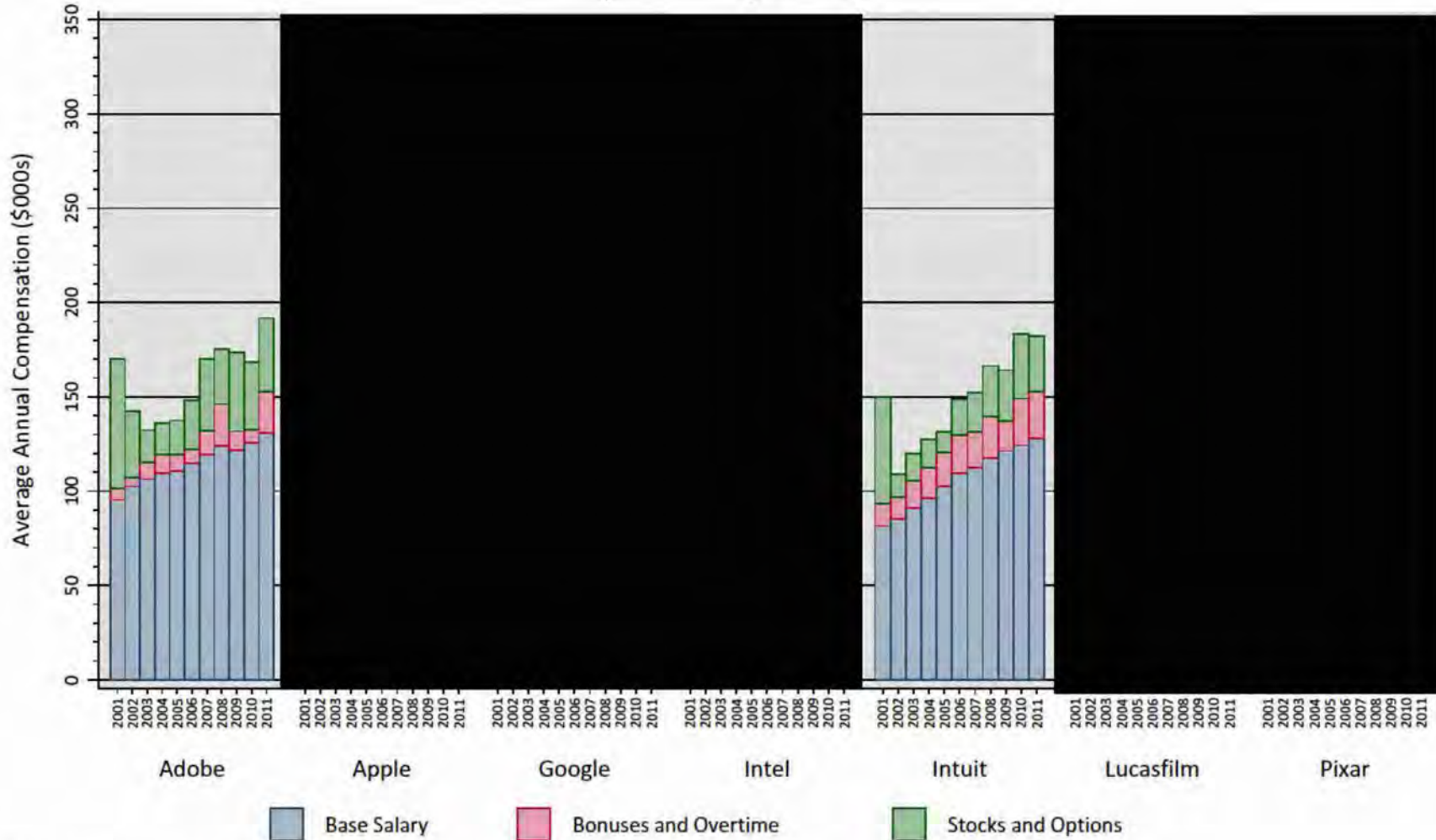


Source: Dr. Leamer's backup data and materials.



### Exhibit 8B

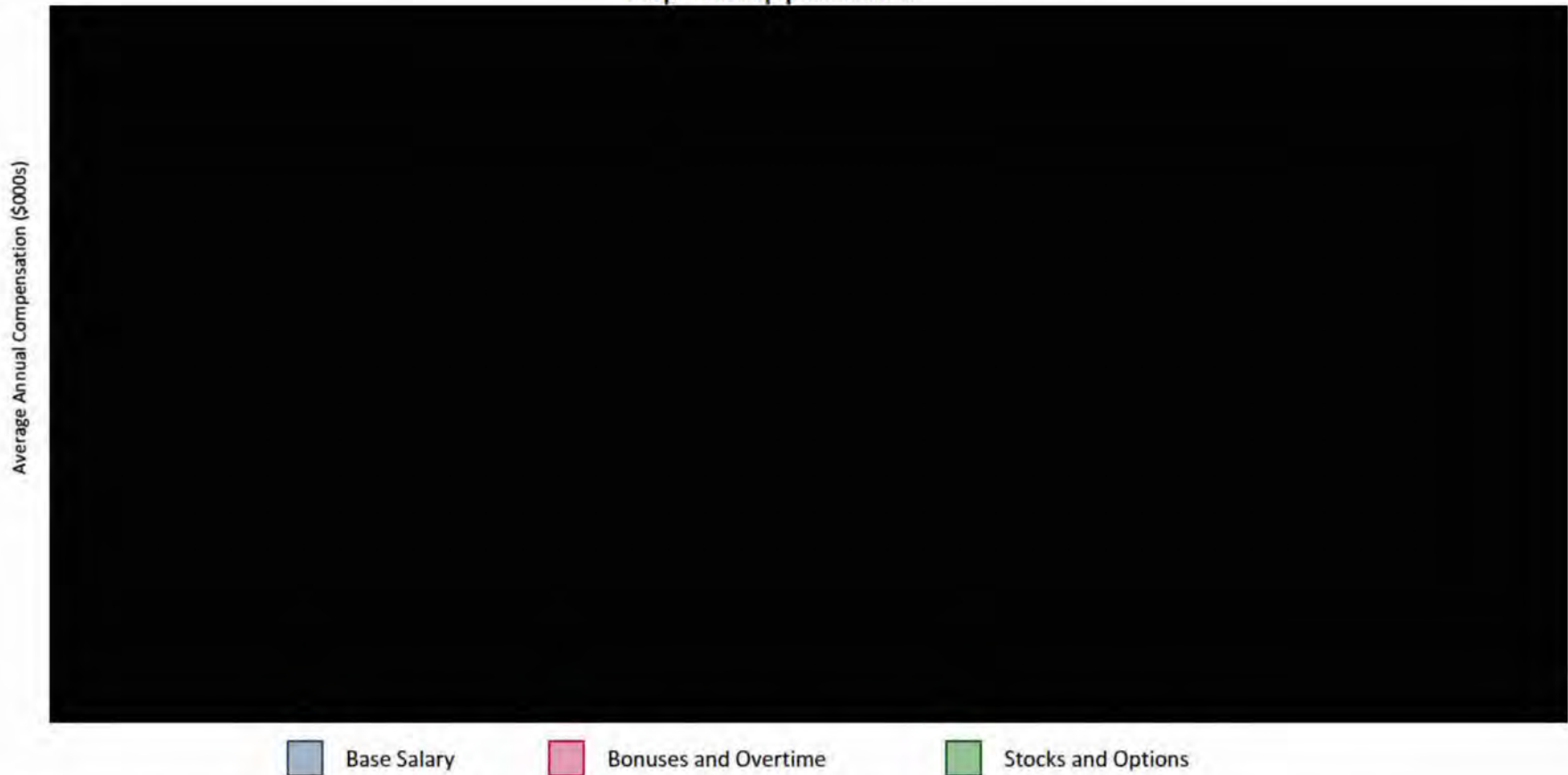
#### Composition of Total Compensation Technical, Creative, and R&D Class



Source: Dr. Leamer's backup data and materials.

## Exhibit 9A

### Composition of Total Compensation for Major Jobs Top 10 Apple Jobs



Notes:

- [1] The top 10 jobs are identified using 2005 through 2009 employment--the same algorithm that Dr. Leamer uses in his Figures 15 through 17.
- [2] Bars are missing when there are fewer than five employees with the relevant job title in the data in the given year.
- [3] Apple's job titles changed in 2005.

Source: Dr. Leamer's backup data and materials.

**Exhibit 9B**  
Composition of Total Compensation for Major Jobs  
Top 10 Google Jobs



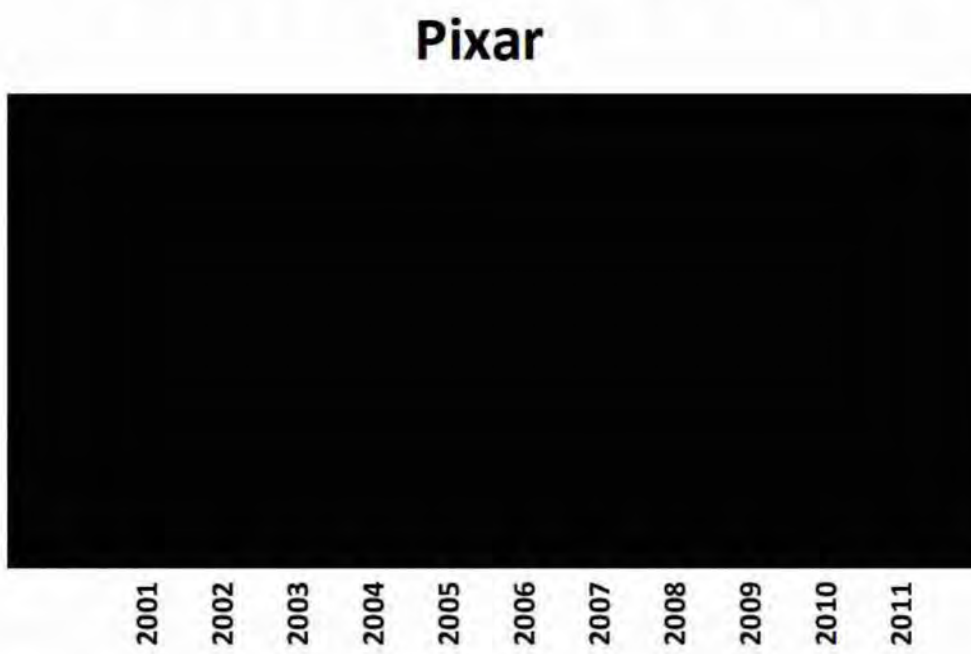
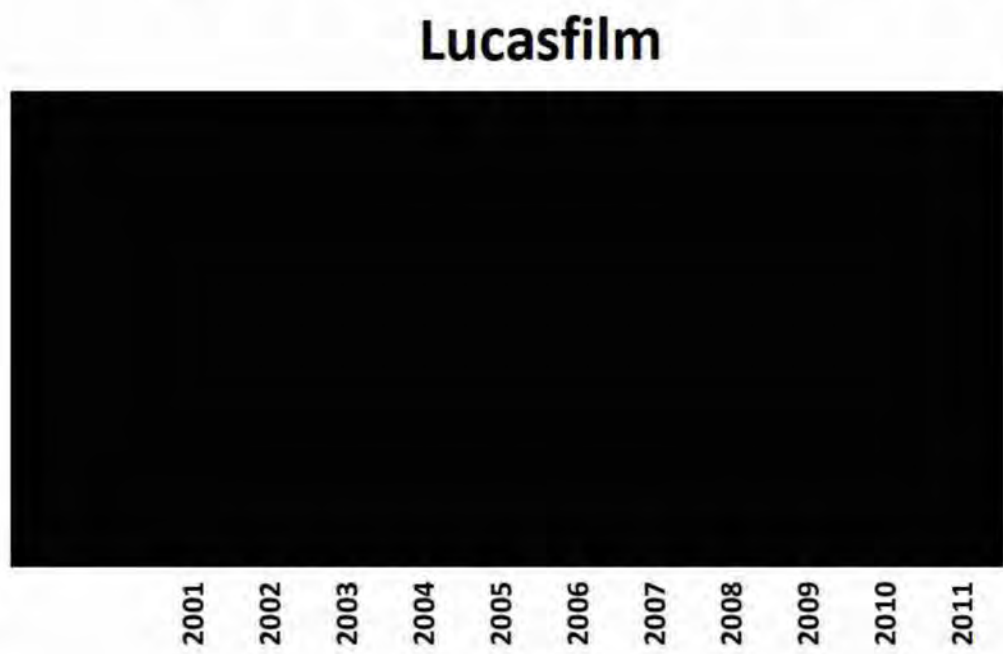
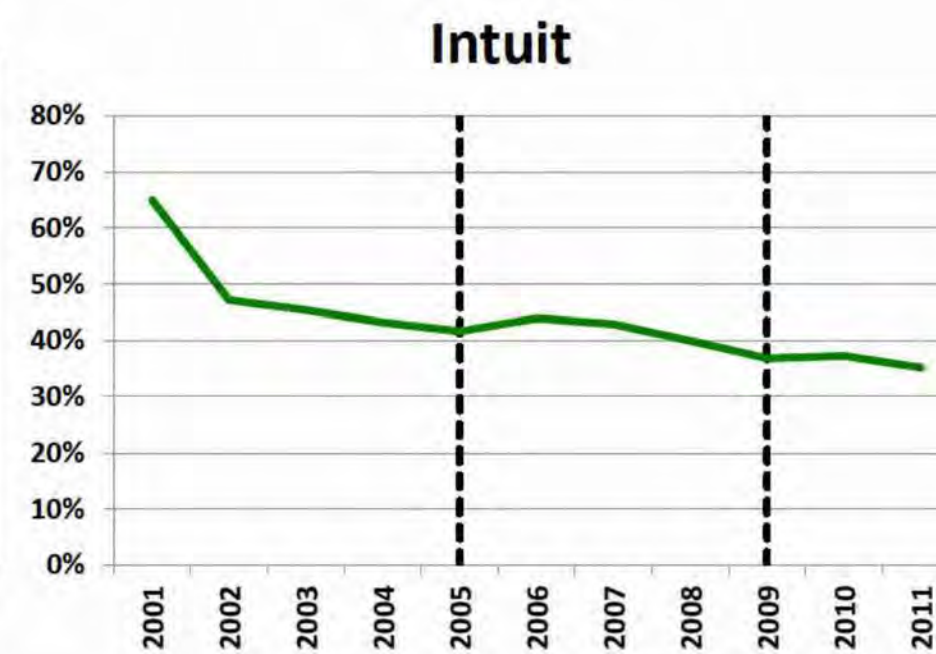
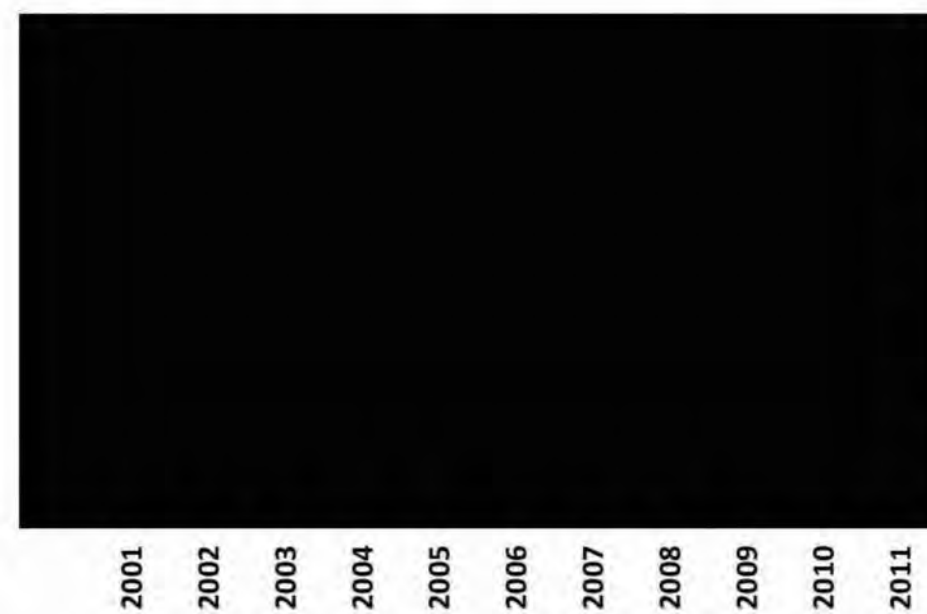
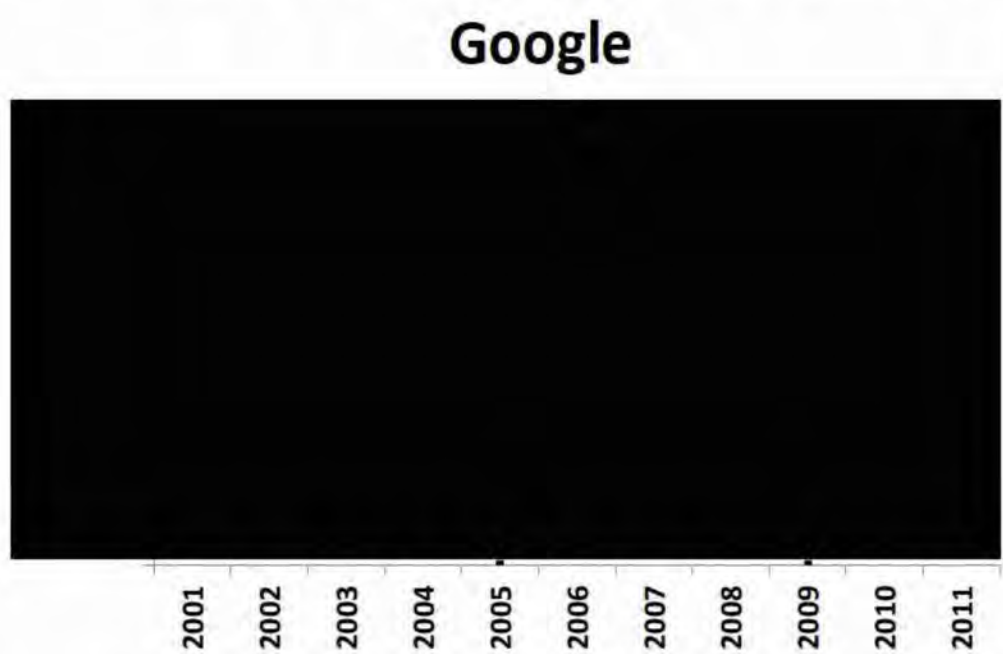
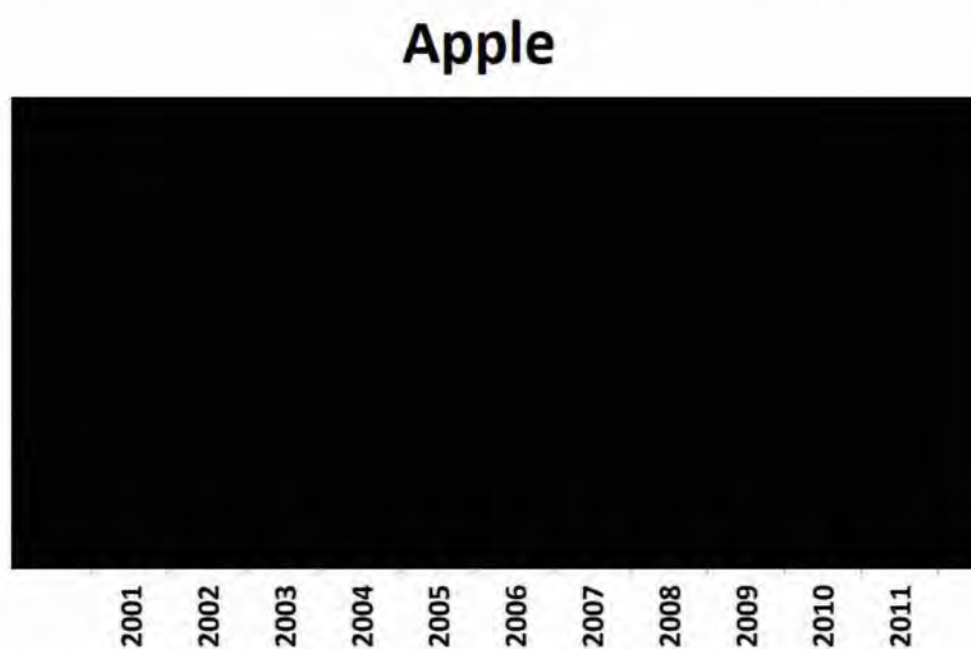
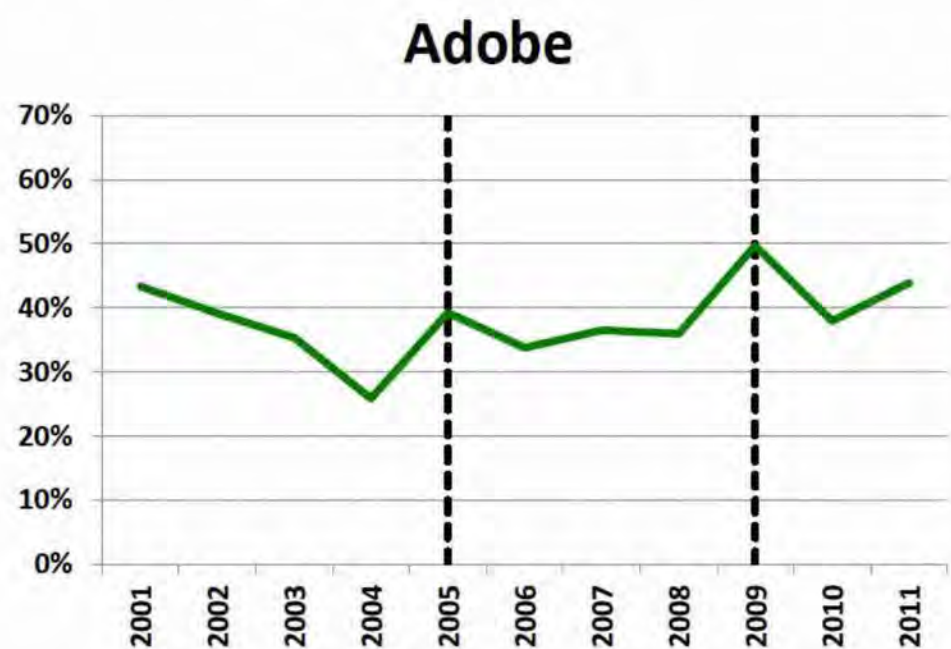
Notes:

- [1] The top 10 jobs are identified using 2005 through 2009 employment--the same algorithm that Dr. Leamer uses in his Figures 15 through 17.
- [2] Bars are missing when there are fewer than five employees with the relevant job title in the data in the given year.

Source: Dr. Leamer's backup data and materials.

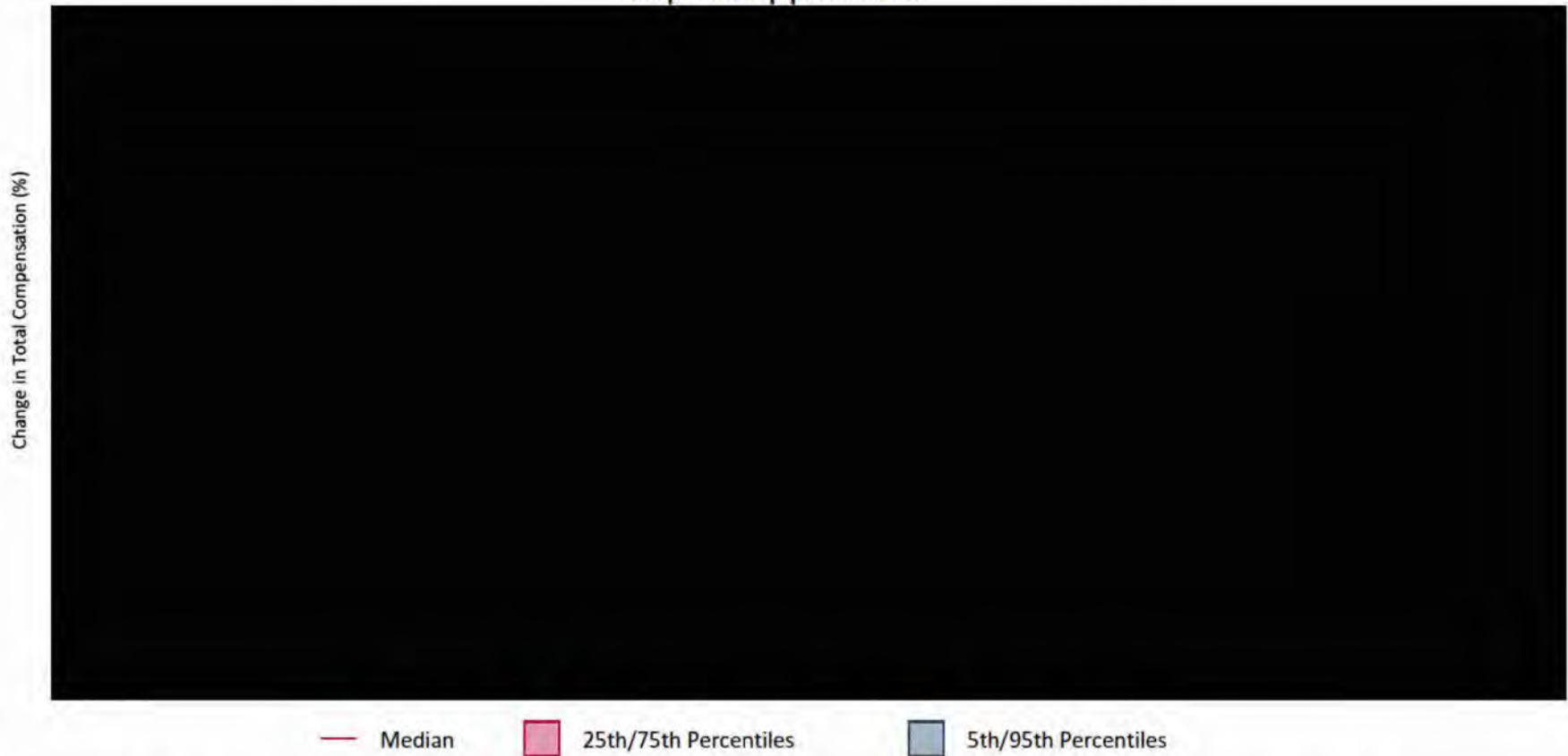
### Exhibit 10

Average Total Compensation per Employee as Percentage of Revenue per Employee (Dr. Leamer's Figure 9 Data)



Source: Dr. Leamer's backup data and materials (Lucasfilm 2001 and 2007 revenue data not provided). Pixar revenue data after 2005 provided by Pixar. Pixar 2006 revenue estimated by multiplying the reported number (for nine months) by 12/9.

**Exhibit 11A**  
Distributions of Annual Changes in Total Compensation  
Top 10 Apple Jobs



Notes:

- [1] The top 10 jobs are identified using 2005 through 2009 employment--the same algorithm that Dr. Leamer uses in his Figures 15 through 17.
- [2] Bars are missing when there are fewer than five employees with the relevant job title in the data in the given year.
- [3] Percent changes are defined as differences in logs.
- [4] Apple's job titles changed in 2005.

Source: Dr. Leamer's backup data and materials.

**Exhibit 11B**  
Distributions of Annual Changes in Total Compensation  
Top 10 Google Jobs



Notes:

- [1] The top 10 jobs are identified using 2005 through 2009 employment--the same algorithm that Dr. Leamer uses in his Figures 15 through 17.
- [2] Bars are missing when there are fewer than five employees with the relevant job title in the data in the given year.
- [3] Percent changes are defined as differences in logs.

Source: Dr. Leamer's backup data and materials.

## Exhibit 12

### R-Squareds in Dr. Leamer's "Compensation Structure" Regressions Are Mostly Attributable to Employer and Job Indicators

	All-Salaried Employee Class			Technical, Creative, and R&D Class		
	R-Squareds in Dr. Leamer's Figure 11	Including Only Employer and Job Indicators	Excluding Employer and Job Indicators	R-Squareds in Dr. Leamer's Figure 13	Including Only Employer and Job Indicators	Excluding Employer and Job Indicators
2001	95%	94%	21%	89%	89%	15%
2002	94%	93%	21%	89%	88%	16%
2003	94%	93%	22%	88%	88%	16%
2004	93%	93%	19%	88%	88%	18%
2005	93%	92%	20%	88%	87%	16%
2006	92%	92%	21%	87%	87%	19%
2007	91%	91%	21%	85%	85%	17%
2008	92%	91%	20%	86%	86%	19%
2009	92%	92%	20%	88%	88%	17%
2010	90%	90%	22%	84%	84%	18%
2011	92%	91%	24%	88%	87%	21%

Source: Dr. Leamer's Figure 11 and 13 regressions.

**Exhibit 13A**  
**Named Plaintiffs' Actual Total Compensation vs. Predictions**  
**by Dr. Leamer's Figure 12 Model**

Named Plaintiff	Employer	Year	Total Comp		Difference	% Difference
			Actual Total Comp	Predicted by Dr. Leamer's Model		
			[1]	[2]	[3] = [1]-[2]	=[3]/[1]
Brandon Marshall	ADOBE	2006	\$ 73,895	\$ 61,035	\$ 12,860	17.4%
Michael Devine	ADOBE	2006	\$ 131,222	\$ 124,424	\$ 6,798	5.2%
Michael Devine	ADOBE	2007	\$ 146,540	\$ 135,001	\$ 11,539	7.9%
Mark Fichtner	INTEL	2001	\$ 151,712	\$ 133,620	\$ 18,091	11.9%
Mark Fichtner	INTEL	2002	\$ 124,426	\$ 120,980	\$ 3,446	2.8%
Mark Fichtner	INTEL	2003	\$ 109,352	\$ 109,349	\$ 3	0.0%
Mark Fichtner	INTEL	2004	\$ 123,374	\$ 120,221	\$ 3,153	2.6%
Mark Fichtner	INTEL	2005	\$ 133,431	\$ 135,403	\$ (1,972)	-1.5%
Mark Fichtner	INTEL	2008	\$ 122,013	\$ 133,469	\$ (11,456)	-9.4%
Mark Fichtner	INTEL	2009	\$ 138,501	\$ 139,125	\$ (624)	-0.5%
Mark Fichtner	INTEL	2010	\$ 152,238	\$ 141,816	\$ 10,422	6.8%
Daniel Stover	INTUIT	2006	\$ 79,129	\$ 91,136	\$ (12,007)	-15.2%
Daniel Stover	INTUIT	2007	\$ 103,265	\$ 105,061	\$ (1,796)	-1.7%
Daniel Stover	INTUIT	2008	\$ 175,177	\$ 108,817	\$ 66,361	37.9%
Daniel Stover	INTUIT	2009	\$ 132,553	\$ 121,416	\$ 11,137	8.4%
Siddharth Hariharan	LUCASFILM	2007	\$ 102,000	\$ 90,819	\$ 11,182	11.0%

Source: Dr. Leamer's Figure 12 regressions.



**Exhibit 13B**  
**Named Plaintiffs' Actual Total Compensation vs. Predictions**  
**by Dr. Leamer's Figure 14 Model**

Named Plaintiff	Employer	Year	Total Comp		Difference	% Difference
			Actual Total Comp	Predicted by Dr. Leamer's Model		
			[1]	[2]	[3] = [1]-[2]	=[3]/[1]
Brandon Marshall	ADOBE	2006	\$ 73,895	\$ 60,754	\$ 13,141	17.8%
Michael Devine	ADOBE	2006	\$ 131,222	\$ 124,661	\$ 6,561	5.0%
Michael Devine	ADOBE	2007	\$ 146,540	\$ 134,724	\$ 11,816	8.1%
Mark Fichtner	INTEL	2001	\$ 151,712	\$ 135,177	\$ 16,534	10.9%
Mark Fichtner	INTEL	2002	\$ 124,426	\$ 121,965	\$ 2,461	2.0%
Mark Fichtner	INTEL	2003	\$ 109,352	\$ 109,866	\$ (514)	-0.5%
Mark Fichtner	INTEL	2004	\$ 123,374	\$ 119,152	\$ 4,222	3.4%
Mark Fichtner	INTEL	2005	\$ 133,431	\$ 134,261	\$ (830)	-0.6%
Mark Fichtner	INTEL	2008	\$ 122,013	\$ 132,988	\$ (10,974)	-9.0%
Mark Fichtner	INTEL	2009	\$ 138,501	\$ 139,074	\$ (573)	-0.4%
Mark Fichtner	INTEL	2010	\$ 152,238	\$ 141,186	\$ 11,052	7.3%
Daniel Stover	INTUIT	2007	\$ 103,265	\$ 105,025	\$ (1,760)	-1.7%
Daniel Stover	INTUIT	2008	\$ 175,177	\$ 108,866	\$ 66,311	37.9%
Daniel Stover	INTUIT	2009	\$ 132,553	\$ 122,644	\$ 9,909	7.5%
Siddharth Hariharan	LUCASFILM	2007	\$ 102,000	\$ 89,439	\$ 12,561	12.3%

Source: Dr. Leamer's Figure 14 regressions.

### Exhibit 14A

## Differences between Actual Compensation and Dr. Leamer's Predicted Compensation Yearly Hedonic Regressions by Defendant for All Salaried Employee Class



Note: The percent difference is calculated as the residual from Dr. Leamer's Figure 12 regression models multiplied by 100.  
Source: Dr. Leamer's backup data and materials.

### Exhibit 14B

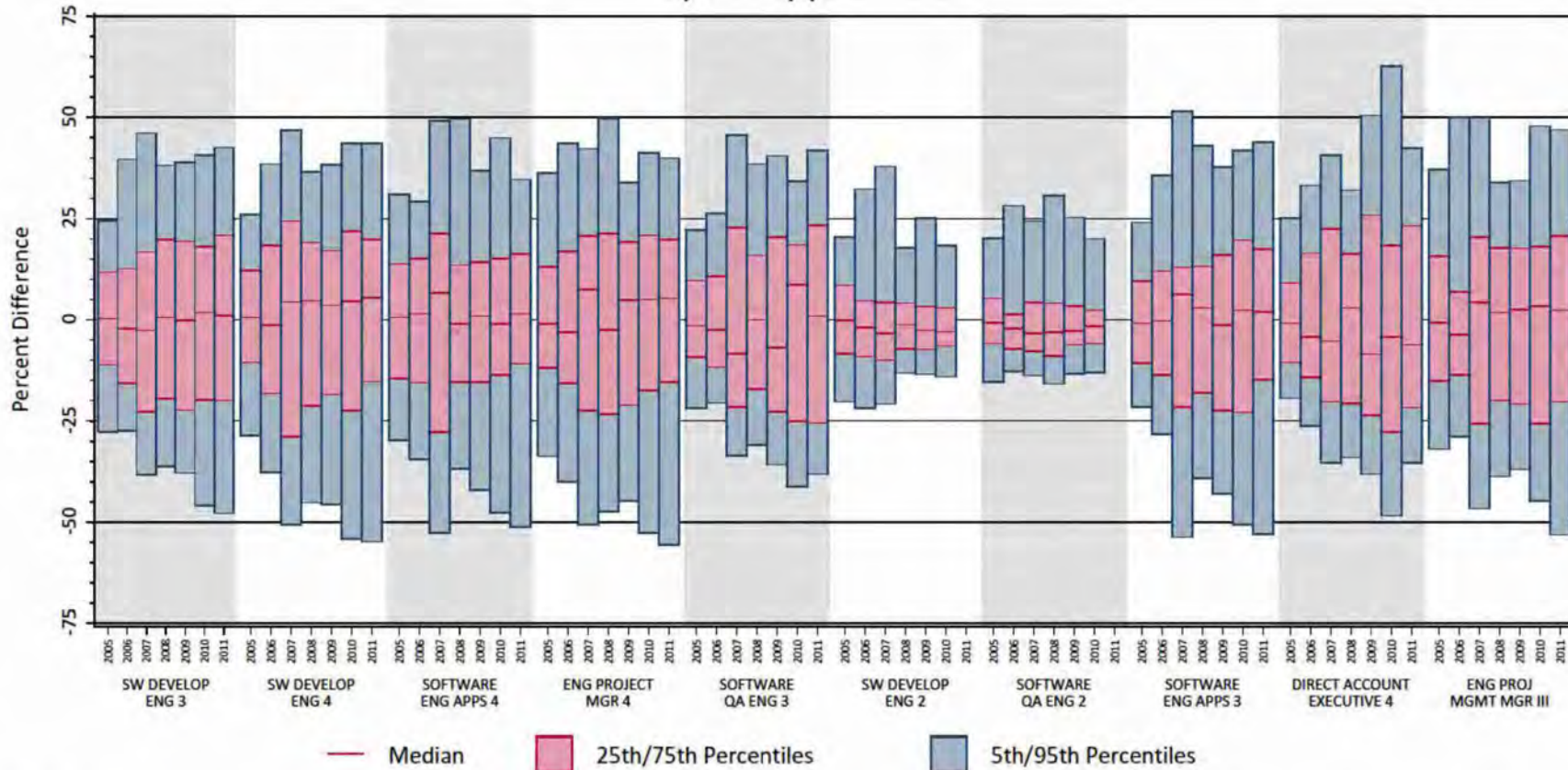
## Differences between Actual Compensation and Dr. Leamer's Predicted Compensation Yearly Hedonic Regressions by Defendant for Technical, Creative, and R&D Class



Note: The percent difference is calculated as the residual from Dr. Leamer's Figure 14 regression models multiplied by 100.  
Source: Dr. Leamer's backup data and materials.

### Exhibit 15A

## Difference between Actual Compensation and Dr. Leamer Predicted Compensation Top 10 Apple Jobs



**Notes:**

- [1] The percent difference is calculated as the residual from Dr. Leamer's Figure 12 regression models multiplied by 100.
- [2] The top 10 jobs are identified using 2005 through 2009 employment--the same algorithm that Dr. Leamer uses in his Figures 15 through 17.
- [3] Bars are missing when there are fewer than five employees with the relevant job title in the data in the given year.
- [4] Apple's job titles changed in 2005.

Source: Dr. Leamer's backup data and materials.

### Exhibit 15B

## Difference between Actual Compensation and Dr. Leamer Predicted Compensation Top 10 Google Jobs



Notes:

- [1] The percent difference is calculated as the residual from Dr. Leamer's Figure 12 regression models multiplied by 100.
- [2] The top 10 jobs are identified using 2005 through 2009 employment--the same algorithm that Dr. Leamer uses in his Figures 15 through 17.
- [3] Bars are missing when there are fewer than five employees with the relevant job title in the data in the given year.

Source: Dr. Leamer's backup data and materials.

## Exhibit 16

### Dr. Leamer's Model Implies Very Large Differences Over Time in the Compensation of Individuals with Identical Characteristics and Starting Compensation Levels (Simulations Based on Dr. Leamer's "Conduct Regression")

	Adobe	Apple	Google	Intel	Intuit	All Firms
<b><u>Difference in Compensation after Two Years</u></b>						
Average	15%	31%	46%	11%	16%	24%
90th Percentile	32%	67%	100%	22%	33%	56%
<b><u>Difference in Compensation after Five Years</u></b>						
Average	29%	53%	62%	16%	22%	37%
90th Percentile	61%	111%	135%	34%	46%	86%

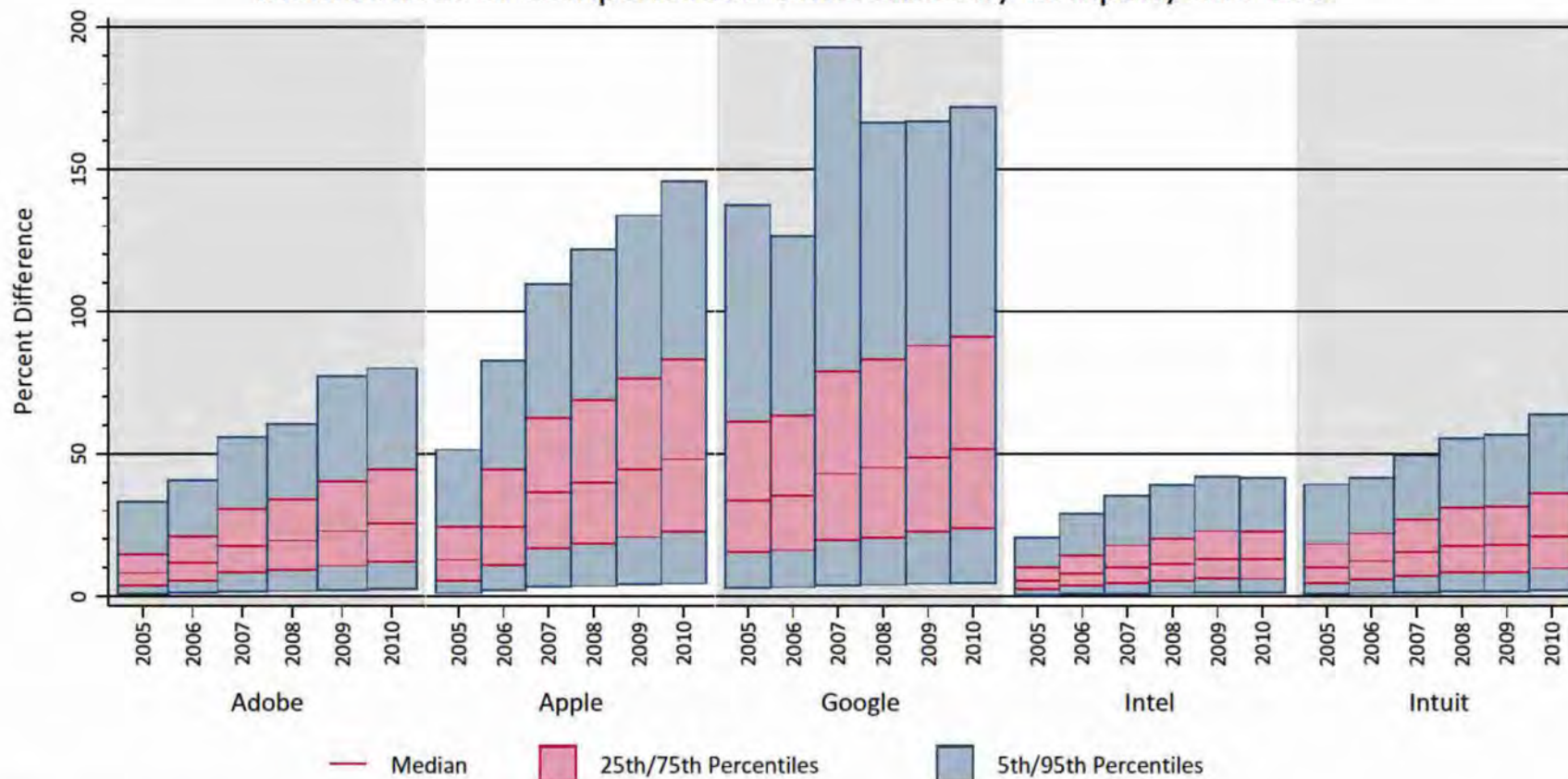
Notes:

- [1] Compensation differences are constructed using coefficients and residuals from Dr. Leamer's Figure 20 regression model.
- [2] Percent differences are defined as differences in logs.
- [3] Based on 50,000 simulations of compensation growth from 2004 through 2009 for each firm.
- [4] Lucasfilm and Pixar are excluded because there is insufficient data to do simulations in all years.

Source: Dr. Leamer's backup data and materials.

### Exhibit 17

## Simulated Compensation Dynamics of Two Identically Situated Employees Distributions of Compensation Differences by Company and Year



**Notes:**

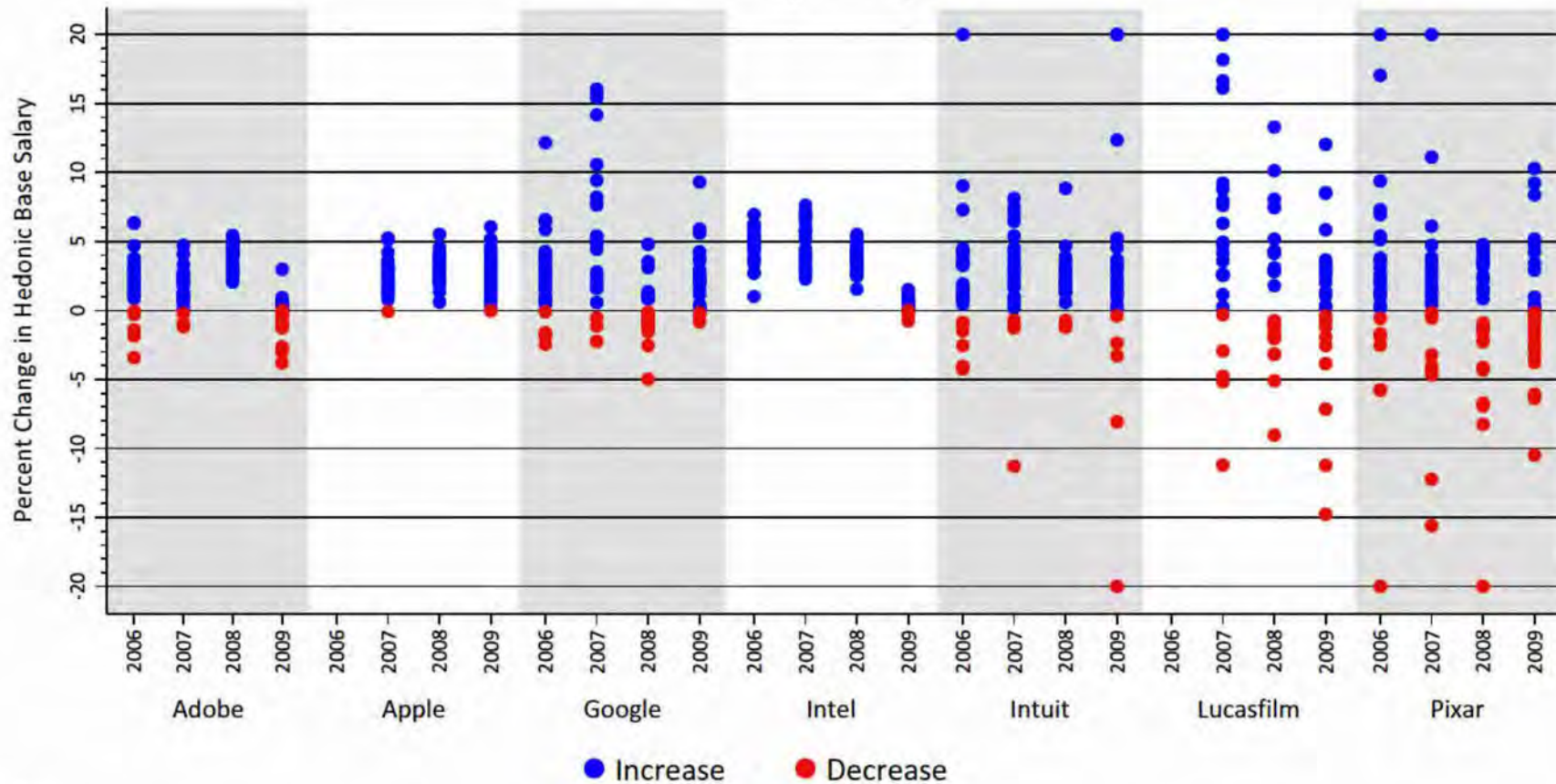
- [1] Compensation differences are constructed using coefficients and residuals from Dr. Leamer's Figure 20 regression model.
- [2] Percent differences are defined as differences in logs.
- [3] Based on 50,000 simulations for each firm.
- [4] Lucasfilm and Pixar are excluded because there is insufficient data to do the simulations in all years.

Source: Dr. Leamer's backup data and materials.

### Exhibit 18A

## Annual Changes in "Constant Attribute Compensation" of Top 25 Job Titles

### Base Salary Changes



**Notes:**

- [1] The top 25 jobs are identified using 2005 through 2009 employment--the same algorithm that Dr. Leamer uses in his Figures 15 through 17.
- [2] Percent changes in hedonic base salary are defined as differences in logs.
- [3] Outliers are capped at +/- 20 percent.

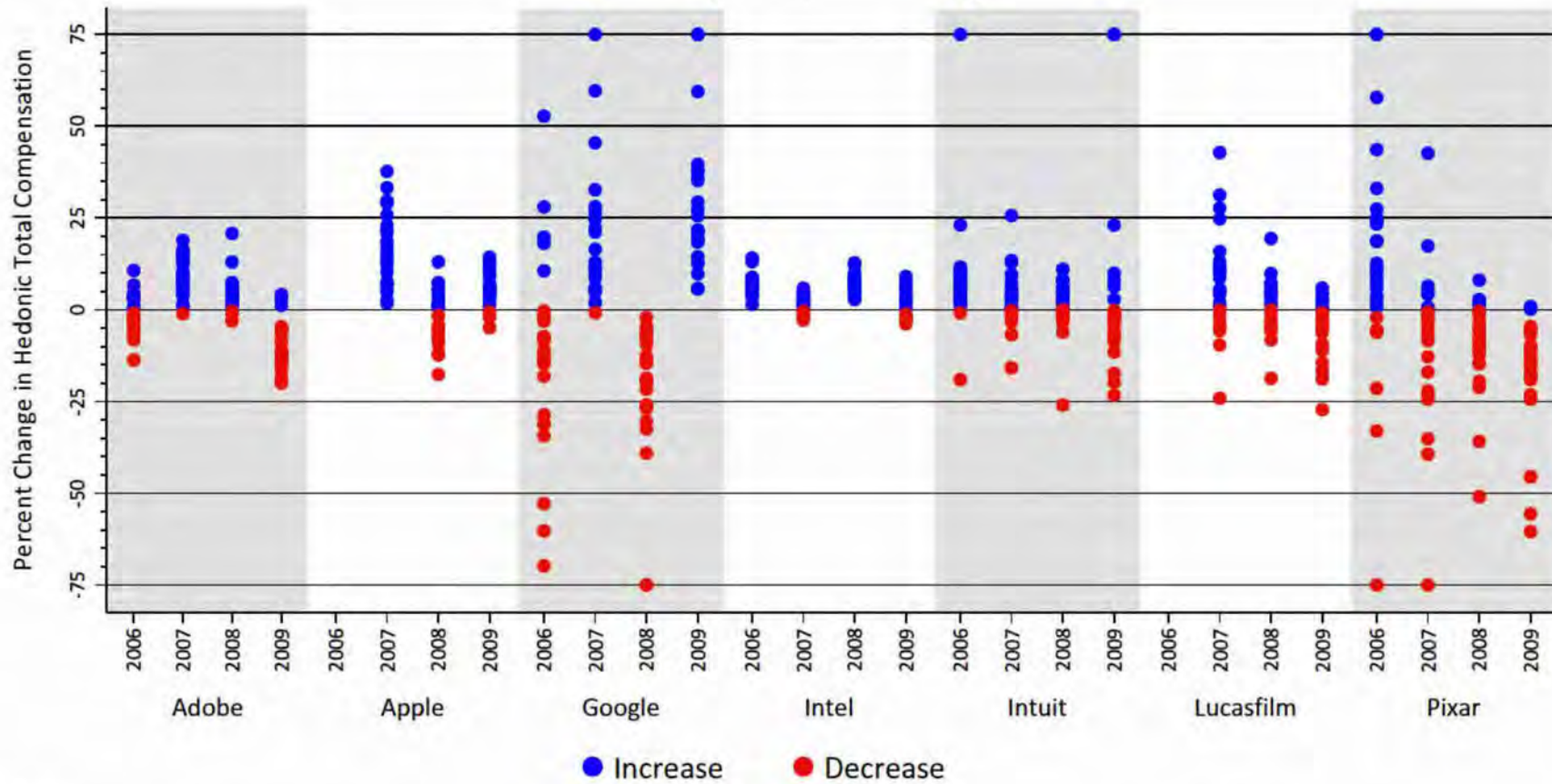
Source: Dr. Leamer's backup data and materials.



### Exhibit 18B

## Annual Changes in "Constant Attribute Compensation" of Top 25 Job Titles

### Total Compensation Changes



**Notes:**

- [1] The top 25 jobs are identified using 2005 through 2009 employment--the same algorithm that Dr. Leamer uses in his Figures 15 through 17.
- [2] Percent changes in hedonic total compensation are defined as differences in logs.
- [3] Outliers are capped at +/- 75 percent.

Source: Dr. Leamer's backup data and materials.

**Exhibit 19****Average Percent Change in Total Compensation**

Dr. Leamer's Figure 19 Disaggregated by Company

vs. Dr. Leamer's  
Figure 19**Average Change in Total Compensation**

Year	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	Pooled
2002	-27.8%	█	█	-2.1%	-27.2%	█	█	-4.7%
2003	0.6%	█	█	-5.1%	8.5%	█	█	-2.3%
2004	1.5%	█	█	13.1%	8.3%	█	█	10.3%
2005	9.8%	█	█	-1.3%	5.6%	█	█	0.5%
2006	6.9%	█	█	10.6%	13.9%	█	█	9.1%
2007	11.2%	█	█	4.5%	8.8%	█	█	7.4%
2008	6.9%	█	█	12.0%	8.8%	█	█	6.8%
2009	-7.5%	█	█	2.9%	-0.1%	█	█	7.4%
2010	3.0%	█	█	7.9%	12.7%	█	█	6.5%
2011	11.1%	█	█	8.7%	1.8%	█	█	9.7%

**Estimated Overpayment/Underpayment - Initial**

Year	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	Pooled
2005	3.4%	4.2%	-8.7%	-12.2%	0.6%	2.8%	35.6%	-9.5%
2006	0.6%	8.8%	-17.2%	-0.4%	8.9%	8.5%	26.8%	-0.9%
2007	4.9%	14.5%	16.4%	-6.4%	3.8%	3.8%	9.0%	-2.6%
2008	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2009	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

**Estimated Overpayment/Underpayment - Cumulative**

Year	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	Pooled
2005	3.4%	4.2%	-8.7%	-12.2%	0.6%	2.8%	35.6%	-9.5%
2006	4.0%	13.0%	-25.9%	-12.5%	9.5%	11.4%	62.3%	-10.3%
2007	8.9%	27.5%	-9.5%	-18.9%	13.3%	15.1%	71.4%	-12.9%
2008	8.9%	27.5%	-9.5%	-18.9%	13.3%	15.1%	71.4%	-12.9%
2009	8.9%	27.5%	-9.5%	-18.9%	13.3%	15.1%	71.4%	-12.9%

Note: This analysis follows Dr. Leamer's methodology in his Figure 19 of treating 2005 as the first year of the agreements for all Defendants, even though for Intuit, Lucasfilm and Pixar the first alleged agreements started in other years.

Source: Leamer Report backup data and programs.

**Exhibit 20****"Undercompensation" Estimates Using Defendant-Specific Conduct Variables and Other Defendant-Specific Interactive Effects in Dr. Leamer's Regression**

vs.

**"Undercompensation" Estimates in Dr. Leamer's Figures 22 and 24**

## All-Salaried Employee Class

Year	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar
2005	-1.82%	-2.54%	12.73%	0.51%		1.70%	25.47%
2006	4.37%	-0.72%	26.90%	-1.89%		9.59%	30.64%
2007	-0.68%	-2.65%	19.16%	-6.26%	-6.45%	13.95%	28.52%
2008	-2.19%	-4.06%	5.70%	-8.01%	-10.24%	14.15%	36.96%
2009	-20.26%	-1.53%	-5.43%	-8.96%	-10.02%	13.79%	31.11%

## All-Salaried Employee Class

Year	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar
2005	-1.61%	-1.59%	-1.78%	-1.67%		-12.13%	-10.56%
2006	-4.28%	-4.43%	-4.44%	-4.70%		-14.63%	-12.44%
2007	-6.64%	-6.94%	-6.39%	-7.46%	-3.24%	-17.24%	-14.28%
2008	-9.08%	-9.56%	-8.40%	-10.05%	-5.64%	-19.94%	-15.76%
2009	-9.15%	-9.73%	-7.51%	-9.95%	-5.70%	-20.12%	-14.65%

## Technical, Creative and R&amp;D Class

Year	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar
2005	-1.92%	-2.01%	11.08%	1.71%		6.60%	28.18%
2006	5.82%	-2.95%	22.47%	0.62%		17.23%	30.70%
2007	-0.05%	-5.23%	13.12%	-3.03%	-6.93%	23.38%	36.34%
2008	-1.29%	-7.33%	-0.88%	-3.44%	-8.59%	24.38%	34.92%
2009	-22.60%	-6.28%	-10.56%	-4.67%	-7.47%	24.05%	28.33%

## Technical, Creative and R&amp;D Class

Year	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar
2005	-1.56%	-1.90%	-3.07%	-1.64%		-10.80%	-9.28%
2006	-4.29%	-4.96%	-7.23%	-3.06%		-14.77%	-10.47%
2007	-6.48%	-7.79%	-9.36%	-3.38%	-3.41%	-18.08%	-10.61%
2008	-8.80%	-10.64%	-11.20%	-4.76%	-5.21%	-20.44%	-11.87%
2009	-8.44%	-10.51%	-9.00%	-4.19%	-4.96%	-20.54%	-9.62%

Source: Leamer Figure 20 and 23 regressions including interactions between company indicators and Dr. Leamer's conduct, age, and hiring rate variables. Pixar revenue data after 2005 are included.

## Exhibit 21A

### Dr. Leamer's Figure 20 Regression Using Corrected Standard Errors

#### All-Salaried Employee Class

Dependant Variable: Log(Total Annual Compensation/CPI)

Variable	Estimate	St. Error	T-Value
Conduct * Age	0.0067 **	0.0031	2.18
Conduct * Age^2	-0.0001 ***	0.0000	-2.45
Conduct * Log(Number of New Hires in the Firm/Number of Employees(-1))	0.0028	0.0247	0.12
Conduct	-0.1647	0.1269	-1.30
ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.6949 ***	0.0608	11.42
APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7404 ***	0.0587	12.62
GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.4945 ***	0.0530	9.33
INTEL * Log(Total Annual Compensation/CPI) (-1)	0.6690 ***	0.0351	19.06
INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.7090 ***	0.0458	15.48
PIXAR * Log(Total Annual Compensation/CPI) (-1)	0.6944 ***	0.1840	3.77
LUCASFILM * Log(Total Annual Compensation/CPI) (-1)	0.8131 ***	0.1069	7.61
ADOBE * Log(Total Annual Compensation/CPI) (-2)	0.2963 ***	0.0461	6.43
APPLE * Log(Total Annual Compensation/CPI) (-2)	0.2610 ***	0.0407	6.41
GOOGLE * Log(Total Annual Compensation/CPI) (-2)	0.3732 ***	0.0453	8.25
INTEL * Log(Total Annual Compensation/CPI) (-2)	0.3001 ***	0.0389	7.71
INTUIT * Log(Total Annual Compensation/CPI) (-2)	0.2551 ***	0.0433	5.89
PIXAR * Log(Total Annual Compensation/CPI) (-2)	0.1983 ***	0.0780	2.54
LUCASFILM * Log(Total Annual Compensation/CPI) (-2)	0.1779 *	0.0979	1.82
Log(Age) (Years)	-0.3591 **	0.1799	-2.00
Log(Age)^2	0.0394 *	0.0233	1.69
Log(Company Tenure) (Months)	0.0107	0.0415	0.26
Log(Company Tenure)^2	-0.0012	0.0043	-0.28
Male	0.0027	0.0020	1.37
DLog(Information Sector Employment in San-Jose)	1.4353 ***	0.3827	3.75
Log(Total Number of Transfers Among Defendants)	0.0961 **	0.0456	2.11
Year (trend)	-0.0038	0.0076	-0.50
Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0154	0.0214	0.72
Log(Total Number of New Hires)	-0.2485 ***	0.0568	-4.37
Log(Firm Revenue Per Employee/CPI) (-1)	-0.1070	0.0785	-1.36
DLog(Firm Revenue Per Employee/CPI) (-1)	0.2170 ***	0.0814	2.67
APPLE	0.0627	0.2642	0.24
GOOGLE	1.0364 ***	0.3351	3.09
INTEL	0.1522	0.2431	0.63
INTUIT	0.1462	0.2151	0.68
PIXAR	0.7251	0.6673	1.09
LUCASFILM	0.1352	0.2762	0.49
Location (State) Indicators	YES		
Constant	YES		
R-Square	<b>0.926</b>		
Observations	<b>504,897</b>		

Note: \*\*\* Significant at 1% level, \*\* Significant at 5% level, \* Significant at 10% level.

Source: Dr. Leamer's backup data and materials. Standard errors clustered on employer-year.

## Exhibit 21B

### Dr. Leamer's Figure 23 Regression Using Corrected Standard Errors

#### Technical, Creative and R&D Class

**Dependant Variable:** Log(Total Annual Compensation/CPI)

Variable	Estimate	St. Error	T-Value
Conduct * Age	0.0079 ***	0.0033	2.38
Conduct * Age^2	-0.0001 ***	0.0000	-2.71
Conduct * Log(Number of New Hires in the Firm/Number of Employees(-1))	-0.0121	0.0281	-0.43
Conduct	-0.2196	0.1362	-1.61
ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.6744 ***	0.0650	10.38
APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7234 ***	0.0570	12.70
GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.4367 ***	0.0672	6.50
INTEL * Log(Total Annual Compensation/CPI) (-1)	0.6401 ***	0.0325	19.67
INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.6703 ***	0.0486	13.81
PIXAR * Log(Total Annual Compensation/CPI) (-1)	0.6491 ***	0.2295	2.83
LUCASFILM * Log(Total Annual Compensation/CPI) (-1)	0.8462 ***	0.0911	9.29
ADOBE * Log(Total Annual Compensation/CPI) (-2)	0.3053 ***	0.0523	5.83
APPLE * Log(Total Annual Compensation/CPI) (-2)	0.2538 ***	0.0391	6.49
GOOGLE * Log(Total Annual Compensation/CPI) (-2)	0.3659 ***	0.0476	7.68
INTEL * Log(Total Annual Compensation/CPI) (-2)	0.3179 ***	0.0353	9.00
INTUIT * Log(Total Annual Compensation/CPI) (-2)	0.2857 ***	0.0439	6.51
PIXAR * Log(Total Annual Compensation/CPI) (-2)	0.1045	0.0896	1.17
LUCASFILM * Log(Total Annual Compensation/CPI) (-2)	0.1448 *	0.0805	1.80
Log(Age) (Years)	-0.5894 ***	0.1877	-3.14
Log(Age)^2	0.0696 ***	0.0239	2.92
Log(Company Tenure) (Months)	0.0297	0.0477	0.62
Log(Company Tenure)^2	-0.0025	0.0049	-0.52
Male	0.0065 ***	0.0024	2.64
DLog(Information Sector Employment in San-Jose)	1.4378 ***	0.4146	3.47
Log(Total Number of Transfers Among Defendants)	0.0973 **	0.0493	1.98
Year (trend)	-0.0008	0.0080	-0.10
Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0240	0.0241	0.99
Log(Total Number of New Hires)	-0.2720 ***	0.0617	-4.41
Log(Firm Revenue Per Employee/CPI) (-1)	-0.0661	0.0853	-0.78
DLog(Firm Revenue Per Employee/CPI) (-1)	0.2068 ***	0.0869	2.38
APPLE	0.1220	0.2718	0.45
GOOGLE	1.3682 ***	0.4309	3.18
INTEL	0.1569	0.2761	0.57
INTUIT	0.1393	0.2268	0.61
PIXAR	1.5864	1.0458	1.52
LUCASFILM	0.0127	0.3184	0.04
Location (State) Indicators	YES		
Constant	YES		
R-Square	<b>0.874</b>		
Observations	<b>292,489</b>		

Note: \*\*\* Significant at 1% level, \*\* Significant at 5% level, \* Significant at 10% level.

Source: Dr. Leamer's backup data and materials. Standard errors clustered on employer-year.

## Exhibit 22A

### Dr. Leamer's Estimates of Undercompensation Are Not Statistically Significant All-Salaried Employee Class

	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar
<b><u>Dr. Leamer's Annual Undercompensation Estimates (Figure 22)</u></b>							
2005	-1.61%	-1.59%	-1.78%	-1.67%		-12.13%	-10.56%
2006	-4.28%	-4.43%	-4.44%	-4.70%		-14.63%	-12.44%
2007	-6.64%	-6.94%	-6.39%	-7.46%	-3.24%	-17.24%	-14.28%
2008	-9.08%	-9.56%	-8.40%	-10.05%	-5.64%	-19.94%	-15.76%
2009	-9.15%	-9.73%	-7.51%	-9.95%	-5.70%	-20.12%	-14.65%
<b><u>T-Statistics for Annual Undercompensation Estimates</u></b>							
2005	-0.94	-0.74	-0.47	-0.96		-1.17	-0.91
2006	-0.88	-0.81	-0.49	-1.49		-0.98	-0.86
2007	-0.90	-0.80	-0.55	-1.62	-0.86	-0.93	-0.88
2008	-0.90	-0.80	-0.60	-1.63	-0.99	-0.95	-0.79
2009	-0.94	-0.82	-0.64	-1.62	-1.04	-0.96	-0.72
<b><u>P-Values for Annual Undercompensation Estimates</u></b>							
2005	35.3%	46.5%	64.1%	34.0%		24.9%	36.8%
2006	38.2%	42.3%	62.7%	14.2%		33.0%	39.3%
2007	37.1%	42.6%	58.7%	11.1%	39.4%	35.5%	38.4%
2008	37.0%	42.6%	55.1%	10.8%	32.6%	34.4%	43.2%
2009	35.0%	41.7%	52.3%	11.2%	30.1%	34.3%	47.7%

## Notes:

[1] Estimates with t-statistics below 1.96 in absolute value (or, equivalently, with p-values greater than 5%) are not statistically significant at the 95% level.

[2] Standard errors are clustered on employer and year.

Source: Dr. Leamer's Figure 20 regression data.

**Exhibit 22B****Dr. Leamer's Estimates of Undercompensation Are Not Statistically Significant  
Technical, Creative, and R&D Class**

	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar
<b><u>Dr. Leamer's Annual Undercompensation Estimates (Figure 24)</u></b>							
2005	-1.56%	-1.90%	-3.07%	-1.64%		-10.80%	-9.28%
2006	-4.29%	-4.96%	-7.23%	-3.06%		-14.77%	-10.47%
2007	-6.48%	-7.79%	-9.36%	-3.38%	-3.41%	-18.08%	-10.61%
2008	-8.80%	-10.64%	-11.20%	-4.76%	-5.21%	-20.44%	-11.87%
2009	-8.44%	-10.51%	-9.00%	-4.19%	-4.96%	-20.54%	-9.62%
<b><u>T-Statistics for Annual Undercompensation Estimates</u></b>							
2005	-0.81	-0.77	-0.71	-0.83		-0.91	-0.78
2006	-0.78	-0.79	-0.72	-0.94		-0.85	-0.72
2007	-0.79	-0.80	-0.75	-0.76	-0.79	-0.83	-0.67
2008	-0.79	-0.80	-0.77	-0.81	-0.83	-0.83	-0.61
2009	-0.79	-0.81	-0.80	-0.72	-0.84	-0.83	-0.49
<b><u>P-Values for Annual Undercompensation Estimates</u></b>							
2005	42.4%	44.7%	48.2%	40.8%		36.8%	44.1%
2006	43.7%	43.0%	47.5%	35.0%		39.9%	47.4%
2007	43.6%	43.0%	45.6%	44.8%	43.1%	41.0%	50.7%
2008	43.5%	42.8%	44.3%	42.4%	40.9%	41.0%	54.1%
2009	43.1%	42.4%	42.8%	47.8%	40.4%	41.2%	62.7%

## Notes:

[1] Estimates with t-statistics below 1.96 in absolute value (or, equivalently, with p-values greater than 5%) are not statistically significant at the 95% level.

[2] Standard errors are clustered on employer and year.

Source: Dr. Leamer's Figure 23 regression data.

**Exhibit 23****"Undercompensation" Estimates Using Pre-Conduct Period  
as Benchmark in Dr. Leamer's Regression****"Undercompensation" Estimates Using Post-Conduct Period  
as Benchmark in Dr. Leamer's Regression**

## All-Salaried Employee Class

Year	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar
2005	-2.71%	-3.61%	-6.33%	-2.81%		-14.56%	-16.52%
2006	-7.94%	-9.12%	-15.64%	-3.65%		-22.11%	-19.53%
2007	-12.15%	-14.47%	-20.77%	-1.56%	-6.18%	-27.43%	-19.88%
2008	-16.55%	-19.95%	-25.25%	-2.74%	-9.00%	-30.44%	-23.69%
2009	-15.87%	-19.92%	-22.16%	-1.37%	-8.34%	-30.04%	-20.65%

## All-Salaried Employee Class

Year	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar
2005	2.35%	2.55%	2.76%	2.29%		14.80%	12.66%
2006	6.66%	6.74%	6.80%	5.08%		19.72%	15.17%
2007	10.43%	10.54%	9.43%	6.72%	4.83%	24.07%	16.81%
2008	14.40%	14.43%	11.85%	9.43%	8.35%	27.74%	19.25%
2009	14.55%	14.49%	10.20%	9.05%	8.51%	28.06%	17.56%

## Technical, Creative and R&amp;D Class

Year	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar
2005	-3.46%	-4.70%	-8.39%	-3.54%		-16.57%	-18.91%
2006	-10.10%	-11.69%	-20.04%	-3.90%		-25.84%	-21.64%
2007	-15.29%	-18.40%	-25.38%	-0.43%	-7.90%	-31.64%	-20.55%
2008	-20.74%	-25.15%	-29.55%	-1.63%	-10.96%	-34.10%	-24.35%
2009	-19.53%	-24.64%	-23.64%	0.33%	-9.96%	-32.41%	-19.40%

## Technical, Creative and R&amp;D Class

Year	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar
2005	2.33%	2.26%	1.81%	2.25%		16.28%	11.56%
2006	6.47%	6.08%	4.52%	5.96%		20.36%	13.40%
2007	10.17%	9.38%	6.50%	9.12%	4.58%	24.38%	14.99%
2008	14.00%	12.71%	8.46%	12.50%	8.08%	28.54%	16.28%
2009	14.25%	12.62%	7.12%	12.37%	8.24%	29.30%	14.15%

Source: Leamer Figure 20 and 23 regressions estimated using conduct and pre-conduct period data only.

Source: Leamer Figure 20 and 23 regressions estimated using conduct and post-conduct period data only.



**Exhibit 24****"Undercompensation" Estimates Predicted Using Non-Conduct Period Data in Dr. Leamer's Regression****vs. "Undercompensation" Estimates in Dr. Leamer's Figures 22 and 24****All-Salaried Employee Class**

Year	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar
2005	5.01%	0.84%	0.72%	-2.96%		2.48%	4.52%
2006	2.65%	5.79%	-5.61%	-2.73%		5.99%	16.84%
2007	4.26%	12.56%	-2.34%	-8.78%	-6.72%	3.78%	-4.45%
2008	4.67%	-0.10%	-18.53%	-7.36%	-10.78%	3.88%	-29.03%
2009	1.00%	2.21%	-3.13%	-7.87%	-12.05%	3.93%	-32.40%

**All-Salaried Employee Class**

Year	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar
2005	-1.61%	-1.59%	-1.78%	-1.67%		-12.13%	-10.56%
2006	-4.28%	-4.43%	-4.44%	-4.70%		-14.63%	-12.44%
2007	-6.64%	-6.94%	-6.39%	-7.46%	-3.24%	-17.24%	-14.28%
2008	-9.08%	-9.56%	-8.40%	-10.05%	-5.64%	-19.94%	-15.76%
2009	-9.15%	-9.73%	-7.51%	-9.95%	-5.70%	-20.12%	-14.65%

**Technical, Creative and R&D Class**

Year	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar
2005	5.83%	0.97%	1.89%	-3.43%		3.05%	11.66%
2006	2.05%	4.03%	-12.09%	-1.29%		6.07%	24.15%
2007	5.83%	9.57%	-7.59%	-5.47%	-6.76%	1.52%	6.44%
2008	5.18%	-4.33%	-25.03%	-2.56%	-8.81%	1.86%	-16.70%
2009	1.46%	-2.26%	-6.45%	-3.09%	-10.53%	1.90%	-23.03%

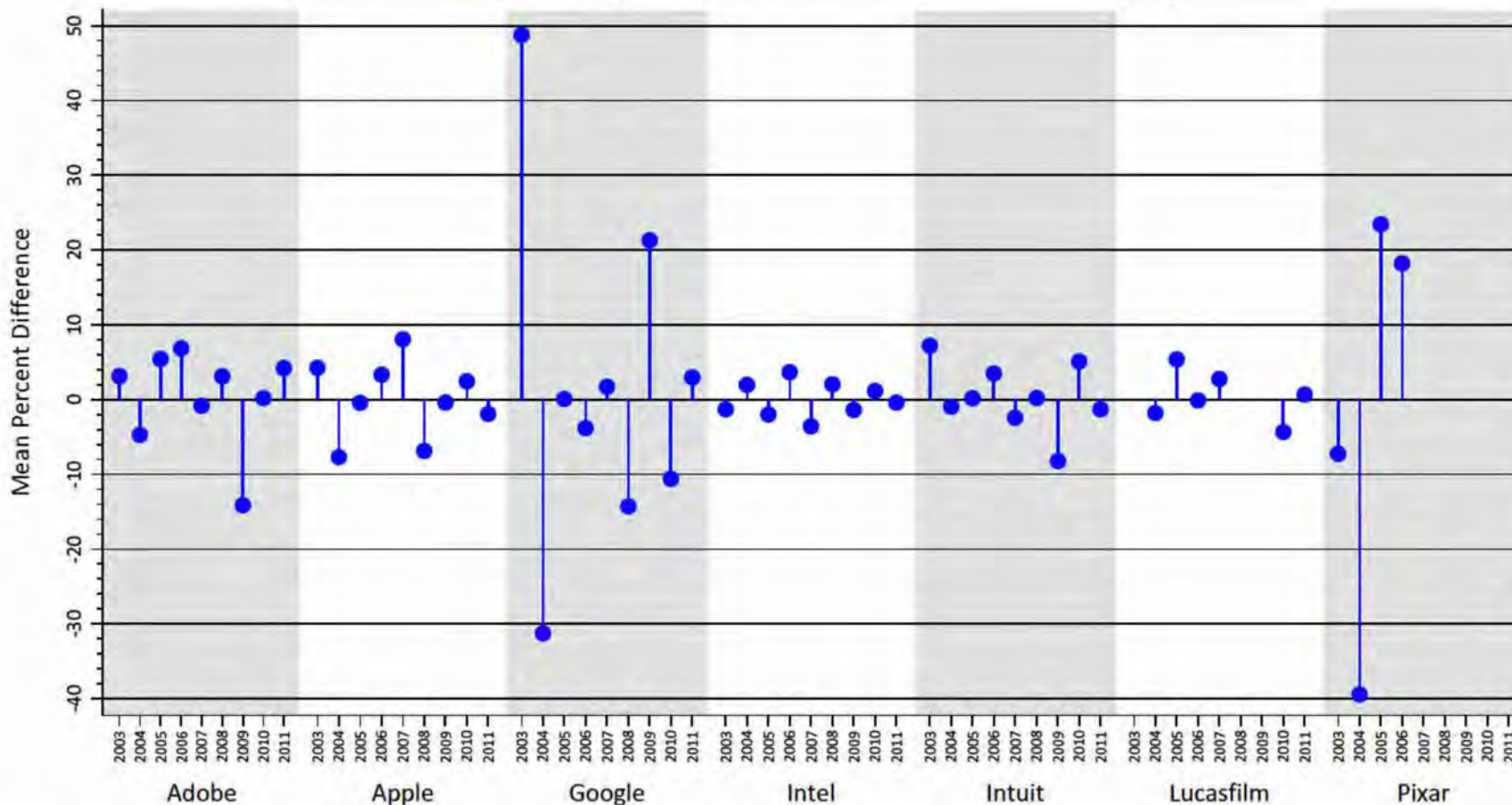
**Technical, Creative and R&D Class**

Year	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar
2005	-1.56%	-1.90%	-3.07%	-1.64%		-10.80%	-9.28%
2006	-4.29%	-4.96%	-7.23%	-3.06%		-14.77%	-10.47%
2007	-6.48%	-7.79%	-9.36%	-3.38%	-3.41%	-18.08%	-10.61%
2008	-8.80%	-10.64%	-11.20%	-4.76%	-5.21%	-20.44%	-11.87%
2009	-8.44%	-10.51%	-9.00%	-4.19%	-4.96%	-20.54%	-9.62%

Source: Leamer Figure 20 and 23 regressions estimated using non-conduct period data.  
Undercompensation calculated using residuals predicted for the conduct period.  
Pixar revenue data after 2005 are included.

### Exhibit 25A

Mean Difference between Actual and Predicted Real Compensation by Company and Year  
 Dr. Leamer's Conduct Regression for the All Salaried Employee Class



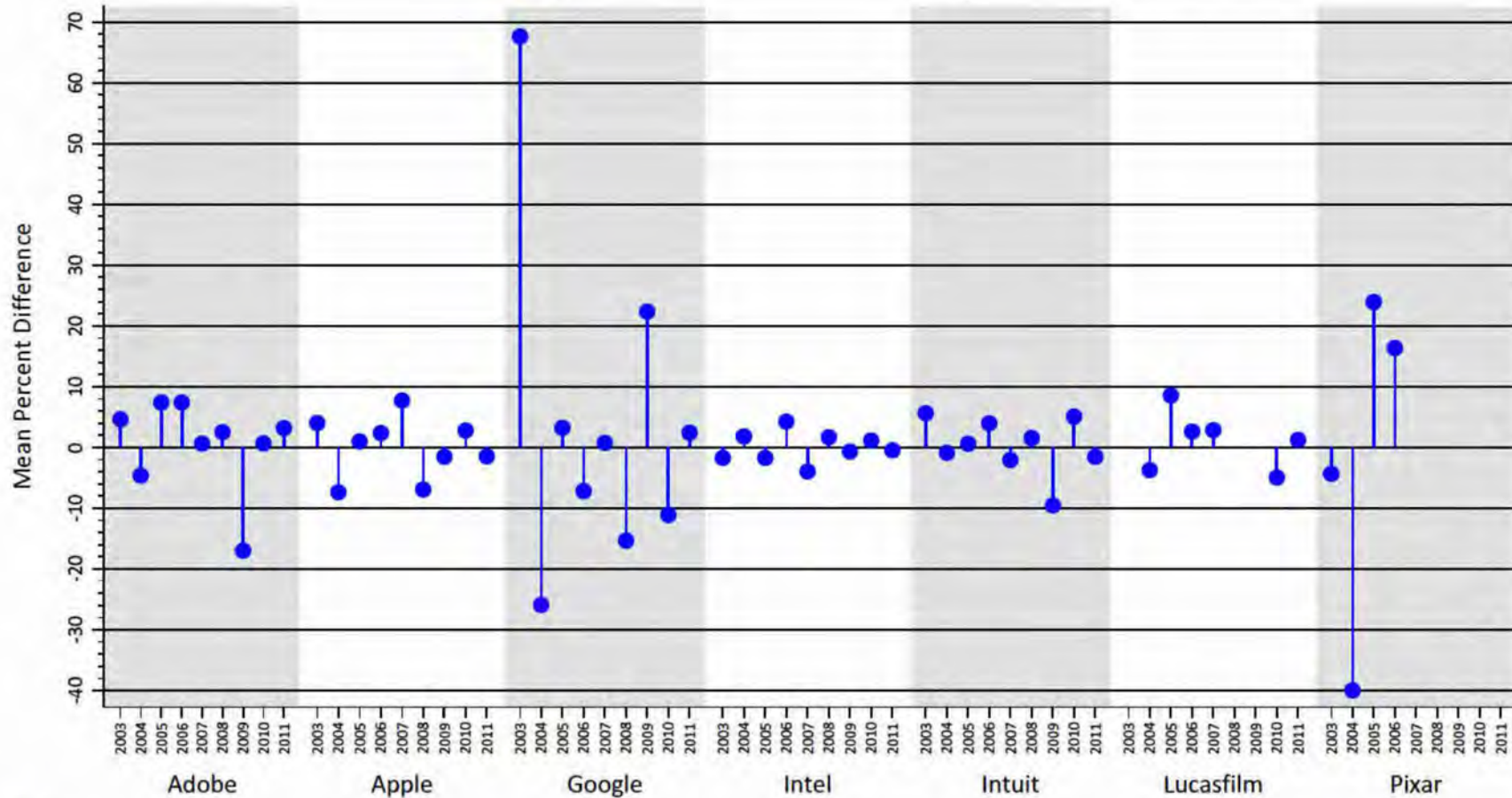
Notes:

- [1] The percent difference is calculated as the residual from Dr. Leamer's Figure 20 regression model multiplied by 100.
- [2] Real compensation, which is the dependant variable in the Dr. Leamer's model, is defined as total annual compensation divided by the consumer price index.

Source: Dr. Leamer's backup data and materials.

### Exhibit 25B

Mean Difference between Actual and Predicted Real Compensation by Company and Year  
 Dr. Leamer's Conduct Regression for the Technical, Creative, and R&D Class



Notes:

- [1] The percent difference is calculated as the residual from Dr. Leamer's Figure 23 regression model multiplied by 100.
- [2] Real compensation, which is the dependant variable in the Dr. Leamer's model, is defined as total annual compensation divided by the consumer price index.

Source: Dr. Leamer's backup data and materials.

**Exhibit 26****"Undercompensation Estimates" Including Change in S&P 500 in Dr. Leamer's Regression****"Undercompensation" Estimates in Dr. Leamer's Figures 22 and 24**

## All-Salaried Employee Class

Year	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar
2005	-0.11%	-0.06%	-0.17%	-0.17%		-1.90%	-1.64%
2006	-0.23%	-0.27%	-0.43%	-0.84%		-1.83%	-1.83%
2007	-0.39%	-0.44%	-0.68%	-1.70%	-0.22%	-1.96%	-2.23%
2008	-0.55%	-0.62%	-1.01%	-2.22%	-0.55%	-2.28%	-2.25%
2009	-0.66%	-0.66%	-1.01%	-2.32%	-0.61%	-2.31%	-2.14%

## All-Salaried Employee Class

Year	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar
2005	-1.61%	-1.59%	-1.78%	-1.67%		-12.13%	-10.56%
2006	-4.28%	-4.43%	-4.44%	-4.70%		-14.63%	-12.44%
2007	-6.64%	-6.94%	-6.39%	-7.46%	-3.24%	-17.24%	-14.28%
2008	-9.08%	-9.56%	-8.40%	-10.05%	-5.64%	-19.94%	-15.76%
2009	-9.15%	-9.73%	-7.51%	-9.95%	-5.70%	-20.12%	-14.65%

## Technical, Creative and R&amp;D Class

Year	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar
2005	0.48%	0.19%	-0.84%	0.41%		3.49%	1.29%
2006	1.20%	0.69%	-1.82%	2.12%		3.17%	1.43%
2007	1.93%	1.00%	-1.87%	4.26%	0.71%	3.38%	2.21%
2008	2.64%	1.32%	-1.74%	5.59%	1.59%	4.37%	1.86%
2009	2.81%	1.40%	-1.15%	5.76%	1.74%	4.57%	1.65%

## Technical, Creative and R&amp;D Class

Year	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar
2005	-1.56%	-1.90%	-3.07%	-1.64%		-10.80%	-9.28%
2006	-4.29%	-4.96%	-7.23%	-3.06%		-14.77%	-10.47%
2007	-6.48%	-7.79%	-9.36%	-3.38%	-3.41%	-18.08%	-10.61%
2008	-8.80%	-10.64%	-11.20%	-4.76%	-5.21%	-20.44%	-11.87%
2009	-8.44%	-10.51%	-9.00%	-4.19%	-4.96%	-20.54%	-9.62%

Source: Leamer Figure 20 and 23 regressions including change in S&P 500 Net Total Return Index (Bloomberg).

## *Curriculum Vitae*

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October 2012

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#### **Current Positions**

July 2005-Present: George J. Stigler Distinguished Service Professor of Economics,  
Department of Economics and Booth School of Business, University of Chicago

Faculty Research Associate, National Bureau of Economic Research

#### **Education**

University of California, Los Angeles, A.B., Economics, 1981

University of Chicago, Ph.D., 1986

Thesis Topic: *Specialization and Human Capital*

#### **Previous Research and Academic Positions**

2002-2005: George J. Stigler Professor of Economics, Department of Economics and  
Booth School of Business, University of Chicago

1993 – 2002: George Pratt Shultz Professor of Business Economics and Industrial  
Relations, University of Chicago

1989 – 1993: Professor of Business Economics and Industrial Relations, University of  
Chicago

1988 – 1989: Associate Professor of Business Economics and Industrial Relations,  
University of Chicago

1986 – 1988: Assistant Professor of Business Economics and Industrial Relations, University of Chicago

1983 – 1986: Lecturer, Booth School of Business, University of Chicago

1982 – 1983: Teaching Associate, Department of Economics, University of Chicago

1979 – 1981: Research Assistant, Unicon Research Corporation, Santa Monica, California

### **Honors and Awards**

2008: John von Neumann Lecture Award, Rajk College, Corvinus University, Budapest

2007: Kenneth J. Arrow Award (with Robert H. Topel)

October 2005: Garfield Research Prize (with Robert H. Topel)

September 2005: MacArthur Foundation Fellow

1998: Elected to the American Academy of Arts & Sciences

1997: John Bates Clark Medalist

1993: Fellow of The Econometric Society

1989 – 1991: Sloan Foundation Fellowship, University of Chicago

1983 – 1984: Earhart Foundation Fellowship, University of Chicago

1981 – 1983: Fellowship, Friedman Fund, University of Chicago

1980 – 1981: Phi Beta Kappa, University of California, Los Angeles

1980 – 1981: Earhart Foundation Fellowship, University of California, Los Angeles

1979 – 1981: Department Scholar, Department of Economics, University of California, Los Angeles

### **Publications**

#### **Books**

Social Economics: Market Behavior in a Social Environment with Gary S. Becker, Cambridge, MA: Harvard University Press (2000).

Measuring the Gains from Medical Research: An Economic Approach edited volume with Robert H. Topel, Chicago: University of Chicago Press (2003).

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Declaration of Kevin M. Murphy, March 2, 2011, in the Matter of TCF National Bank v. Ben S. Bernanke, Janet L. Yellen, Kevin M. Warsh, Elizabeth A. Duke, Daniel K. Tarullo and Sarah Bloom Raskin, the Board of Governors of the Federal Reserve System, in their official capacities; and John Walsh, Comptroller of the Currency, in his official capacity.

Expert Report of Kevin M. Murphy, April 11, 2011, in the Matter of Dattel Holdings, LTD., and Dattel Design & Development, Inc., v. Microsoft Corporation., The United States District Court Northern District of California.

Declaration of Kevin M. Murphy, May 26, 2011, filed with the National Labor Relations Board on behalf of the National Basketball Players Association.

Deposition of Kevin M. Murphy, June 14, 2011, in the Matter of Dattel Holdings, LTD., and Dattel Design & Development, Inc., v. Microsoft Corporation., The United States District Court Northern District of California.

Expert Report of Kevin M. Murphy, July 1, 2011, in the Matter of Certain Gaming and Entertainment Consoles, Related Software, and Components Thereof., The United States International Trade Commission.

Expert Report of Kevin M. Murphy, August 17, 2011, in the Matter of American Airlines, Inc. v. Sabre Inc., et al., The Judicial District of Tarrant County, Texas 67<sup>th</sup> Judicial District.

Expert Report of Kevin M. Murphy, August 19, 2011, in the Matter of Motor Fuel Temperature Sales Litigation., The United States District Court for the District of Kansas.

Deposition of Kevin M. Murphy, September 6, 2011, in the Matter of Certain Gaming and Entertainment Consoles, Related Software, and Components Thereof., The United States International Trade Commission.

Expert Report of Kevin M. Murphy, September 9, 2011, in the Matter of State of New York v. Intel Corporation., The United States District Court for the District of Delaware.

Deposition of Kevin M. Murphy, September 14, 2011, in the Matter of Motor Fuel Temperature Sales Litigation., The United States District Court for the District of Kansas.

Direct Testimony of Kevin M. Murphy, September 27, 2011, in the Matter of Certain Gaming and Entertainment Consoles, Related Software, and Components Thereof., The United States International Trade Commission.

Deposition of Kevin M. Murphy, October 8-10, 2011, in the Matter of State of New York v. Intel Corporation., The United States District Court for the District of Delaware.

Report of Kevin M. Murphy, October 10, 2011, in connection with dispute between NRLC and railroad employees, National Mediation Board Case Nos. A-13569; A-13570; A-13572; A-13573; A-13574; A-13575; A-13592, before Emergency Board No. 243.

Hearing Testimony of Kevin M. Murphy, October 13, 2011, in connection with dispute between NRLC and railroad employees, National Mediation Board Case Nos. A-13569; A-13570; A-13572; A-13573; A-13574; A-13575; A-13592, before Emergency Board No. 243.

Expert Report of Kevin M. Murphy, October 17, 2011, in the Matter of State of New Hampshire v. Hess Corporation, et al., The State of New Hampshire Superior Court.

Declaration of Kevin M. Murphy, December 1, 2011, the Matter of Motor Fuel Temperature Sales Litigation., The United States District Court for the District of Kansas.

Expert Report of Kevin M. Murphy, December 5, 2011, in the Matter of Retractable Technologies, Inc. and Thomas Shaw v. Becton, Dickinson and Company., The United States District Court for the Eastern District of Texas Marshall Division.

Trial Testimony of Kevin M. Murphy, December 7-8, 2011, in the Matter of Novell, Incorporated v. Microsoft Corporation., The United States District Court Northern District of Maryland.

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Trial Testimony of Kevin M. Murphy, January 18, 2012, in the Matter of Certain Gaming and Entertainment Consoles, Related Software, and Components Thereof., The United States International Trade Commission.

Supplemental Expert Report of Kevin M. Murphy, February 23, 2012, in the Matter of State of New Hampshire v. Hess Corporation, et al., The State of New Hampshire Superior Court.

Affidavit of Kevin M. Murphy, March 12, 2012, in the Matter of Sharon Price and Michael Fruth, Individually and on Behalf of Others Similarly Situated vs. Philip Morris Incorporated, The United States Circuit Court, Third Judicial Court, Madison County, Illinois.

Declaration of Kevin M. Murphy, May 3, 2012, in the Matter of Retractable Technologies, Inc. and Thomas Shaw v. Becton, Dickinson and Company., The United States District Court for the Eastern District of Texas Marshall Division.

Comments of Kevin M. Murphy of DirecTV, LLC, June 22, 2012, in the Matter of Revision of the Commission's Program Access Rules; News Corporation and the DIRECTV Group, Inc., Transferors, and Liberty Media Corporation, Transferee, for Authority to Transfer Control; Applications for Consent to the Assignment and/or Transfer of Control of Licenses, Adelphia Communications Corporation (and Subsidiaries, Debtors-in-Possession), Assignors, to Time Warner Cable, Inc. (Subsidiaries), Assignees, et al., Federal Communications Commission.

Expert Report of Kevin M. Murphy, July 20, 2012, in the Matter of American Airlines v. Sabre, Inc., Sabre Holdings Corp., and Sabre Travel International Ltd., The United States Judicial District Tarrant County, Texas 67<sup>th</sup> Judicial District.

Declaration of Kevin M. Murphy, July 21, 2012, in the Matter of Kirk Dahl v. Bain Capital Partners, LLC., The United States District Court District of Massachusetts.

Expert Report of Kevin M. Murphy, July 23, 2012, in the Matter of Kirk Dahl v. Bain Capital Partners, LLC., The United States District Court District of Massachusetts.

Expert Report of Kevin M. Murphy, July 24, 2012, in the Matter of Microsoft Corporation v. Motorola, Inc., The United States District Court Western District of Washington at Seattle.

Deposition of Kevin M. Murphy, August 22, 2012, in the Matter of Microsoft Corporation v. Motorola, Inc., The United States District Court Western District of Washington at Seattle.

"Economic Analysis of the Impact on DIRECTV's Subscribership of Carrying an RSN: Evidence from San Diego," August 31, 2012, submitted in the Matter of Revision of the Commission's Program Access Rules; News Corporation and the DIRECTV Group, Inc., Transferors, and Liberty Media Corporation, Transferee, for Authority to Transfer Control; Applications for Consent to the Assignment and/or Transfer of Control of Licenses, Adelphia Communications Corporation (and Subsidiaries, Debtors-in-Possession), Assignors, to Time Warner Cable, Inc. (Subsidiaries), Assignees, et al., Federal Communications Commission.)

Expert Report of Kevin M. Murphy, September 7, 2102, in the Matter of Willard R. Brown, et al. v The American Tobacco Co., Inc., et al., Superior Court for the State of California for the County of San Diego.

Deposition of Kevin M. Murphy, September 14, 2012, in the Matter of Willard R. Brown, et al. v The American Tobacco Co., Inc., et al., Superior Court for the State of California for the County of San Diego.

Deposition of Kevin M. Murphy, September 24, 2012, in the Matter of American Airlines Inc. v Sabre, Inc., Sabre Holdings Corp., and Sabre Travel International LTD for the State of Texas for the Judicial District of Tarrant County.

Expert Report of Kevin M. Murphy, October 10, 2102, in the Matter of Avery Dennison Corporation v. 3M Innovative Properties and 3M Company, The United States District Court for the District of Minnesota.



**Appendix B: Materials Relied Upon**

<b><u>Court Documents</u></b>
Plaintiffs' Notice of Motion and Motion for Class Certification, and Memorandum of Law in Support (October 1, 2012)
Consolidated Amended Complaint in Re: High-Tech Employee Antitrust Litigation (September 2, 2011)
Expert Report of Edward E. Leamer, Ph.D. (October 1, 2012)
Leamer Backup
Plaintiffs' First Set of Requests for Production of Documents (October 3, 2011)
Declaration of Tina M. Evangelista in Support of Opposition to Class Certification
Declaration of Chris Galy
Declaration of Danny McKell in Support of Defendant's Opposition to Plaintiff's Motion for Class Certification
Declaration of Donna Morris of Adobe Systems Inc. in Support of Defendants' Opposition to Plaintiffs' Motion for Class Certification
Declaration of Frank Wagner in Support of Defendants' Opposition to Plaintiffs' Motion for Class Certification
Declaration of Jeff Vjungco of Adobe Systems Inc. in Support of Defendants' Opposition to Plaintiffs' Motion for Class Certification
Declaration of Lori McAdams in Support of Defendants' Opposition to Plaintiffs' Motion for Class Certification
Declaration of Mason Stubblefield
Declaration of Michelle Maupin in Support of Defendants' Opposition to Plaintiffs' Motion for Class Certification
Declaration of Steven Burmeister in Support of Defendants' Opposition to Plaintiffs' Motion for Class Certification
Declaration of Rosemary Arriada Keiper of Adobe Systems Inc. in Support of Defendants' Opposition to Plaintiffs' Motion for Class Certification
Deposition of Lori McAdams and Exhibits (August 2, 2012)
Deposition of Arnon Geshuri and Exhibits (August 17, 2012)
Deposition of Danielle Lambert and Exhibits (October 2, 2012)
Deposition of Donna Morris and Exhibits (August 21, 2012)
Deposition of James Morris and Exhibits (August 3, 2012)
Deposition of Jeffrey Vjungco and Exhibits (October 5, 2012)
Deposition of Mark Bentley and Exhibits (August 23, 2012)
Deposition of Michael Devine and Exhibits (October 24, 2012)
Deposition of Brandon Marshall and Exhibits (October 22, 2012)
Deposition of Daniel Stover and Exhibits (October 29, 2012)
Deposition of Mark Fichtner and Exhibits (October 15, 2012)
Deposition of Siddharth Hariharan and Exhibits (October 12, 2012)
Deposition of Edward Leamer and Exhibits (October 26, 2012)

Deposition of Jack Gilmore and Exhibits (June 28, 2012)
Deposition of Denise Miller and Exhibits (June 28, 2012)
Deposition of Steven Burmeister and Exhibits (June 27, 2012)
Deposition of Shawna Dougherty and Exhibits (July 12, 2012)
Deposition of Mai Tran and Exhibits (June 26, 2012)
Deposition of John Schirm and Exhibits (June 29, 2012)
Deposition of Jaime Yu and Exhibits (July 17, 2012)
Deposition of Matthew Howard and Exhibits (July 17, 2012)
Deposition of Shiloh Kuz and Exhibits (June 26, 2012)
Deposition of Michelle Deneau and Exhibits (June 26, 2012)
Deposition of Robert DeMartini and Exhibits (June 26, 2012)
Deposition of Rebecca del Torro and Exhibits (June 21, 2012)
Deposition of Amber Gay Remaley and Exhibits (June 21, 2012)
Deposition of Mary Kathleen Galle and Exhibits (June 21, 2012)
Deposition of Eleterio Cruzat and Exhibits (June 22, 2012)
Plaintiff Michael Devine's Answers and Objections to Defendants' First Set of Interrogatories (March 27, 2012)
Plaintiff Mark Fichtner Answers and Objections to Defendants' First Set of Interrogatories (March 28, 2012)
Plaintiff Siddharth Hariharan's Answers and Objections to Defendants' First Set of Interrogatories (March 27, 2012)
Plaintiff Brandon Marshall's Answers and Objections to Defendants' First Set of Interrogatories (March 27, 2012)
Plaintiff Daniel Stover's Answers and Objections to Defendants' First Set of Interrogatories (March 28, 2012)
Final Judgment in United States of America v. Adobe Systems Inc. et al (March 17, 2011)
[Proposed] Final Judgment in United States of America v. Lucasfilm Ltd. (May 9, 2011)
<b><u>Interviews Conducted by Kevin Murphy</u></b>
August 23, 2012: Jeff Vijungco, Adobe
August 23, 2012: Donna Morris, Adobe
July 27, 2012: Interview with Mark Bentley, Apple
August 30, 2012: Interview with Steve Burmeister, Apple
August 31, 2012: Interview with Seth Williams, Google
August 30, 2012: Interview with Frank Wagner, Google
July 25, 2012: Interview with Christina Dickenson, Intel
June 19, 2012: Interview with Danny McKell, Intel
July 26, 2012: Interview with Mason Stubbenfeld, Intuit
September 6, 2012: Interview with Chris Galy, Intuit
August 30, 2012: Interview with Michelle Maupin, Lucasfilm
August 16, 2012: Interview with Laurie McAdams, Pixar

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Robert H. Topel and Michael P. Ward, "Job Mobility and the Careers of Young Men," 107 The Quarterly Journal of Economics 2 (1992)
William Samuelson, "Bargaining Under Asymmetric Information," Econometrica 52 (1984)
<b><u>Websites</u></b>
<a href="http://online.wsj.com/article/SB10001424052970203750404577173031991814896.html">http://online.wsj.com/article/SB10001424052970203750404577173031991814896.html</a>
<a href="http://online.wsj.com/article/SB124269038041932531.html">http://online.wsj.com/article/SB124269038041932531.html</a>
<a href="http://techcrunch.com/2007/11/21/facebook-stealing-googlers-at-an-alarming-rate/">http://techcrunch.com/2007/11/21/facebook-stealing-googlers-at-an-alarming-rate/</a>
<a href="http://www.aeaweb.org/honors_awards/clark_medal.php">http://www.aeaweb.org/honors_awards/clark_medal.php</a>
<a href="http://www.dailytech.com/Google+Finds+That+Perks+Cant+Keep+Some+Employees+From+Leaving/article11794.htm">http://www.dailytech.com/Google+Finds+That+Perks+Cant+Keep+Some+Employees+From+Leaving/article11794.htm</a>

<b><u>Bates Documents</u></b>
76550DOC000014
231APPLE04166
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<b><u>Other</u></b>
Pixar Data - Pixar revenues 2005 - 2011.xlsx

## Appendix 1A

### Analysis of Hires from Other Defendants (All-Salaried Employee Class)

Panel A: 2001-2012

Hiring Company	Last Previous Company within 1 year									Percentage of Row Total							
	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	Other	Total	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	
Adobe																	
Apple																	
Google																	
Intel																	
Intuit																	
Lucasfilm	0	6	0	2	0		10	1,351	1,369	0.00%	0.44%	0.00%	0.15%	0.00%		0.73%	
Pixar	3	8	6	1	2	12		1,335	1,367	0.22%	0.59%	0.44%	0.07%	0.15%	0.88%		
<b>All Defendants</b>	<b>222</b>	<b>218</b>	<b>54</b>	<b>293</b>	<b>98</b>	<b>37</b>	<b>35</b>	<b>91,014</b>	<b>91,971</b>	<b>0.24%</b>	<b>0.24%</b>	<b>0.06%</b>	<b>0.32%</b>	<b>0.11%</b>	<b>0.04%</b>	<b>0.04%</b>	

Panel B: 2001-2004

Hiring Company	Last Previous Company within 1 year									Percentage of Row Total							
	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	Other	Total	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	
Adobe																	
Apple																	
Google																	
Intel																	
Intuit																	
Lucasfilm	0	1	0	1	0		3	402	407	0.00%	0.25%	0.00%	0.25%	0.00%		0.74%	
Pixar	0	4	0	0	1	3		431	439	0.00%	0.91%	0.00%	0.00%	0.23%	0.68%		
<b>All Defendants</b>	<b>34</b>	<b>45</b>	<b>0</b>	<b>34</b>	<b>15</b>	<b>6</b>	<b>5</b>	<b>23,042</b>	<b>23,181</b>	<b>0.15%</b>	<b>0.19%</b>	<b>0.00%</b>	<b>0.15%</b>	<b>0.06%</b>	<b>0.03%</b>	<b>0.02%</b>	

Panel C: 2005-2009

Hiring Company	Last Previous Company within 1 year									Percentage of Row Total							
	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	Other	Total	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	
Adobe																	
Apple																	
Google																	
Intel																	
Intuit																	
Lucasfilm	0	5	0	1	0		5	788	799	0.00%	0.63%	0.00%	0.13%	0.00%		0.63%	
Pixar	1	3	5	1	1	6		657	674	0.15%	0.45%	0.74%	0.15%	0.15%	0.89%		
<b>All Defendants</b>	<b>104</b>	<b>97</b>	<b>27</b>	<b>167</b>	<b>44</b>	<b>17</b>	<b>18</b>	<b>43,595</b>	<b>44,069</b>	<b>0.24%</b>	<b>0.22%</b>	<b>0.06%</b>	<b>0.38%</b>	<b>0.10%</b>	<b>0.04%</b>	<b>0.04%</b>	

Panel D: 2010-2012

Hiring Company	Last Previous Company within 1 year									Percentage of Row Total							
	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	Other	Total	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	
Adobe																	
Apple																	
Google																	
Intel																	
Intuit																	
Lucasfilm	0	0	0	0	0		2	161	163	0.00%	0.00%	0.00%	0.00%	0.00%		1.23%	
Pixar	2	1	1	0	0	3		247	254	0.79%	0.39%	0.39%	0.00%	0.00%	1.18%		
<b>All Defendants</b>	<b>84</b>	<b>76</b>	<b>27</b>	<b>92</b>	<b>39</b>	<b>14</b>	<b>12</b>	<b>24,377</b>	<b>24,721</b>	<b>0.34%</b>	<b>0.31%</b>	<b>0.11%</b>	<b>0.37%</b>	<b>0.16%</b>	<b>0.06%</b>	<b>0.05%</b>	

Note: This analysis excludes hires indicated as acquisitions and hires showing the same defendant company as their immediate previous employer within one year of the hiring.

Source: Dr. Leamer's employee data.

## Appendix 1B

### Analysis of Separations Going to Other Defendants (All-Salaried Employee Class)

Panel A: 2001-2012

Separation Company	Next Company within 1 year									Percentage of Row Total							
	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	Other	Total	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	
Adobe																	
Apple																	
Google																	
Intel																	
Intuit																	
Lucasfilm	0	9	15	1	0		12	1,490	1,527	0.00%	0.59%	0.98%	0.07%	0.00%		0.79%	
Pixar	0	11	6	2	0	7		726	752	0.00%	1.46%	0.80%	0.27%	0.00%	0.93%		
<b>All Defendants</b>	<b>122</b>	<b>326</b>	<b>336</b>	<b>35</b>	<b>74</b>	<b>15</b>	<b>31</b>	<b>72,287</b>	<b>73,226</b>	<b>0.17%</b>	<b>0.45%</b>	<b>0.46%</b>	<b>0.05%</b>	<b>0.10%</b>	<b>0.02%</b>	<b>0.04%</b>	

Panel B: 2001-2004

Separation Company	Next Company within 1 year									Percentage of Row Total							
	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	Other	Total	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	
Adobe																	
Apple																	
Google																	
Intel																	
Intuit																	
Lucasfilm	0	3	2	0	0		4	580	589	0.00%	0.51%	0.34%	0.00%	0.00%		0.68%	
Pixar	0	2	1	0	0	3		229	235	0.00%	0.85%	0.43%	0.00%	0.00%	1.28%		
<b>All Defendants</b>	<b>28</b>	<b>55</b>	<b>24</b>	<b>3</b>	<b>22</b>	<b>5</b>	<b>9</b>	<b>25,399</b>	<b>25,545</b>	<b>0.11%</b>	<b>0.22%</b>	<b>0.09%</b>	<b>0.01%</b>	<b>0.09%</b>	<b>0.02%</b>	<b>0.04%</b>	

Panel C: 2005-2009

Separation Company	Next Company within 1 year									Percentage of Row Total							
	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	Other	Total	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	
Adobe																	
Apple																	
Google																	
Intel																	
Intuit																	
Lucasfilm	0	3	5	1	0		5	655	669	0.00%	0.45%	0.75%	0.15%	0.00%		0.75%	
Pixar	0	4	3	2	0	2		329	340	0.00%	1.18%	0.88%	0.59%	0.00%	0.59%		
<b>All Defendants</b>	<b>70</b>	<b>151</b>	<b>182</b>	<b>17</b>	<b>39</b>	<b>8</b>	<b>16</b>	<b>35,375</b>	<b>35,858</b>	<b>0.20%</b>	<b>0.42%</b>	<b>0.51%</b>	<b>0.05%</b>	<b>0.11%</b>	<b>0.02%</b>	<b>0.04%</b>	

Panel D: 2010-2012

Separation Company	Next Company within 1 year									Percentage of Row Total							
	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	Other	Total	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	
Adobe																	
Apple																	
Google																	
Intel																	
Intuit																	
Lucasfilm	0	3	8	0	0		3	255	269	0.00%	1.12%	2.97%	0.00%	0.00%		1.12%	
Pixar	0	5	2	0	0	2		168	177	0.00%	2.82%	1.13%	0.00%	0.00%	1.13%		
<b>All Defendants</b>	<b>24</b>	<b>120</b>	<b>130</b>	<b>15</b>	<b>13</b>	<b>2</b>	<b>6</b>	<b>11,513</b>	<b>11,823</b>	<b>0.20%</b>	<b>1.01%</b>	<b>1.10%</b>	<b>0.13%</b>	<b>0.11%</b>	<b>0.02%</b>	<b>0.05%</b>	

Note: This analysis excludes separations that appear as immediately rehired by the same defendant company within one year.

Source: Dr. Leamer's employee data.

## Appendix 1C

### Analysis of Hires from Other DNCC Defendants (All-Salaried Employee Class)

**Panel A: 2001-2012**

Hiring Company	Last Previous Company within 1 year			Percentage of Row Total	
	DNCC Defendant	Non DNCC-Defendant	Total	DNCC Defendant	Non DNCC-Defendant
Adobe					
Apple					
Google					
Intel					
Intuit					
Lucasfilm	16	1,353	1,369	1.17%	98.83%
Pixar	21	1,346	1,367	1.54%	98.46%
<b>All Defendants</b>	<b>725</b>	<b>91,246</b>	<b>91,971</b>	<b>0.79%</b>	<b>99.21%</b>

**Panel B: 2001-2004**

Hiring Company	Last Previous Company within 1 year			Percentage of Row Total	
	DNCC Defendant	Non DNCC-Defendant	Total	DNCC Defendant	Non DNCC-Defendant
Adobe					
Apple					
Google					
Intel					
Intuit					
Lucasfilm	4	403	407	0.98%	99.02%
Pixar	7	432	439	1.59%	98.41%
<b>All Defendants</b>	<b>110</b>	<b>23,071</b>	<b>23,181</b>	<b>0.47%</b>	<b>99.53%</b>

**Panel C: 2005-2009**

Hiring Company	Last Previous Company within 1 year			Percentage of Row Total	
	DNCC Defendant	Non DNCC-Defendant	Total	DNCC Defendant	Non DNCC-Defendant
Adobe					
Apple					
Google					
Intel					
Intuit					
Lucasfilm	10	789	799	1.25%	98.75%
Pixar	10	664	674	1.48%	98.52%
<b>All Defendants</b>	<b>346</b>	<b>43,723</b>	<b>44,069</b>	<b>0.79%</b>	<b>99.21%</b>

**Panel D: 2010-2012**

Hiring Company	Last Previous Company within 1 year			Percentage of Row Total	
	DNCC Defendant	Non DNCC-Defendant	Total	DNCC Defendant	Non DNCC-Defendant
Adobe					
Apple					
Google					
Intel					
Intuit					
Lucasfilm	2	161	163	1.23%	98.77%
Pixar	4	250	254	1.57%	98.43%
<b>All Defendants</b>	<b>269</b>	<b>24,452</b>	<b>24,721</b>	<b>1.09%</b>	<b>98.91%</b>

**Notes:**

This analysis excludes hires indicated as acquisitions and hires showing the same defendant company as their immediate previous employer within one year of the hiring.

Adobe allegedly had a DNCC agreement with Apple.

Apple allegedly had DNCC agreements with Adobe, Google, Intel, Intuit, Lucasfilm, and Pixar.

Google allegedly had DNCC agreements with Apple, Intel, and Intuit.

Intel allegedly had DNCC agreements with Apple, Google, and Pixar.

Intuit allegedly had DNCC agreements with Apple and Google.

Lucasfilm allegedly had DNCC agreements with Apple and Pixar.

Pixar allegedly had DNCC agreements with Apple, Intel, and Lucasfilm.

Source: Dr. Leamer's employee data.

## Appendix 1D

### Analysis of Separations Going to Other DNCC Defendants (All-Salaried Employee Class)

**Panel A: 2001-2012**

Separation Company	Next Company within 1 year			Percentage of Row Total	
	DNCC Defendant	Non DNCC-Defendant	Total	DNCC Defendant	Non DNCC-Defendant
Adobe					
Apple					
Google					
Intel					
Intuit					
Lucasfilm	21	1,506	1,527	1.38%	98.62%
Pixar	20	732	752	2.66%	97.34%
<b>All Defendants</b>	<b>712</b>	<b>72,514</b>	<b>73,226</b>	<b>0.97%</b>	<b>99.03%</b>

**Panel B: 2001-2004**

Separation Company	Next Company within 1 year			Percentage of Row Total	
	DNCC Defendant	Non DNCC-Defendant	Total	DNCC Defendant	Non DNCC-Defendant
Adobe					
Apple					
Google					
Intel					
Intuit					
Lucasfilm	7	582	589	1.19%	98.81%
Pixar	5	230	235	2.13%	97.87%
<b>All Defendants</b>	<b>116</b>	<b>25,429</b>	<b>25,545</b>	<b>0.45%</b>	<b>99.55%</b>

**Panel C: 2005-2009**

Separation Company	Next Company within 1 year			Percentage of Row Total	
	DNCC Defendant	Non DNCC-Defendant	Total	DNCC Defendant	Non DNCC-Defendant
Adobe					
Apple					
Google					
Intel					
Intuit					
Lucasfilm	8	661	669	1.20%	98.80%
Pixar	8	332	340	2.35%	97.65%
<b>All Defendants</b>	<b>350</b>	<b>35,508</b>	<b>35,858</b>	<b>0.98%</b>	<b>99.02%</b>

**Panel D: 2010-2012**

Separation Company	Next Company within 1 year			Percentage of Row Total	
	DNCC Defendant	Non DNCC-Defendant	Total	DNCC Defendant	Non DNCC-Defendant
Adobe					
Apple					
Google					
Intel					
Intuit					
Lucasfilm	6	263	269	2.23%	97.77%
Pixar	7	170	177	3.95%	96.05%
<b>All Defendants</b>	<b>246</b>	<b>11,577</b>	<b>11,823</b>	<b>2.08%</b>	<b>97.92%</b>

**Notes:**

This analysis excludes separations that appear as immediately rehired by the same defendant company within one year.

Adobe allegedly had a DNCC agreement with Apple.

Apple allegedly had DNCC agreements with Adobe, Google, Intel, Intuit, Lucasfilm, and Pixar.

Google allegedly had DNCC agreements with Apple, Intel, and Intuit.

Intel allegedly had DNCC agreements with Apple, Google, and Pixar.

Intuit allegedly had DNCC agreements with Apple and Google.

Lucasfilm allegedly had DNCC agreements with Apple and Pixar.

Pixar allegedly had DNCC agreements with Apple, Intel, and Lucasfilm.

Source: Dr. Leamer's employee data.



## Appendix 2A

### Analysis of Hires from Other Defendants (Technical, Creative and R&D Class)

Panel A: 2001-2012

Hiring Company	Last Previous Company within 1 year									Percentage of Row Total							
	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	Other	Total	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	
Adobe																	
Apple																	
Google																	
Intel																	
Intuit																	
Lucasfilm	0	5	0	0	0		6	532	543	0.00%	0.92%	0.00%	0.00%	0.00%		1.10%	
Pixar	2	7	3	1	2	8		762	785	0.25%	0.89%	0.38%	0.13%	0.25%	1.02%		
<b>All Defendants</b>	<b>159</b>	<b>150</b>	<b>29</b>	<b>191</b>	<b>59</b>	<b>24</b>	<b>25</b>	<b>53,110</b>	<b>53,747</b>	<b>0.30%</b>	<b>0.28%</b>	<b>0.05%</b>	<b>0.36%</b>	<b>0.11%</b>	<b>0.04%</b>	<b>0.05%</b>	

Panel B: 2001-2004

Hiring Company	Last Previous Company within 1 year									Percentage of Row Total							
	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	Other	Total	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	
Adobe																	
Apple																	
Google																	
Intel																	
Intuit																	
Lucasfilm	0	0	0	0	0		1	56	57	0.00%	0.00%	0.00%	0.00%	0.00%		1.75%	
Pixar	0	3	0	0	1	1		234	239	0.00%	1.26%	0.00%	0.00%	0.42%	0.42%		
<b>All Defendants</b>	<b>17</b>	<b>32</b>	<b>0</b>	<b>17</b>	<b>7</b>	<b>3</b>	<b>2</b>	<b>12,271</b>	<b>12,349</b>	<b>0.14%</b>	<b>0.26%</b>	<b>0.00%</b>	<b>0.14%</b>	<b>0.06%</b>	<b>0.02%</b>	<b>0.02%</b>	

Panel C: 2005-2009

Hiring Company	Last Previous Company within 1 year									Percentage of Row Total							
	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	Other	Total	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	
Adobe																	
Apple																	
Google																	
Intel																	
Intuit																	
Lucasfilm	0	5	0	0	0		5	387	397	0.00%	1.26%	0.00%	0.00%	0.00%		1.26%	
Pixar	0	3	3	1	1	4		394	406	0.00%	0.74%	0.74%	0.25%	0.25%	0.99%		
<b>All Defendants</b>	<b>81</b>	<b>65</b>	<b>15</b>	<b>99</b>	<b>29</b>	<b>10</b>	<b>18</b>	<b>25,718</b>	<b>26,035</b>	<b>0.31%</b>	<b>0.25%</b>	<b>0.06%</b>	<b>0.38%</b>	<b>0.11%</b>	<b>0.04%</b>	<b>0.07%</b>	

Panel D: 2010-2012

Hiring Company	Last Previous Company within 1 year									Percentage of Row Total							
	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	Other	Total	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	
Adobe																	
Apple																	
Google																	
Intel																	
Intuit																	
Lucasfilm	0	0	0	0	0		0	89	89	0.00%	0.00%	0.00%	0.00%	0.00%		0.00%	
Pixar	2	1	0	0	0	3		134	140	1.43%	0.71%	0.00%	0.00%	0.00%	2.14%		
<b>All Defendants</b>	<b>61</b>	<b>53</b>	<b>14</b>	<b>75</b>	<b>23</b>	<b>11</b>	<b>5</b>	<b>15,121</b>	<b>15,363</b>	<b>0.40%</b>	<b>0.34%</b>	<b>0.09%</b>	<b>0.49%</b>	<b>0.15%</b>	<b>0.07%</b>	<b>0.03%</b>	

Note: This analysis excludes hires indicated as acquisitions and hires showing the same defendant company as their immediate previous employer within one year of the hiring.  
Source: Dr. Leamer's employee data.

## Appendix 2B

### Analysis of Separations Going to Other Defendants (Technical, Creative and R&D Class)

Panel A: 2001-2012

Separation Company	Next Company within 1 year									Percentage of Row Total						
	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	Other	Total	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar
Adobe																
Apple																
Google																
Intel																
Intuit																
Lucasfilm	0	3	7	1	0		5	333	349	0.00%	0.86%	2.01%	0.29%	0.00%		1.43%
Pixar	0	7	5	2	0		5	378	397	0.00%	1.76%	1.26%	0.50%	0.00%		1.26%
<b>All Defendants</b>	<b>74</b>	<b>223</b>	<b>259</b>	<b>23</b>	<b>37</b>		<b>18</b>	<b>36,356</b>	<b>36,999</b>	<b>0.20%</b>	<b>0.60%</b>	<b>0.70%</b>	<b>0.06%</b>	<b>0.10%</b>	<b>0.02%</b>	<b>0.05%</b>

Panel B: 2001-2004

Separation Company	Next Company within 1 year									Percentage of Row Total						
	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	Other	Total	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar
Adobe																
Apple																
Google																
Intel																
Intuit																
Lucasfilm	0	0	0	0	0		0	7	7	0.00%	0.00%	0.00%	0.00%	0.00%		0.00%
Pixar	0	1	1	0	0		3	106	111	0.00%	0.90%	0.90%	0.00%	0.00%		2.70%
<b>All Defendants</b>	<b>21</b>	<b>25</b>	<b>12</b>	<b>1</b>	<b>11</b>		<b>3</b>	<b>11,001</b>	<b>11,077</b>	<b>0.19%</b>	<b>0.23%</b>	<b>0.11%</b>	<b>0.01%</b>	<b>0.10%</b>	<b>0.03%</b>	<b>0.03%</b>

Panel C: 2005-2009

Separation Company	Next Company within 1 year									Percentage of Row Total						
	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	Other	Total	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar
Adobe																
Apple																
Google																
Intel																
Intuit																
Lucasfilm	0	0	1	1	0		2	197	201	0.00%	0.00%	0.50%	0.50%	0.00%		1.00%
Pixar	0	4	3	2	0		2	175	186	0.00%	2.15%	1.61%	1.08%	0.00%		1.08%
<b>All Defendants</b>	<b>41</b>	<b>102</b>	<b>143</b>	<b>12</b>	<b>20</b>		<b>9</b>	<b>18,863</b>	<b>19,196</b>	<b>0.21%</b>	<b>0.53%</b>	<b>0.74%</b>	<b>0.06%</b>	<b>0.10%</b>	<b>0.03%</b>	<b>0.05%</b>

Panel D: 2010-2012

Separation Company	Next Company within 1 year									Percentage of Row Total						
	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar	Other	Total	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar
Adobe																
Apple																
Google																
Intel																
Intuit																
Lucasfilm	0	3	6	0	0		3	129	141	0.00%	2.13%	4.26%	0.00%	0.00%		2.13%
Pixar	0	2	1	0	0		0	97	100	0.00%	2.00%	1.00%	0.00%	0.00%		0.00%
<b>All Defendants</b>	<b>12</b>	<b>96</b>	<b>104</b>	<b>10</b>	<b>6</b>		<b>6</b>	<b>6,492</b>	<b>6,726</b>	<b>0.18%</b>	<b>1.43%</b>	<b>1.55%</b>	<b>0.15%</b>	<b>0.09%</b>	<b>0.00%</b>	<b>0.09%</b>

Note: This analysis excludes separations that appear as immediately rehired by the same defendant company within one year.

Source: Dr. Leamer's employee data.

## Appendix 2C

### Analysis of Hires from Other DNCC Defendants (Technical, Creative and R&D Class)

**Panel A: 2001-2012**

Hiring Company	Last Previous Company within 1 year			Percentage of Row Total	
	DNCC Defendant	Non DNCC-Defendant	Total	DNCC Defendant	Non DNCC-Defendant
Adobe					
Apple					
Google					
Intel					
Intuit					
Lucasfilm	11	532	543	2.03%	97.97%
Pixar	16	769	785	2.04%	97.96%
<b>All Defendants</b>	<b>482</b>	<b>53,265</b>	<b>53,747</b>	<b>0.90%</b>	<b>99.10%</b>

**Panel B: 2001-2004**

Hiring Company	Last Previous Company within 1 year			Percentage of Row Total	
	DNCC Defendant	Non DNCC-Defendant	Total	DNCC Defendant	Non DNCC-Defendant
Adobe					
Apple					
Google					
Intel					
Intuit					
Lucasfilm	1	56	57	1.75%	98.25%
Pixar	4	235	239	1.67%	98.33%
<b>All Defendants</b>	<b>61</b>	<b>12,288</b>	<b>12,349</b>	<b>0.49%</b>	<b>99.51%</b>

**Panel C: 2005-2009**

Hiring Company	Last Previous Company within 1 year			Percentage of Row Total	
	DNCC Defendant	Non DNCC-Defendant	Total	DNCC Defendant	Non DNCC-Defendant
Adobe					
Apple					
Google					
Intel					
Intuit					
Lucasfilm	10	387	397	2.52%	97.48%
Pixar	8	398	406	1.97%	98.03%
<b>All Defendants</b>	<b>228</b>	<b>25,807</b>	<b>26,035</b>	<b>0.88%</b>	<b>99.12%</b>

**Panel D: 2010-2012**

Hiring Company	Last Previous Company within 1 year			Percentage of Row Total	
	DNCC Defendant	Non DNCC-Defendant	Total	DNCC Defendant	Non DNCC-Defendant
Adobe					
Apple					
Google					
Intel					
Intuit					
Lucasfilm	0	89	89	0.00%	100.00%
Pixar	4	136	140	2.86%	97.14%
<b>All Defendants</b>	<b>193</b>	<b>15,170</b>	<b>15,363</b>	<b>1.26%</b>	<b>98.74%</b>

**Notes:**

This analysis excludes hires indicated as acquisitions and hires showing the same defendant company as their immediate previous employer within one year of the hiring.

Adobe allegedly had a DNCC agreement with Apple.

Apple allegedly had DNCC agreements with Adobe, Google, Intel, Intuit, Lucasfilm, and Pixar.

Google allegedly had DNCC agreements with Apple, Intel, and Intuit.

Intel allegedly had DNCC agreements with Apple, Google, and Pixar.

Intuit allegedly had DNCC agreements with Apple and Google.

Lucasfilm allegedly had DNCC agreements with Apple and Pixar.

Pixar allegedly had DNCC agreements with Apple, Intel, and Lucasfilm.

Source: Dr. Leamer's employee data.

## Appendix 2D

### Analysis of Separations Going to Other DNCC Defendants (Technical, Creative and R&D Class)

**Panel A: 2001-2012**

Separation Company	Next Company within 1 year			Percentage of Row Total	
	DNCC Defendant	Non DNCC-Defendant	Total	DNCC Defendant	Non DNCC-Defendant
Adobe					
Apple					
Google					
Intel					
Intuit					
Lucasfilm	8	341	349	2.29%	97.71%
Pixar	14	383	397	3.53%	96.47%
<b>All Defendants</b>	<b>498</b>	<b>36,501</b>	<b>36,999</b>	<b>1.35%</b>	<b>98.65%</b>

**Panel B: 2001-2004**

Separation Company	Next Company within 1 year			Percentage of Row Total	
	DNCC Defendant	Non DNCC-Defendant	Total	DNCC Defendant	Non DNCC-Defendant
Adobe					
Apple					
Google					
Intel					
Intuit					
Lucasfilm	0	7	7	0.00%	100.00%
Pixar	4	107	111	3.60%	96.40%
<b>All Defendants</b>	<b>61</b>	<b>11,016</b>	<b>11,077</b>	<b>0.55%</b>	<b>99.45%</b>

**Panel C: 2005-2009**

Separation Company	Next Company within 1 year			Percentage of Row Total	
	DNCC Defendant	Non DNCC-Defendant	Total	DNCC Defendant	Non DNCC-Defendant
Adobe					
Apple					
Google					
Intel					
Intuit					
Lucasfilm	2	199	201	1.00%	99.00%
Pixar	8	178	186	4.30%	95.70%
<b>All Defendants</b>	<b>248</b>	<b>18,948</b>	<b>19,196</b>	<b>1.29%</b>	<b>98.71%</b>

**Panel D: 2010-2012**

Separation Company	Next Company within 1 year			Percentage of Row Total	
	DNCC Defendant	Non DNCC-Defendant	Total	DNCC Defendant	Non DNCC-Defendant
Adobe					
Apple					
Google					
Intel					
Intuit					
Lucasfilm	6	135	141	4.26%	95.74%
Pixar	2	98	100	2.00%	98.00%
<b>All Defendants</b>	<b>189</b>	<b>6,537</b>	<b>6,726</b>	<b>2.81%</b>	<b>97.19%</b>

**Notes:**

This analysis excludes separations that appear as immediately rehired by the same defendant company within one year.

Adobe allegedly had a DNCC agreement with Apple.

Apple allegedly had DNCC agreements with Adobe, Google, Intel, Intuit, Lucasfilm, and Pixar.

Google allegedly had DNCC agreements with Apple, Intel, and Intuit.

Intel allegedly had DNCC agreements with Apple, Google, and Pixar.

Intuit allegedly had DNCC agreements with Apple and Google.

Lucasfilm allegedly had DNCC agreements with Apple and Pixar.

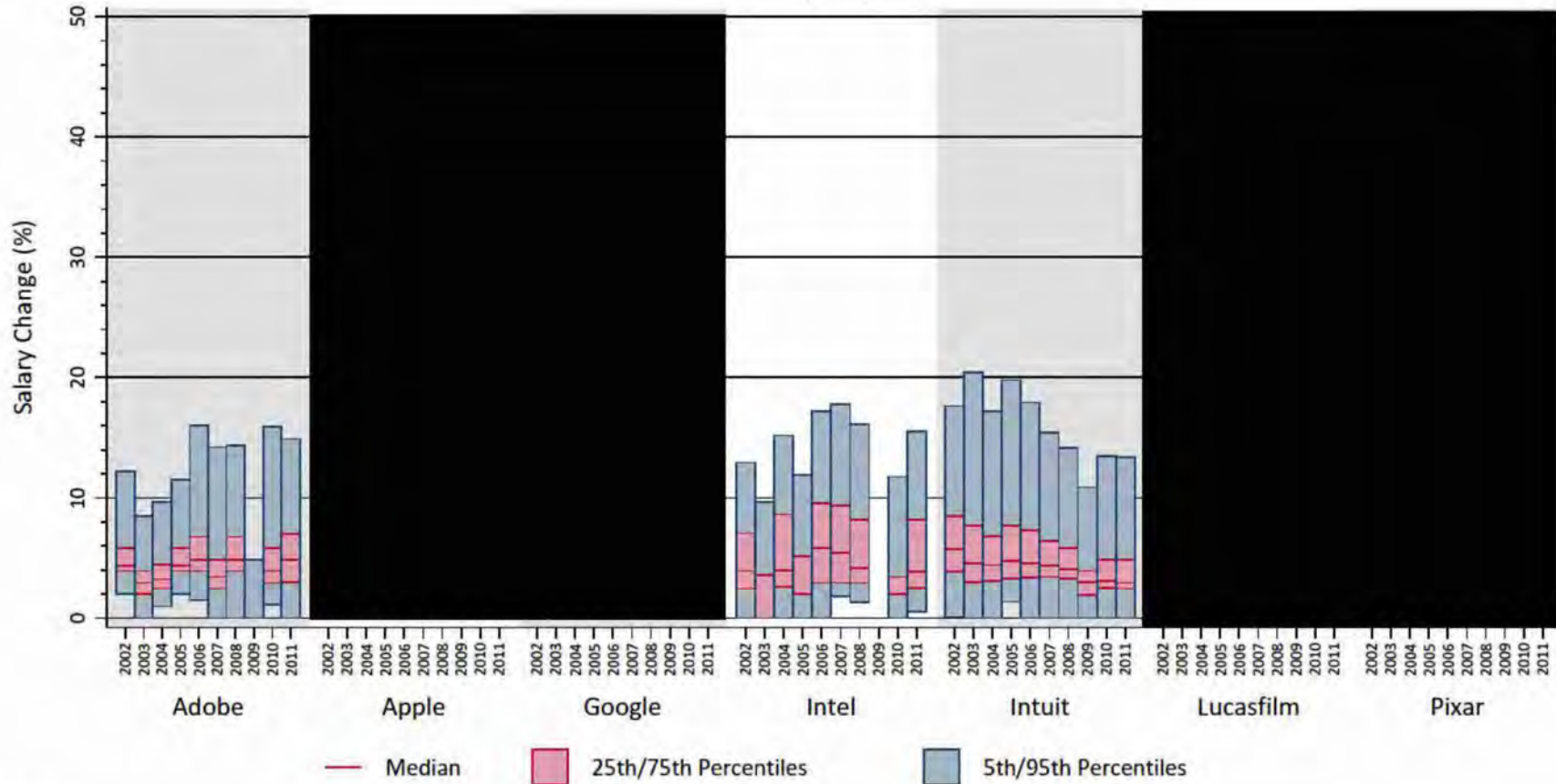
Pixar allegedly had DNCC agreements with Apple, Intel, and Lucasfilm.

Source: Dr. Leamer's employee data.

### Appendix 3A

## Distributions of Annual Changes in Base Salaries

### All Salaried Employee Class



**Notes:**

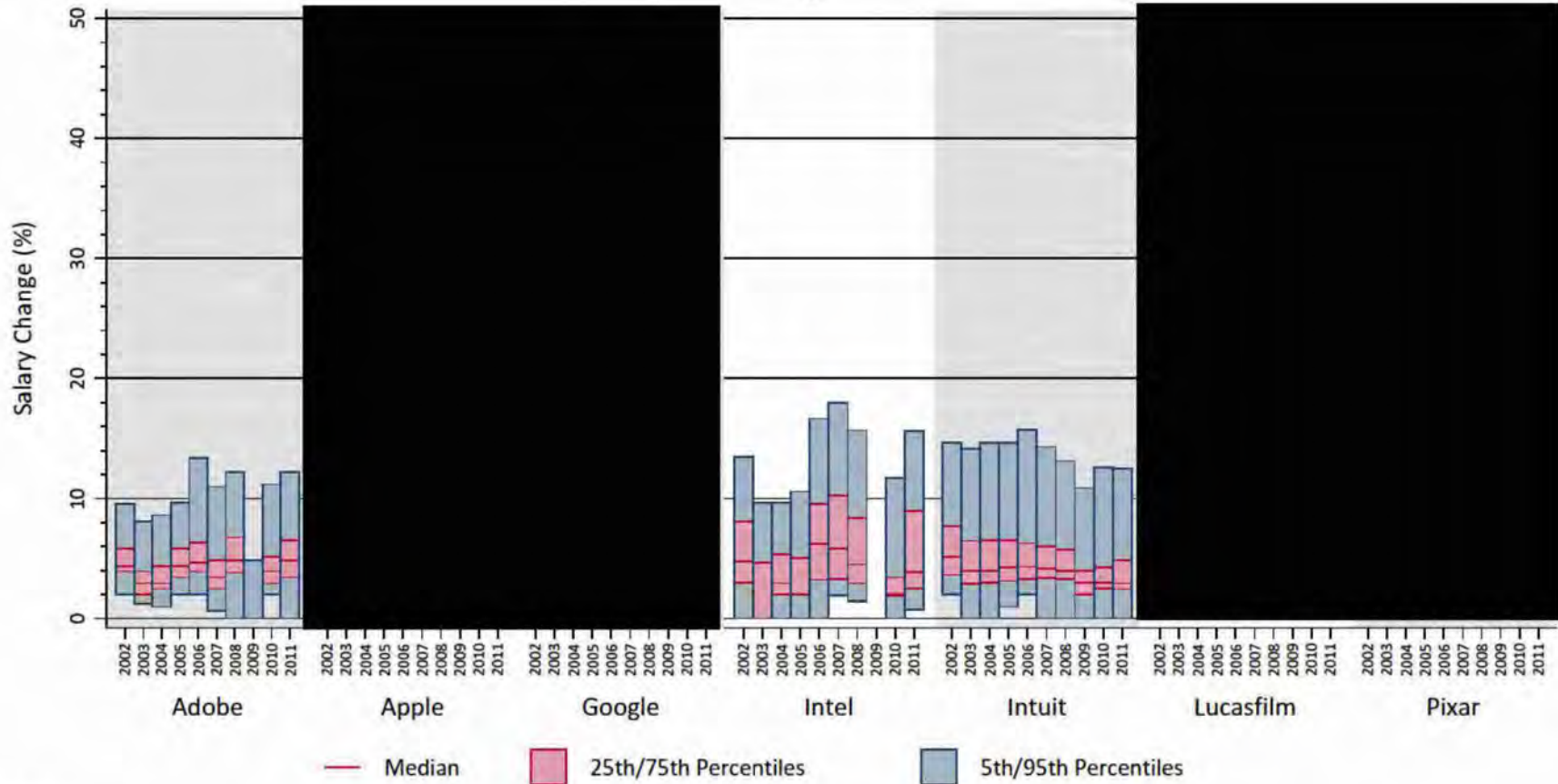
- [1] Percent salary changes are defined as the log of the current year's salary minus the log of the previous year's salary multiplied by 100.
- [2] Some defendants had salary freezes in certain years. The 95th percentile salary change was zero at Intel in 2009; and the 75th percentile salary change was zero at Adobe in 2009, Apple in 2002, and Pixar in 2003.

Source: Dr. Leamer's backup data and materials.

### Appendix 3B

## Distributions of Annual Changes in Base Salaries

### Technical, Creative, and R&D Class

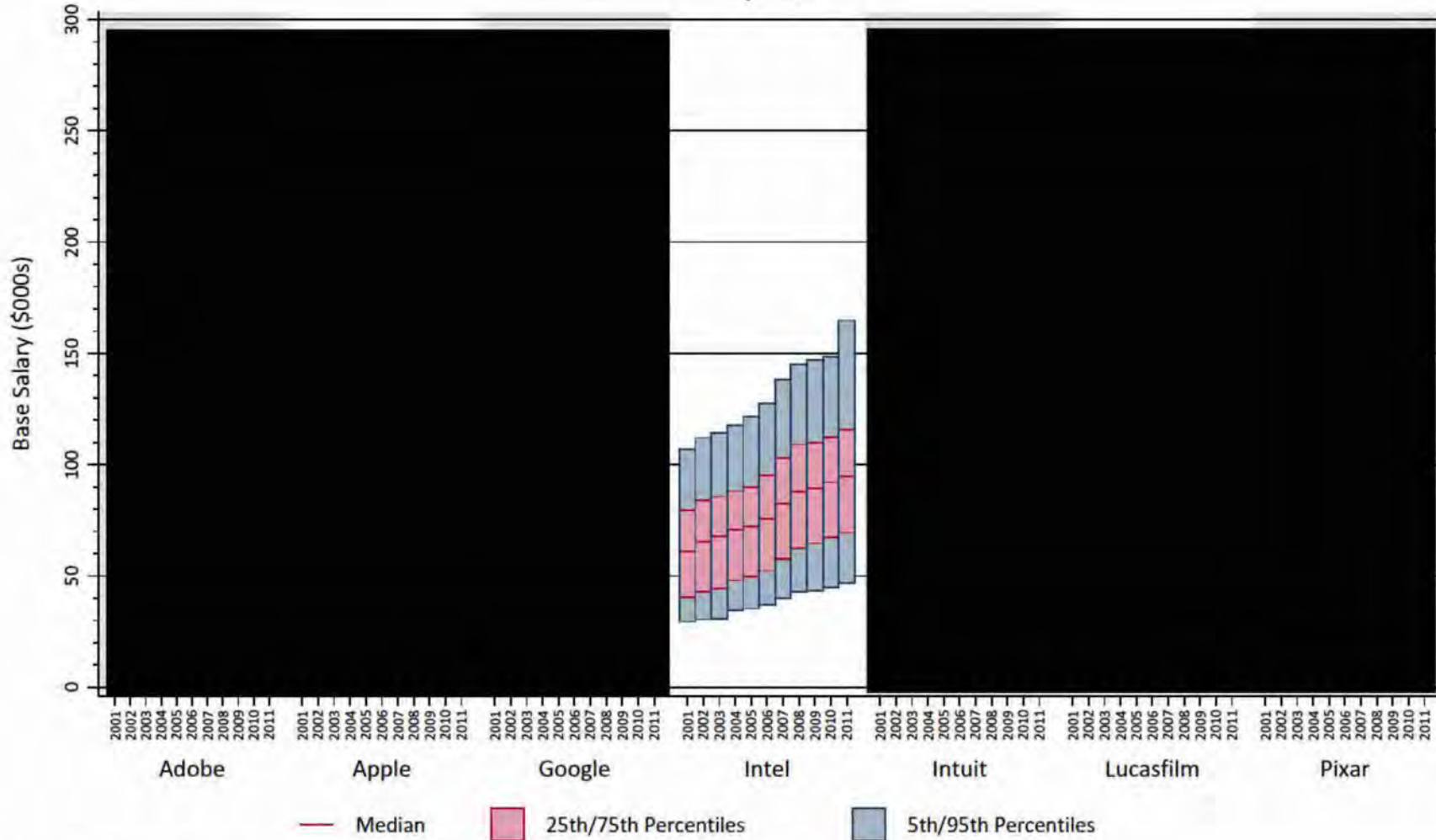


**Notes:**

- [1] Percent salary changes are defined as the log of the current year's salary minus the log of the previous year's salary multiplied by 100.
- [2] Some defendants had salary freezes in certain years. The 95th percentile salary change was zero at Intel in 2009 and Pixar in 2003; and the 75th percentile salary change was zero at Adobe in 2009, Apple in 2002, and Google in 2002.

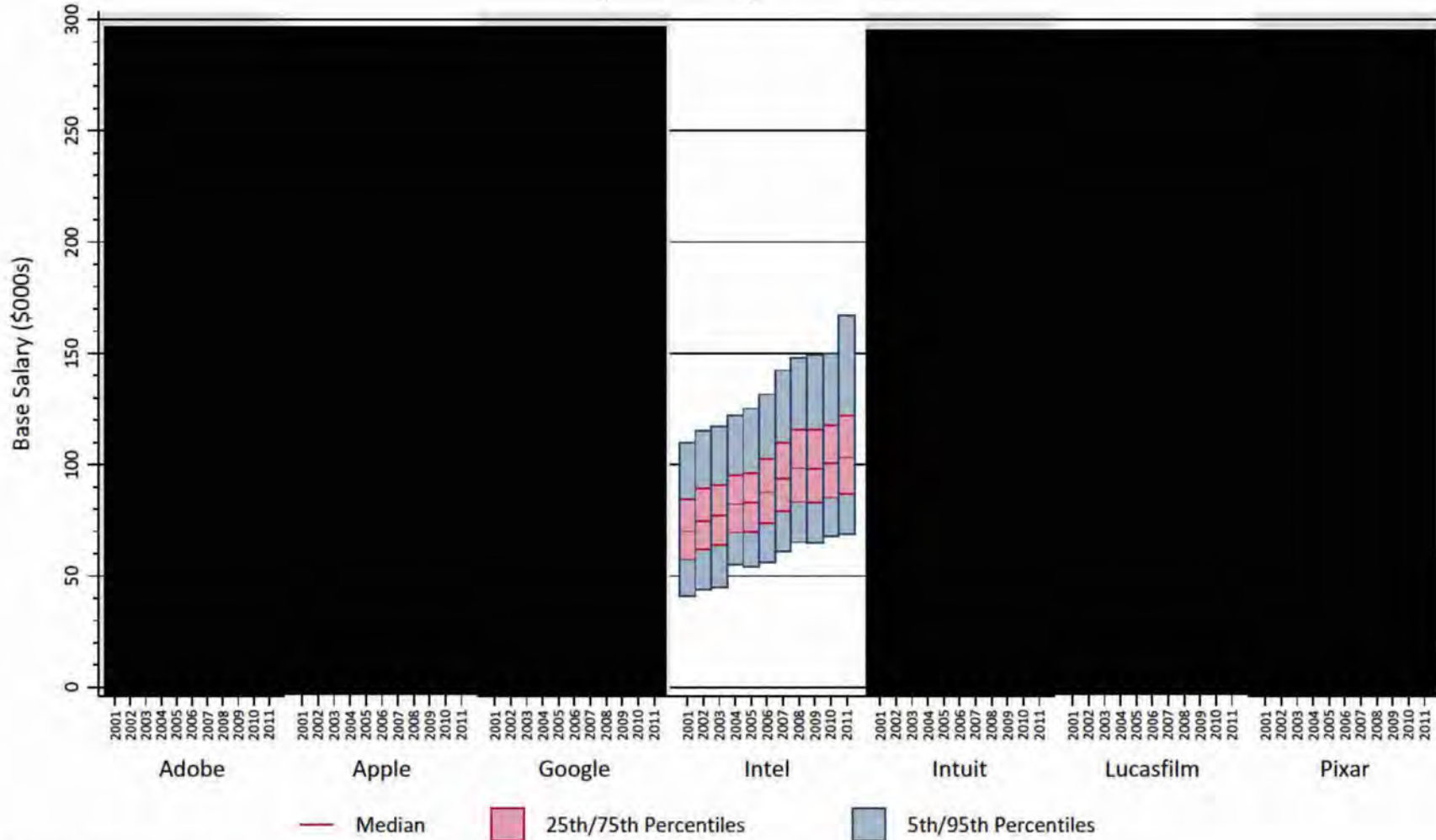
Source: Dr. Leamer's backup data and materials.

### Appendix 4A Distributions of Base Salaries All Salaried Employee Class



Source: Dr. Leamer's backup data and materials.

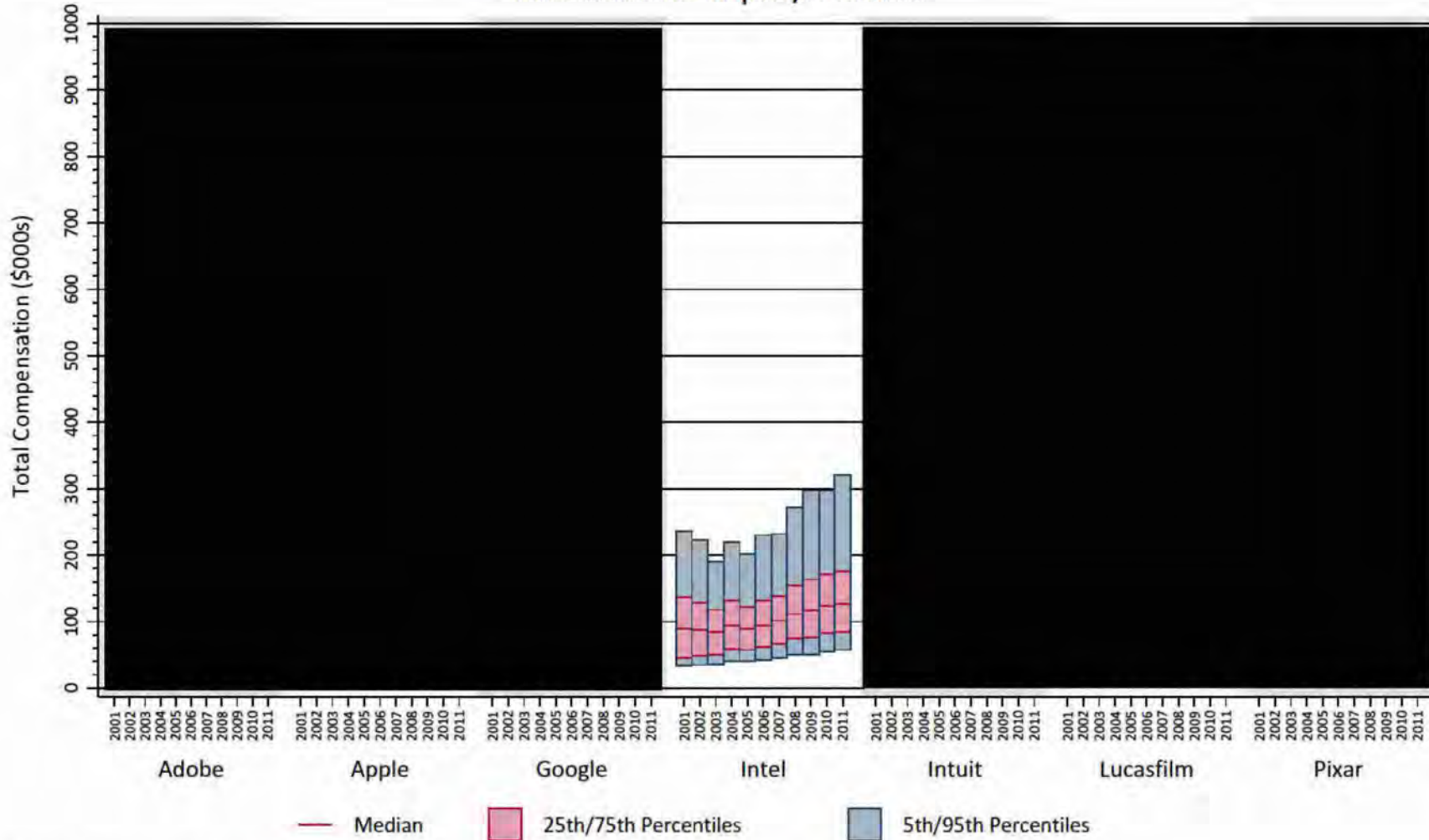
### Appendix 4B Distributions of Base Salaries Technical, Creative, and R&D Class



Source: Dr. Leamer's backup data and materials.

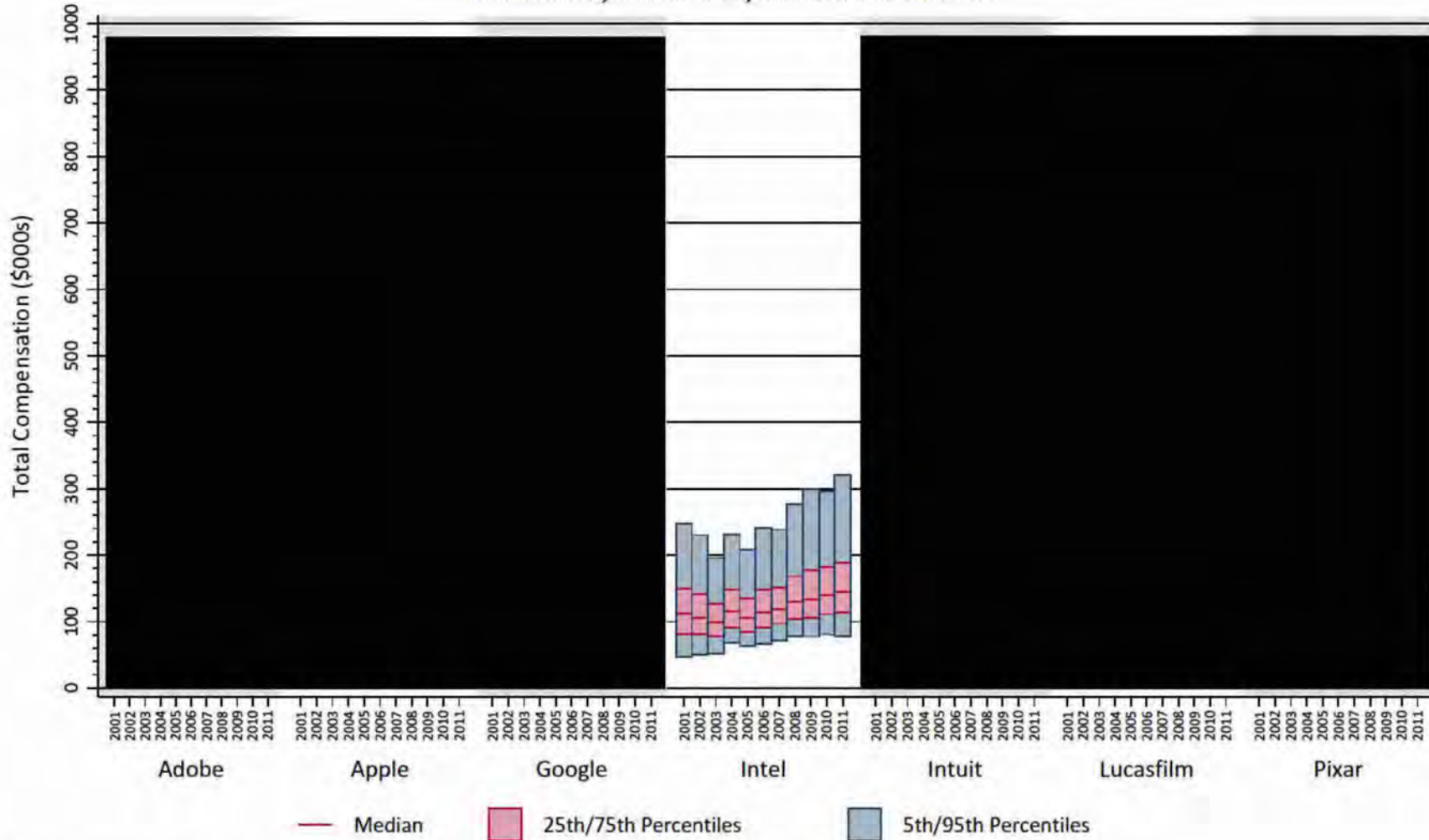


### Appendix 4C Distributions of Total Compensation All Salaried Employee Class



Source: Dr. Leamer's backup data and materials.

### Appendix 4D Distributions of Total Compensation Technical, Creative, and R&D Class

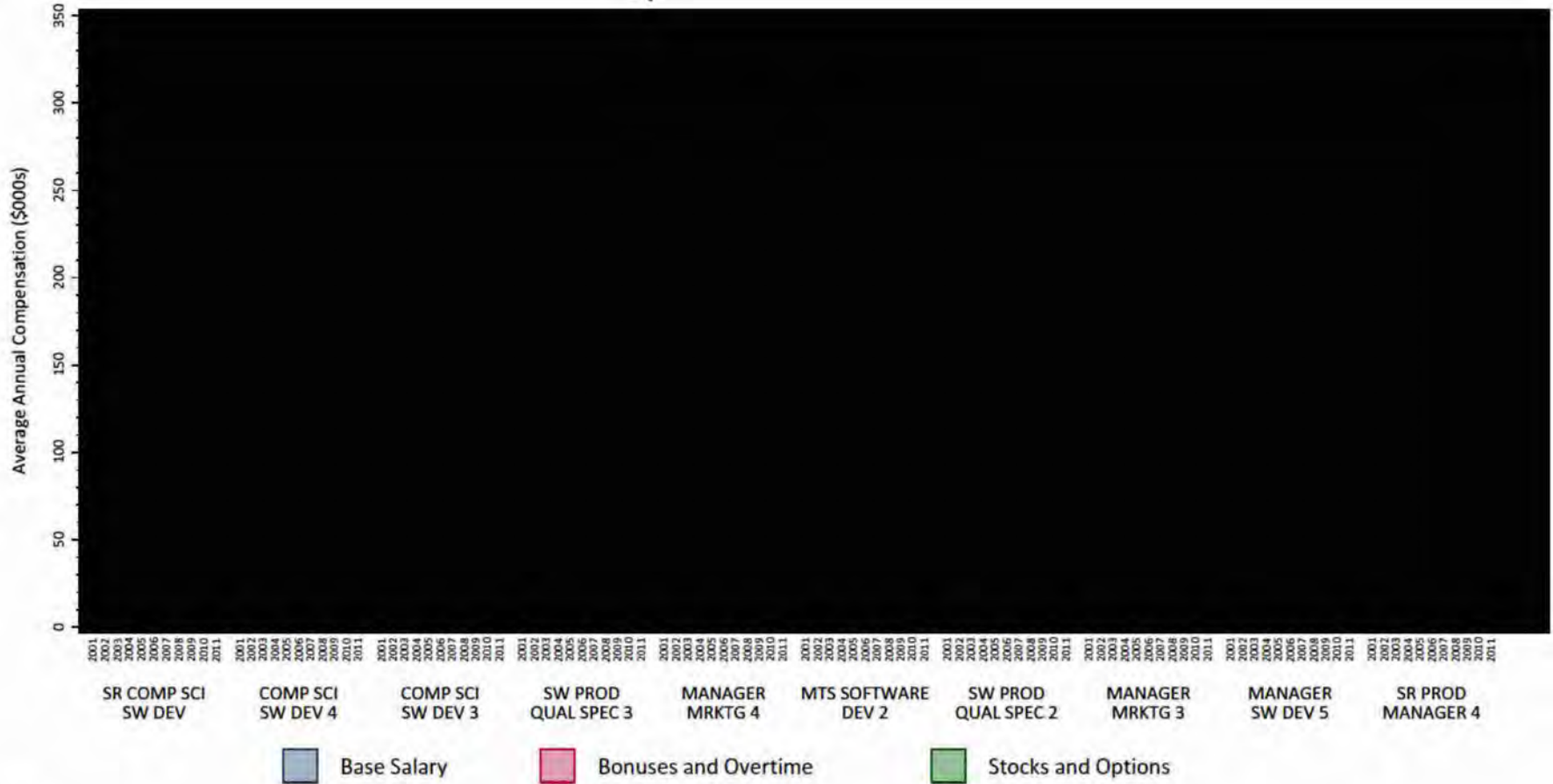


Source: Dr. Leamer's backup data and materials.

## Appendix 5A

### Composition of Total Compensation for Major Jobs

#### Top 10 Adobe Jobs



**Notes:**

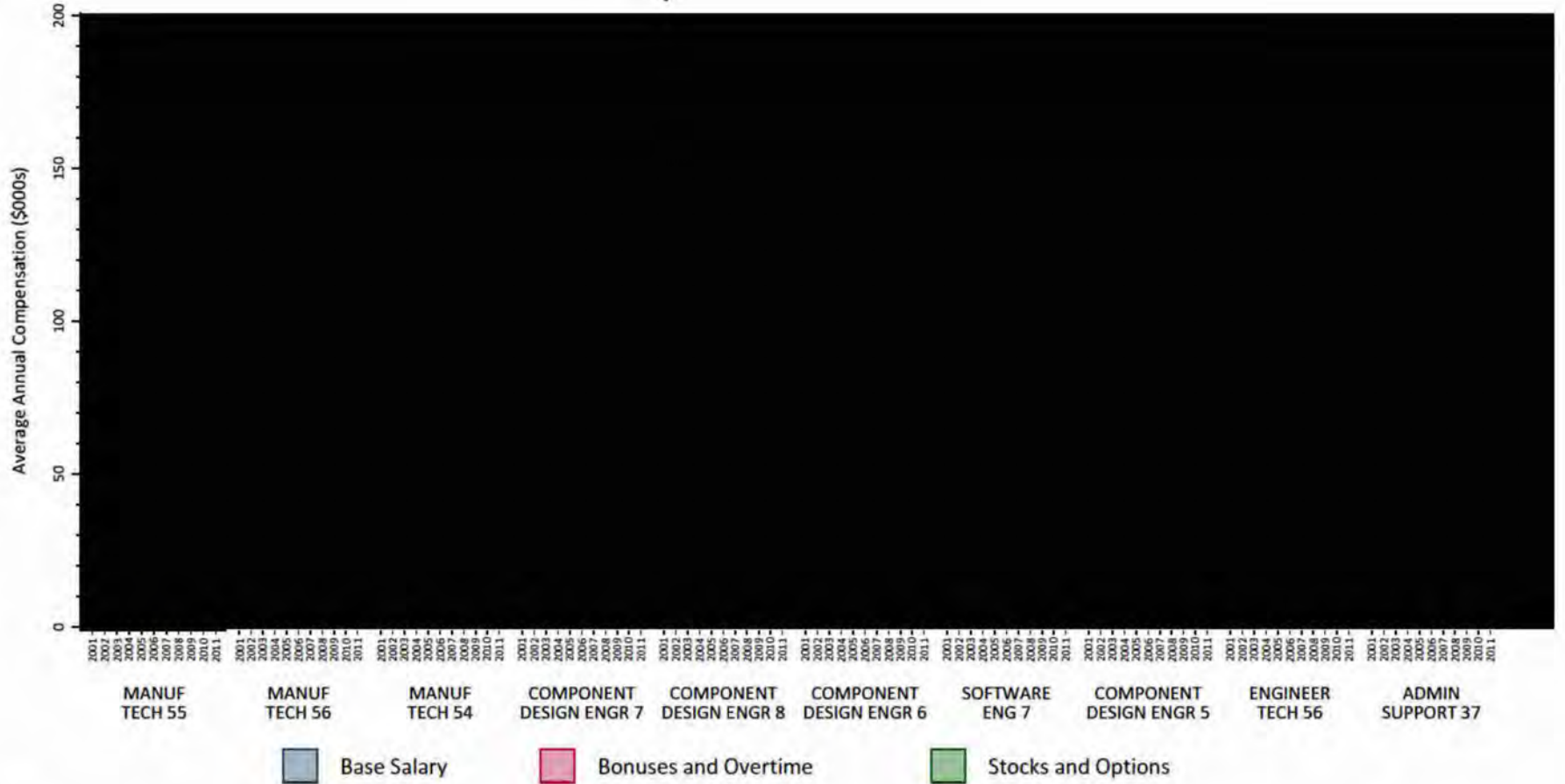
- [1] The top 10 jobs are identified using 2005 through 2009 employment--the same algorithm that Dr. Leamer uses in his Figures 15 through 17.
- [2] Bars are missing when there are fewer than five employees with the relevant job title in the data in the given year.

Source: Dr. Leamer's backup data and materials.

## Appendix 5B

### Composition of Total Compensation for Major Jobs

#### Top 10 Intel Jobs



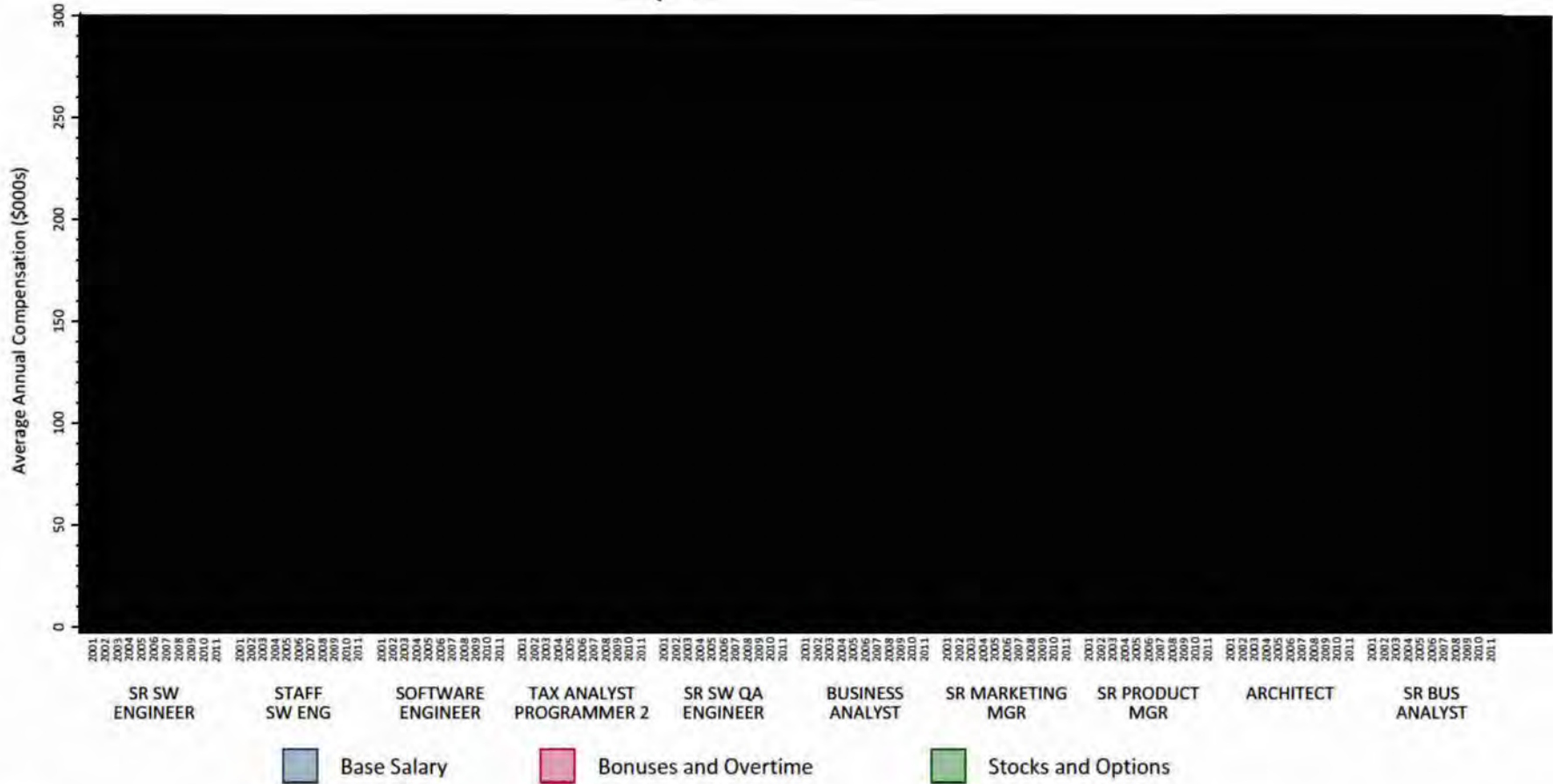
**Notes:**

- [1] The top 10 jobs are identified using 2005 through 2009 employment--the same algorithm that Dr. Leamer uses in his Figures 15 through 17.
- [2] Bars are missing when there are fewer than five employees with the relevant job title in the data in the given year.

Source: Dr. Leamer's backup data and materials.

## Appendix 5C

### Composition of Total Compensation for Major Jobs Top 10 Intuit Jobs



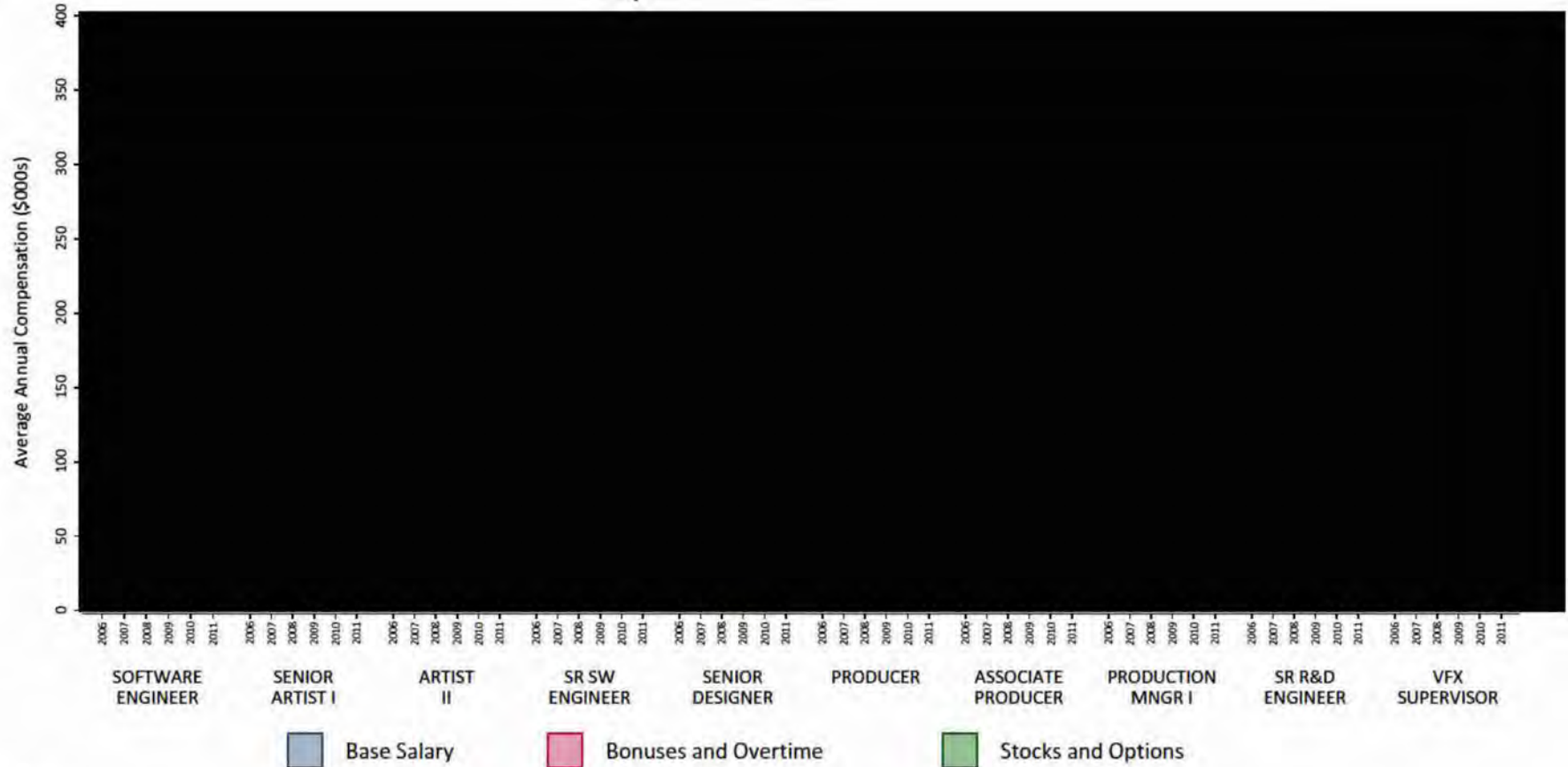
**Notes:**

- [1] The top 10 jobs are identified using 2005 through 2009 employment--the same algorithm that Dr. Leamer uses in his Figures 15 through 17.
- [2] Bars are missing when there are fewer than five employees with the relevant job title in the data in the given year.

Source: Dr. Leamer's backup data and materials.

## Appendix 5D

### Composition of Total Compensation for Major Jobs Top 10 Lucasfilm Jobs



**Notes:**

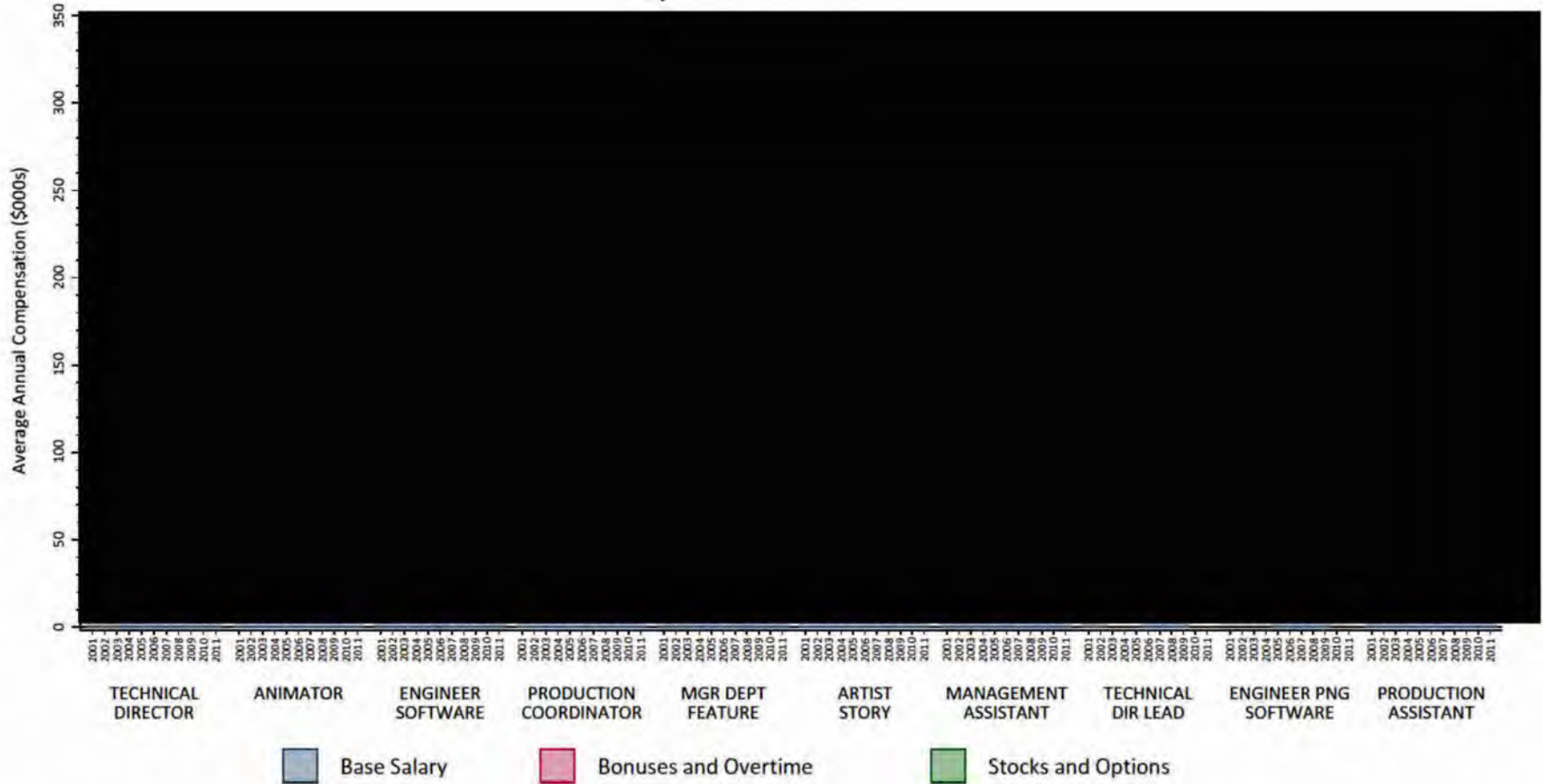
- [1] The top 10 jobs are identified using 2005 through 2009 employment--the same algorithm that Dr. Leamer uses in his Figures 15 through 17.
- [2] Bars are missing when there are fewer than five employees with the relevant job title in the data in the given year.
- [3] Lucasfilm data are missing job titles prior to 2006.

Source: Dr. Leamer's backup data and materials.

## Appendix 5E

### Composition of Total Compensation for Major Jobs

#### Top 10 Pixar Jobs



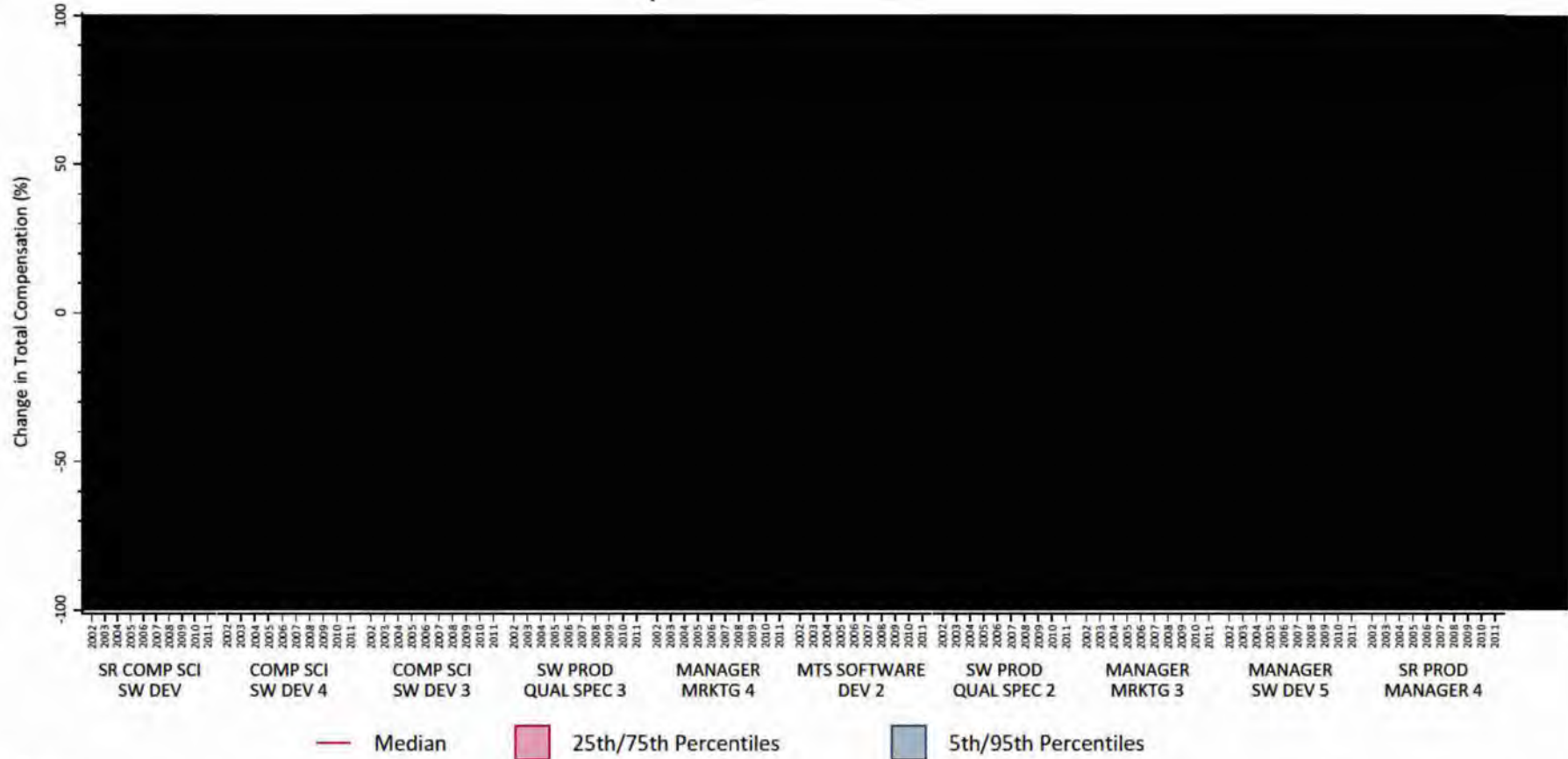
**Notes:**

- [1] The top 10 jobs are identified using 2005 through 2009 employment--the same algorithm that Dr. Leamer uses in his Figures 15 through 17.
- [2] Bars are missing when there are fewer than five employees with the relevant job title in the data in the given year.

Source: Dr. Leamer's backup data and materials.

## Appendix 6A

### Distributions of Annual Changes in Total Compensation Top 10 Adobe Jobs



**Notes:**

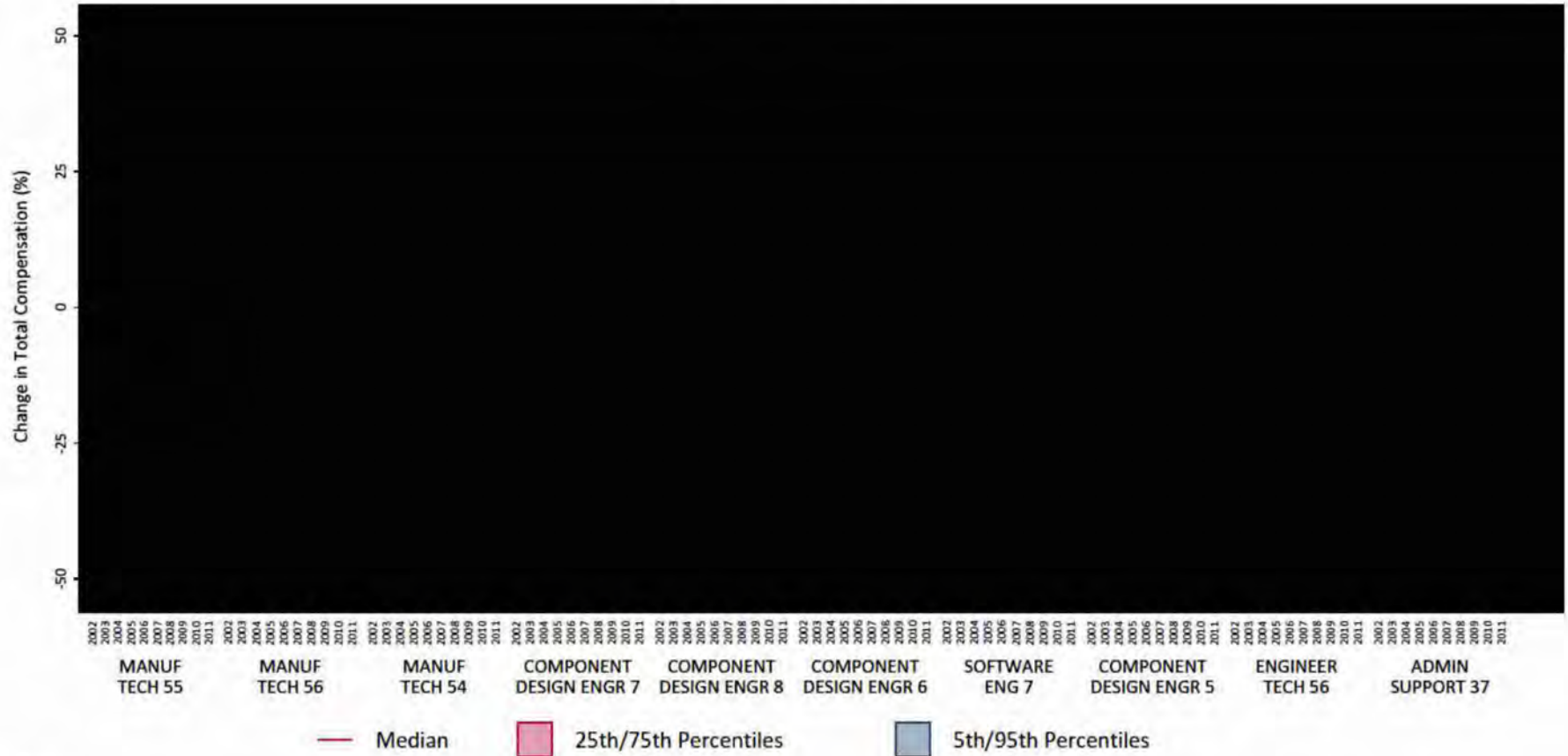
- [1] The top 10 jobs are identified using 2005 through 2009 employment--the same algorithm that Dr. Leamer uses in his Figures 15 through 17.
- [2] Bars are missing when there are fewer than five employees with the relevant job title in the data in the given year.
- [3] Percent changes are defined as differences in logs.

Source: Dr. Leamer's backup data and materials.



## Appendix 6B

### Distributions of Annual Changes in Total Compensation Top 10 Intel Jobs



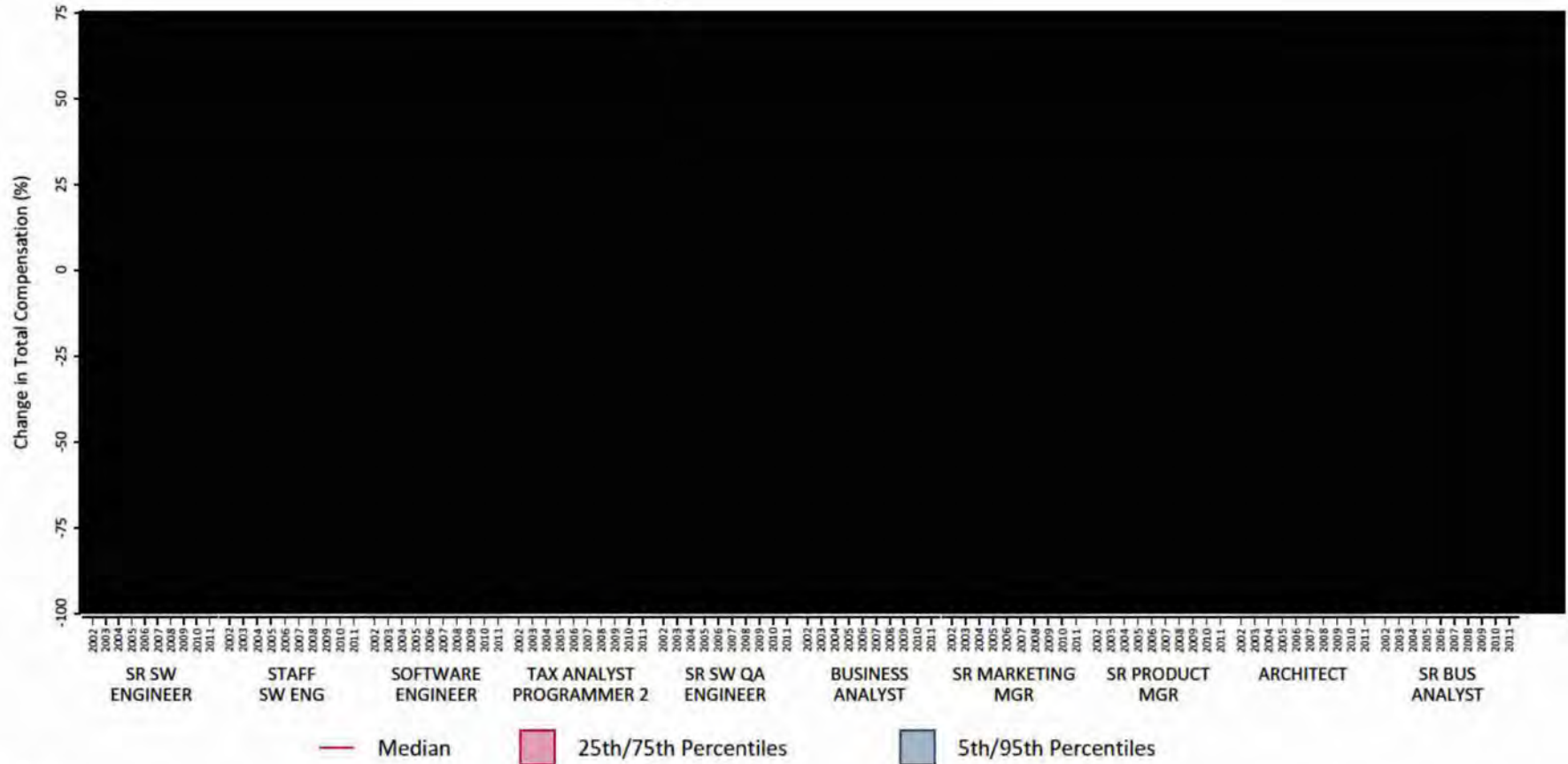
**Notes:**

- [1] The top 10 jobs are identified using 2005 through 2009 employment--the same algorithm that Dr. Leamer uses in his Figures 15 through 17.
- [2] Bars are missing when there are fewer than five employees with the relevant job title in the data in the given year.
- [3] Percent changes are defined as differences in logs.

Source: Dr. Leamer's backup data and materials.

## Appendix 6C

### Distributions of Annual Changes in Total Compensation Top 10 Intuit Jobs



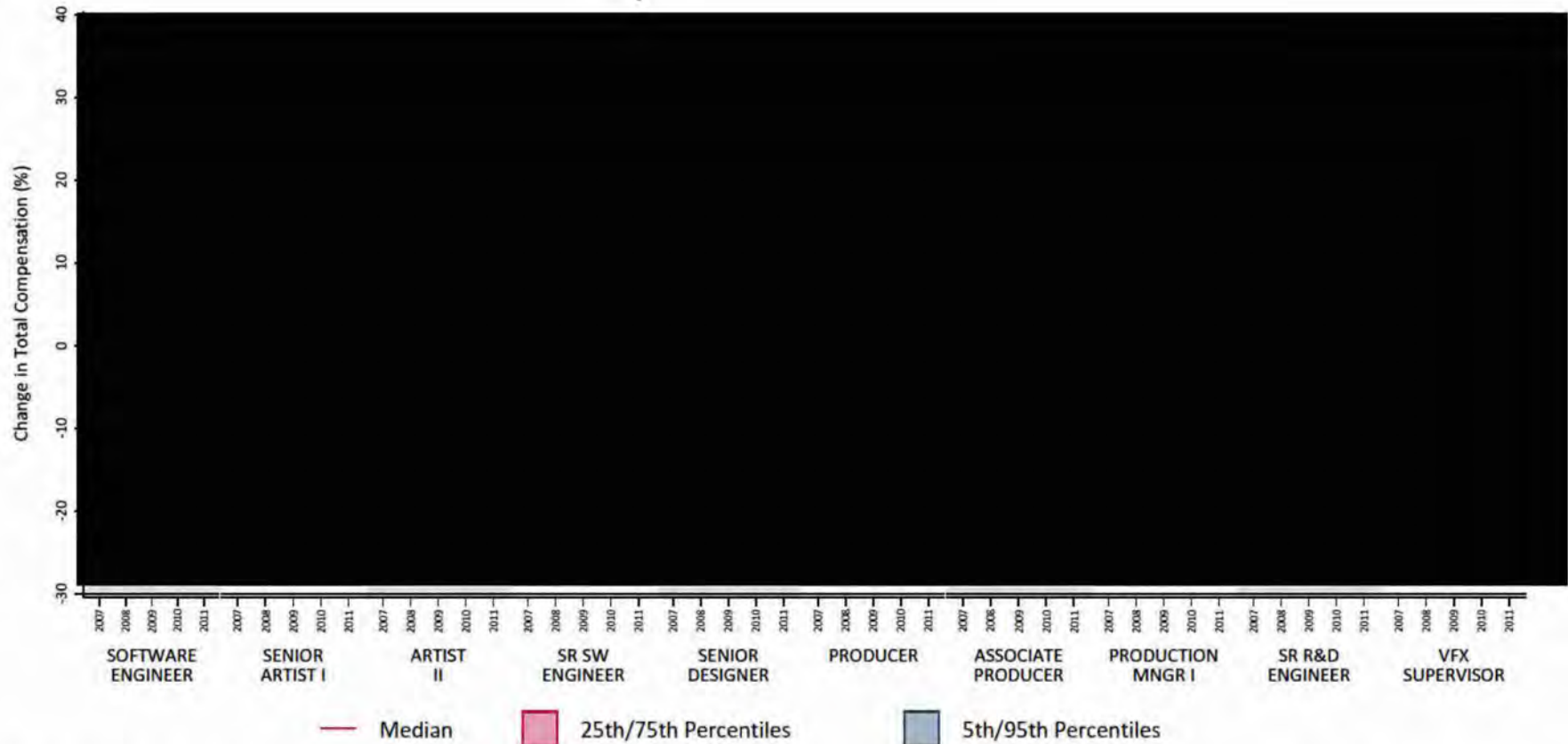
**Notes:**

- [1] The top 10 jobs are identified using 2005 through 2009 employment--the same algorithm that Dr. Leamer uses in his Figures 15 through 17.
- [2] Bars are missing when there are fewer than five employees with the relevant job title in the data in the given year.
- [3] Percent changes are defined as differences in logs.

Source: Dr. Leamer's backup data and materials.

## Appendix 6D

### Distributions of Annual Changes in Total Compensation Top 10 Lucasfilm Jobs



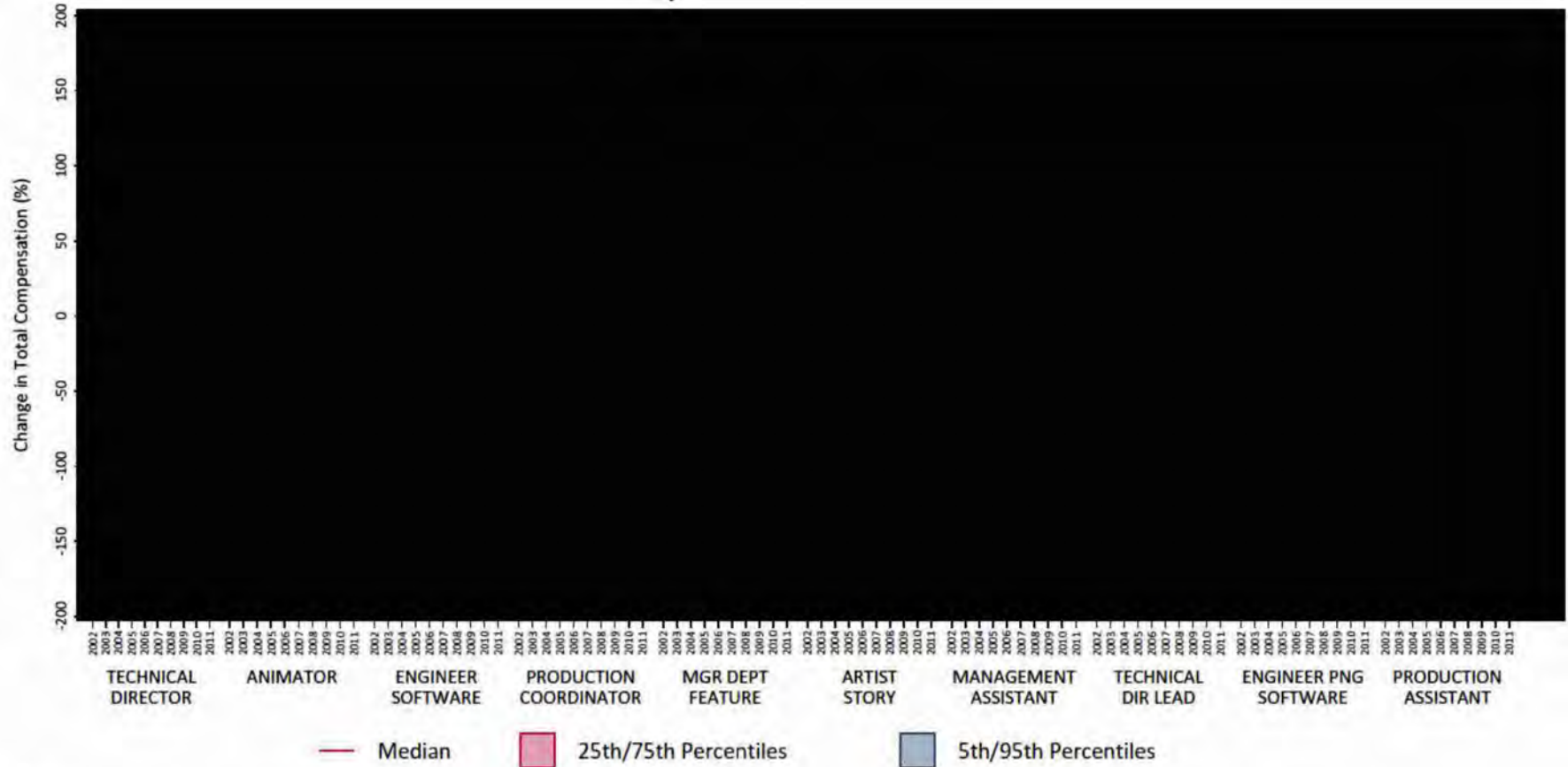
**Notes:**

- [1] The top 10 jobs are identified using 2005 through 2009 employment--the same algorithm that Dr. Leamer uses in his Figures 15 through 17.
- [2] Bars are missing when there are fewer than five employees with the relevant job title in the data in the given year.
- [3] Percent changes are defined as differences in logs.
- [4] Lucasfilm data are missing job titles prior to 2006.

Source: Dr. Leamer's backup data and materials.

## Appendix 6E

### Distributions of Annual Changes in Total Compensation Top 10 Pixar Jobs



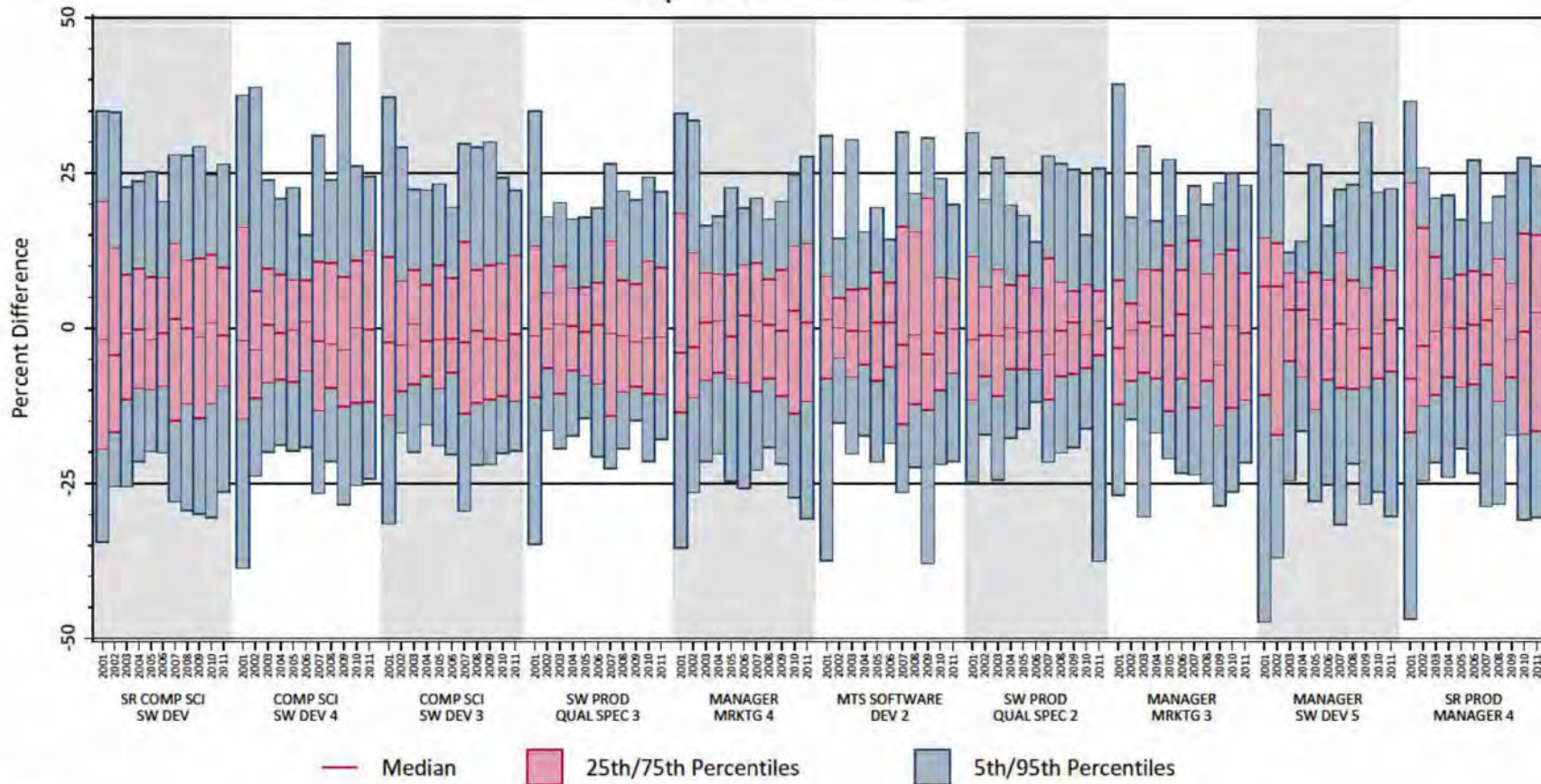
**Notes:**

- [1] The top 10 jobs are identified using 2005 through 2009 employment--the same algorithm that Dr. Leamer uses in his Figures 15 through 17.
- [2] Bars are missing when there are fewer than five employees with the relevant job title in the data in the given year.
- [3] Percent changes are defined as differences in logs.

Source: Dr. Leamer's backup data and materials.

### Appendix 7A

## Difference between Actual Compensation and Dr. Leamer Predicted Compensation Top 10 Adobe Jobs



**Notes:**

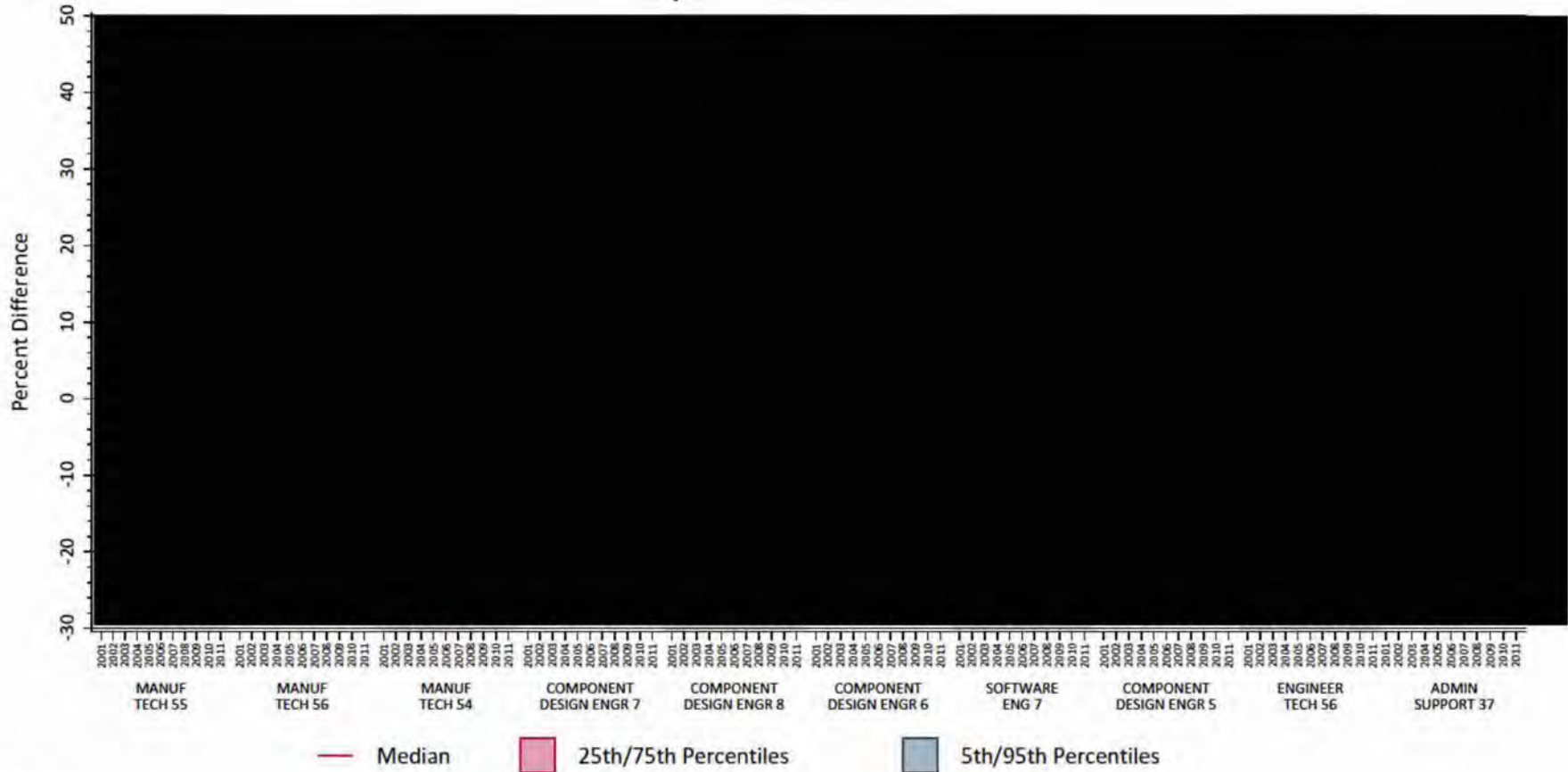
- [1] The percent difference is calculated as the residual from Dr. Leamer's Figure 12 regression models multiplied by 100.
- [2] The top 10 jobs are identified using 2005 through 2009 employment--the same algorithm that Dr. Leamer uses in his Figures 15 through 17.
- [3] Bars are missing when there are fewer than five employees with the relevant job title in the data in the given year.

Source: Dr. Leamer's backup data and materials.

### Appendix 7B

## Difference between Actual Compensation and Dr. Leamer Predicted Compensation

### Top 10 Intel Jobs



**Notes:**

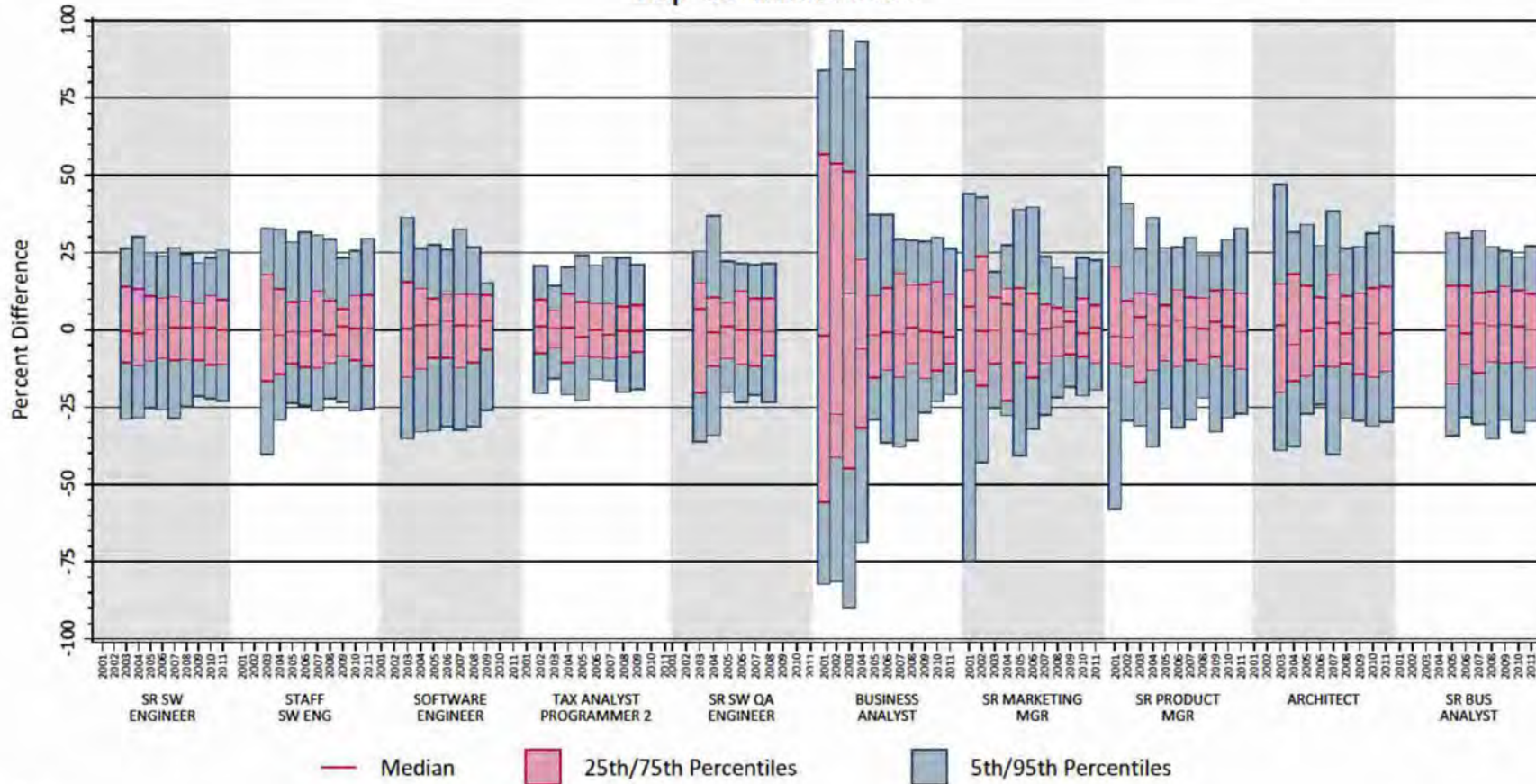
- [1] The percent difference is calculated as the residual from Dr. Leamer's Figure 12 regression models multiplied by 100.
- [2] The top 10 jobs are identified using 2005 through 2009 employment--the same algorithm that Dr. Leamer uses in his Figures 15 through 17.
- [3] Bars are missing when there are fewer than five employees with the relevant job title in the data in the given year.

Source: Dr. Leamer's backup data and materials.

### Appendix 7C

## Difference between Actual Compensation and Dr. Leamer Predicted Compensation

### Top 10 Intuit Jobs



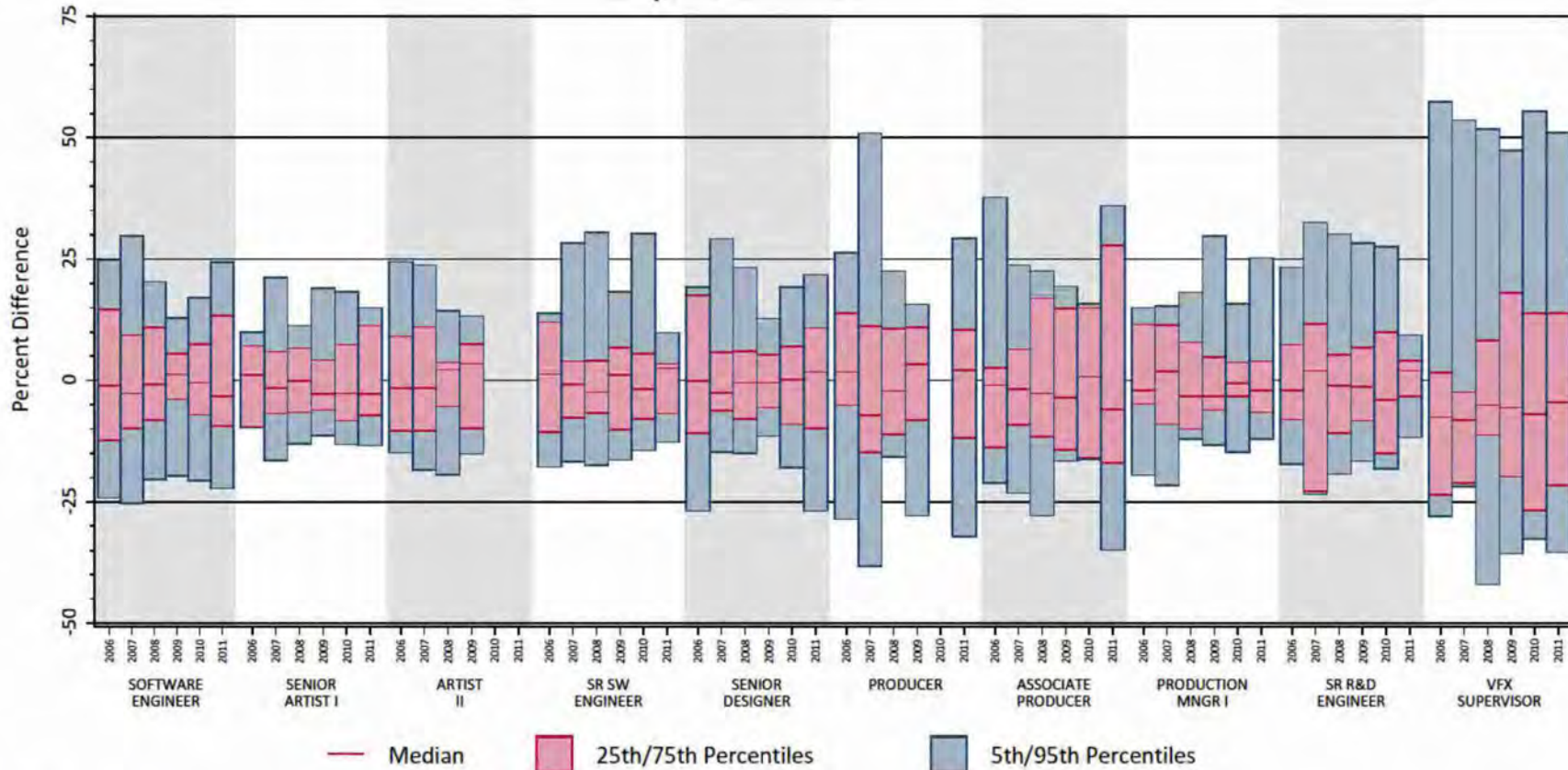
**Notes:**

- [1] The percent difference is calculated as the residual from Dr. Leamer's Figure 12 regression models multiplied by 100.
- [2] The top 10 jobs are identified using 2005 through 2009 employment--the same algorithm that Dr. Leamer uses in his Figures 15 through 17.
- [3] Bars are missing when there are fewer than five employees with the relevant job title in the data in the given year.

Source: Dr. Leamer's backup data and materials.

### Appendix 7D

## Difference between Actual Compensation and Dr. Leamer Predicted Compensation Top 10 Lucasfilm Jobs



**Notes:**

- [1] The percent difference is calculated as the residual from Dr. Leamer's Figure 12 regression models multiplied by 100.
- [2] The top 10 jobs are identified using 2005 through 2009 employment--the same algorithm that Dr. Leamer uses in his Figures 15 through 17.
- [3] Bars are missing when there are fewer than five employees with the relevant job title in the data in the given year.
- [4] Lucasfilm data are missing job titles prior to 2006.

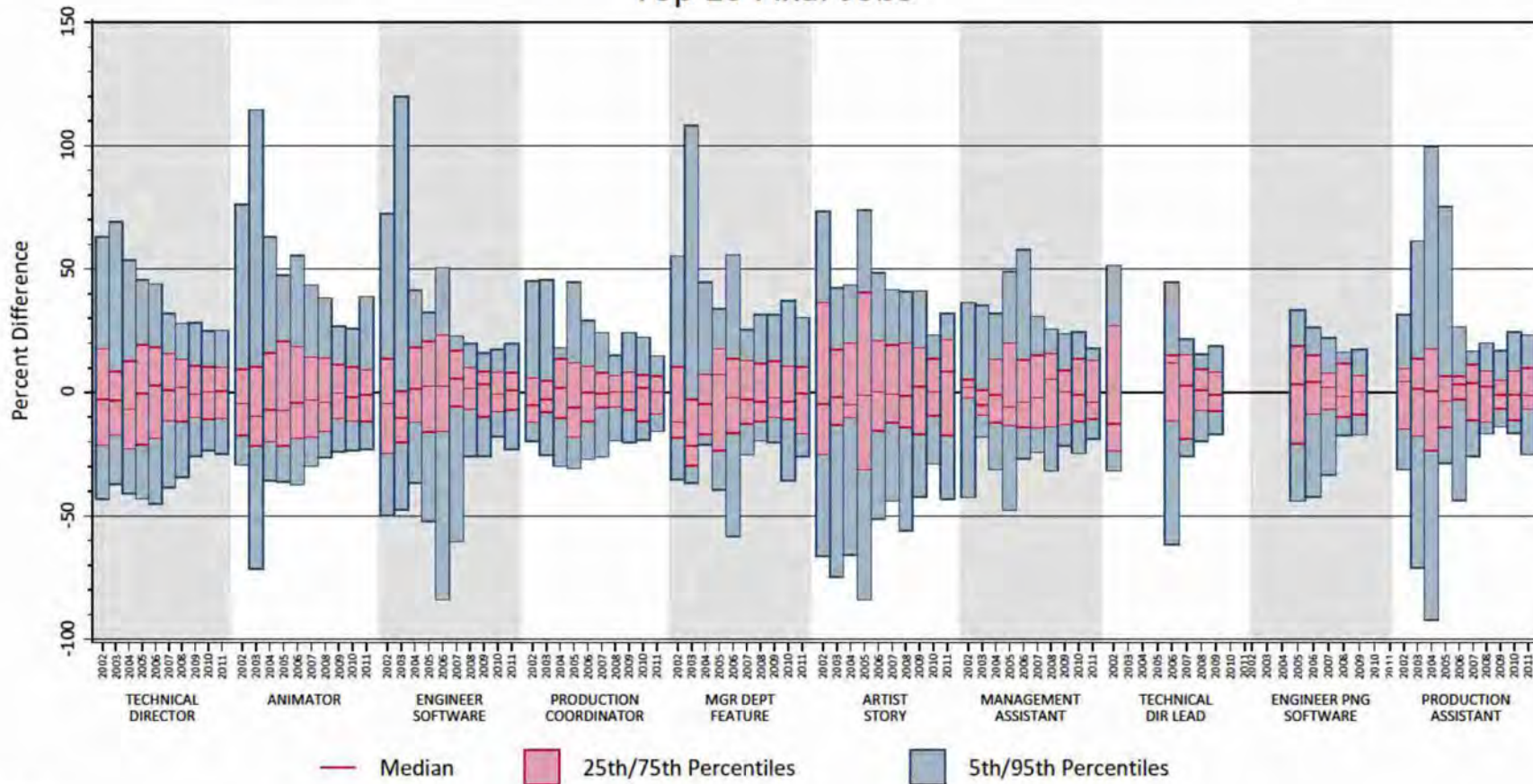
Source: Dr. Leamer's backup data and materials.



### Appendix 7E

## Difference between Actual Compensation and Dr. Leamer Predicted Compensation

### Top 10 Pixar Jobs



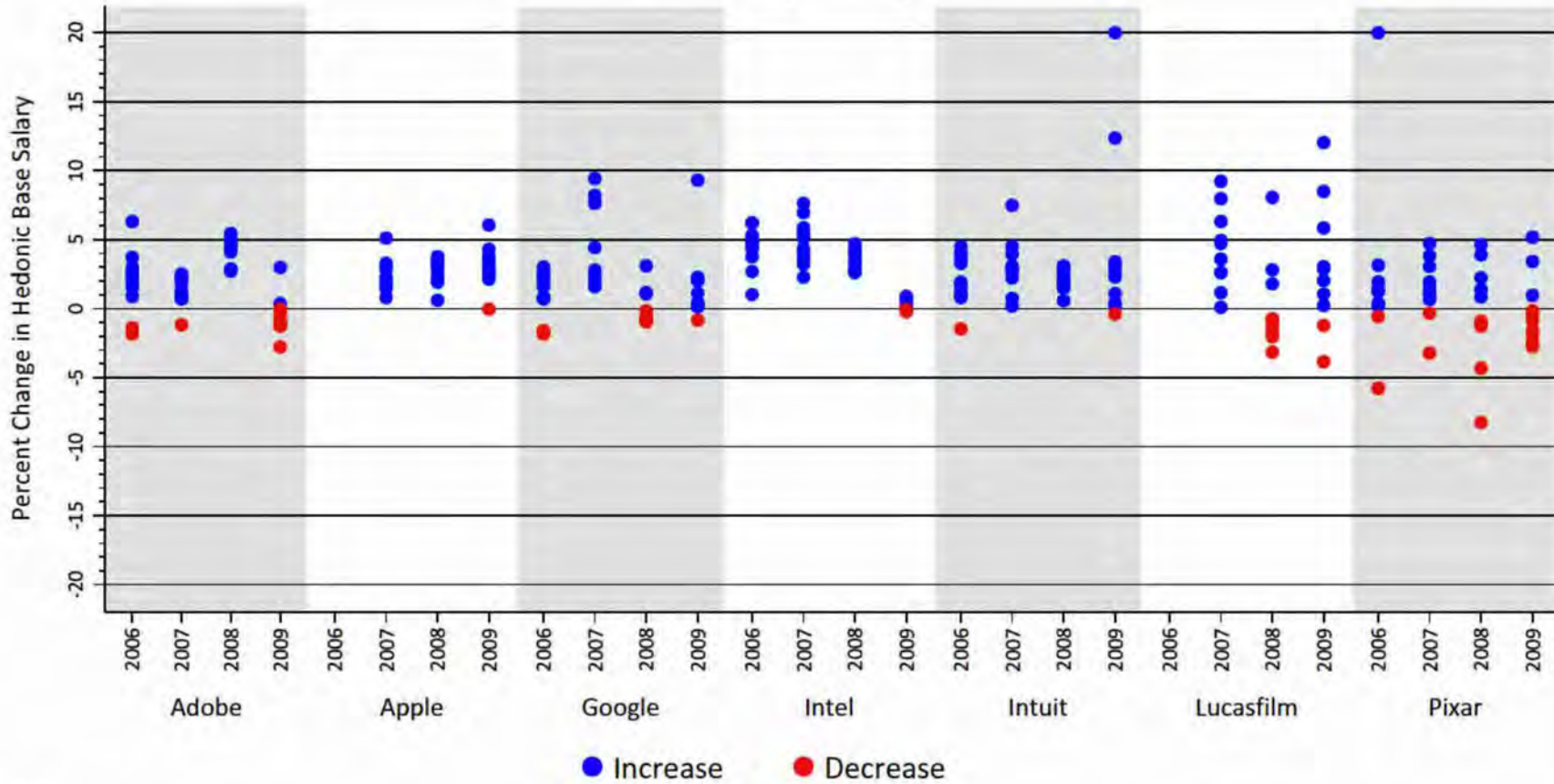
**Notes:**

- [1] The percent difference is calculated as the residual from Dr. Leamer's Figure 12 regression models multiplied by 100.
- [2] The top 10 jobs are identified using 2005 through 2009 employment--the same algorithm that Dr. Leamer uses in his Figures 15 through 17.
- [3] Bars are missing when there are fewer than five employees with the relevant job title in the data in the given year.

Source: Dr. Leamer's backup data and materials.

## Appendix 8A

### Annual Changes in "Constant Attribute Compensation" of Top 10 Job Titles Base Salary Changes



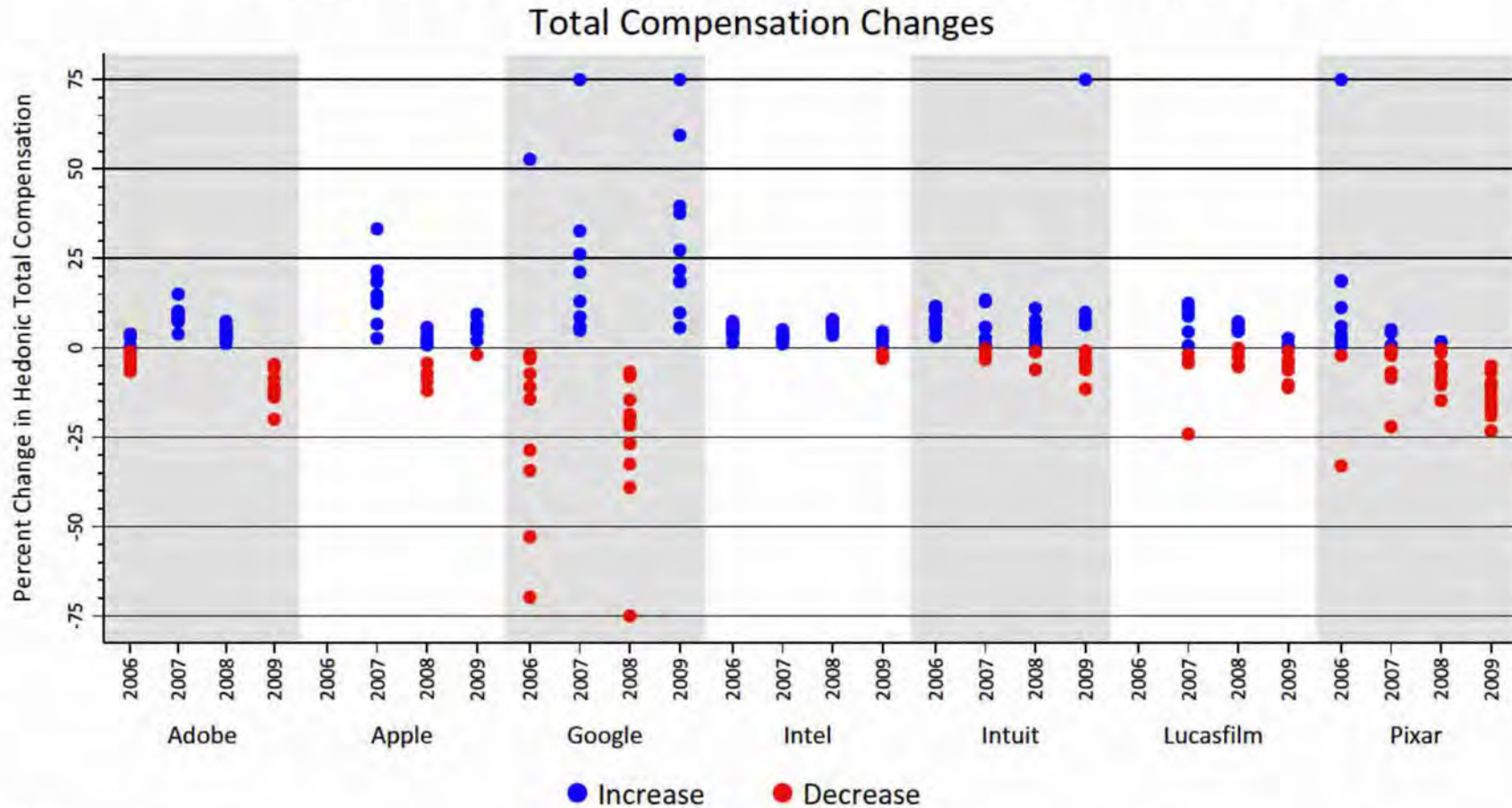
**Notes:**

- [1] The top 10 jobs are identified using 2005 through 2009 employment--the same algorithm that Dr. Leamer uses in his Figures 15 through 17.
- [2] Percent changes in hedonic base salary are defined as differences in logs.
- [3] Outliers are capped at +/- 20 percent.

Source: Dr. Leamer's backup data and materials.

## Appendix 8B

### Annual Changes in "Constant Attribute Compensation" of Top 10 Job Titles



**Notes:**

- [1] The top 10 jobs are identified using 2005 through 2009 employment--the same algorithm that Dr. Leamer uses in his Figures 15 through 17.
- [2] Percent changes in hedonic total compensation are defined as differences in logs.
- [3] Outliers are capped at +/- 75 percent.

Source: Dr. Leamer's backup data and materials.

## Appendix 9A

### Dr. Leamer's Figure 20 Regression Including Defendant-Specific Conduct Variables and Other Defendant-Specific Interactive Effects

#### All-Salaried Employee Class

Dependant Variable: Log(Total Annual Compensation/CPI)

Variable	Estimate	St. Error	T-Value
ADOBE * Conduct * Age	-0.0047 *	0.0026	-1.79
APPLE * Conduct * Age	0.0079 ***	0.0015	5.34
GOOGLE * Conduct * Age	0.0067 ***	0.0020	3.38
INTEL * Conduct * Age	0.0032 ***	0.0006	5.78
INTUIT * Conduct * Age	0.0018	0.0024	0.75
PIXAR * Conduct * Age	0.0152 ***	0.0042	3.59
LUCASFILM * Conduct * Age	-0.0027	0.0074	-0.37
ADOBE * Conduct * Age^2	0.0000	0.0000	1.26
APPLE * Conduct * Age^2	-0.0001 ***	0.0000	-5.58
GOOGLE * Conduct * Age^2	-0.0001 ***	0.0000	-3.44
INTEL * Conduct * Age^2	0.0000 ***	0.0000	-6.83
INTUIT * Conduct * Age^2	0.0000	0.0000	-0.78
PIXAR * Conduct * Age^2	-0.0002 ***	0.0001	-3.52
LUCASFILM * Conduct * Age^2	0.0000	0.0001	0.19
ADOBE * Conduct * Log(Number of New Hires in the Firm/Number of Employees(-1))	0.8370 ***	0.0376	22.24
APPLE * Conduct * Log(Number of New Hires in the Firm/Number of Employees(-1))	-0.3141 ***	0.0250	-12.57
GOOGLE * Conduct * Log(Number of New Hires in the Firm/Number of Employees(-1))	0.3453 ***	0.0061	56.20
INTEL * Conduct * Log(Number of New Hires in the Firm/Number of Employees(-1))	0.0323 ***	0.0020	16.45
INTUIT * Conduct * Log(Number of New Hires in the Firm/Number of Employees(-1))	-0.0213 *	0.0127	-1.67
PIXAR * Conduct * Log(Number of New Hires in the Firm/Number of Employees(-1))	0.1142 ***	0.0342	3.34
LUCASFILM * Conduct * Log(Number of New Hires in the Firm/Number of Employees(-1))	0.0664 ***	0.0169	3.92
ADOBE * Conduct	1.8691 ***	0.0976	19.15
APPLE * Conduct	-0.7391 ***	0.0549	-13.46
GOOGLE * Conduct	0.2602 ***	0.0380	6.84
INTEL * Conduct	0.0240 *	0.0132	1.81
INTUIT * Conduct	-0.1416 ***	0.0576	-2.46
PIXAR * Conduct	0.0277	0.1164	0.24
LUCASFILM * Conduct	0.2427	0.1636	1.48
ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.7079 ***	0.0056	125.95
APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7265 ***	0.0027	272.85
GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.5121 ***	0.0017	294.66
INTEL * Log(Total Annual Compensation/CPI) (-1)	0.6721 ***	0.0023	286.66
INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.7202 ***	0.0059	121.40
PIXAR * Log(Total Annual Compensation/CPI) (-1)	0.6619 ***	0.0056	117.60
LUCASFILM * Log(Total Annual Compensation/CPI) (-1)	0.8067 ***	0.0360	22.42
ADOBE * Log(Total Annual Compensation/CPI) (-2)	0.2868 ***	0.0055	52.13
APPLE * Log(Total Annual Compensation/CPI) (-2)	0.2828 ***	0.0028	102.17
GOOGLE * Log(Total Annual Compensation/CPI) (-2)	0.3466 ***	0.0017	207.40
INTEL * Log(Total Annual Compensation/CPI) (-2)	0.2964 ***	0.0023	129.91
INTUIT * Log(Total Annual Compensation/CPI) (-2)	0.2541 ***	0.0057	44.21
PIXAR * Log(Total Annual Compensation/CPI) (-2)	0.1743 ***	0.0053	32.60
LUCASFILM * Log(Total Annual Compensation/CPI) (-2)	0.1922 ***	0.0365	5.26
ADOBE * Log(Age)	0.4727 **	0.2194	2.15
APPLE * Log(Age)	-1.0913 ***	0.1256	-8.69
GOOGLE * Log(Age)	1.0010 ***	0.1547	6.47
INTEL * Log(Age)	-0.2981 ***	0.0485	-6.15
INTUIT * Log(Age)	-0.8571 ***	0.1696	-5.05
PIXAR * Log(Age)	-0.0441	0.4413	-0.10

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LUCASFILM * Log(Age)	0.0240	0.8306	0.03
ADOBE * Log(Age)^2	-0.0695 ***	0.0297	-2.34
APPLE * Log(Age)^2	0.1235 ***	0.0170	7.24
GOOGLE * Log(Age)^2	-0.1483 ***	0.0214	-6.92
INTEL * Log(Age)^2	0.0348 ***	0.0066	5.30
INTUIT * Log(Age)^2	0.1010 ***	0.0229	4.41
PIXAR * Log(Age)^2	0.0166	0.0605	0.27
LUCASFILM * Log(Age)^2	-0.0085	0.1115	-0.08
Log(Company Tenure) (Months)	-0.0167 ***	0.0050	-3.36
Log(Company Tenure)^2	0.0017 ***	0.0005	3.14
Male	0.0025 ***	0.0005	4.62
DLog(Information Sector Employment in San-Jose)	1.5574 ***	0.0183	85.30
Log(Total Number of Transfers Among Defendants)	0.0770 ***	0.0018	42.53
Year (trend)	-0.0025 ***	0.0003	-7.90
ADOBE * Log(Number of New Hires in the Firm/Number of Employees(-1))	-0.0441 ***	0.0095	-4.63
APPLE * Log(Number of New Hires in the Firm/Number of Employees(-1))	0.0461 ***	0.0066	6.94
GOOGLE * Log(Number of New Hires in the Firm/Number of Employees(-1))	-0.2261 ***	0.0026	-86.41
INTEL * Log(Number of New Hires in the Firm/Number of Employees(-1))	0.0049 ***	0.0013	3.77
INTUIT * Log(Number of New Hires in the Firm/Number of Employees(-1))	0.0808 ***	0.0046	17.61
PIXAR * Log(Number of New Hires in the Firm/Number of Employees(-1))	-0.1603 ***	0.0308	-5.20
LUCASFILM * Log(Number of New Hires in the Firm/Number of Employees(-1))	-0.0217	0.0154	-1.41
Log(Total Number of New Hires)	-0.2292 ***	0.0026	-89.66
Log(Firm Revenue Per Employee/CPI) (-1)	-0.0915 ***	0.0043	-21.15
DLog(Firm Revenue Per Employee/CPI) (-1)	0.1646 ***	0.0033	50.39
APPLE	3.3227 ***	0.4646	7.15
GOOGLE	-0.0066	0.4898	-0.01
INTEL	1.6772 ***	0.4130	4.06
INTUIT	2.9576 ***	0.5094	5.81
PIXAR	1.3942	0.9009	1.55
LUCASFILM	0.9044	1.5907	0.57
Location (State) Indicators	YES		
Constant	YES		
R-Square	<b>0.928</b>		
Observations	<b>508,969</b>		

Note: \*\*\* Significant at 1% level, \*\* Significant at 5% level, \* Significant at 10% level.

Source: Dr. Leamer's backup data and materials. Pixar revenue data after 2005 are included.

## Appendix 9B

### Dr. Leamer's Figure 23 Regression Including Defendant-Specific Conduct Variables and Other Defendant-Specific Interactive Effects Technical, Creative and R&D Class

Dependant Variable: Log(Total Annual Compensation/CPI)

Variable	Estimate	St. Error	T-Value
ADOBE * Conduct * Age	-0.0062 *	0.0033	-1.85
APPLE * Conduct * Age	0.0090 ***	0.0020	4.54
GOOGLE * Conduct * Age	0.0074 ***	0.0025	2.93
INTEL * Conduct * Age	0.0035 ***	0.0008	4.42
INTUIT * Conduct * Age	-0.0011	0.0037	-0.29
PIXAR * Conduct * Age	0.0102 *	0.0056	1.83
LUCASFILM * Conduct * Age	0.0036	0.0182	0.20
ADOBE * Conduct * Age^2	0.0001	0.0000	1.37
APPLE * Conduct * Age^2	-0.0001 ***	0.0000	-4.65
GOOGLE * Conduct * Age^2	-0.0001 ***	0.0000	-3.01
INTEL * Conduct * Age^2	0.0000 ***	0.0000	-5.07
INTUIT * Conduct * Age^2	0.0000	0.0000	0.17
PIXAR * Conduct * Age^2	-0.0001 *	0.0001	-1.92
LUCASFILM * Conduct * Age^2	-0.0001	0.0002	-0.41
ADOBE * Conduct * Log(Number of New Hires in the Firm/Number of Employees(-1))	0.9854 ***	0.0482	20.45
APPLE * Conduct * Log(Number of New Hires in the Firm/Number of Employees(-1))	-0.1272 ***	0.0345	-3.68
GOOGLE * Conduct * Log(Number of New Hires in the Firm/Number of Employees(-1))	0.3276 ***	0.0088	37.18
INTEL * Conduct * Log(Number of New Hires in the Firm/Number of Employees(-1))	0.0388 ***	0.0026	14.83
INTUIT * Conduct * Log(Number of New Hires in the Firm/Number of Employees(-1))	-0.0750 ***	0.0194	-3.87
PIXAR * Conduct * Log(Number of New Hires in the Firm/Number of Employees(-1))	-0.0642	0.0440	-1.46
LUCASFILM * Conduct * Log(Number of New Hires in the Firm/Number of Employees(-1))	0.0820 ***	0.0276	2.97
ADOBE * Conduct	2.2161 ***	0.1241	17.85
APPLE * Conduct	-0.4323 ***	0.0747	-5.79
GOOGLE * Conduct	0.2078 ***	0.0494	4.21
INTEL * Conduct	0.0548 ***	0.0185	2.97
INTUIT * Conduct	-0.1868 **	0.0875	-2.14
PIXAR * Conduct	-0.2066	0.1508	-1.37
LUCASFILM * Conduct	0.2062	0.3662	0.56
ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.6754 ***	0.0075	89.78
APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7040 ***	0.0037	192.60
GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.4607 ***	0.0022	207.91
INTEL * Log(Total Annual Compensation/CPI) (-1)	0.6429 ***	0.0029	219.78
INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.6772 ***	0.0088	76.81
PIXAR * Log(Total Annual Compensation/CPI) (-1)	0.6202 ***	0.0084	73.65
LUCASFILM * Log(Total Annual Compensation/CPI) (-1)	0.7676 ***	0.0695	11.04
ADOBE * Log(Total Annual Compensation/CPI) (-2)	0.3112 ***	0.0074	42.05
APPLE * Log(Total Annual Compensation/CPI) (-2)	0.2864 ***	0.0038	74.62
GOOGLE * Log(Total Annual Compensation/CPI) (-2)	0.3478 ***	0.0021	162.51
INTEL * Log(Total Annual Compensation/CPI) (-2)	0.3113 ***	0.0028	109.66
INTUIT * Log(Total Annual Compensation/CPI) (-2)	0.2930 ***	0.0085	34.49
PIXAR * Log(Total Annual Compensation/CPI) (-2)	0.0956 ***	0.0076	12.61
LUCASFILM * Log(Total Annual Compensation/CPI) (-2)	0.2340 ***	0.0702	3.34
ADOBE * Log(Age)	0.3557	0.2812	1.26
APPLE * Log(Age)	-1.2304 ***	0.1670	-7.37
GOOGLE * Log(Age)	0.1880	0.1917	0.98
INTEL * Log(Age)	-0.3725 ***	0.0699	-5.33
INTUIT * Log(Age)	-1.0874 ***	0.2520	-4.31
PIXAR * Log(Age)	0.6246	0.5776	1.08

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LUCASFILM * Log(Age)	-0.4933	1.5449	-0.32
ADOBE * Log(Age)^2	-0.0547	0.0381	-1.43
APPLE * Log(Age)^2	0.1382 ***	0.0228	6.07
GOOGLE * Log(Age)^2	-0.0387	0.0265	-1.46
INTEL * Log(Age)^2	0.0449 ***	0.0095	4.73
INTUIT * Log(Age)^2	0.1305 ***	0.0342	3.82
PIXAR * Log(Age)^2	-0.0667	0.0793	-0.84
LUCASFILM * Log(Age)^2	0.0634	0.2101	0.30
Log(Company Tenure) (Months)	0.0021	0.0067	0.31
Log(Company Tenure)^2	0.0003	0.0007	0.47
Male	0.0058 ***	0.0008	7.21
DLog(Information Sector Employment in San-Jose)	1.6830 ***	0.0250	67.20
Log(Total Number of Transfers Among Defendants)	0.0854 ***	0.0024	35.18
Year (trend)	-0.0004	0.0004	-0.99
ADOBE * Log(Number of New Hires in the Firm/Number of Employees(-1))	-0.0497 ***	0.0122	-4.06
APPLE * Log(Number of New Hires in the Firm/Number of Employees(-1))	0.0349 ***	0.0092	3.81
GOOGLE * Log(Number of New Hires in the Firm/Number of Employees(-1))	-0.2318 ***	0.0037	-63.00
INTEL * Log(Number of New Hires in the Firm/Number of Employees(-1))	0.0041 ***	0.0018	2.34
INTUIT * Log(Number of New Hires in the Firm/Number of Employees(-1))	0.1109 ***	0.0069	16.17
PIXAR * Log(Number of New Hires in the Firm/Number of Employees(-1))	-0.0495	0.0394	-1.26
LUCASFILM * Log(Number of New Hires in the Firm/Number of Employees(-1))	-0.0296	0.0227	-1.31
Log(Total Number of New Hires)	-0.2643 ***	0.0035	-76.33
Log(Firm Revenue Per Employee/CPI) (-1)	-0.0435 ***	0.0058	-7.45
DLog(Firm Revenue Per Employee/CPI) (-1)	0.1532 ***	0.0044	35.02
APPLE	3.4399 ***	0.5998	5.73
GOOGLE	1.5131 ***	0.6217	2.43
INTEL	1.6323 ***	0.5322	3.07
INTUIT	3.2415 ***	0.6919	4.68
PIXAR	0.8473	1.1715	0.72
LUCASFILM	1.4582	2.8740	0.51
Location (State) Indicators	YES		
Constant	YES		
R-Square	<b>0.879</b>		
Observations	<b>295,136</b>		

Note: \*\*\* Significant at 1% level, \*\* Significant at 5% level, \* Significant at 10% level.

Source: Dr. Leamer's backup data and materials. Pixar revenue data after 2005 are included.

## Appendix 10A

### Dr. Leamer's Figure 20 Regression Using a Single Conduct Variable

#### All-Salaried Employee Class

**Dependant Variable:** Log(Total Annual Compensation/CPI)

Variable	Estimate	St. Error	T-Value
Conduct	-0.0344 ***	0.0008	-41.98
ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.6978 ***	0.0054	129.27
APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7416 ***	0.0026	279.85
GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.4943 ***	0.0017	293.50
INTEL * Log(Total Annual Compensation/CPI) (-1)	0.6687 ***	0.0024	282.48
INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.7117 ***	0.0057	124.33
PIXAR * Log(Total Annual Compensation/CPI) (-1)	0.6961 ***	0.0069	100.42
LUCASFILM * Log(Total Annual Compensation/CPI) (-1)	0.8118 ***	0.0363	22.36
ADOBE * Log(Total Annual Compensation/CPI) (-2)	0.2934 ***	0.0053	55.74
APPLE * Log(Total Annual Compensation/CPI) (-2)	0.2595 ***	0.0027	95.36
GOOGLE * Log(Total Annual Compensation/CPI) (-2)	0.3734 ***	0.0016	229.06
INTEL * Log(Total Annual Compensation/CPI) (-2)	0.3005 ***	0.0023	130.49
INTUIT * Log(Total Annual Compensation/CPI) (-2)	0.2522 ***	0.0055	45.49
PIXAR * Log(Total Annual Compensation/CPI) (-2)	0.1992 ***	0.0067	29.64
LUCASFILM * Log(Total Annual Compensation/CPI) (-2)	0.1798 ***	0.0367	4.90
Log(Age) (Years)	-0.0105	0.0328	-0.32
Log(Age)^2	-0.0076 *	0.0044	-1.72
Log(Company Tenure) (Months)	0.0083 *	0.0050	1.66
Log(Company Tenure)^2	-0.0009 *	0.0006	-1.66
Male	0.0027 ***	0.0005	5.02
DLog(Information Sector Employment in San-Jose)	1.4135 ***	0.0136	103.90
Log(Total Number of Transfers Among Defendants)	0.0959 ***	0.0015	63.66
Year (trend)	-0.0039 ***	0.0003	-14.53
Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0169 ***	0.0008	21.61
Log(Total Number of New Hires)	-0.2478 ***	0.0021	-116.78
Log(Firm Revenue Per Employee/CPI) (-1)	-0.1027 ***	0.0034	-30.20
DLog(Firm Revenue Per Employee/CPI) (-1)	0.2162 ***	0.0033	66.49
APPLE	0.0607 ***	0.0162	3.75
GOOGLE	1.0320 ***	0.0174	59.42
INTEL	0.1516 ***	0.0146	10.40
INTUIT	0.1473 ***	0.0193	7.64
PIXAR	0.7075 ***	0.0422	16.77
LUCASFILM	0.1256 ***	0.0480	2.61
Location (State) Indicators	YES		
Constant	YES		
R-Square	<b>0.926</b>		
Observations	<b>504,897</b>		

Note: \*\*\* Significant at 1% level, \*\* Significant at 5% level, \* Significant at 10% level.

Source: Dr. Leamer's backup data and materials.



## Appendix 10B

### Dr. Leamer's Figure 23 Regression Using a Single Conduct Variable

#### Technical, Creative and R&D Class

**Dependant Variable:** Log(Total Annual Compensation/CPI)

Variable	Estimate	St. Error	T-Value
Conduct	-0.0234 ***	0.0011	-20.94
ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.6643 ***	0.0072	91.76
APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7212 ***	0.0037	197.36
GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.4403 ***	0.0022	203.78
INTEL * Log(Total Annual Compensation/CPI) (-1)	0.6407 ***	0.0030	215.53
INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.6578 ***	0.0084	78.28
PIXAR * Log(Total Annual Compensation/CPI) (-1)	0.6523 ***	0.0106	61.69
LUCASFILM * Log(Total Annual Compensation/CPI) (-1)	0.8457 ***	0.0692	12.21
ADOBE * Log(Total Annual Compensation/CPI) (-2)	0.3158 ***	0.0071	44.58
APPLE * Log(Total Annual Compensation/CPI) (-2)	0.2581 ***	0.0038	68.54
GOOGLE * Log(Total Annual Compensation/CPI) (-2)	0.3629 ***	0.0021	173.68
INTEL * Log(Total Annual Compensation/CPI) (-2)	0.3171 ***	0.0029	110.18
INTUIT * Log(Total Annual Compensation/CPI) (-2)	0.2967 ***	0.0081	36.48
PIXAR * Log(Total Annual Compensation/CPI) (-2)	0.1054 ***	0.0097	10.89
LUCASFILM * Log(Total Annual Compensation/CPI) (-2)	0.1456 **	0.0694	2.10
Log(Age) (Years)	-0.1807 ***	0.0463	-3.90
Log(Age)^2	0.0146 **	0.0063	2.32
Log(Company Tenure) (Months)	0.0326 ***	0.0068	4.78
Log(Company Tenure)^2	-0.0028 ***	0.0008	-3.78
Male	0.0065 ***	0.0008	7.89
DLog(Information Sector Employment in San-Jose)	1.5271 ***	0.0189	80.81
Log(Total Number of Transfers Among Defendants)	0.0983 ***	0.0020	48.08
Year (trend)	-0.0009 ***	0.0004	-2.52
Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0154 ***	0.0011	14.31
Log(Total Number of New Hires)	-0.2724 ***	0.0029	-93.07
Log(Firm Revenue Per Employee/CPI) (-1)	-0.0811 ***	0.0047	-17.17
DLog(Firm Revenue Per Employee/CPI) (-1)	0.2127 ***	0.0044	48.43
APPLE	0.1244 ***	0.0245	5.08
GOOGLE	1.3816 ***	0.0259	53.33
INTEL	0.1573 ***	0.0219	7.19
INTUIT	0.1486 ***	0.0315	4.71
PIXAR	1.5543 ***	0.0771	20.17
LUCASFILM	0.0296	0.1038	0.29
Location (State) Indicators	YES		
Constant	YES		
R-Square	<b>0.874</b>		
Observations	<b>292,489</b>		

Note: \*\*\* Significant at 1% level, \*\* Significant at 5% level, \* Significant at 10% level.

Source: Dr. Leamer's backup data and materials.

## Appendix 10C

### "Undercompensation" Estimates Using a Single Conduct Variable in Dr. Leamer's Regression

vs.

### "Undercompensation" Estimates in Dr. Leamer's Figures 22 and 24

#### All-Salaried Employee Class

Year	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar
2005	-1.72%	-1.72%	-1.72%	-1.72%		-11.95%	-10.29%
2006	-4.63%	-4.71%	-4.28%	-4.58%		-14.77%	-12.23%
2007	-7.17%	-7.37%	-6.19%	-7.02%	-3.44%	-17.58%	-14.00%
2008	-9.80%	-10.13%	-8.10%	-9.51%	-5.88%	-20.36%	-15.61%
2009	-9.80%	-10.28%	-7.17%	-9.32%	-5.91%	-20.55%	-14.52%

#### All-Salaried Employee Class

Year	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar
2005	-1.61%	-1.59%	-1.78%	-1.67%		-12.13%	-10.56%
2006	-4.28%	-4.43%	-4.44%	-4.70%		-14.63%	-12.44%
2007	-6.64%	-6.94%	-6.39%	-7.46%	-3.24%	-17.24%	-14.28%
2008	-9.08%	-9.56%	-8.40%	-10.05%	-5.64%	-19.94%	-15.76%
2009	-9.15%	-9.73%	-7.51%	-9.95%	-5.70%	-20.12%	-14.65%

#### Technical, Creative and R&D Class

Year	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar
2005	-1.17%	-1.17%	-1.17%	-1.17%		-8.33%	-6.08%
2006	-3.12%	-3.19%	-2.86%	-3.09%		-10.31%	-6.85%
2007	-4.78%	-4.94%	-4.03%	-4.69%	-2.34%	-12.27%	-7.45%
2008	-6.50%	-6.73%	-5.15%	-6.33%	-3.88%	-14.22%	-7.92%
2009	-6.42%	-6.71%	-4.31%	-6.13%	-3.83%	-14.40%	-6.54%

#### Technical, Creative and R&D Class

Year	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar
2005	-1.56%	-1.90%	-3.07%	-1.64%		-10.80%	-9.28%
2006	-4.29%	-4.96%	-7.23%	-3.06%		-14.77%	-10.47%
2007	-6.48%	-7.79%	-9.36%	-3.38%	-3.41%	-18.08%	-10.61%
2008	-8.80%	-10.64%	-11.20%	-4.76%	-5.21%	-20.44%	-11.87%
2009	-8.44%	-10.51%	-9.00%	-4.19%	-4.96%	-20.54%	-9.62%

Source: Leamer Figure 20 and 23 regressions excluding conduct interactions with age and hiring rate.

## Appendix 11A

### Dr. Leamer's Figure 20 Regression Including Defendant-Specific Conduct Variables

#### All-Salaried Employee Class

**Dependant Variable:** Log(Total Annual Compensation/CPI)

Variable	Estimate	St. Error	T-Value
ADOBE * Conduct	0.0053 *	0.0028	1.89
APPLE * Conduct	-0.0139 ***	0.0019	-7.37
GOOGLE * Conduct	-0.0969 ***	0.0021	-45.25
INTEL * Conduct	-0.0304 ***	0.0009	-33.37
INTUIT * Conduct	-0.0600 ***	0.0026	-23.17
PIXAR * Conduct	0.0396 ***	0.0048	8.34
LUCASFILM * Conduct	0.0000	0.0075	0.00
ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.6855 ***	0.0056	122.85
APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7361 ***	0.0027	276.84
GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.4858 ***	0.0017	283.31
INTEL * Log(Total Annual Compensation/CPI) (-1)	0.6721 ***	0.0024	283.28
INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.7173 ***	0.0058	122.92
PIXAR * Log(Total Annual Compensation/CPI) (-1)	0.6857 ***	0.0055	124.10
LUCASFILM * Log(Total Annual Compensation/CPI) (-1)	0.7984 ***	0.0364	21.92
ADOBE * Log(Total Annual Compensation/CPI) (-2)	0.3056 ***	0.0055	56.03
APPLE * Log(Total Annual Compensation/CPI) (-2)	0.2645 ***	0.0027	96.26
GOOGLE * Log(Total Annual Compensation/CPI) (-2)	0.3741 ***	0.0016	228.53
INTEL * Log(Total Annual Compensation/CPI) (-2)	0.2976 ***	0.0023	128.96
INTUIT * Log(Total Annual Compensation/CPI) (-2)	0.2466 ***	0.0056	43.72
PIXAR * Log(Total Annual Compensation/CPI) (-2)	0.1758 ***	0.0053	33.30
LUCASFILM * Log(Total Annual Compensation/CPI) (-2)	0.2003 ***	0.0369	5.43
Log(Age) (Years)	-0.0244	0.0327	-0.75
Log(Age)^2	-0.0057	0.0044	-1.28
Log(Company Tenure) (Months)	-0.0128 ***	0.0050	-2.55
Log(Company Tenure)^2	0.0013 ***	0.0006	2.42
Male	0.0032 ***	0.0005	5.82
DLog(Information Sector Employment in San-Jose)	1.4228 ***	0.0136	104.42
Log(Total Number of Transfers Among Defendants)	0.0800 ***	0.0015	53.90
Year (trend)	-0.0032 ***	0.0003	-12.13
Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0128 ***	0.0008	16.20
Log(Total Number of New Hires)	-0.2273 ***	0.0021	-108.21
Log(Firm Revenue Per Employee/CPI) (-1)	-0.0677 ***	0.0033	-20.55
DLog(Firm Revenue Per Employee/CPI) (-1)	0.1461 ***	0.0029	50.95
APPLE	0.0492 ***	0.0163	3.02
GOOGLE	1.0950 ***	0.0176	62.24
INTEL	0.1587 ***	0.0147	10.82
INTUIT	0.1818 ***	0.0193	9.40
PIXAR	0.7905 ***	0.0264	29.96
LUCASFILM	0.0271	0.0503	0.54
Location (State) Indicators	YES		
Constant	YES		
R-Square	<b>0.926</b>		
Observations	<b>508,969</b>		

Note: \*\*\* Significant at 1% level, \*\* Significant at 5% level, \* Significant at 10% level.

Source: Dr. Leamer's backup data and materials. Pixar revenue data after 2005 are included.

## Appendix 11B

### Dr. Leamer's Figure 23 Regression Including Defendant-Specific Conduct Variables

Technical, Creative and R&D Class

**Dependant Variable:** Log(Total Annual Compensation/CPI)

Variable	Estimate	St. Error	T-Value
ADOBE * Conduct	0.0175 ***	0.0036	4.80
APPLE * Conduct	-0.0227 ***	0.0026	-8.71
GOOGLE * Conduct	-0.1219 ***	0.0029	-42.51
INTEL * Conduct	-0.0124 ***	0.0012	-10.12
INTUIT * Conduct	-0.0512 ***	0.0040	-12.96
PIXAR * Conduct	0.0800 ***	0.0061	13.10
LUCASFILM * Conduct	0.0204	0.0130	1.57
ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.6517 ***	0.0075	86.93
APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7204 ***	0.0036	197.54
GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.4279 ***	0.0022	195.45
INTEL * Log(Total Annual Compensation/CPI) (-1)	0.6449 ***	0.0030	217.17
INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.6682 ***	0.0086	77.99
PIXAR * Log(Total Annual Compensation/CPI) (-1)	0.6623 ***	0.0081	81.28
LUCASFILM * Log(Total Annual Compensation/CPI) (-1)	0.7861 ***	0.0701	11.21
ADOBE * Log(Total Annual Compensation/CPI) (-2)	0.3285 ***	0.0074	44.62
APPLE * Log(Total Annual Compensation/CPI) (-2)	0.2566 ***	0.0038	67.66
GOOGLE * Log(Total Annual Compensation/CPI) (-2)	0.3684 ***	0.0021	175.48
INTEL * Log(Total Annual Compensation/CPI) (-2)	0.3140 ***	0.0029	109.24
INTUIT * Log(Total Annual Compensation/CPI) (-2)	0.2870 ***	0.0083	34.76
PIXAR * Log(Total Annual Compensation/CPI) (-2)	0.1014 ***	0.0075	13.58
LUCASFILM * Log(Total Annual Compensation/CPI) (-2)	0.2148 ***	0.0707	3.04
Log(Age) (Years)	-0.2111 ***	0.0461	-4.58
Log(Age)^2	0.0187 ***	0.0063	2.99
Log(Company Tenure) (Months)	0.0011	0.0068	0.16
Log(Company Tenure)^2	0.0005	0.0008	0.73
Male	0.0067 ***	0.0008	8.24
DLog(Information Sector Employment in San-Jose)	1.5258 ***	0.0189	80.88
Log(Total Number of Transfers Among Defendants)	0.0805 ***	0.0020	40.21
Year (trend)	0.0000	0.0004	-0.08
Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0145 ***	0.0011	13.40
Log(Total Number of New Hires)	-0.2548 ***	0.0029	-88.38
Log(Firm Revenue Per Employee/CPI) (-1)	-0.0402 ***	0.0045	-8.91
DLog(Firm Revenue Per Employee/CPI) (-1)	0.1324 ***	0.0038	34.60
APPLE	0.1309 ***	0.0246	5.32
GOOGLE	1.4469 ***	0.0261	55.52
INTEL	0.1653 ***	0.0220	7.53
INTUIT	0.1840 ***	0.0315	5.83
PIXAR	1.3668 ***	0.0455	30.03
LUCASFILM	-0.0872	0.1064	-0.82
Location (State) Indicators	YES		
Constant	YES		
R-Square	<b>0.874</b>		
Observations	<b>295,136</b>		

Note: \*\*\* Significant at 1% level, \*\* Significant at 5% level, \* Significant at 10% level.

Source: Dr. Leamer's backup data and materials. Pixar revenue data after 2005 are included.

## Appendix 11C

### "Undercompensation" Estimates Using Defendant-Specific Conduct Variables in Dr. Leamer's Regression

### "Undercompensation" Estimates in Dr. Leamer's Figures 22 and 24

vs.

#### All-Salaried Employee Class

#### All-Salaried Employee Class

Year	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar
2005	0.26%	-0.69%	-4.85%	-1.52%		0.01%	11.48%
2006	0.71%	-1.90%	-12.04%	-4.06%		0.01%	13.46%
2007	1.09%	-2.97%	-17.35%	-6.23%	-6.00%	0.01%	15.21%
2008	1.49%	-4.08%	-22.63%	-8.44%	-10.30%	0.02%	16.76%
2009	1.49%	-4.13%	-19.91%	-8.28%	-10.36%	0.02%	15.16%

Year	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar
2005	-1.61%	-1.59%	-1.78%	-1.67%		-12.13%	-10.56%
2006	-4.28%	-4.43%	-4.44%	-4.70%		-14.63%	-12.44%
2007	-6.64%	-6.94%	-6.39%	-7.46%	-3.24%	-17.24%	-14.28%
2008	-9.08%	-9.56%	-8.40%	-10.05%	-5.64%	-19.94%	-15.76%
2009	-9.15%	-9.73%	-7.51%	-9.95%	-5.70%	-20.12%	-14.65%

#### Technical, Creative and R&D Class

#### Technical, Creative and R&D Class

Year	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar
2005	0.87%	-1.13%	-6.09%	-0.62%		7.02%	21.01%
2006	2.32%	-3.08%	-14.79%	-1.64%		8.71%	23.69%
2007	3.55%	-4.78%	-20.76%	-2.50%	-5.12%	10.39%	25.82%
2008	4.82%	-6.50%	-26.52%	-3.37%	-8.55%	12.08%	27.50%
2009	4.74%	-6.47%	-22.04%	-3.27%	-8.46%	12.24%	22.83%

Year	Adobe	Apple	Google	Intel	Intuit	Lucasfilm	Pixar
2005	-1.56%	-1.90%	-3.07%	-1.64%		-10.80%	-9.28%
2006	-4.29%	-4.96%	-7.23%	-3.06%		-14.77%	-10.47%
2007	-6.48%	-7.79%	-9.36%	-3.38%	-3.41%	-18.08%	-10.61%
2008	-8.80%	-10.64%	-11.20%	-4.76%	-5.21%	-20.44%	-11.87%
2009	-8.44%	-10.51%	-9.00%	-4.19%	-4.96%	-20.54%	-9.62%

Source: Leamer Figure 20 and 23 regressions excluding conduct interactions with age and hiring rate, and including company-conduct interactions. Pixar revenue data after 2005 are included.

## Appendix 12A

### Dr. Leamer's Figure 20 Regression Using Pre-Conduct Period as Benchmark

#### All-Salaried Employee Class

Dependant Variable: Log(Total Annual Compensation/CPI)

Variable	Estimate	St. Error	T-Value
Conduct * Age	0.0056 ***	0.0005	10.83
Conduct * Age^2	-0.0001 ***	0.0000	-11.78
Conduct * Log(Number of New Hires In the Firm/Number of Employees(-1))	-0.0391 ***	0.0010	-40.01
Conduct	-0.2432 ***	0.0111	-21.97
ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.7667 ***	0.0062	122.75
APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7374 ***	0.0033	223.86
GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.5619 ***	0.0023	245.29
INTEL * Log(Total Annual Compensation/CPI) (-1)	0.6743 ***	0.0026	263.51
INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.7086 ***	0.0062	114.53
PIXAR * Log(Total Annual Compensation/CPI) (-1)	0.6957 ***	0.0056	123.46
LUCASFILM * Log(Total Annual Compensation/CPI) (-1)	0.7392 ***	0.0390	18.95
ADOBE * Log(Total Annual Compensation/CPI) (-2)	0.2167 ***	0.0061	35.43
APPLE * Log(Total Annual Compensation/CPI) (-2)	0.2637 ***	0.0034	77.79
GOOGLE * Log(Total Annual Compensation/CPI) (-2)	0.3504 ***	0.0020	178.13
INTEL * Log(Total Annual Compensation/CPI) (-2)	0.2932 ***	0.0025	118.61
INTUIT * Log(Total Annual Compensation/CPI) (-2)	0.2459 ***	0.0059	41.50
PIXAR * Log(Total Annual Compensation/CPI) (-2)	0.1477 ***	0.0054	27.16
LUCASFILM * Log(Total Annual Compensation/CPI) (-2)	0.2434 ***	0.0395	6.16
Log(Age) (Years)	-0.4166 ***	0.0537	-7.75
Log(Age)^2	0.0498 ***	0.0073	6.79
Log(Company Tenure) (Months)	0.0684 ***	0.0057	12.04
Log(Company Tenure)^2	-0.0068 ***	0.0006	-10.87
Male	0.0030 ***	0.0006	4.83
DLog(Information Sector Employment in San-Jose)	1.2592 ***	0.0166	75.70
Log(Total Number of Transfers Among Defendants)	0.0789 ***	0.0018	42.98
Year (trend)	-0.0105 ***	0.0003	-29.97
Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0197 ***	0.0010	19.03
Log(Total Number of New Hires)	-0.2174 ***	0.0030	-71.92
Log(Firm Revenue Per Employee/CPI) (-1)	0.0928 ***	0.0045	20.50
DLog(Firm Revenue Per Employee/CPI) (-1)	0.1286 ***	0.0033	38.95
APPLE	-0.1111 ***	0.0194	-5.71
GOOGLE	0.6086 ***	0.0217	28.00
INTEL	0.1019 ***	0.0173	5.89
INTUIT	0.2270 ***	0.0223	10.17
PIXAR	0.9625 ***	0.0302	31.82
LUCASFILM	-0.1298 **	0.0626	-2.07
Location (State) Indicators	YES		
Constant	YES		
R-Square	<b>0.924</b>		
Observations	<b>381,288</b>		

Note: \*\*\* Significant at 1% level, \*\* Significant at 5% level, \* Significant at 10% level.

Source: Dr. Leamer's backup data and materials. Pixar revenue data after 2005 are included.

## Appendix 12B

### Dr. Leamer's Figure 23 Regression Using Pre-Conduct Period as Benchmark

#### Technical, Creative and R&D Class

Dependant Variable: Log(Total Annual Compensation/CPI)

Variable	Estimate	St. Error	T-Value
Conduct * Age	0.0061 ***	0.0008	8.05
Conduct * Age^2	-0.0001 ***	0.0000	-8.90
Conduct * Log(Number of New Hires In the Firm/Number of Employees(-1))	-0.0546 ***	0.0013	-40.90
Conduct	-0.2967 ***	0.0159	-18.61
ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.7426 ***	0.0083	89.58
APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7137 ***	0.0047	151.39
GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.4868 ***	0.0031	157.85
INTEL * Log(Total Annual Compensation/CPI) (-1)	0.6285 ***	0.0032	195.11
INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.6641 ***	0.0093	71.55
PIXAR * Log(Total Annual Compensation/CPI) (-1)	0.6794 ***	0.0084	81.00
LUCASFILM * Log(Total Annual Compensation/CPI) (-1)	0.6826 ***	0.0827	8.25
ADOBE * Log(Total Annual Compensation/CPI) (-2)	0.2307 ***	0.0081	28.45
APPLE * Log(Total Annual Compensation/CPI) (-2)	0.2675 ***	0.0049	54.82
GOOGLE * Log(Total Annual Compensation/CPI) (-2)	0.3341 ***	0.0026	129.27
INTEL * Log(Total Annual Compensation/CPI) (-2)	0.3232 ***	0.0031	104.05
INTUIT * Log(Total Annual Compensation/CPI) (-2)	0.2842 ***	0.0088	32.11
PIXAR * Log(Total Annual Compensation/CPI) (-2)	0.0644 ***	0.0078	8.27
LUCASFILM * Log(Total Annual Compensation/CPI) (-2)	0.2566 ***	0.0822	3.12
Log(Age) (Years)	-0.5769 ***	0.0798	-7.23
Log(Age)^2	0.0720 ***	0.0109	6.59
Log(Company Tenure) (Months)	0.0994 ***	0.0079	12.64
Log(Company Tenure)^2	-0.0093 ***	0.0009	-10.65
Male	0.0065 ***	0.0009	6.89
DLog(Information Sector Employment in San-Jose)	1.1685 ***	0.0234	49.89
Log(Total Number of Transfers Among Defendants)	0.0782 ***	0.0025	30.91
Year (trend)	-0.0042 ***	0.0005	-8.83
Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0239 ***	0.0014	16.49
Log(Total Number of New Hires)	-0.2084 ***	0.0043	-48.83
Log(Firm Revenue Per Employee/CPI) (-1)	0.1131 ***	0.0062	18.39
DLog(Firm Revenue Per Employee/CPI) (-1)	0.1164 ***	0.0044	26.21
APPLE	-0.0573 **	0.0292	-1.96
GOOGLE	1.1501 ***	0.0330	34.87
INTEL	0.1375 ***	0.0256	5.38
INTUIT	0.2064 ***	0.0364	5.67
PIXAR	1.5840 ***	0.0521	30.41
LUCASFILM	0.0853	0.1652	0.52
Location (State) Indicators	YES		
Constant	YES		
R-Square	<b>0.866</b>		
Observations	<b>216,253</b>		

Note: \*\*\* Significant at 1% level, \*\* Significant at 5% level, \* Significant at 10% level.

Source: Dr. Leamer's backup data and materials. Pixar revenue data after 2005 are included.

## Appendix 12C

### Dr. Leamer's Figure 20 Regression Using Post-Conduct Period as Benchmark

#### All-Salaried Employee Class

**Dependant Variable:** Log(Total Annual Compensation/CPI)

Variable	Estimate	St. Error	T-Value
Conduct * Age	0.0078 ***	0.0006	13.85
Conduct * Age^2	-0.0001 ***	0.0000	-13.31
Conduct * Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0114 ***	0.0009	12.67
Conduct	-0.0973 ***	0.0121	-8.06
ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.7630 ***	0.0069	110.30
APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7349 ***	0.0029	250.23
GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.5002 ***	0.0018	277.95
INTEL * Log(Total Annual Compensation/CPI) (-1)	0.6763 ***	0.0034	200.70
INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.8207 ***	0.0103	79.39
PIXAR * Log(Total Annual Compensation/CPI) (-1)	0.7036 ***	0.0058	122.35
LUCASFILM * Log(Total Annual Compensation/CPI) (-1)	0.8750 ***	0.0378	23.12
ADOBE * Log(Total Annual Compensation/CPI) (-2)	0.2528 ***	0.0070	36.11
APPLE * Log(Total Annual Compensation/CPI) (-2)	0.2602 ***	0.0031	85.08
GOOGLE * Log(Total Annual Compensation/CPI) (-2)	0.3684 ***	0.0017	213.20
INTEL * Log(Total Annual Compensation/CPI) (-2)	0.3235 ***	0.0034	95.84
INTUIT * Log(Total Annual Compensation/CPI) (-2)	0.1548 ***	0.0104	14.95
PIXAR * Log(Total Annual Compensation/CPI) (-2)	0.1769 ***	0.0055	32.24
LUCASFILM * Log(Total Annual Compensation/CPI) (-2)	0.1143 ***	0.0382	2.99
Log(Age) (Years)	-0.6760 ***	0.0560	-12.08
Log(Age)^2	0.0797 ***	0.0076	10.55
Log(Company Tenure) (Months)	-0.0254 ***	0.0058	-4.39
Log(Company Tenure)^2	0.0020 ***	0.0006	3.21
Male	0.0021 ***	0.0006	3.34
DLog(Information Sector Employment in San-Jose)	-0.8493 ***	0.0541	-15.70
Log(Total Number of Transfers Among Defendants)	0.0287 ***	0.0019	15.14
Year (trend)	0.0113 ***	0.0005	23.30
Log(Number of New Hires In the Firm/Number of Employees(-1))	-0.0325 ***	0.0012	-26.15
Log(Total Number of New Hires)	0.0683 ***	0.0059	11.64
Log(Firm Revenue Per Employee/CPI) (-1)	-0.0268 ***	0.0040	-6.61
DLog(Firm Revenue Per Employee/CPI) (-1)	0.1248 ***	0.0032	39.43
APPLE	0.2203 ***	0.0187	11.80
GOOGLE	1.1437 ***	0.0196	58.31
INTEL	0.0757 ***	0.0169	4.47
INTUIT	0.2278 ***	0.0247	9.23
PIXAR	0.8522 ***	0.0283	30.13
LUCASFILM	0.1705 ***	0.0507	3.36
Location (State) Indicators	YES		
Constant	YES		
R-Square	<b>0.922</b>		
Observations	<b>399,299</b>		

Note: \*\*\* Significant at 1% level, \*\* Significant at 5% level, \* Significant at 10% level.

Source: Dr. Leamer's backup data and materials. Pixar revenue data after 2005 are included.



## Appendix 12D

### Dr. Leamer's Figure 23 Regression Using Post-Conduct Period as Benchmark

#### Technical, Creative and R&D Class

Dependant Variable: Log(Total Annual Compensation/CPI)

Variable	Estimate	St. Error	T-Value
Conduct * Age	0.0096 ***	0.0008	12.31
Conduct * Age^2	-0.0001 ***	0.0000	-11.96
Conduct * Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0008	0.0012	0.70
Conduct	-0.1544 ***	0.0165	-9.37
ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.7523 ***	0.0092	81.89
APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7161 ***	0.0039	181.32
GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.4438 ***	0.0023	193.37
INTEL * Log(Total Annual Compensation/CPI) (-1)	0.6464 ***	0.0041	156.05
INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.7732 ***	0.0151	51.22
PIXAR * Log(Total Annual Compensation/CPI) (-1)	0.7071 ***	0.0085	83.39
LUCASFILM * Log(Total Annual Compensation/CPI) (-1)	0.9511 ***	0.0719	13.24
ADOBE * Log(Total Annual Compensation/CPI) (-2)	0.2530 ***	0.0094	26.98
APPLE * Log(Total Annual Compensation/CPI) (-2)	0.2581 ***	0.0041	62.57
GOOGLE * Log(Total Annual Compensation/CPI) (-2)	0.3655 ***	0.0022	165.61
INTEL * Log(Total Annual Compensation/CPI) (-2)	0.3478 ***	0.0041	84.01
INTUIT * Log(Total Annual Compensation/CPI) (-2)	0.1837 ***	0.0151	12.18
PIXAR * Log(Total Annual Compensation/CPI) (-2)	0.1052 ***	0.0078	13.57
LUCASFILM * Log(Total Annual Compensation/CPI) (-2)	0.0413	0.0720	0.57
Log(Age) (Years)	-0.9447 ***	0.0755	-12.51
Log(Age)^2	0.1145 ***	0.0102	11.21
Log(Company Tenure) (Months)	-0.0094	0.0078	-1.21
Log(Company Tenure)^2	0.0008	0.0009	0.98
Male	0.0065 ***	0.0009	6.91
DLog(Information Sector Employment in San-Jose)	-0.9430 ***	0.0718	-13.14
Log(Total Number of Transfers Among Defendants)	0.0088 ***	0.0026	3.41
Year (trend)	0.0148 ***	0.0006	22.84
Log(Number of New Hires In the Firm/Number of Employees(-1))	-0.0367 ***	0.0017	-21.93
Log(Total Number of New Hires)	0.0834 ***	0.0078	10.64
Log(Firm Revenue Per Employee/CPI) (-1)	-0.0112 **	0.0054	-2.05
DLog(Firm Revenue Per Employee/CPI) (-1)	0.1110 ***	0.0042	26.40
APPLE	0.2949 ***	0.0283	10.42
GOOGLE	1.4735 ***	0.0292	50.43
INTEL	0.0390	0.0255	1.53
INTUIT	0.2932 ***	0.0406	7.21
PIXAR	1.2492 ***	0.0487	25.67
LUCASFILM	0.0692	0.1083	0.64
Location (State) Indicators	YES		
Constant	YES		
R-Square	<b>0.869</b>		
Observations	<b>236,748</b>		

Note: \*\*\* Significant at 1% level, \*\* Significant at 5% level, \* Significant at 10% level.

Source: Dr. Leamer's backup data and materials. Pixar revenue data after 2005 are included.

## Appendix 13A

### Dr. Leamer's Figure 20 Regression Estimated Using Non-Conduct Period Data

#### All-Salaried Employee Class

**Dependant Variable:** Log(Total Annual Compensation/CPI)

Variable	Estimate	St. Error	T-Value
ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.6108 ***	0.0072	84.47
APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7408 ***	0.0036	205.55
GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.4578 ***	0.0026	175.14
INTEL * Log(Total Annual Compensation/CPI) (-1)	0.6685 ***	0.0034	196.94
INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.7266 ***	0.0063	115.16
PIXAR * Log(Total Annual Compensation/CPI) (-1)	0.8377 ***	0.0219	38.18
LUCASFILM * Log(Total Annual Compensation/CPI) (-1)	0.9990 ***	0.0845	11.82
ADOBE * Log(Total Annual Compensation/CPI) (-2)	0.3441 ***	0.0067	51.72
APPLE * Log(Total Annual Compensation/CPI) (-2)	0.2708 ***	0.0036	74.65
GOOGLE * Log(Total Annual Compensation/CPI) (-2)	0.3957 ***	0.0028	141.55
INTEL * Log(Total Annual Compensation/CPI) (-2)	0.2620 ***	0.0032	81.66
INTUIT * Log(Total Annual Compensation/CPI) (-2)	0.2413 ***	0.0060	40.26
PIXAR * Log(Total Annual Compensation/CPI) (-2)	0.1329 ***	0.0201	6.60
LUCASFILM * Log(Total Annual Compensation/CPI) (-2)	0.0161	0.0856	0.19
Log(Age) (Years)	0.0292	0.0436	0.67
Log(Age)^2	-0.0122 **	0.0059	-2.07
Log(Company Tenure) (Months)	-0.0613 ***	0.0071	-8.59
Log(Company Tenure)^2	0.0064 ***	0.0008	8.21
Male	0.0041 ***	0.0007	5.58
DLog(Information Sector Employment in San-Jose)	1.3739 ***	0.0252	54.58
Log(Total Number of Transfers Among Defendants)	0.0610 ***	0.0027	22.79
Year (trend)	0.0028 ***	0.0007	3.93
Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0365 ***	0.0013	27.33
Log(Total Number of New Hires)	-0.2303 ***	0.0053	-43.47
Log(Firm Revenue Per Employee/CPI) (-1)	-0.0961 ***	0.0048	-19.94
DLog(Firm Revenue Per Employee/CPI) (-1)	0.0715 ***	0.0062	11.50
APPLE	-0.2454 ***	0.0216	-11.37
GOOGLE	0.8453 ***	0.0233	36.31
INTEL	0.1981 ***	0.0195	10.18
INTUIT	-0.0736 ***	0.0242	-3.04
PIXAR	-0.0559	0.0473	-1.18
LUCASFILM	-0.2748 ***	0.0708	-3.88
Location (State) Indicators	YES		
Constant	YES		
R-Square	<b>0.937</b>		
Observations	<b>237,351</b>		

Note: \*\*\* Significant at 1% level, \*\* Significant at 5% level, \* Significant at 10% level.

Source: Dr. Leamer's backup data and materials. Pixar revenue data after 2005 are included.

## Appendix 13B

### Dr. Leamer's Figure 23 Regression Estimated Using Non-Conduct Period Data

#### Technical, Creative and R&D Class

**Dependant Variable:** Log(Total Annual Compensation/CPI)

Variable	Estimate	St. Error	T-Value
ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.5929 ***	0.0100	59.23
APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7428 ***	0.0049	151.07
GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.4205 ***	0.0033	129.36
INTEL * Log(Total Annual Compensation/CPI) (-1)	0.6526 ***	0.0043	153.41
INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.7101 ***	0.0092	76.79
PIXAR * Log(Total Annual Compensation/CPI) (-1)	0.9381 ***	0.0359	26.12
LUCASFILM * Log(Total Annual Compensation/CPI) (-1)	0.9713 ***	0.1224	7.94
ADOBE * Log(Total Annual Compensation/CPI) (-2)	0.3475 ***	0.0092	37.69
APPLE * Log(Total Annual Compensation/CPI) (-2)	0.2392 ***	0.0050	48.28
GOOGLE * Log(Total Annual Compensation/CPI) (-2)	0.3895 ***	0.0036	108.96
INTEL * Log(Total Annual Compensation/CPI) (-2)	0.2660 ***	0.0040	66.55
INTUIT * Log(Total Annual Compensation/CPI) (-2)	0.2593 ***	0.0087	29.69
PIXAR * Log(Total Annual Compensation/CPI) (-2)	0.0343	0.0307	1.12
LUCASFILM * Log(Total Annual Compensation/CPI) (-2)	0.0629	0.1247	0.50
Log(Age) (Years)	-0.2740 ***	0.0614	-4.46
Log(Age)^2	0.0282 ***	0.0083	3.38
Log(Company Tenure) (Months)	-0.0758 ***	0.0096	-7.89
Log(Company Tenure)^2	0.0086 ***	0.0011	8.09
Male	0.0071 ***	0.0011	6.43
DLog(Information Sector Employment in San-Jose)	1.3635 ***	0.0362	37.70
Log(Total Number of Transfers Among Defendants)	0.0650 ***	0.0038	17.33
Year (trend)	0.0034 ***	0.0011	3.16
Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0495 ***	0.0018	26.92
Log(Total Number of New Hires)	-0.2480 ***	0.0078	-31.98
Log(Firm Revenue Per Employee/CPI) (-1)	-0.0458 ***	0.0067	-6.82
DLog(Firm Revenue Per Employee/CPI) (-1)	0.0388 ***	0.0086	4.51
APPLE	-0.1750 ***	0.0326	-5.37
GOOGLE	0.9977 ***	0.0343	29.13
INTEL	0.2041 ***	0.0293	6.96
INTUIT	-0.1603 ***	0.0388	-4.13
PIXAR	-0.1585 *	0.0893	-1.77
LUCASFILM	-0.5484 ***	0.1265	-4.34
Location (State) Indicators	YES		
Constant	YES		
R-Square	<b>0.895</b>		
Observations	<b>137,271</b>		

Note: \*\*\* Significant at 1% level, \*\* Significant at 5% level, \* Significant at 10% level.

Source: Dr. Leamer's backup data and materials. Pixar revenue data after 2005 are included.

## Appendix 14A

### Dr. Leamer's Figure 20 Regression Including Change in S&P 500

#### All-Salaried Employee Class

**Dependant Variable:** Log(Total Annual Compensation/CPI)

Variable	Estimate	St. Error	T-Value
Conduct * Age	0.0066 ***	0.0005	13.98
Conduct * Age^2	-0.0001 ***	0.0000	-13.83
Conduct * Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0043 ***	0.0008	5.54
Conduct	-0.1309 ***	0.0100	-13.04
ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.6894 ***	0.0054	126.98
APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7449 ***	0.0027	280.12
GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.4988 ***	0.0017	293.05
INTEL * Log(Total Annual Compensation/CPI) (-1)	0.6678 ***	0.0024	282.12
INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.7070 ***	0.0058	122.77
PIXAR * Log(Total Annual Compensation/CPI) (-1)	0.6943 ***	0.0069	100.22
LUCASFILM * Log(Total Annual Compensation/CPI) (-1)	0.8204 ***	0.0363	22.62
ADOBE * Log(Total Annual Compensation/CPI) (-2)	0.3023 ***	0.0053	57.04
APPLE * Log(Total Annual Compensation/CPI) (-2)	0.2581 ***	0.0027	94.33
GOOGLE * Log(Total Annual Compensation/CPI) (-2)	0.3694 ***	0.0016	225.49
INTEL * Log(Total Annual Compensation/CPI) (-2)	0.3012 ***	0.0023	130.80
INTUIT * Log(Total Annual Compensation/CPI) (-2)	0.2567 ***	0.0056	46.04
PIXAR * Log(Total Annual Compensation/CPI) (-2)	0.1985 ***	0.0067	29.56
LUCASFILM * Log(Total Annual Compensation/CPI) (-2)	0.1737 ***	0.0366	4.74
Log(Age) (Years)	-0.3495 ***	0.0415	-8.42
Log(Age)^2	0.0380 ***	0.0056	6.74
Log(Company Tenure) (Months)	0.0039	0.0050	0.78
Log(Company Tenure)^2	-0.0005	0.0006	-0.92
Male	0.0027 ***	0.0005	4.93
DLog(Information Sector Employment in San-Jose)	1.5373 ***	0.0151	101.59
Log(Total Number of Transfers Among Defendants)	0.0566 ***	0.0020	27.69
DLog(S&P 500 Net Total Return Index/CPI)	0.0656 ***	0.0023	28.72
Year (trend)	0.0026 ***	0.0003	7.45
Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0135 ***	0.0009	14.55
Log(Total Number of New Hires)	-0.2182 ***	0.0024	-92.01
Log(Firm Revenue Per Employee/CPI) (-1)	-0.1319 ***	0.0037	-36.14
DLog(Firm Revenue Per Employee/CPI) (-1)	0.2371 ***	0.0033	70.97
APPLE	0.0747 ***	0.0162	4.62
GOOGLE	1.0592 ***	0.0174	60.95
INTEL	0.1542 ***	0.0146	10.59
INTUIT	0.1485 ***	0.0193	7.71
PIXAR	0.7001 ***	0.0422	16.60
LUCASFILM	0.1483 ***	0.0480	3.09
Location (State) Indicators	YES		
Constant	YES		
R-Square	<b>0.926</b>		
Observations	<b>504,897</b>		

Note: \*\*\* Significant at 1% level, \*\* Significant at 5% level, \* Significant at 10% level.

Source: Dr. Leamer's backup data and materials.

## Appendix 14B

### Dr. Leamer's Figure 23 Regression Including Change in S&P 500

#### Technical, Creative and R&D Class

**Dependant Variable:** Log(Total Annual Compensation/CPI)

Variable	Estimate	St. Error	T-Value
Conduct * Age	0.0077 ***	0.0007	11.44
Conduct * Age^2	-0.0001 ***	0.0000	-11.18
Conduct * Log(Number of New Hires In the Firm/Number of Employees(-1))	-0.0099 ***	0.0010	-9.44
Conduct	-0.1717 ***	0.0141	-12.16
ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.6662 ***	0.0073	91.42
APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7299 ***	0.0037	199.33
GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.4425 ***	0.0022	202.73
INTEL * Log(Total Annual Compensation/CPI) (-1)	0.6405 ***	0.0030	215.77
INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.6672 ***	0.0085	78.91
PIXAR * Log(Total Annual Compensation/CPI) (-1)	0.6508 ***	0.0106	61.63
LUCASFILM * Log(Total Annual Compensation/CPI) (-1)	0.8548 ***	0.0691	12.37
ADOBE * Log(Total Annual Compensation/CPI) (-2)	0.3141 ***	0.0071	44.00
APPLE * Log(Total Annual Compensation/CPI) (-2)	0.2505 ***	0.0038	66.22
GOOGLE * Log(Total Annual Compensation/CPI) (-2)	0.3607 ***	0.0021	171.44
INTEL * Log(Total Annual Compensation/CPI) (-2)	0.3177 ***	0.0029	110.53
INTUIT * Log(Total Annual Compensation/CPI) (-2)	0.2888 ***	0.0082	35.32
PIXAR * Log(Total Annual Compensation/CPI) (-2)	0.1053 ***	0.0097	10.90
LUCASFILM * Log(Total Annual Compensation/CPI) (-2)	0.1398 **	0.0692	2.02
Log(Age) (Years)	-0.5757 ***	0.0587	-9.80
Log(Age)^2	0.0676 ***	0.0080	8.46
Log(Company Tenure) (Months)	0.0204 ***	0.0068	3.00
Log(Company Tenure)^2	-0.0016 **	0.0008	-2.14
Male	0.0064 ***	0.0008	7.86
DLog(Information Sector Employment in San-Jose)	1.5716 ***	0.0209	75.07
Log(Total Number of Transfers Among Defendants)	0.0443 ***	0.0028	16.05
DLog(S&P 500 Net Total Return Index/CPI)	0.0881 ***	0.0031	28.55
Year (trend)	0.0078 ***	0.0005	16.67
Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0213 ***	0.0013	16.62
Log(Total Number of New Hires)	-0.2308 ***	0.0033	-70.79
Log(Firm Revenue Per Employee/CPI) (-1)	-0.1028 ***	0.0051	-20.31
DLog(Firm Revenue Per Employee/CPI) (-1)	0.2359 ***	0.0045	52.12
APPLE	0.1328 ***	0.0244	5.44
GOOGLE	1.4013 ***	0.0259	54.09
INTEL	0.1574 ***	0.0218	7.20
INTUIT	0.1378 ***	0.0315	4.38
PIXAR	1.5355 ***	0.0770	19.94
LUCASFILM	0.0399	0.1036	0.38
Location (State) Indicators	YES		
Constant	YES		
R-Square	<b>0.875</b>		
Observations	<b>292,489</b>		

Note: \*\*\* Significant at 1% level, \*\* Significant at 5% level, \* Significant at 10% level.

Source: Dr. Leamer's backup data and materials.

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**IN THE UNITED STATES DISTRICT COURT  
FOR THE NORTHERN DISTRICT OF CALIFORNIA  
SAN JOSE DIVISION**

**CONFIDENTIAL – TO BE FILED UNDER SEAL  
SUBJECT TO PROTECTIVE ORDER**

**IN RE: HIGH-TECH EMPLOYEES ANTITRUST  
LITIGATION**

**No. 11-CV-2509-LHK**

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**THIS DOCUMENT RELATES TO:**

**ALL ACTIONS**

**SUPPLEMENTAL EXPERT REPORT OF EDWARD E. LEAMER, PH.D.**

**May 10, 2013**

[REDACTED]

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## I. Introduction, Assignment, and Summary of Conclusions

1. I have been asked by counsel for Class Plaintiffs in this matter to respond to the following questions regarding my prior analysis and further analysis that can be conducted based on the available data in this case. I have been asked to focus my response on the employees belonging to the proposed Technical, Creative and R&D Class (“Technical Class”) identified in my initial report.
2. **Question #1:** Does the total compensation of Technical Class employees in specific job titles move together over time, further confirming the existence of a somewhat rigid pay structure at each Defendant?
3. **Answer:** When asked in the deposition (p283) “Could a nonrigid wage structure, as you’ve defined it, lead to parallel lines?” I responded to what I thought to be a hypothetical with “Yes, it could.” I should have added that this would require highly unusual external labor market conditions which dictated the parallel movements of vast numbers of titles. Markets typically are not so orderly, and prices of, for example, gold, silver, copper and zinc do not normally move in parallel. For that reason, I regard the parallel movements of compensation for so many titles not only to be consistent with a “somewhat rigid wage structure” but also evidence specifically in favor of the hypothesis that internal equity played an important role in determining compensation in all these firms. In this report, I confirm this opinion with two additional empirical studies. I have estimated regression models that allow me to separate the contributions of internal and external forces, and found that the internal forces are evident but the external forces are not. I have also compared average compensation for the Technical Class of titles and the non-technical employees for all the defendants. I found that the compensation curves of these two groups within each firm are highly parallel while the compensation curves for the same group from two different firms move in a much more disparate way. This again is saying that the internal forces are evident but the external forces are more difficult to detect.
4. In this Report, I present correlations that compare the movement *over time* of the average compensation of each title with the average compensation of the firm’s Technical Class. To accommodate titles that cannot be accessed on a title-by-

title basis due to insufficient data (approximately 63 percent of Technical Class titles, but representing just 6 percent of Class Period employee-years), I also analyzed correlations of relatively narrow groups of employees (each comprising approximately a tenth of the Technical Class employees of that firm). These correlations are computed for *all* titles, not just 20. They reveal that there is large amount of co-movement of compensation among most of the Technical Class titles of each defendant. These correlations are consistent with a top-down budgeting method in which all members of the firm in any given year receive a common compensation increment, which is adjusted somewhat by title and possibly by individual within the title depending on specific circumstances. The evident, substantial, common, firm-wide component of compensation is what creates what I previously called a “somewhat rigid” salary structure, which allows the effects of the anti-cold-calling conspiracy to spread broadly across each firm.

5. **Question #2:** Do the data show additional evidence that internal factors such as internal equity partly drove the Defendants’ compensation structures, as opposed to only external market forces?
6. **Answer:** I have analyzed a model of sharing of compensation effects, title by title, within Defendant firms relative to movements of other Technical Class employees compensation. Again, to accommodate titles that cannot be accessed title-by-title (approximately 70 percent of Technical Class titles, but representing just 8.4 percent of Class Period employee-years), I also analyzed the compensation of relatively narrow groups of employees against the compensation of the overall Technical Class employees.
7. Specifically, I report below estimated multiple regression models that explain the year-by-year increases in average compensation at the title level in terms of four explanatory variables: (1) increases in average Technical Class compensation; (2) the previous year’s ratio of average Technical Class compensation divided by the average title compensation; (3) the previous year’s ratio of firm-wide average revenue divided by the average title compensation; (4) the percent change in software jobs in the San Jose-Sunnyvale-Santa Clara Metropolitan Statistical Area (hereafter: San Jose MSA).

8. I find that the vast majority of individuals fall within titles or groups that show 1) positive contemporaneous sharing of compensation effects, and 2) sharing across time that would spread gains in compensation across other job titles. This is consistent with my previous opinion that all or almost all Defendants' employees would have been impacted by the non-compete agreements. Furthermore, the sharing of gains over time strongly indicates the existence of an internal sharing force driving the structure of class member compensation, rather than only external market forces.
9. **Question #3:** Do the data show the existence of large groups of class members who necessarily would not have been harmed by a restriction on cold-calling?
10. **Answer:** No. I have performed the above-mentioned statistical analyses separately for distinct subgroups of employees grouped by compensation level. I do not find persuasive evidence to suggest that there are sizeable groups whose compensation might have been disconnected from Defendants' somewhat rigid compensation structure. The correlation and regression analysis I performed in this regard show ripple and spillover effects across employees in very different roles. The analysis shows that when each title or group is studied separately, on a case-by-case basis, it is found that, compensation almost always moves with the collection of other titles or groups. All these groups, no matter how much they differ in the job titles they contain, are found to be tied closely together.
11. **Question # 4:** Is it possible to identify and exclude from the Technical Class job titles based on a lack of these positive correlative relationships?
12. **Answer:** No. Although the vast majority of titles exhibit strong positive correlations with the overall Technical Class, there certainly are exceptions. One might consider titles with negative correlations with the overall Technical Class to be candidates for exclusion from the class. However, this is not justified statistically because statistical variability can cause some negative correlation estimates among the thousands of titles even if all the true correlations are positive. An appropriate statistical model for this kind of data allows some pooling of evidence across titles, and when this is done the analysis indicates that corrected estimated of many of these negatives is positive. In other words,

it matters for interpreting the evidence about each title that the vast majority of estimated correlations are positive.

13. In sum, the statistical analysis I conduct here--in conjunction with the economic and econometric evidence in my original reports--supports my original finding of a somewhat rigid pay structure at each Defendant that would have transmitted the effects of the agreements broadly, including throughout the Technical Class.

## **II. Defendants' Use of Compensation Structures**

14. Most, if not all, of these defendants subscribe to services that are intended to provide them information about "market" prices for various jobs. Such information helps them keep compensation packages in line with the external opportunities, with or without the imminent threat of loss of an employee. However, these external sources provide broad industry averages with limited relevance and reliability. Regardless of what these services suggest, their information cannot compare with the information conveyed by an actual outside offer. That can ring off a loud alarm that is heard all the way up to the CEO.
15. The information by an outside offer or even a cold call can stimulate a response by management that can go much beyond the specific individual directly affected. A chain of similarities can transmit a bump in compensation for a single individual broadly across a firm for two reasons. First, when management becomes aware of an attractive outside opportunity for one individual this may make management aware also of the implicit competitive threat to similar individuals and management may feel it wise to make a preemptive move against that threat by an increase in compensation for these newly-threatened similar employees. Though the "market" does not require a bump in compensation for these similar individuals until they actually receive an outside offer, preemptive action can minimize the disruption to employee loyalty that might occur when an employee discovers that he or she had been "unfairly" undercompensated. A broad preemptive response is completely analogous to salary increases that are tied to information provided by

employment services regarding the compensation offered by the “market.” These responses are broad and not necessarily individual-based.

16. Similarity in worth is one reason why salaries can be tied together. Fairness is the second reason why a bump in compensation for a single individual can be transmitted broadly across a firm. A critical problem with “market-based” individual compensation is that the productivity of each worker in most salaried jobs is difficult to determine with accuracy, yet the range of achieved productivity can be broad. Firms need to use HR policies that encourage high levels of productivity. The highest levels of productivity come from contented employees who are committed to the mission of the enterprise. In order to maintain or to increase the contentment and commitment, it is essential for management to treat employees “fairly.” As discussed in the paragraph above, a strictly market view of employee compensation doesn’t require an increase in salary of any individual until an outside threat actually materializes, but the force of “fairness” can necessitate preemptive increases in compensation. In addition, employees are likely to have their own views of job and performance similarity, and these employees can have their productivity adversely affected if they perceive that some employees are receiving “unfairly” high compensation compared with them.
17. Fairness is a matter of personal opinion and there is no sure way to know exactly who feels equivalent to the employee who got that bump in compensation and who doesn’t really care. The title and grade structure of compensation may reflect management’s views of what is fair and it may influence the perception of similarity that determines employee fairness beliefs. This is the reason why companies tend to follow guidelines laid out in terms of salary ranges, so employees can be assured that their compensation falls within reasonable range of their colleagues.

### III. Empirical Methodologies for Exploring the Somewhat Rigid Salary Structure

#### A. Choice of Aggregation Level

18. The data set I explore is composed of compensation records of salaried individuals on the payrolls of the Defendants. These individuals are grouped by the Defendants by title and (for some of the Defendants) the titles are grouped by grade. Based on instructions from counsel regarding the employees in the Class, except for Lucasfilm I limit the inquiry to the titles that have been identified as Technical Class titles.<sup>1</sup>
19. These data could be studied at the individual level, at the title level or some more aggregated groups. I have chosen to work first with the title averages, because the individual data is likely to be dominated by forces that operate at the individual level, which can make it difficult to detect the firm wide effects including the spread of the anti-cold-calling agreements broadly across the firms. Averaging across individuals in a title can average out the individual effects, thus making the firm-wide effects more transparent. In addition, a title-level analysis provides a clearer perspective on the compensation structures the documentary evidence shows Defendants used to manage their many employees and maintain internal equity among their employees.
20. I have discovered that the title-by-title analysis works well for many titles but there are some titles that were used only briefly, and there are other titles that are sparsely populated and that seem much influenced by the idiosyncratic individual behavior which still masks the firm-wide effect that I am seeking to estimate. The data set contains only eleven annual observations which is adequate for the statistical work, but not plentiful. Titles that have fewer annual observations tend to produce what statisticians call “statistically insignificant” results, meaning the data sets are too small to yield accurate estimates. This is particularly troublesome for Apple which had a title restructuring in 2005 and

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<sup>1</sup> Because Lucasfilm did not provide title data prior to 2006, there are insufficient years of data unless the inquiry is expanded to cover all Lucasfilm employees. Hence, the analysis presented below is limited to Technical Class for all Defendants, except Lucasfilm, for whom it applies to all employees.

for Lucasfilm which did not provide titles prior to 2006. In addition titles that include just a few individuals may not benefit much from the averaging across individuals and furthermore, unlike the individual data, the title compensation for sparsely populated titles can vary wildly as individuals come and go. I give some examples below of Adobe titles with highly variable headcounts and highly variable median ages.

21. To deal with the limitations of the title-by-title data, I also include the same type of statistical work but applied to ten groups of titles in each firm. I have formed the ten groups of titles by ordering the titles by average base compensation and then splitting the titles into ten deciles (based on the number of employee-years).<sup>2</sup>

### **B. Correlation Analysis of Compensation Structure**

22. Economists often look to correlation coefficients to measure statistically how closely different variables move together. Correlation coefficients range in absolute value from 0 to 1. One indicates perfect correlation, zero indicates no relationship. The sign on the correlation indicates whether or not the series in question move in the same direction. I begin my analysis of Defendant compensation structures with compensation correlations.
23. There are two types of correlations relevant for determining if the compensation movements of two series are similar: correlation of compensation levels and correlations of compensation *changes*. The correlations of the log of the levels of compensation emphasize longer run movements and the correlations of the change in the log of the levels focus on year-by-year movements.

### **C. Regression Analysis of Compensation Structure**

24. Correlation of title compensation and class compensation could come from sharing effects but could also come from third variables that operate on both

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<sup>2</sup> For several Defendants, certain large titles made splits into ten groups impractical. In those cases a smaller number of groups was used.

title and class compensation at the same time, for example, “market forces.” To confirm the existence of a somewhat rigid compensation structure revealed by my correlation analysis, I examine (company by company) a multiple regression model which forces the class compensation to compete with other variables as an explanation of title compensation.

25. This regression model explains increases in title average real (inflation adjusted) total compensation and includes the increase in class average real total compensation as one of four explanatory variables.<sup>3</sup> By including the increase in class compensation in the equation, the regression encompasses the correlation analysis of these two variables. In the multiple regression setting, this variable allows us to determine at a particular defendant the extent to which title and class compensation move together, *after controlling for the other variables in the equation*, in particular, after controlling for “market forces.” If the coefficient of this variable were equal to one, then the employee would inherit 100 percent of the class compensation changes and in that sense the two would be closely tied together. This is the first sharing effect.
26. The regression model includes a second sharing variable, which is the ratio of class compensation to title compensation in the previous year. While the first sharing effect measures the extent to which the two compensation levels move together, the second measures the extent to which corrective action is taken at the company when they move apart. If the coefficient is positive on this variable it means that following periods in which the class average compensation at the company is abnormally high compared with the title, the title tends to get a special increase in compensation to bring it back in line with the class
27. The regression model requires both of these sharing variables to compete against two other determinants of title compensation at the company. One of these other variables is the previous year’s ratio of firm-wide average revenue divided by the average title compensation. This variable allows us to determine

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<sup>3</sup> For each title regression I exclude from the class average real total compensation, the compensation of the title itself.



which titles, if any, share increases in firm revenue overall. It might be expected that critical technical and creative workers are the ones who would have revenue sharing relationships with their firms since they may have an accentuated effect on the firm's success.

28. The fourth variable is the percent growth in software jobs in the San Jose- MSA. This the external job market variable which is intended to reflect how hot or cold was the technical job market generally, not just in the San Jose MSA.
29. I illustrate this regression in Figure 1, as estimated for one Intel title.<sup>4</sup> In this example, the two coefficients for the two sharing variables are positive, meaning that workers with this title can expect to receive a compensation increase if 1) there are general increases in the compensation of other Technical Class titles at the firm, and 2) a title that received a relatively small percent increase relative to other Technical Class titles at the company last year will tend to receive a larger increase in subsequent years. This indicates a positive sharing and internal equity effect. Both the contemporaneous and lagged coefficients suggest that internal equity forces move in a fashion that helps align worker's compensation together with that of employees in other roles at the firm.

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<sup>4</sup> As mentioned before this regression is estimated separately for each title and company. Titles that do not afford a sufficient number of observations (6 observations, or 7 consecutive years) are treated as 'Not Estimated' and are excluded from the coefficient distribution calculations presented in this report.

**Figure 1****Illustrative Example of Compensation Sharing Regression Model  
Intel Named Plaintiff Title SOFTWARE\_ENGINEER\_7**

Variable	Coefficient	Std.-Error	T-value	P-value
(1)	(2)	(3)	(4)	(5)
<i>Dependant Variable</i>				
DLog(Title Average Annual Total Compensation)				
<i>Contemporaneous Effect Variable</i>				
DLog(R&D Average Annual Total Compensation)	0.784 ***	0.064	12.238	0.000
<i>Lagged Effect Variable</i>				
Log( R&D Avg Annual Total Comp (-1) / ( Title Avg Annual Total Compensation (-1)	0.251 *	0.098	2.562	0.051
<i>External Forces Variables</i>				
Log( Firm Revenue Per Employee (-1) / ( Title Avg Annual Total Compensation (-1)	-0.032	0.094	-0.346	0.743
DLog( San-Jose Information Sector Employment)	0.092	0.126	0.731	0.498
Constant	-0.223	0.541	-0.411	0.698
Observations	10			
R-squared	0.986			

Note: (1) \*\*\* Significant at 1% level; \*\* Significant at 5% level; \* Significant at 10% level.

(2) Title Average Compensation is computed as the average of title employee's annual total compensation.

R&D Avg Total Comp is computed over all Technical, Creative and R&D employees other than the title itself

(3) All Compensation Variables are Inflation Adjusted

Source: Defendants' employee compensation data

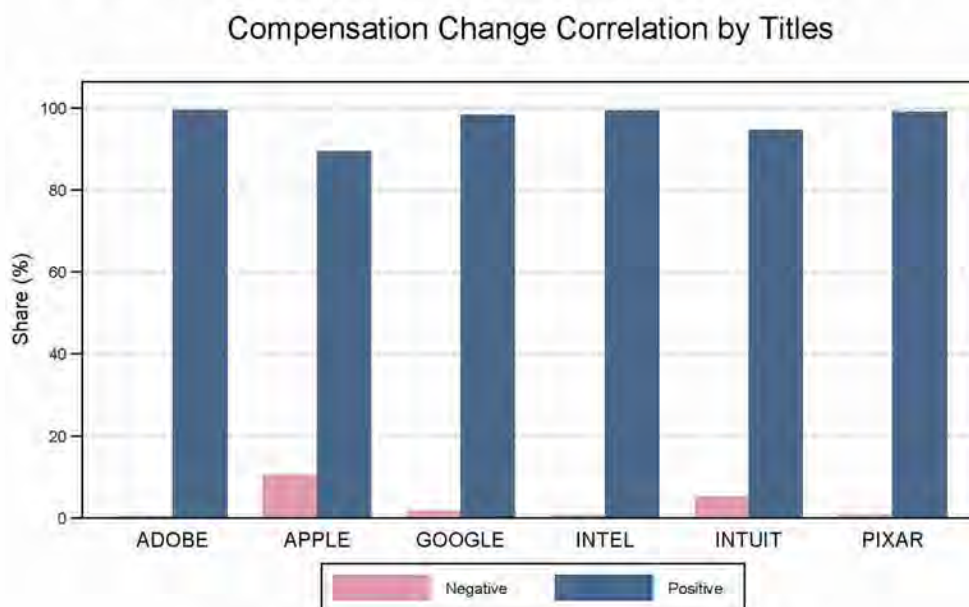
**IV. Results of Title Based Correlations and Multiple Regressions****A. Title-by-Title Correlation Analysis of Compensation Structure**

30. The correlations for all Defendants are reported in Exhibit 1 (Adobe) and Exhibit 2 (other Defendants). Below I will discuss the Adobe results in detail, but here it is enough to summarize the overall results with Figure 2 and Figure 3, which indicate the fractions of titles (weighted by employee years) with positive correlations between title compensation and Technical Class compensation at the same firm, restricted to titles with six or more annual

observations. The titles with five or fewer tend to produce a more extreme distribution of correlations.

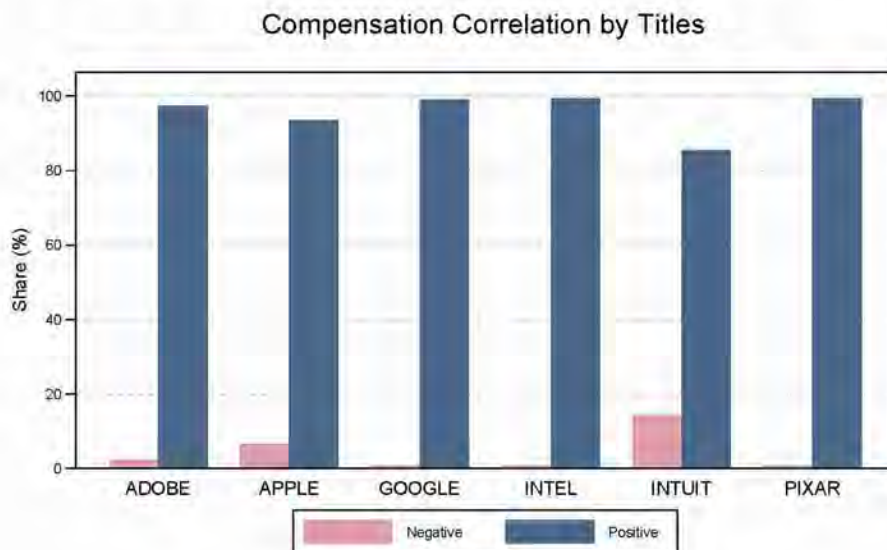
31. Although there are some negative estimated correlations, that does not mean that any true correlations are negative. These estimates are computed with statistical error which is large enough to produce some negative estimates among the thousands of titles included even if all true correlations were positive.
32. Moreover, the fact that the vast majority of cases are positive is strong support for the conclusion that all the true correlations are positive. There are formal statistical methods that allow pooling of results across titles based on the assumption that the titles probably have similar correlations. These methods would shrink the estimates for each title toward the mean across all titles, which is of course positive. Once this shrinkage is done, the results indicate that for many of these negatives the corrected results will be positive, strengthening the conclusion that all titles in the class share movements with the class overall.

**Figure 2: Large Share of Change Correlations are Positive**



Source: Defendant Employee Compensation Data; Correlation Analysis

Note: Distribution of growth in avg compensation correlation over titles with six or more years of data. Weighted by class-period employee years

**Figure 3: Large Share of Level Correlations are Positive**

Source: Defendant Employee Compensation Data; Correlation Analysis

Note: Distribution of log avg compensation correlation over titles with six or more years of data.  
Weighted by class-period employee years

33. It is not just statistical variability that can explain the negative or small correlations. Changes in the composition of employees within a title as employees come and go can cause changes in title compensation and mask the normal correlation with the class overall. I will illustrate this point below with a close examination of some of the Adobe titles that have low or negative correlations with the class.

**Figure 4****Summary of Compensation Change Correlation**

<u>Employer</u>	Positive Sign		Negative Sign		<u>Total</u>
	<u>Significant</u> (Percent)	<u>Not Significant</u> (Percent)	<u>Significant</u> (Percent)	<u>Not Significant</u> (Percent)	
<b>ADOBE</b>	67 %	32 %	0 %	0 %	100 %
<b>APPLE</b>	54	35	1	10	100
<b>GOOGLE</b>	76	22	0	2	100
<b>INTEL</b>	94	6	0	1	100
<b>INTUIT</b>	81	14	0	5	100
<b>PIXAR</b>	86	13	0	1	100

Source: Defendants' employee compensation data; Correlation Analysis

Note: Distribution of growth in compensation correlation over titles with six or more years of data.  
Weighted by class-period employee years.

**Figure 5****Summary of Compensation Level Correlation**

<u>Employer</u>	Positive Sign		Negative Sign		<u>Total</u>
	<u>Significant</u> (Percent)	<u>Not Significant</u> (Percent)	<u>Significant</u> (Percent)	<u>Not Significant</u> (Percent)	
<b>ADOBE</b>	92 %	5 %	0 %	3 %	100 %
<b>APPLE</b>	78	16	1	5	100
<b>GOOGLE</b>	83	16	0	1	100
<b>INTEL</b>	85	14	0	1	100
<b>INTUIT</b>	45	40	2	12	100
<b>PIXAR</b>	84	15	0	0	100

Source: Defendants' employee compensation data; Correlation Analysis

Note: Distribution of log avg compensation correlation over titles with six or more years of data.  
Weighted by class-period employee years.

**B. Title-by-Title Multiple Regressions**

34. As described above, I also analyzed a multiple regression model of compensation that explains the year-by-year increases in average compensation at the title level in terms of four explanatory variables: (1) increases in average Technical Class compensation at the firm; (2) the previous year's ratio of average Technical Class compensation at the firm divided by the average title compensation; (3) The previous year's ratio of firm-wide average revenue divided by the average title compensation; (4) the percent change in software jobs in the San Jose MSA.
35. The data set is limited to eleven annual observations from 2001 to 2011, and many titles have fewer observations. A four-variable regression is a heavy burden with such data, which is reflected in the number of statistically insignificant coefficients. The statistically insignificant results are particularly prevalent for the external market effects and the revenue-sharing effects.<sup>5</sup> The two sharing variables have more statistically significant coefficients. In other words, in the competition for statistical significance, it is sharing that wins.
36. I present in Figure 6 and Figure 7, below, class-wide results for titles with at least seven observations (approximately 30 percent of all Technical Class titles and more than 91 percent of their Class Period employee years).
37. Those results show the following. First, the vast majority of titles have a positive sharing effect in either the contemporaneous relationship or the lagged relationship. Second, of those that are negative a small fraction are statistically significant. Third, even these negative results occur in the context of body of evidence that there is a general relationship supported by sharing relationships for the vast majority of titles. Many of these are statistically significant. In sum, this analysis provides support for internal relationships across all Class titles at a

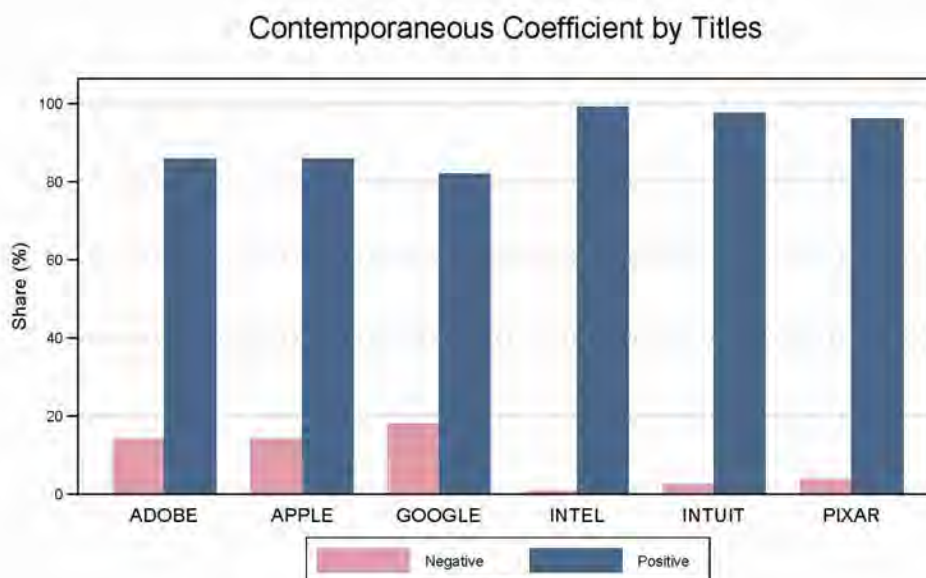
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<sup>5</sup> This model is completely appropriate if the sharing force came from the class overall, equally across all titles. If on the other hand, title A were connected only to title B, then my attempt to link A to the class overall would yield a small and probably insignificant effect unless the variability in compensation of the class were largely determined by variability in compensation of title B. To put this in simple terms, the model that I am estimating makes it less likely not more likely to find a sharing effect.

firm that would tend to make impact of the agreements common to all Class members.

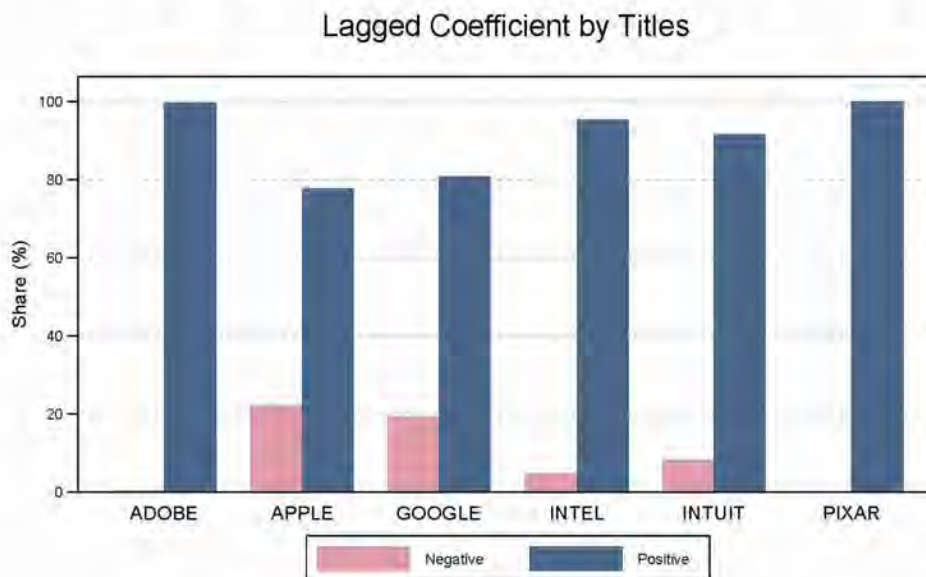
38. Thus, the vast majority of these titles have a positive internal equity sharing relationship with other Technical Class titles at the same firm. The implication of these results is to support my previous conclusion that the impact of the alleged non-compete agreements would be common across the class and common across the Technical Class employees in particular.

**Figure 6: Large Share of Contemporaneous Coefficients are Positive**



Source: Defendant Employee Compensation Data; Regression Analysis

Note: Distribution of estimated contemporaneous coefficient over titles with seven or more years of data. Weighted by class-period employee years

**Figure 7: Large Share of Lagged Coefficients are Positive**

Source: Defendant Employee Compensation Data; Regression Analysis

Note: Distribution of estimated lagged coefficient over titles with seven or more years of data. Weighted by class-period employee years

**Figure 8****Summary of Contemporaneous and Lagged Net Effect**

Employer	Positive Sign		Negative Sign		Total
	Significant (Percent)	Not Significant (Percent)	Significant (Percent)	Not Significant (Percent)	
<b>ADOBE</b>	22 %	75 %	0 %	3 %	100 %
<b>APPLE</b>	23	62	0	14	100
<b>GOOGLE</b>	12	69	2	17	100
<b>INTEL</b>	88	11	0	1	100
<b>INTUIT</b>	73	23	0	4	100
<b>PIXAR</b>	60	39	0	0	100

Source: Defendants' employee compensation data; Regression Analysis

Note: Distribution of the sum of estimated contemporaneous and lagged coefficients over titles with six or more years of data. Weighted by class-period employee years.



39. It may be important to understand that in principle there is a matrix of sharing relationships that connect titles directly affected by the conspiracy with other titles that are tied together with these affected titles. For example, with 101 Adobe titles in the class with six or more observations, this would require potentially the estimation of a 101 by 101 matrix of connections, which is far too many parameters to estimate with only eleven years of data. The regressions that I have estimated have a much simpler structure connecting each title not separately with all of the other titles but instead with the Adobe-wide variables.<sup>6</sup>
40. The regression results for Adobe titles with seven or more years of data are reported in Exhibit 1. The first two Sections give descriptive information about the data and the two correlations. These titles are sorted by the correlations of the log levels of average real compensation (Column 7). Column (9) which is the correlation between the percent change in average real compensation is more relevant here because this correlation is part of the estimated regression.<sup>7</sup> The regression coefficients of the four variables are collected together in Section 3 and the corresponding t-statistics are reported to their right in Section 4.
41. Roughly, a t-statistic in excess of 2 in absolute value is said to produce “statistically significant” estimate by conventional standards. For that reason, t-statistics in excess of 2 are highlighted. Among the titles with eleven years of data it is the two sharing variables that jump out with high t-statistics, more often the “corrective” variable (Column 16) than the class-wide contemporaneous effect (Column 15). The external market variable (Column 18) has a t-value in excess of 2 only 4 of 41 titles, and the revenue variable (Column 17) has one negative and no positive significant t-stats. The results are more mixed deeper into the table as the number of observations diminishes.

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<sup>6</sup> As I noted above, this model looks for a sharing force that comes from the class overall, equally across all titles. If on the other hand, title A were connected only to title B, then my attempt to link A to the class overall would yield a small and probably insignificant effect unless the variability in compensation of the class were largely determined by variability in compensation of title B. The model that I am estimating makes it less likely not more likely to find a sharing effect.

<sup>7</sup> The increment in the fit of the model associated with the last three explanatory variables can be found by comparing the R-sq in the last column with the squared of the correlation.

42. This confirms the summary above, providing direct evidence of sharing across titles. The almost always positive coefficients on the “corrective” variable equal to the lagged ratio of compensation relative to title compensation in the title indicates that if the title compensation departs from its normal relationship with the class, then corrective action is taken to either raise or lower compensation in the title.

## **V. Decile Based Correlations and Multiple Regressions**

43. The title-based study just described by necessity excludes titles that are infrequently populated. To include these titles in this study, I have formed groups of titles on which to conduct the correlation analysis and the multiple regressions. I split each Defendant’s Technical Class titles into ten groups. To form the ten groups, I ranked titles on the basis of average (inflation-adjusted) total compensation over the lifetime of the title and then divided these up into deciles based on employee-years.<sup>8</sup>

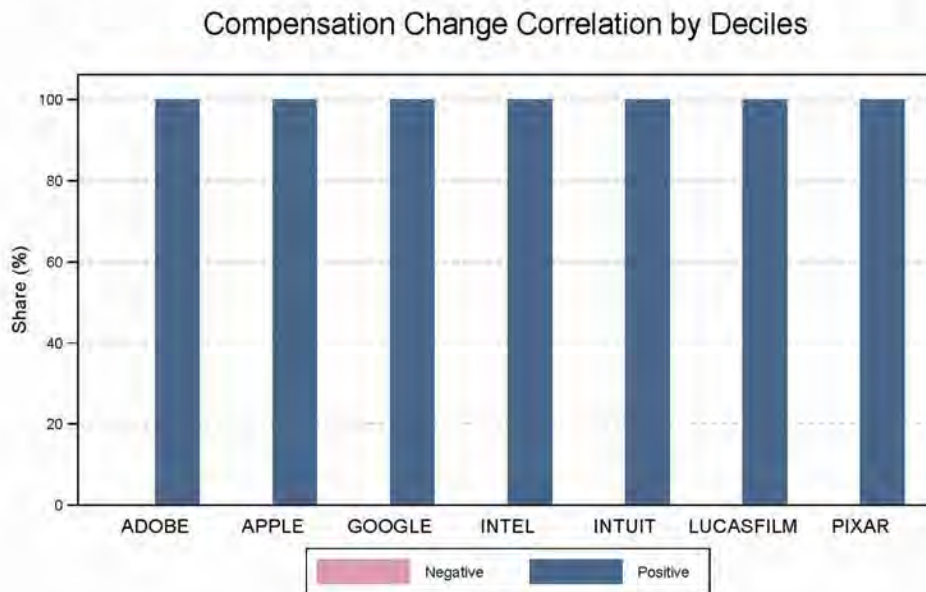
### **A. Decile Based Correlation Analysis**

44. The correlation analysis of the ten groups yields strong evidence of both short and long-run compensation structures for each subgroup of the Defendants’ Technical Class employees. Figure 9 and Figure 10 indicate the numbers of the ten groups that had positive correlations with the Technical Class: 10 out of 10 for the levels correlation and 10 out of 10 for the percent change correlations. Thus, every group shares in its firm’s compensation structure. Every group shows both immediate and long-run correlation structure for every group. This is consistent with and supports my conclusion that the Defendants’ compensation was semi-rigid.

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<sup>8</sup> Since Lucasfilm did not provide title data, individuals were ranked in a similar fashion for Lucasfilm. Although I attempted to break the firms up into 10 equal sized groups (equal based on employee years), some groups end up being larger than others because of some big titles.

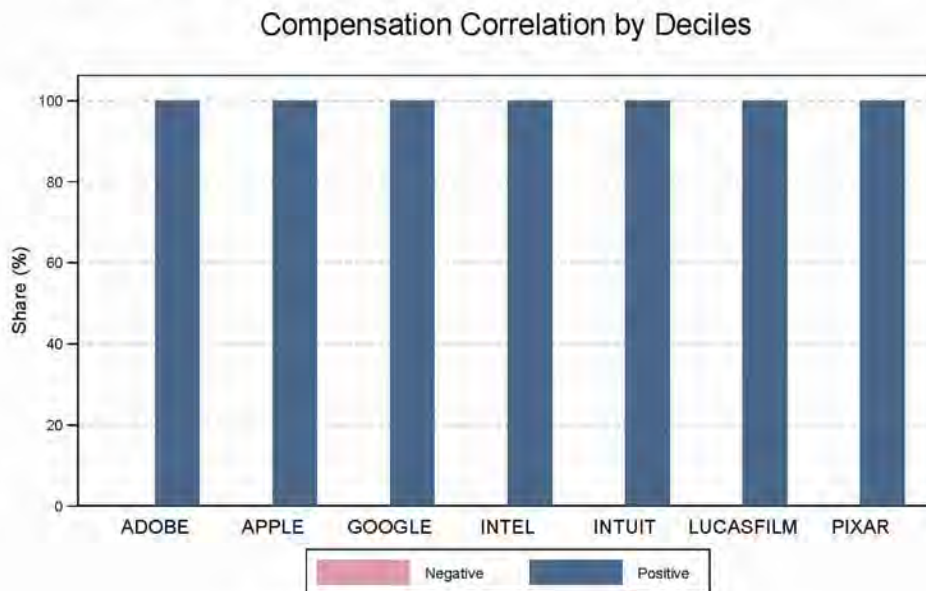
**Figure 9: Large Share of Change Correlations are Positive**



Source: Defendant Employee Compensation Data; Correlation Analysis

Note: Distribution of growth in avg compensation correlation weighted by class-period employee years

**Figure 10: Large Share of Level Correlations are Positive**



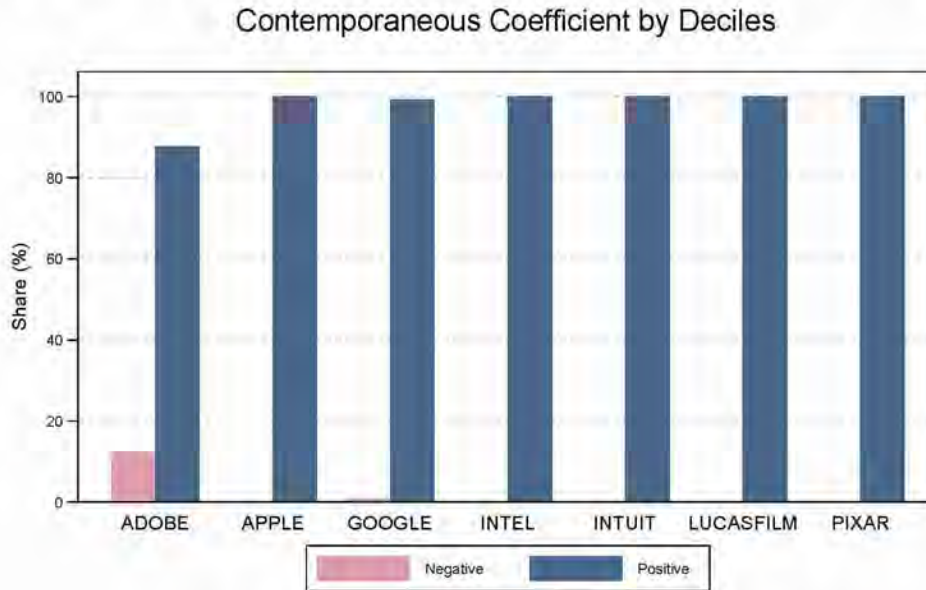
Source: Defendant Employee Compensation Data; Correlation Analysis

Note: Distribution of log avg compensation correlation weighted by class-period employee years

## B. Decile Based Multiple Regression Results

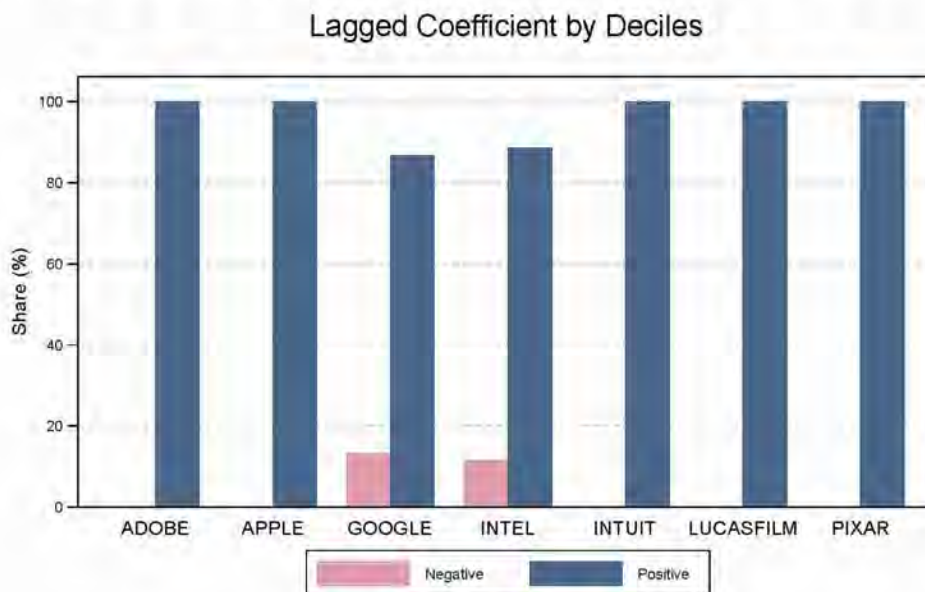
45. Multiple regressions have also been estimated with these decile data. As summarized in Figure 11 and Figure 12, below, positive sharing effects—both contemporaneous and lagged—are the rule.

**Figure 11: Large Share of Contemporaneous Coefficients are Positive**



Source: Defendant Employee Compensation Data; Regression Analysis

Note: Distribution of estimated contemporaneous coefficient weighted by class-period employee years

**Figure 12: Large Share of Lagged Coefficients are Positive**

Source: Defendant Employee Compensation Data, Regression Analysis

Note: Distribution of estimated lagged coefficient weighted by class-period employee years

46. The almost always positive coefficients on the “corrective” variable in Figure 12 indicate that if the title compensation of a decile departs from its normal relationship with the class, then corrective action is taken to either raise or lower compensation in the decile. The cold-calling conspiracy that would have direct impact suppressing wages in some titles would have some effect on the class-wide averages which in turn would suppress compensation in all or almost all of the titles in the class.
47. Figure 11 and Figure 12 contain a few instances of negative estimates. There are several important things to note. First, every group has a positive sharing effect in either the contemporaneous relationship or the lagged relationship. Second those that are negative are not statistically significant. Third, these occur in the context of evidence of positive sharing relationships for almost every group. Many of these are statistically significant. In sum, this analysis provides support for internal relationships across all these groups that would tend to make impact common to each.

48. Here I want to issue another warning about misinterpretation of negative coefficients. It is important to realize that these coefficients can be affected by the changing composition of the workforce within each title.<sup>9</sup> For instance, adding a number of junior workers might bring down the title's average compensation (or vice versa) for reasons unrelated to the question of whether workers share broadly in things such as the gains of the company and the impact of the unlawful agreements. Idiosyncratic variability of individual characteristics within a title is going to be a bigger problem for titles with just a few employees and for titles that experience large changes<sup>10</sup> in their headcounts.
49. Taking into account the limitations of these data, I find no compelling reason in this analysis to exclude any of the titles from the Technical Class.

## **VI. Additional Exploration of Adobe Correlations**

50. To test this opinion I have closely examined the correlation outputs for the Adobe dataset as set forth below. They confirm my view. I have similarly examined the data of the other defendants, and find nothing in that data to contradict this conclusion.

### ***1. Adobe Correlation Results***

51. The numerical correlations reported in compare the movement of real compensation for each title in the Technical Class with the movement of the compensation of the Technical Class overall, but excluding the selected title. A high positive correlation means that compensation of a title moves in a way that is similar to compensation in the rest of the Technical Class, thus supporting the conclusion that the title and the class have "coordinated" compensation levels, a fact which is consistent with sharing of gains and broad impact of the anti-cold-

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<sup>9</sup> I previously demonstrated with the Common Factors Analysis that compensation at the individual level in any year depends on the title but also depends on measured individual characteristics including age. This is statistical confirmation that at least some individual characteristics matter, and this raises the possibility that changes in the individual characteristics within a title can cause changes in title compensation that can mask the firm-wide common component.

<sup>10</sup> Though a stable headcount can come from equal numbers of departures and new arrivals.

calling conspiracy whether it directly affects the title under study or the rest of the Technical Class.

52. Titles are included in the table if they are populated in 6 or more years. The correlations based on 5 or fewer observations are often statistically insignificant. The table is sorted first by the number of years the title was populated, from 11 to 6, and then by the correlation of the title with the Technical Class overall. Titles with the strongest statistical correlation with the Technical Class at Adobe are shaded in green. Titles with the weakest statistical correlation with the Technical Class at Adobe are shaded in yellow.
53. The first column of numbers in Exhibit 1 has the first year of data for each title. This is important since the early years from 2001 to 2003 had a sharp decline in Technical Class compensation for Adobe, as illustrated in Figure 13 and these early years thus are an important test bed for identifying which titles moved together. It would not be surprising to find statistically weaker results if these years are not included.

**Figure 13**

Adobe Technical Class Average Total Compensation



Source: Defendant Employee Compensation Data

Note: Inflation-adjusted average compensation with 2011 as base year

54. The second column reports the number of years during which the title was populated. This is also important since the statistical accuracy of the estimate of correlation depends on the number of observations. For that reason, I have truncated this table at the number of years equal to 6 or more since the cases with 5 or fewer years populated are estimated with greater statistical error.
55. The third column measures the number of employee-years.

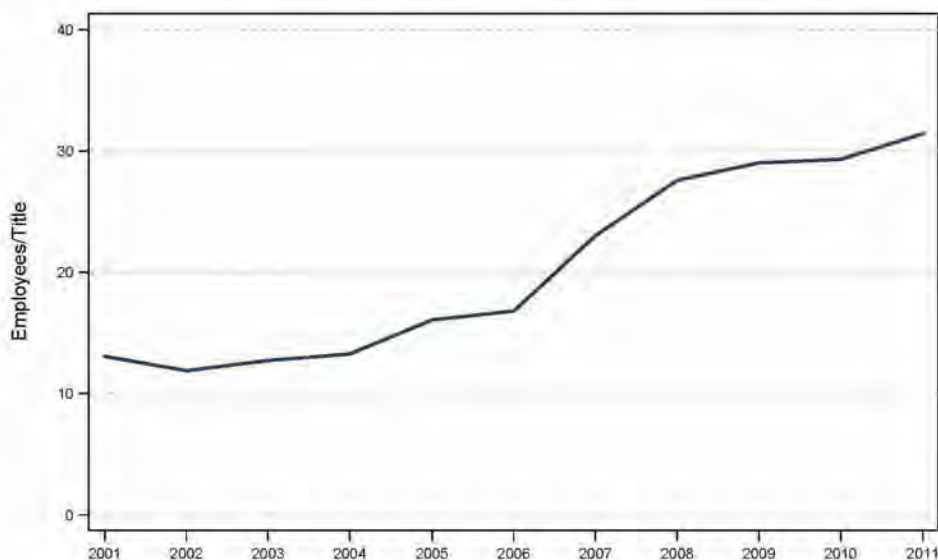
## ***2. Headcount Matters for Interpreting Correlations***

56. It is my view that compensation is influenced by the title structure, but not fully determined by the title structure. Variables like age, experience, company tenure and personal characteristics are likely to have an impact on compensation, and consequently some of the change in compensation at the title level comes from changes in the distribution of employee characteristics as employees come and go. Titles that have just a few employees may have unusual employee characteristics, and titles that lose or gain a large fraction of employees may have variability in average compensation that is substantially influenced by variability of these characteristics, which masks a close connection with the Technical Class overall.
57. The Technical Class overall has experienced a rising headcount, as illustrated in Figure 14. Titles with movement in headcounts similar to the Technical Class may experience similar movements in employee characteristics, while titles that are losing workers or gaining workers much more rapidly than the Technical Class overall may have average compensation histories different from the Technical Class, not because there is no sharing, but because the group of employees in the title is changing enough to mask the sharing.



**Figure 14**

## Adobe Technical Class Average Headcount per Title



Source: Defendant Employee Compensation Data

**3. Correlations**

58. As described above, there are two types of correlations which are relevant for determining if the movements of the two series are similar. The first column of correlations (Section 2) in Exhibit 1 compares the logarithm of average total real compensation in the title and the logarithm of average real total compensation of the rest of the Technical Class. The third column of Section 2 compares the *change* in the logarithm of average real total compensation of the title with the Technical Class (excluding the title).
59. The corresponding t-statistics for these correlations are reported immediately following each correlation and the statistically significant correlations with t-statistics greater than two are shaded. The table is sorted first by the number of years in which the title is populated and second by the correlation between the log levels.
60. The statistically most significant correlations with the shaded t-statistics come from the longest time series with all eleven years of data populated. That is a

feature of any statistical exercise – the longer is the time series the more statistically significant are the findings.

61. There are no negative correlations for the 41 titles with all eleven years populated. These positive correlations are statistically larger than zero (statistically significant) in 39 out of the 41 cases.

#### **4. Outliers**

62. To fully understand these correlations, and the significance (or not) of the anomalies, it may be helpful to look at some data displays. Figure 15 and Figure 16 have the average real compensation for ten Adobe titles and for the Adobe employees in the Technical Class overall. Figure 15 illustrates the five titles with eleven years of data that are most highly correlated with the Technical Class overall, and Figure 16 has the least correlated titles. All these titles move together. The title with the lowest correlation is TECHNICAL\_WRITER\_2 which is different, but not dramatically so.

**Figure 15: Selected Adobe Titles with a Full 11 years of Data**

Most Correlated Titles Average Total Compensation



Source: Defendant Employee Compensation Data; Correlation Analysis  
Note: Titles with highest log compensation correlation among fully populated titles  
inflation-adjusted average total compensation with 2011 as base year

**Figure 16**

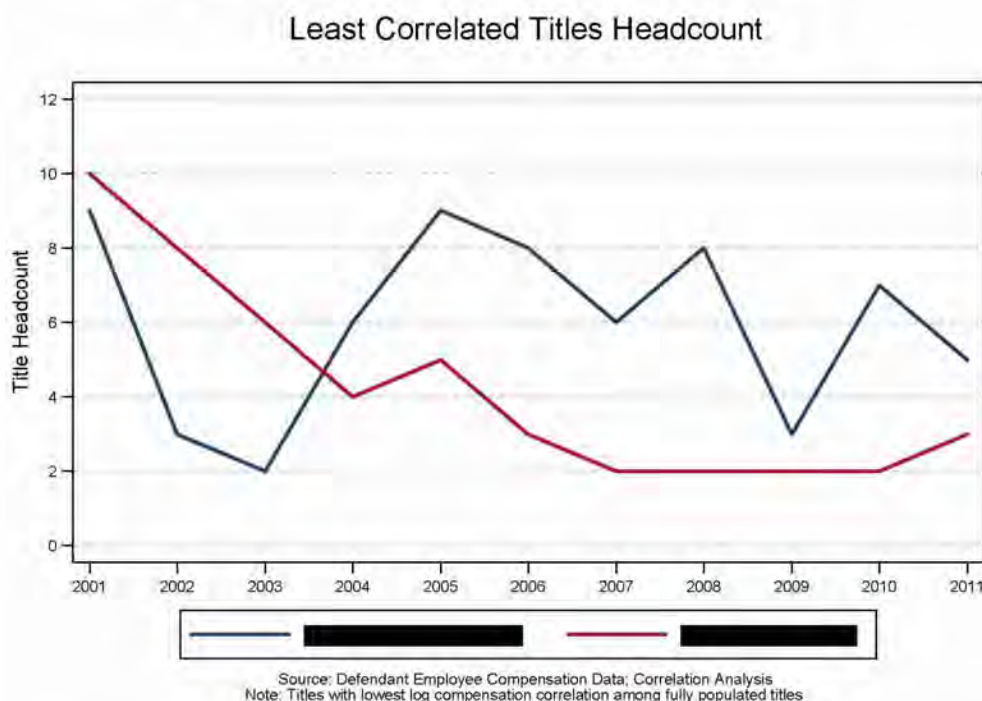
Least Correlated Titles Average Total Compensation



Source: Defendant Employee Compensation Data; Correlation Analysis  
Note: Titles with highest log compensation correlation among fully populated titles  
inflation-adjusted average total compensation with 2011 as base year

63. However, as noted above, when headcounts change substantially, employee characteristics may change substantially too. The headcounts for the two titles with the lowest correlation are illustrated in Figure 17. The headcount for [REDACTED], is very volatile with a standard deviation of the percent change equal to 72 percent compared with the Technical Class benchmark of 11 percent. [REDACTED] title is basically withering away, with an average annual percent increase of -12 percent compared with the Technical Class benchmark of +5 percent.

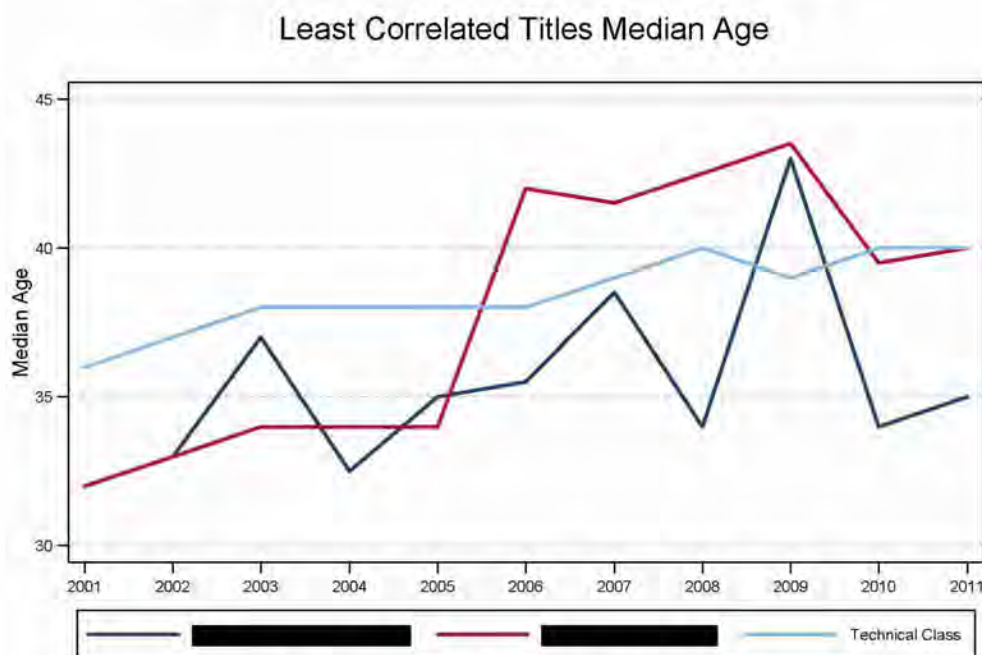
**Figure 17: Headcounts: Least Correlated Titles**



64. The variability in the headcounts for these two titles is not just a hypothetical problem. It has affected substantially the median ages for these titles which are contrasted with the median age of the Technical Class overall in Figure 18. In contrast to the smooth elevation of the median age of the class, the median age of [REDACTED] has a big jump upward in 2006, and the median age of [REDACTED] is highly volatile. These facts surely contribute to the apparent disconnect between compensation in these titles and compensation in the Technical Class overall. And, in any event, these results

offer no reason to question my conclusion that Adobe exhibits a somewhat rigid pay structure that applied to all of its salaried employees, including those in these titles. I offer these two examples simply to illustrate the point that the presence of a few outlier titles in the analyses does not challenge our basic conclusions about how these companies pay their employees, which are also supported by economic theory and the evidentiary. I have not seen any evidence, let alone convincing evidence, that any of these titles would not have been harmed by the anti-competitive behavior I have studied.

**Figure 18: Median ages: Least Correlated Titles**



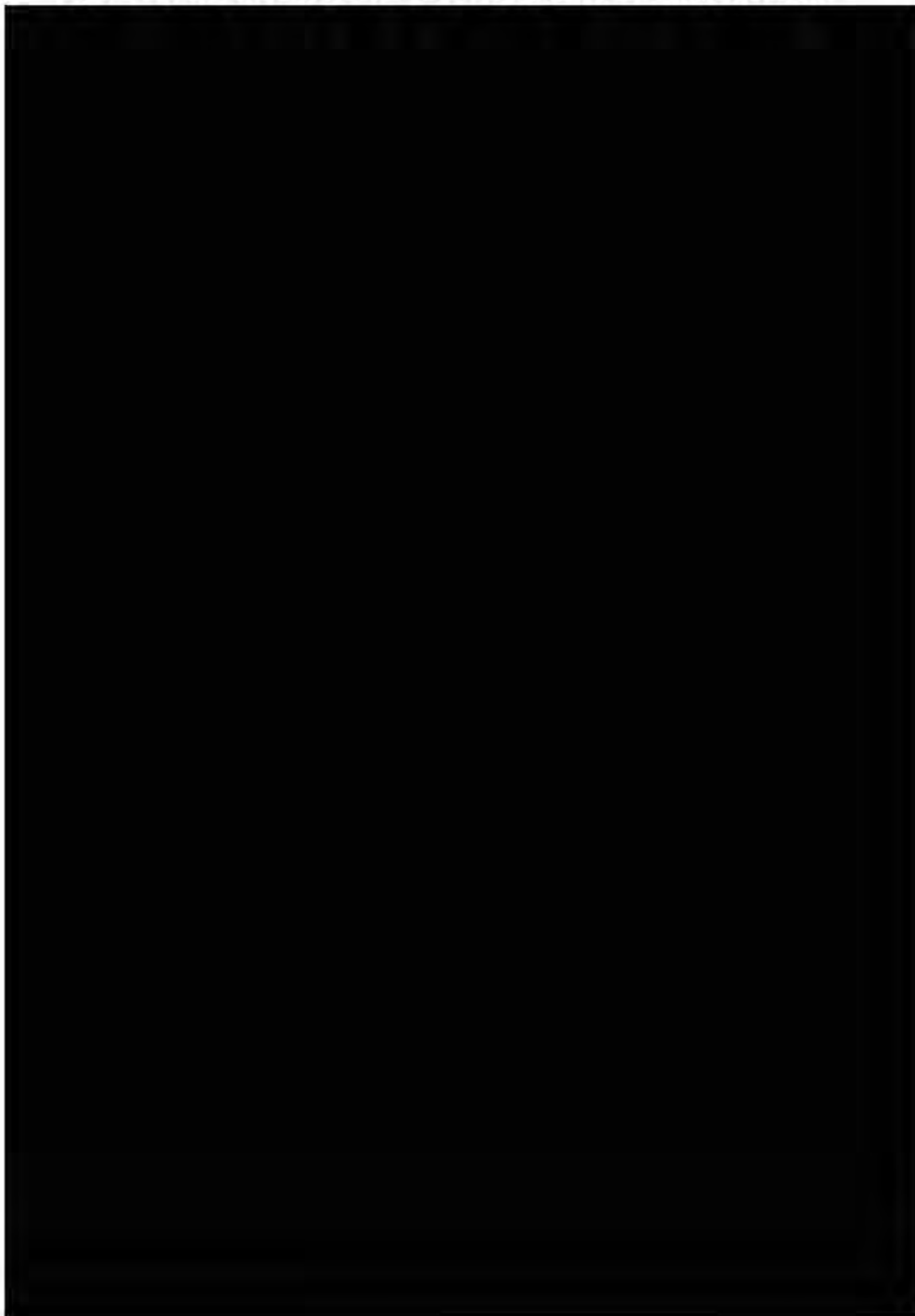
## VII. Internal Versus External Forces

65. The regression analysis reported above indicates that the internal sharing effects are generally more detectable than either revenue sharing or the external market forces. I expand on this finding in this section with an examination of the average real compensation for the Technical Class employees and the non-Technical Class employees of each of the defendants. I show here that there is generally more correlation within firms between these two groups, than between

firms for either group. Thus again I observe that the internal sharing forces are very evident while the external market forces are more difficult to detect.

66. Figure 19 below illustrates for each defendant the average total compensation for the Technical Class employees (RD) and for the non-Technical Class employees (NRD). For most defendants these two subgroups have total compensation that closely tracks one another. It should also be evident that average total compensation is generally much more similar within each firm than between firms. In other words, the internal sharing forces dominate and keep the compensation of the Technical Class employees and the non-Technical Class employees closely aligned.
67. This visual observation is confirmed numerically by the computation of the correlations over time of the change in logarithms of the average total real compensation between these fourteen groups of employees, reported in Table 1. Correlations in excess of 0.9 are shaded. The boxes down the diagonal contain the within firm correlations between RD and NRD. Correlations outside these boxes refer to comparisons between firms. Four out of five of the shaded correlations are in these boxes, and in addition Google has an internal correlation of 0.86. Furthermore, the within firm correlation is the largest correlation in every row and column except for Lucasfilm. Lucasfilm has a very short time series with very little variability in the percent change in compensation, making it hard to estimate correlation. The Pixar data are contaminated by very large bonuses for producers and directors in 2002 and 2006.
68. Table 2 has the levels correlations that capture the longer term co-movements of the compensation series. These confirm the importance of the internal forces compared with the external forces. forces for all but Lucasfilm, in the sense that the within firm correlation is the largest correlation in every row and column except for Lucasfilm. Lucasfilm and Intel appear to move together only because the Lucasfilm data is confined to a brief period of stable growth of compensation at both firms.

**Figure 19: Defendant RD vs. NRD Average Total Compensation**



**Table 1**  
**Correlations of Changes in Defendants' Average Total Compensation**  
**2001-2011**

		Adobe		Apple		Google		Intel		Intuit		Lucasfilm		Pixar	
		NRD	RD	NRD	RD	NRD	RD	NRD	RD	NRD	RD	NRD	RD	NRD	RD
Adobe	NRD	1.00	0.94	0.66	0.56	0.17	-0.16	0.47	0.60	0.63	0.60	0.19	-0.62	-0.53	-0.53
	RD	0.94	1.00	0.64	0.65	0.13	-0.24	0.34	0.45	0.53	0.51	-0.12	-0.67	-0.51	-0.37
Apple	NRD	0.66	0.64	1.00	0.93	0.48	0.17	0.02	0.16	0.85	0.73	-0.08	-0.87	-0.56	-0.16
	RD	0.56	0.65	0.93	1.00	0.42	0.07	-0.12	0.00	0.77	0.63	-0.11	-0.83	-0.45	0.05
Google	NRD	0.17	0.13	0.48	0.42	1.00	0.86	-0.51	-0.39	0.20	0.17	0.49	-0.89	-0.62	0.21
	RD	-0.16	-0.24	0.17	0.07	0.86	1.00	-0.53	-0.50	-0.09	-0.06	0.68	-0.83	-0.50	0.19
Intel	NRD	0.47	0.34	0.02	-0.12	-0.51	-0.53	1.00	0.97	0.31	0.30	-0.01	0.92	0.00	-0.89
	RD	0.60	0.45	0.16	0.00	-0.39	-0.50	0.97	1.00	0.38	0.33	0.23	0.70	-0.03	-0.89
Intuit	NRD	0.63	0.53	0.85	0.77	0.20	-0.09	0.31	0.38	1.00	0.91	-0.15	-0.17	-0.43	-0.28
	RD	0.60	0.51	0.73	0.63	0.17	-0.06	0.30	0.33	0.91	1.00	-0.51	0.55	-0.63	-0.34
Lucasfilm	NRD	0.19	-0.12	-0.08	-0.11	0.49	0.68	-0.01	0.23	-0.15	-0.51	1.00	-0.24	0.03	-0.38
	RD	-0.62	-0.67	-0.87	-0.83	-0.89	-0.83	0.92	0.70	-0.17	0.55	-0.24	1.00	0.58	-0.29
Pixar	NRD	-0.53	-0.51	-0.56	-0.45	-0.62	-0.50	0.00	-0.03	-0.43	-0.63	0.03	0.58	1.00	0.29
	RD	-0.53	-0.37	-0.16	0.05	0.21	0.19	-0.89	-0.89	-0.28	-0.34	-0.38	-0.29	0.29	1.00

Note: Values above 0.9 shaded.

Source: Defendants' employee compensation data.



**Table 2**  
**Correlations of Defendants' Average Total Compensation**  
**2001-2011**

		Adobe		Apple		Google		Intel		Intuit		Lucasfilm		Pixar	
		NRD	RD	NRD	RD	NRD	RD	NRD	RD	NRD	RD	NRD	RD	NRD	RD
Adobe	NRD	1.00	0.88	-0.17	-0.17	-0.43	-0.73	0.18	0.58	0.50	0.41	0.15	-0.04	-0.33	-0.38
	RD	0.88	1.00	0.24	0.27	-0.05	-0.63	0.47	0.72	0.69	0.61	0.40	0.32	-0.48	-0.51
Apple	NRD	-0.17	0.24	1.00	0.99	0.91	0.38	0.65	0.33	0.64	0.68	0.74	0.58	-0.48	-0.39
	RD	-0.17	0.27	0.99	1.00	0.90	0.33	0.69	0.37	0.64	0.66	0.83	0.72	-0.46	-0.40
Google	NRD	-0.43	-0.05	0.91	0.90	1.00	0.67	0.53	0.13	0.36	0.44	0.81	0.59	-0.46	-0.28
	RD	-0.73	-0.63	0.38	0.33	0.67	1.00	-0.05	-0.44	-0.20	-0.08	0.47	0.04	-0.22	0.12
Intel	NRD	0.18	0.47	0.65	0.69	0.53	-0.05	1.00	0.87	0.64	0.66	0.93	0.98	-0.54	-0.86
	RD	0.58	0.72	0.33	0.37	0.13	-0.44	0.87	1.00	0.65	0.62	0.91	0.96	-0.48	-0.90
Intuit	NRD	0.50	0.69	0.64	0.64	0.36	-0.20	0.64	0.65	1.00	0.94	0.63	0.54	-0.55	-0.54
	RD	0.41	0.61	0.68	0.66	0.44	-0.08	0.66	0.62	0.94	1.00	0.78	0.91	-0.72	-0.62
Lucasfilm	NRD	0.15	0.40	0.74	0.83	0.81	0.47	0.93	0.91	0.63	0.78	1.00	0.88	-0.63	-0.83
	RD	-0.04	0.32	0.58	0.72	0.59	0.04	0.98	0.96	0.54	0.91	0.88	1.00	-0.62	-0.86
Pixar	NRD	-0.33	-0.48	-0.48	-0.46	-0.46	-0.22	-0.54	-0.48	-0.55	-0.72	-0.63	-0.62	1.00	0.65
	RD	-0.38	-0.51	-0.39	-0.40	-0.28	0.12	-0.86	-0.90	-0.54	-0.62	-0.83	-0.86	0.65	1.00

Note: Values above 0.9 shaded.

Source: Defendants' employee compensation data.

CONFIDENTIAL

5/10/2013

A handwritten signature in cursive script, appearing to read "Ed E. Leamer".

---

Edward E. Leamer, Ph.D.

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Supplemental Expert Report of Edward E. Leamer, Ph.D.

0375

# Exhibit 1

Exhibit 1  
Adobe

Job Title	Section 1						Section 2				Section 3				Section 4				Section 5		Section 6	
	First Year	Years of Data	Total Emp-Years	Avg Emp	dlog Avg	dlog Std Dev	Level Correlation Coeff	T-Stat	Change Correlation Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C+L	T-Stat	Obs.	z
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
2001	11	170	15	0.27	0.34	0.90	6.07	0.89	5.55	1.18	1.04	0.12	0.02	8.15	3.71	1.77	0.07	2.22	8.15	10	0.98	
2001	11	311	28	0.05	0.19	0.89	5.89	0.78	3.55	1.07	1.18	-0.09	-0.31	0.67	1.38	-0.25	-0.25	2.25	1.66	10	0.74	
2001	11	371	34	0.11	0.16	0.89	5.73	0.79	3.59	0.67	1.33	-0.12	-0.34	0.66	1.95	-0.45	-0.36	2.01	1.99	10	0.81	
2001	11	29	3	0.16	0.65	0.87	5.37	0.78	3.56	2.67	1.08	-0.33	-0.48	1.49	1.80	-0.80	-0.32	3.75	2.24	10	0.79	
2001	11	82	7	0.10	0.25	0.85	4.87	0.72	2.97	0.89	1.09	-0.46	0.58	0.65	1.99	-1.23	0.39	1.97	1.39	10	0.77	
2001	11	108	10	-0.03	0.40	0.84	4.73	0.82	4.08	0.93	0.88	0.04	0.51	2.41	3.32	0.37	1.38	1.81	3.34	10	0.94	
2001	11	96	9	0.12	0.37	0.84	4.65	0.85	4.56	0.80	0.59	0.05	0.84	1.93	2.98	0.45	1.89	1.38	2.66	10	0.95	
2001	11	250	23	0.04	0.16	0.84	4.60	0.85	4.47	1.28	0.97	0.08	0.19	2.40	3.37	0.47	0.37	2.25	2.83	10	0.93	
2001	11	559	51	0.11	0.20	0.83	4.53	0.88	5.31	0.94	0.80	0.21	-0.04	2.27	2.28	1.45	-0.08	1.74	3.24	10	0.92	
2001	11	93	8	0.11	0.26	0.81	4.19	0.67	2.54	3.21	0.89	-0.24	-1.55	1.03	0.75	-0.30	-0.62	4.10	1.49	10	0.63	
2001	11	14	1	0.00	0.45	0.80	3.97	0.63	2.29	2.50	0.06	0.51	-0.17	0.50	0.04	0.40	-0.04	2.57	0.56	10	0.57	
2001	11	152	14	0.28	0.15	0.78	3.74	0.72	2.96	0.54	0.65	0.13	0.54	0.98	1.60	0.89	1.07	1.19	1.43	10	0.81	
2001	11	202	18	0.06	0.25	0.78	3.74	0.70	2.78	0.68	1.24	0.21	0.34	1.30	4.29	1.40	0.67	1.91	3.24	10	0.92	
2001	11	550	50	0.06	0.18	0.78	3.70	0.95	8.29	0.99	0.15	0.06	0.43	2.67	0.54	0.47	0.94	1.14	2.66	10	0.82	
2001	11	234	21	0.07	0.22	0.78	3.68	0.73	2.06	0.97	1.14	0.12	0.29	1.50	2.19	0.43	0.46	2.11	2.32	10	0.86	
2001	11	273	25	0.17	0.19	0.77	3.60	0.74	3.11	0.34	1.32	0.23	0.33	0.60	2.67	1.59	0.66	1.66	2.77	10	0.83	
2001	11	327	30	0.11	0.14	0.74	3.34	0.82	4.00	0.66	0.40	0.11	0.19	1.39	1.12	0.74	0.36	1.06	1.67	10	0.78	
2001	11	434	39	0.07	0.18	0.74	3.29	0.65	2.39	0.72	1.09	0.21	0.30	1.29	2.64	1.33	0.56	1.82	2.39	10	0.84	
2001	11	196	18	0.13	0.24	0.74	3.27	0.82	4.06	1.23	0.57	0.09	0.02	1.48	1.38	0.29	0.02	1.80	1.87	10	0.78	
2001	11	353	32	-0.06	0.19	0.73	3.23	0.56	1.91	0.81	1.43	0.17	0.44	1.59	6.09	1.21	0.94	2.23	3.21	10	0.87	
2001	11	309	28	0.08	0.23	0.71	3.03	0.61	2.30	0.96	1.13	0.06	0.24	1.27	2.23	0.24	0.34	2.09	1.95	10	0.73	
2001	11	94	9	0.08	0.27	0.71	3.03	0.62	2.25	0.65	1.02	0.11	0.58	0.89	2.25	0.49	0.79	1.68	1.74	10	0.83	
2001	11	2095	190	0.05	0.13	0.70	2.91	0.69	2.68	0.26	0.49	0.12	0.35	0.60	1.35	0.88	0.79	0.79	1.25	10	0.72	
2001	11	514	47	0.08	0.22	0.70	2.90	0.63	2.27	0.71	0.97	0.08	0.45	0.91	2.89	0.29	0.57	1.68	1.66	10	0.77	
2001	11	35	3	0.00	0.32	0.69	2.90	0.53	1.75	0.58	1.09	0.15	-0.15	0.45	2.12	0.47	-0.09	1.67	1.05	10	0.81	
2001	11	215	20	0.07	0.53	0.69	2.88	0.46	1.48	0.35	1.26	-0.07	0.47	0.51	3.49	-0.39	0.69	1.61	1.88	10	0.82	
2001	11	496	45	0.05	0.20	0.67	2.74	0.75	3.18	0.08	0.47	0.14	0.56	0.17	1.29	0.89	0.91	0.56	0.87	10	0.83	
2001	11	466	42	0.06	0.11	0.67	2.74	0.69	2.71	0.27	0.62	0.10	0.27	0.49	1.62	0.59	0.48	0.89	1.33	10	0.71	
2001	11	234	21	0.09	0.33	0.67	2.71	0.77	3.39	0.10	0.27	-0.17	1.23	0.21	1.12	-1.01	2.21	0.38	0.63	10	0.87	
2001	11	1441	131	0.06	0.19	0.65	2.55	0.48	1.56	0.24	0.71	0.11	0.54	0.35	1.51	0.58	0.89	0.94	0.98	10	0.61	
2001	11	302	27	0.00	0.21	0.64	2.49	0.91	6.03	0.62	0.10	-0.17	0.94	2.20	0.67	-1.72	2.57	0.72	2.18	10	0.95	
2001	11	222	20	0.09	0.15	0.63	2.44	0.62	2.22	0.05	0.45	0.11	0.75	0.07	1.04	0.51	0.95	0.50	0.52	10	0.50	
2001	11	975	89	-0.12	0.23	0.63	2.42	0.48	1.55	0.24	0.49	0.00	0.40	0.39	1.05	-0.01	0.71	0.73	0.86	10	0.42	
2001	11	2041	186	0.05	0.20	0.61	2.33	0.57	1.94	0.07	0.43	0.14	0.55	0.14	1.04	0.80	1.04	0.50	0.67	10	0.62	
2001	11	56	5	0.03	0.54	0.61	2.32	0.52	1.70	0.27	1.04	0.08	1.06	0.36	2.06	0.39	1.55	1.30	1.43	10	0.83	
2001	11	2064	188	0.05	0.08	0.61	2.29	0.52	1.71	-0.07	0.44	0.13	0.65	-0.14	1.13	0.82	1.29	0.37	0.52	10	0.66	
2001	11	109	9	0.09	0.31	0.60	2.27	0.61	2.20	1.92	0.91	0.00	-3.12	1.44	1.96	0.00	2.95	2.83	2.36	10	0.86	
2001	11	1008	92	0.06	0.27	0.59	2.17	0.56	1.91	0.36	0.56	0.26	0.29	0.57	1.18	1.41	0.48	0.91	1.09	10	0.62	
2001	11	41	4	0.00	0.59	0.58	2.11	0.34	1.02	0.41	1.61	0.19	-0.56	0.42	2.35	0.55	-0.42	2.01	1.37	10	0.71	
2001	11	66	6	-0.06	0.72	0.51	1.77	0.37	1.13	-1.62	-0.86	-0.57	1.57	-4.28	-3.06	-6.64	3.82	-2.48	-3.98	10	0.91	
2001	11	47	4	-0.12	0.30	0.09	0.26	0.14	0.40	-1.20	0.28	-0.07	1.62	-1.61	1.16	-0.33	2.35	-0.92	-1.12	10	0.61	
2002	10	36	4	0.10	0.40	0.80	3.72	0.77	3.22	1.91	1.28	-0.39	0.00	1.54	1.76	-1.17	0.00	3.19	2.59	9	0.78	
2002	10	37	4	0.08	0.43	0.14	0.39	-0.39	-1.93	0.12	1.09	0.06	0.40	0.19	2.35	0.43	0.73	1.20	1.25	9	0.76	
2002	10	26	3	0.00	0.48	-0.02	-0.06	0.14	0.37	3.38	0.87	0.35	5.30	1.21	1.33	0.52	1.81	4.25	1.45	9	0.96	
2002	10	330	33	0.20	0.29	-0.13	-0.37	0.08	0.22	-0.35	0.30	0.13	0.64	-1.22	1.84	1.72	1.89	-0.05	-0.13	9	0.83	
2001	9	44	5	-0.30	0.50	0.52	1.59	0.46	1.28	-0.47	0.51	0.04	1.39	-0.42	0.97	0.12	1.19	0.04	0.03	8	0.71	
2001	9	104	12	-0.21	0.48	0.30	0.85	0.37	0.99	-0.36	1.29	0.16	1.66	-0.15	0.67	0.10	0.56	0.93	0.47	8	0.51	
2004	8	94	12	0.30	0.91	0.84	3.82	0.63	1.80	1.70	0.88	-0.61	1.82	3.22	4.89	6.25	3.47	2.59	6.88	7	0.98	
2001	8	143	18	-0.40	1.08	0.70	2.98	0.68	2.05	1.42	1.60	0.16	0.45	4.02	3.62	1.15	0.85	3.02	7.37	7	0.98	
2001	8	8	1	0.00	0.00	0.62	1.92	-0.36	-0.78	4.15	2.48	-0.14	-0.81	1.02	1.65	-0.13	-0.19	6.63	1.22	6	0.90	
2001	8	93	12	-0.28	1.28	0.56	1.84	0.52	1.37	-0.50	0.43	-0.07	1.14	-0.33	0.71	-0.13	0.66	-0.07	-0.05	7	0.60	
2001	8	88	11	-0.10	1.44	0.38	1.02	0.58	1.58	0.41	2.01	-0.02	2.16	0.60	3.63	-0.07	2.27	2.42	3.61	7	0.93	
2001	8	64	8	-0.43	0.54	0.31	0.80	0.30	0.71	1.40	0.61	0.54	0.47	0.63	0.51	0.47	-0.28	2.01	1.01	7	0.50	
2004	8	80	6	0.14	0.33	0.28	0.73	0.65	1.89	1.28	0.54	0.27	2.40	4.47	4.48	2.92	3.61	1.82	6.05	7	0.99	
2001	8	32	4	0.20	0.81	0.15	0.36	0.40	0.75													
2004	8	18	2	0.00	0.61	-0.17	-0.41	0.60	1.66	1.10	0.60	0.04	2.14	1.76	2.36	0.15	2.00	1.76	2.76	7	0.91	

Exhibit 1  
Adobe

Job Title	Section 1						Section 2				Section 3				Section 4				Section 5		Section 6	
	First Year	Years of Data	Total Emp-Years	Avg Emp	dlog Avg	dlog Std Dev	Level Correlation Coeff	T-Stat	Change Correlation Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	Obs.	z
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
2005	7	22	3	0.18	0.41	0.76	2.64	-0.15	-0.31	0.14	0.93	-0.38	-0.36	0.11	1.48	-0.68	-0.21	1.07	0.60	6	0.91	
2001	7	42	6	-0.27	0.76	0.57	1.56	0.39	0.84	-3.13	2.20	-0.57	3.68	-2.63	2.79	-1.65	2.42	-0.93	-1.11	6	0.93	
2001	7	88	13	-0.41	0.33	0.53	1.38	0.38	0.82	-3.36	5.49	-1.61	7.47	-4.02	6.77	-3.57	5.53	2.13	10.60	6	1.00	
2001	7	17	2	0.00	0.36	0.48	1.21	0.93	4.88	0.58	0.42	-0.13	0.77	0.54	0.84	-0.54	0.89	1.00	0.71	6	0.95	
2005	7	93	13	0.00	0.27	0.40	0.98	0.97	7.56	1.30	0.10	0.07	0.02	2.76	0.28	0.24	0.03	1.40	1.76	6	0.94	
2005	7	59	8	0.05	0.30	0.08	0.18	0.52	1.21	0.49	0.70	0.24	-0.26	0.34	0.76	0.40	-0.13	1.19	0.61	6	0.73	
2001	6	46	8	0.14	0.21	0.98	10.31	0.90	3.49													
2001	6	25	4	0.36	0.95	0.97	8.18	0.86	2.98													
2001	6	19	3	-0.06	0.45	0.96	7.28	0.93	4.41													
2001	6	87	15	0.03	0.12	0.96	6.72	0.83	2.55													
2001	6	13	2	-0.28	1.05	0.94	8.50	0.94	4.92													
2001	6	69	15	0.11	0.43	0.94	5.29	0.82	2.47													
2001	6	108	18	0.01	0.23	0.93	5.23	0.74	1.90													
2001	6	20	3	0.00	0.20	0.93	5.11	0.78	2.17													
2001	6	16	3	-0.06	0.70	0.92	4.77	0.58	1.23													
2001	6	33	6	-0.08	0.33	0.92	4.62	0.66	1.52													
2001	6	22	4	0.03	0.74	0.89	3.99	0.94	4.80													
2001	6	23	4	0.22	0.49	0.89	3.60	0.67	1.54													
2001	6	35	6	0.09	0.26	0.89	3.87	0.91	3.90													
2001	6	57	10	0.06	0.53	0.88	3.77	0.47	0.91													
2001	6	10	2	0.22	0.32	0.88	3.74	0.50	1.00													
2001	6	24	4	-0.25	1.15	0.88	3.70	0.83	2.11													
2001	6	21	4	-0.36	0.59	0.88	3.66	0.49	0.97													
2001	6	92	15	0.19	0.16	0.87	3.60	0.78	2.16													
2001	6	68	11	0.00	0.21	0.86	3.44	0.66	1.51													
2001	6	13	2	0.00	0.29	0.86	3.43	0.59	1.28													
2001	6	27	5	0.42	0.63	0.86	3.38	0.74	1.92													
2001	6	8	1	0.09	0.49	0.85	3.28	0.93	4.31													
2001	6	15	3	-0.08	0.34	0.85	3.18	0.27	0.40													
2001	6	26	4	-0.04	0.41	0.82	2.84	0.76	2.03													
2006	6	7	1	-0.14	0.31	0.81	2.81	0.85	2.85													
2001	6	18	3	0.00	0.51	0.67	1.79	0.43	0.82													
2001	6	105	18	-0.04	0.36	0.66	1.74	0.68	1.90													
2006	6	27	5	0.14	0.46	0.62	1.57	0.61	1.34													
2006	6	19	3	-0.08	0.52	0.61	1.55	0.54	1.11													
2001	6	15	3	-0.14	0.90	0.61	1.54	-0.14	-0.24													
2001	6	12	2	0.22	0.32	0.57	1.39	0.76	2.05													
2001	6	15	3	-0.22	0.32	0.57	1.38	0.56	1.17													
2006	6	19	3	0.28	0.53	0.34	0.72	-0.21	-0.38													
2004	6	6	1	0.00	0.00	0.13	0.26	0.28	0.50													
2001	6	15	3	0.06	0.73	0.10	0.20	0.42	1.36													
2001	6	11	2	0.08	0.52	0.03	0.05	0.16	0.28													
2002	6	115	19	0.40	0.29	-0.03	-0.06	-0.72	-1.47													
2002	6	11	2	-0.14	0.31	-0.17	-0.34	0.11	0.20													
2006	6	24	4	0.37	0.73	-0.45	-1.00	-0.93	-4.22													

# Exhibit 2

Exhibit 2  
Apple

Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years of Data	Total Emp-Years	Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect		r2
			Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C+L	T-Stat	
	11	294	0.98	13.53	0.74	3.11	0.80	0.04	0.34	-0.06	1.64	0.05	0.81	-0.13	0.84	0.70	0.71
	11	501	0.98	13.42	0.87	4.91	2.46	1.09	-0.70	-0.67	5.33	1.71	-1.82	-1.18	3.56	4.85	0.92
	11	223	0.98	13.33	0.65	2.41	1.15	0.97	0.09	-0.08	2.58	1.52	0.26	-0.19	2.12	2.15	0.73
	11	169	0.97	12.72	0.70	2.79	1.29	1.49	-0.57	0.28	2.17	1.67	-1.00	0.46	2.78	2.20	0.72
	11	352	0.95	9.16	0.71	2.82	0.92	-0.22	0.76	0.16	1.56	-0.39	1.55	0.20	0.71	0.72	0.78
	11	189	0.93	7.38	0.84	4.39	1.69	0.36	0.20	0.87	1.81	0.38	0.26	0.87	2.04	1.39	0.82
	11	428	0.91	6.72	0.65	2.45	0.81	4.63	-2.48	1.62	0.53	2.82	-2.28	1.57	5.14	2.93	0.82
	11	156	0.88	5.54	0.39	1.21	0.71	0.25	0.26	-0.02	0.95	0.38	0.40	-0.67	0.96	0.77	0.29
	11	118	0.68	2.82	0.36	1.09	0.58	0.17	-0.11	-0.23	0.86	0.31	-0.16	-0.24	0.75	0.70	0.16
	11	686	-0.49	-1.69	0.43	1.33	0.66	0.47	-0.15	-0.49	0.68	0.60	-0.18	-0.40	1.13	0.73	0.52
	11	58	-0.50	-1.71	0.07	0.20	0.03	-0.11	0.21	-0.27	0.05	-0.38	0.49	-0.47	-0.09	-0.11	0.10
	10	82	-0.67	-2.52	0.03	0.08	-0.38	0.08	0.18	0.01	-0.39	0.10	0.22	0.01	-0.30	-0.19	0.34
	10	184	-0.81	-3.84	-0.25	-0.68	-0.17	0.08	0.18	-0.20	-0.20	0.11	0.24	-0.81	-0.09	-0.07	0.40
	10	110	-0.81	-3.93	0.71	2.64	0.69	0.07	-0.04	-0.53	2.98	0.46	-0.18	-1.86	0.76	2.06	0.75
	10	66	-0.89	-5.57	0.04	0.11	-0.14	-0.06	0.06	0.20	-1.03	-0.53	0.47	-1.12	-0.20	-0.92	0.36
	9	116	-0.85	-4.33	-0.55	-1.59	-0.43	0.03	0.14	-0.95	-1.37	0.14	0.54	-1.36	-0.39	-0.79	0.83
	8	44	0.98	11.69	0.59	1.27	1.84	3.27	-2.40	1.69							
	8	55	0.97	9.97	0.78	2.48	0.30	0.21	1.02	-0.21	1.13	0.37	3.49	-0.93	0.50	0.73	0.90
	8	19	0.76	2.89	-0.62	-1.78	-0.16	0.16	0.02	-0.78	-0.78	0.97	0.13	-1.91	0.00	-0.01	0.86
	8	52	-0.82	-3.57	0.02	0.05	0.14	0.08	-0.13	-0.07	0.50	0.28	-0.51	-0.36	0.22	0.40	0.57
	8	13	-0.96	-7.90	0.24	0.55	0.09	0.05	-0.03	-0.22	0.84	0.55	-0.27	-0.69	0.14	0.78	0.51
	7	71	0.99	22.21	0.95	5.95	0.54	-0.46	0.07	0.06	1.39	-0.22	0.15	0.04	0.08	0.03	0.94
	7	193	0.99	20.45	0.95	6.20	1.49	1.49	-0.41	-0.82	12.30	3.86	-2.99	1.89	2.98	0.80	1.00
	7	626	0.99	16.77	0.94	5.77	1.41	1.40	-0.29	0.07	30.92	4.57	-3.71	0.27	2.82	6.34	1.00
	7	184	0.99	16.70	0.96	6.91	1.16	1.48	-0.31	0.23	3.69	0.99	-0.69	0.27	2.64	1.81	0.97
	7	2560	0.99	14.96	0.92	4.55	0.88	0.60	0.16	-0.65	10.23	3.85	1.64	-3.23	1.48	7.27	0.99
	7	29	0.99	13.76	0.81	2.81	0.24	-0.38	0.98	0.32	0.48	-0.29	0.14	0.12	-0.14	-0.08	0.80
	7	253	0.98	12.12	0.92	4.72	0.76	1.16	0.20	-0.64	1.85	1.01	0.73	-0.66	1.92	1.84	0.95
	7	130	0.98	10.75	0.89	3.94	-0.47	5.06	1.65	-5.63	-0.64	1.93	1.97	-1.78	4.59	2.36	0.97
	7	447	0.98	10.68	0.95	6.15	1.48	0.65	0.02	-0.45	2.89	0.47	0.04	-0.35	2.12	1.64	0.96
	7	244	0.98	10.66	0.88	3.63	-0.18	-4.02	1.70	-0.93	-0.73	-3.21	3.80	-7.34	-4.20	-2.81	1.00
	7	125	0.98	9.93	0.86	3.39	0.99	1.14	0.05	0.09	4.26	3.10	0.20	0.19	2.14	5.47	0.98
	7	1364	0.98	9.91	-0.93	-4.96	0.85	0.41	0.34	-1.08	5.64	1.91	2.09	-2.89	1.26	4.61	0.99
	7	54	0.97	9.77	0.81	2.81	1.59	2.35	-1.09	2.20	5.11	4.37	-4.08	2.80	3.94	6.55	0.98
	7	236	0.97	9.58	0.97	7.42	0.99	0.57	0.28	-0.18	2.55	1.18	0.76	-0.24	1.56	3.63	0.97
	7	475	0.97	9.33	0.84	3.04	0.55	0.80	0.42	-1.16	2.01	1.71	1.67	-1.34	1.35	2.55	0.95
	7	1304	0.97	9.17	0.81	2.81	0.66	0.37	0.03	-0.87	8.39	3.50	0.50	-5.68	1.03	6.50	0.99
	7	110	0.97	8.72	0.95	6.06	1.93	1.07	-0.23	0.24	108.02	31.38	-14.63	4.22	3.00	79.73	1.00
	7	902	0.97	8.62	0.62	2.84	0.82	0.68	0.49	-1.09	13.99	3.16	7.98	-7.66	1.52	14.05	1.00
	7	371	0.97	8.61	0.94	5.61	0.64	-0.22	0.04	-0.32	3.23	-0.70	0.13	-0.45	0.42	1.05	0.95
	7	68	0.97	8.25	0.96	6.93	1.64	0.38	0.00	-0.12	1.64	0.20	0.00	-0.08	2.03	1.35	0.93
	7	61	0.96	8.15	0.59	1.48	0.73	0.90	0.29	-1.36	2.84	2.23	1.66	-2.62	1.63	2.69	0.95
	7	26	0.96	8.01	0.86	3.40	5.03	1.10	0.85	-1.59	8.22	0.94	-1.26	-0.56	4.13	3.04	0.99
	7	549	0.96	7.91	0.94	5.57	1.06	-0.90	0.48	-0.87	21.14	-4.50	9.58	-8.12	0.16	0.82	1.00
	7	127	0.96	7.88	0.93	5.24	2.07	1.20	-0.26	0.97	3.58	1.36	-0.58	0.57	3.27	3.97	0.97
	7	118	0.95	7.80	0.69	1.90	1.62	1.95	-0.25	1.40	4.18	3.14	-0.85	1.50	3.57	3.90	0.97
	7	682	0.96	7.79	0.88	3.70	1.09	0.81	0.48	-0.70	3.58	2.55	2.39	-1.62	1.80	4.59	0.98
	7	167	0.96	7.75	0.91	4.31	1.32	0.59	0.02	0.75	1.37	0.39	0.03	0.46	1.82	1.38	0.91
	7	146	0.96	7.71	0.62	1.59	0.74	0.99	0.05	-0.79	3.63	3.13	0.34	-1.83	1.72	3.72	0.96
	7	29	0.96	7.63	0.56	1.36	1.70	2.20	-0.62	1.55	2.79	2.35	-1.22	1.13	3.91	2.72	0.94
	7	121	0.96	7.62	0.87	3.46	-0.61	5.97	-1.48	-0.02	-1.34	5.40	-4.59	-0.04	5.36	7.02	0.99
	7	63	0.96	7.52	0.90	4.06	2.37	2.06	-0.91	2.63	16.54	8.37	-8.14	4.46	4.43	16.33	1.00
	7	1363	0.96	7.33	0.91	4.37	0.94	0.75	0.28	-3.10	1.79	0.89	0.73	-1.05	1.89	1.98	0.94
	7	16	0.95	7.10	0.73	2.15	2.74	8.01	-4.63	8.30	9.55	7.14	-6.76	4.97	10.75	8.46	0.99

**Exhibit 2**  
**Apple**

Job Title	Section 1		Section 2				Section 3					Section 4				Section 5		Section 6
	Years of Data	Total Emp-Years	Level Correlation Coeff	T-Stat	Change Correlation Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	r2	
	7	17	0.95	7.08	0.71	2.01	1.88	6.65	-3.30	7.09	7.10	9.22	-8.26	6.61	8.54	10.88	1.00	
	7	127	0.95	6.94	0.52	1.21	0.56	0.19	-0.28	1.66	15.61	2.26	-7.87	16.05	0.75	7.07	1.00	
	7	143	0.95	6.80	0.83	2.99	-0.30	3.49	0.41	-0.56	-0.28	2.08	-0.91	-0.41	3.19	2.94	0.95	
	7	63	0.95	6.73	0.69	1.92	1.09	2.55	-0.84	2.00	2.49	4.60	-2.54	2.18	3.64	5.17	0.98	
	7	45	0.95	6.73	0.99	12.42	2.37	-0.57	0.11	-0.28	3.89	-0.73	0.43	-0.38	1.80	3.15	0.98	
	7	98	0.95	6.52	0.84	3.11	0.42	-0.03	0.15	-0.86	2.29	-0.16	0.60	-1.47	0.39	1.18	0.93	
	7	70	0.94	6.46	0.88	3.72	1.03	3.36	0.26	1.34	1.02	0.65	0.33	0.29	4.39	1.02	0.95	
	7	182	0.94	6.42	0.96	7.04	1.85	0.66	-0.02	-0.43	20.57	4.80	-0.28	-1.92	2.51	19.20	1.00	
	7	2915	0.94	6.33	0.60	1.52	0.75	0.73	-0.18	-0.36	3.05	2.18	-0.96	-0.70	1.48	2.83	0.92	
	7	134	0.94	6.30	0.65	1.76	0.94	1.02	-0.16	0.07	8.01	7.07	-1.52	0.25	1.97	9.04	0.99	
	7	143	0.94	6.27	0.48	1.10	0.38	0.26	0.73	-1.64	0.87	0.46	1.94	-1.39	0.64	0.68	0.84	
	7	476	0.94	6.23	0.91	4.31	3.20	-2.65	-1.18	5.55	2.00	-1.31	-1.16	1.44	0.53	0.75	0.96	
	7	53	0.94	6.18	0.79	2.54	1.14	0.91	0.12	0.64	3.07	1.95	0.41	0.78	2.05	3.12	0.98	
	7	275	0.94	6.09	0.70	1.97	0.82	0.80	0.45	-1.06	2.39	1.55	1.08	-1.39	1.62	2.24	0.97	
	7	255	0.93	5.78	0.74	2.21	-0.07	2.18	0.57	-1.09	-0.15	4.59	2.06	-1.39	2.11	4.69	0.98	
	7	300	0.93	5.69	0.38	0.82	0.33	0.33	-0.09	-0.42	1.51	1.22	-0.67	-1.12	0.65	1.43	0.82	
	7	125	0.93	5.69	0.79	2.56	0.64	1.88	0.03	0.58	5.01	16.56	0.79	2.97	2.52	18.16	1.00	
	7	352	0.93	5.65	0.51	1.18	0.99	1.54	-0.48	-0.24	4.29	4.47	-2.58	-0.49	2.53	5.03	0.97	
	7	18	0.93	5.63	0.72	2.10	1.20	1.08	-0.14	0.10	2.30	1.36	-0.24	0.08	2.28	2.10	0.97	
	7	115	0.93	5.58	0.27	0.57	0.71	0.94	0.28	-1.78	0.41	0.33	0.52	-1.46	1.65	0.36	0.76	
	7	33	0.93	5.56	0.55	1.31	1.06	1.69	-0.48	-0.89	11.73	10.86	-6.30	-4.69	2.75	12.46	1.00	
	7	16	0.93	5.55	0.47	1.06	2.57	3.07	-1.01	2.89	2.51	2.15	-1.27	1.18	5.64	2.42	0.92	
	7	33	0.93	5.46	0.68	1.85	0.43	0.40	0.43	-1.40	0.92	0.30	0.85	-1.10	0.83	0.59	0.92	
	7	297	0.92	5.42	0.84	3.04	0.57	1.74	0.21	-0.65	0.73	2.15	0.46	-0.55	2.30	2.76	0.95	
	7	57	0.92	5.39	0.72	2.05	0.69	0.70	0.36	-0.74	2.04	2.46	0.95	-0.86	1.39	2.85	0.94	
	7	58	0.92	5.35	0.78	2.48	0.81	0.46	0.29	-0.50	3.21	2.06	0.77	-0.78	1.28	3.10	0.94	
	7	24	0.92	5.30	0.67	1.80	2.23	2.43	-1.17	-0.57	5.76	2.33	-1.86	-0.37	4.65	3.32	1.00	
	7	115	0.92	5.30	0.64	1.68	0.86	0.53	0.05	-1.73	81.85	34.93	6.57	63.66	1.39	58.99	1.00	
	7	103	0.92	5.23	0.35	0.74	0.71	2.91	-1.10	-0.88	1.67	3.08	-2.22	-0.72	3.62	3.03	0.94	
	7	35	0.92	5.21	0.59	1.45	0.67	4.66	-1.95	0.99	1.56	5.08	-4.15	0.64	5.33	5.82	0.99	
	7	49	0.92	5.14	0.67	1.79	1.20	0.72	0.03	-2.50	2.41	0.57	0.03	-1.91	1.92	1.15	0.98	
	7	23	0.92	5.12	0.89	3.94	1.50	-0.38	0.73	-0.15	3.16	-0.60	1.79	-0.15	1.12	1.44	0.98	
	7	431	0.91	5.03	-0.24	-0.90	-0.05	0.05	0.05	-0.41	-0.10	0.09	-0.19	-0.45	0.01	0.01	0.23	
	7	21	0.91	4.94	0.54	1.30	3.18	3.81	-0.09	4.43	4.28	3.52	-0.31	2.38	6.99	3.91	0.96	
	7	64	0.91	4.93	0.33	0.71	0.14	0.85	0.65	-1.56	2.39	11.13	11.42	-6.65	0.99	9.56	1.00	
	7	56	0.91	4.86	0.93	4.90	3.28	-0.05	-0.48	-3.16	26.16	-0.30	-13.49	-7.06	3.23	35.05	1.00	
	7	14	0.91	4.86	-0.40	-0.86	-0.07	-0.01	-0.16	0.43	-1.14	0.23	-1.50	1.66	-0.08	-0.84	0.79	
	7	59	0.91	4.83	0.88	3.68	1.77	1.31	-0.18	0.90	13.53	9.61	-1.45	2.78	3.09	24.05	1.00	
	7	48	0.90	4.69	-0.20	-0.42	0.20	0.71	0.09	-0.37	102.47	285.17	64.33	73.80	0.91	225.62	1.00	
	7	108	0.90	4.67	0.18	0.37	0.56	0.99	-0.05	-1.00	0.88	1.11	-0.11	-0.78	1.53	1.10	0.64	
	7	79	0.90	4.60	0.58	1.43	2.25	2.31	-0.78	1.25	38.83	27.91	-13.71	7.62	4.56	34.64	1.00	
	7	7	0.90	4.59	0.85	3.17	1.51	0.38	0.42	-1.42	5.15	0.96	1.67	-2.03	1.89	3.45	0.99	
	7	109	0.90	4.56	0.66	1.75	0.62	-0.68	0.79	1.44	0.91	-0.52	1.31	0.68	-0.06	-0.05	0.92	
	7	78	0.90	4.54	0.66	1.76	0.71	3.16	-0.98	-1.60	1.07	2.06	-1.27	-1.10	3.87	2.30	0.94	
	7	240	0.89	4.48	0.98	9.92	1.92	-0.16	-0.02	0.42	2.63	-0.31	-0.05	0.39	1.77	2.79	0.97	
	7	330	0.89	4.48	0.84	3.12	-0.25	1.86	0.99	-1.48	-0.16	1.60	0.94	-0.80	1.61	1.45	0.92	
	7	123	0.89	4.46	0.46	1.04	0.94	1.67	-0.18	-1.32	15.21	13.64	-4.06	-10.29	2.01	15.88	1.00	
	7	22	0.89	4.45	0.84	3.09	0.72	1.53	0.46	1.41	6.32	24.02	5.39	10.38	2.25	20.45	1.00	
	7	242	0.89	4.45	0.21	0.42	0.45	0.63	0.82	-1.10	0.56	0.71	0.44	-0.28	1.08	0.73	0.46	
	7	13	0.89	4.43	0.60	1.50	0.25	5.91	-2.76	-2.58	0.21	0.98	-0.82	-0.84	6.17	1.04	0.81	
	7	32	0.89	4.41	0.94	5.69	1.90	0.59	0.31	0.22	4.09	1.22	0.98	0.24	2.40	3.79	0.99	
	7	130	0.89	4.34	0.94	5.72	1.20	-0.23	0.25	-0.86	2.24	-0.34	0.58	-0.74	0.97	1.36	0.95	
	7	24	0.89	4.34	0.57	1.38	1.48	2.06	-0.58	-0.57	7.04	7.13	-3.42	-1.13	3.35	8.33	0.99	
	7	245	0.89	4.30	0.68	1.88	0.59	0.07	0.68	-1.60	0.97	0.11	0.86	-1.01	0.65	0.59	0.75	



Exhibit 2  
Apple

Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years of Data	Total Emp-Years	Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect		r2
			Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	
7	37	0.88	4.25	-0.04	-0.07	0.57	0.88	-0.53	0.36	1.77	2.44	-2.49	0.57	1.45	2.29	0.89	
7	34	0.88	4.25	0.15	0.30	1.13	2.90	-1.26	0.78	2.87	5.65	-3.68	0.93	4.03	5.04	0.98	
7	8	0.88	-4.20	0.89	3.94	1.47	-0.70	0.91	-1.65	9.23	-2.78	5.87	-4.83	0.78	2.67	1.00	
7	103	0.88	4.17	0.40	0.87	0.34	0.62	0.43	-0.72	1.28	1.65	1.75	-1.23	0.96	1.71	0.99	
7	7	0.88	-4.15	0.72	2.05	0.53	0.22	-0.32	-0.27	3.42	1.74	-1.18	-0.56	0.75	3.01	0.94	
7	8	0.88	-4.11	-0.04	-0.09	0.44	1.15	0.14	-0.78	0.71	1.55	0.31	-0.53	1.58	1.29	0.81	
7	28	0.88	4.08	0.45	1.02	0.07	3.01	-0.73	-2.35	0.56	12.67	-6.31	-6.82	3.09	11.84	1.00	
7	61	0.88	4.08	0.20	0.55	1.31	2.69	-1.24	-1.51	3.08	3.00	-2.32	-2.70	4.00	3.06	0.99	
7	25	0.87	4.01	0.59	1.45	0.28	3.71	-1.43	-0.39	8.63	82.49	-54.77	-6.26	3.99	78.44	1.00	
7	7	0.87	3.98	0.26	0.53	1.98	2.62	-1.42	5.06	1.68	2.14	-1.30	1.91	4.61	2.14	0.98	
7	801	0.87	3.94	0.85	3.21	3.43	-3.62	-0.07	-3.76	2.07	-1.57	-0.14	1.48	-0.19	-0.18	0.94	
7	74	0.87	3.94	0.61	1.53	0.61	1.04	0.29	-1.97	1.40	2.07	0.84	-1.88	1.64	2.22	0.93	
7	192	0.87	3.93	-0.50	-1.16	-0.27	0.05	0.31	-0.87	-0.23	0.04	0.66	-0.51	-0.22	-0.10	0.51	
7	11	0.87	3.91	0.49	1.14	-0.28	2.39	-0.62	-0.66	-0.16	0.99	-0.48	-0.16	2.11	0.87	0.81	
7	116	0.87	3.89	0.21	0.43	6.50	7.89	-2.48	6.50	2.30	2.22	-1.95	1.50	14.39	2.27	0.94	
7	239	0.87	3.89	0.89	3.90	0.95	-0.13	0.56	-0.89	1.43	-0.16	1.08	-0.59	0.82	0.81	0.90	
7	10	0.86	3.83	0.54	1.30	-4.35	-6.24	-1.52	-7.36	-0.67	0.87	-0.63	-0.57	1.80	0.66	0.80	
7	44	0.86	3.78	0.52	1.22	-0.32	-0.27	0.00	0.96	-0.20	-0.17	0.00	0.74	-0.59	-0.21	0.54	
7	21	0.86	3.69	0.69	1.91	0.77	-0.40	0.84	1.36	0.94	-0.44	1.35	0.74	0.37	0.30	0.95	
7	17	0.85	3.65	0.68	1.84	1.99	1.43	-0.04	-0.81	2.93	1.69	-0.07	-0.45	3.42	2.63	0.97	
7	563	0.85	3.60	0.92	4.56	1.94	-0.26	-0.17	0.60	0.89	-0.17	-0.12	0.17	1.68	1.12	0.84	
7	12	0.85	3.58	0.06	0.12	0.12	0.13	-0.26	-0.46	0.51	0.68	-1.37	-0.74	0.25	0.65	0.79	
7	57	0.85	3.58	0.46	1.03	-0.26	1.45	0.06	1.52	-0.14	1.18	0.96	0.40	1.19	0.60	0.89	
7	145	0.85	3.57	0.90	4.16	1.96	-0.40	-0.23	2.66	15.41	-5.76	-2.47	0.44	1.55	13.27	1.00	
7	33	0.85	3.55	0.04	0.07	0.55	0.93	0.28	-2.78	0.76	0.91	0.66	-3.50	1.48	0.86	0.95	
7	131	0.85	3.55	0.76	2.36	0.54	0.17	0.73	-1.81	1.90	0.72	2.37	-2.35	0.71	1.63	0.96	
7	267	0.84	3.52	-0.16	-0.32	0.22	0.40	1.27	-2.14	0.14	0.19	0.35	-0.20	0.51	0.17	0.51	
7	47	0.84	3.45	0.29	0.60	0.83	1.09	0.45	1.22	1.10	1.76	0.48	0.69	1.91	1.62	0.85	
7	60	0.84	3.42	0.52	1.21	0.88	0.25	-0.30	-0.36	0.54	0.17	-0.26	-0.29	1.09	0.41	0.86	
7	8	0.84	3.40	-0.06	-0.12	0.13	3.20	-1.30	-2.42	0.36	3.70	-2.62	-2.29	3.33	3.00	0.97	
7	50	0.83	3.35	0.61	1.56	0.65	0.05	0.93	-1.36	4.31	0.32	7.83	-4.65	0.70	2.62	1.00	
7	57	0.83	3.34	0.11	0.22	0.25	0.75	0.33	-0.60	0.87	2.96	1.13	-0.67	1.00	2.16	0.95	
7	20	0.83	3.33	-0.35	0.75	0.24	0.46	0.99	1.46	0.59	1.17	1.77	1.65	0.70	1.04	0.99	
7	20	0.83	3.32	-0.38	-0.83	-0.34	1.47	-0.20	-0.34	-2.79	7.80	-1.91	-1.02	1.14	3.94	1.00	
7	40	0.82	3.24	0.94	5.74	1.96	-0.82	0.43	0.51	3.60	-1.74	1.46	0.51	1.14	2.01	0.98	
7	144	0.82	3.24	0.91	4.27	1.43	-0.33	0.57	-0.59	1.18	-0.30	0.81	-0.23	1.11	0.79	0.89	
7	23	0.82	3.21	0.55	1.31	-1.37	-5.78	2.74	-18.75	-0.55	-1.16	1.17	-1.69	-7.16	-0.96	0.99	
7	72	0.82	3.17	-0.01	-0.02	-0.59	-0.65	-1.04	2.30	-0.45	-0.50	-0.46	0.44	-1.24	-0.49	0.22	
7	47	0.81	3.07	0.71	2.01	1.22	0.50	0.87	-1.01	2.88	1.31	2.57	-1.08	1.72	2.53	0.98	
7	19	0.80	3.03	0.04	0.08	2.69	4.63	-3.04	0.25	9.26	12.00	-10.11	0.44	7.32	11.71	1.00	
7	49	0.80	3.01	0.92	4.70	1.73	0.34	0.98	-0.22	2.31	0.88	1.06	-0.16	2.08	2.10	0.97	
7	29	0.80	3.01	0.94	5.36	2.26	0.64	-0.32	-0.27	10.93	8.05	-1.48	-1.13	2.90	13.34	1.00	
7	23	0.80	3.01	-0.58	-1.42	-0.22	0.76	0.03	0.23	-0.21	0.66	0.05	0.10	0.54	0.26	0.76	
7	332	0.78	2.78	0.90	4.05	1.12	0.36	0.31	-0.44	4.74	2.55	0.95	-0.89	1.48	4.45	0.99	
7	109	0.77	2.74	0.59	1.45	0.35	-0.21	0.95	-2.33	0.61	-0.28	2.10	-1.70	0.13	0.12	0.92	
7	19	0.77	2.68	0.66	1.76	-0.37	1.16	0.51	1.22	-0.10	0.75	0.29	0.23	0.79	0.20	0.84	
7	13	0.76	2.65	0.89	3.97	1.36	0.10	0.69	-1.38	1.23	0.13	0.90	-0.68	1.47	1.02	0.92	
7	11	0.74	2.49	-0.72	-2.05	-0.09	1.42	-0.90	1.22	-0.09	1.62	-1.38	0.68	1.33	0.76	0.87	
7	103	0.74	2.48	0.30	0.62	0.49	0.98	0.23	-1.43	1.27	2.94	0.68	-1.50	1.47	2.39	0.95	
7	38	0.74	2.45	0.27	0.57	1.08	3.23	-1.67	0.78	1.70	5.32	-3.32	0.56	4.31	4.19	0.98	
7	98	0.73	2.40	0.54	1.29	1.10	0.25	1.33	-1.24	2.47	0.67	3.13	-1.27	1.35	1.85	0.96	
7	103	0.73	2.39	-0.04	-0.08	0.34	0.64	0.29	-2.45	2.71	5.28	3.23	-0.15	0.99	4.33	0.99	
7	135	0.72	2.34	0.07	0.14	-0.09	0.65	0.91	-0.28	-0.15	1.69	1.26	-0.14	0.56	0.68	0.95	
7	14	0.72	2.32	0.74	2.23	-2.58	0.95	3.21	19.13	-0.23	0.38	0.42	1.02	-1.62	-0.12	0.91	

Exhibit 2  
Apple

Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years of Data	Total Emp-Years	Level Correlation Coeff	Level Correlation T-Stat	Change Correlation Coeff	Change Correlation T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	r2
7	24	24	0.70	2.22	0.23	0.48	-0.23	-0.43	0.85	-0.85	-15.24	-28.90	49.37	-12.29	-0.66	-25.59	1.00
7	25	25	0.70	2.20	0.68	1.86	0.94	0.69	0.33	-3.50	0.89	0.45	0.39	-1.53	1.62	0.82	0.88
7	38	38	0.70	2.20	0.79	2.56	0.17	2.45	-7.19	-19.15	1.03	2.54	-0.73	-0.53	11.52	1.20	0.97
7	18	18	0.66	1.95	0.11	0.22	2.32	2.16	-0.46	7.71	1.39	1.67	-0.35	1.99	4.48	1.69	0.93
7	58	58	0.66	1.95	0.07	0.15	-0.76	0.61	1.32	-2.62	-1.44	1.90	2.40	-1.36	-0.14	-0.20	0.97
7	26	26	0.65	1.90	0.43	0.95	1.80	1.35	-0.95	0.78	1.91	1.85	-0.84	0.32	3.16	2.12	0.83
7	13	13	0.65	1.90	0.51	1.18	-1.56	2.39	-0.40	6.21	-0.64	1.99	-0.29	1.79	0.83	0.26	0.99
7	51	51	0.64	1.88	0.23	0.47	1.80	1.79	-0.28	0.82	1.11	1.29	-0.21	0.21	3.59	1.32	0.74
7	14	14	0.64	1.87	0.38	0.82	0.56	0.52	0.89	-4.00	1.07	1.02	2.18	-3.39	1.08	1.20	0.97
7	57	57	0.64	1.86	-0.03	-0.05	-0.09	0.08	1.16	-3.51	-2.94	2.71	47.78	-40.82	-0.01	-0.26	1.00
7	11	11	0.63	1.82	0.45	1.01	1.08	1.26	-0.17	-1.18	3.40	3.03	-0.42	-1.01	2.93	3.65	0.97
7	24	24	0.63	1.80	0.57	1.40	-0.12	-7.51	4.87	-14.39	-0.13	-2.03	2.22	-3.54	-7.63	-1.69	0.99
7	127	127	0.62	1.70	0.04	0.08	2.05	1.95	4.08	-9.17	7.13	7.37	9.16	-8.99	4.01	7.51	0.99
7	45	45	0.62	1.79	0.82	2.90	1.18	0.46	0.62	0.77	1.08	0.92	0.90	0.58	1.64	1.07	0.97
7	36	36	0.58	1.58	0.86	3.38	3.09	0.55	-1.14	3.47	0.92	0.56	-0.39	0.63	3.64	0.88	0.87
7	52	52	0.57	1.57	0.56	1.34	0.91	-0.24	2.01	5.19	0.41	-0.17	1.13	1.29	0.67	0.21	0.91
7	137	137	0.56	1.51	0.25	0.51	0.93	0.88	-0.89	-1.03	2.28	2.86	-1.87	-1.16	1.81	2.82	0.94
7	18	18	0.55	1.49	0.33	0.69	-0.11	-0.48	2.73	-4.49	-0.25	-1.33	3.40	-0.55	-0.59	-0.78	0.98
7	13	13	0.55	1.48	0.52	1.23	0.42	-1.07	2.09	-2.76	0.47	-1.46	3.04	-1.39	-0.65	-0.46	0.97
7	59	59	0.55	1.46	0.06	0.12	0.37	0.17	0.75	-5.12	0.25	0.10	0.87	-2.95	0.54	0.18	0.93
7	16	16	0.54	1.45	0.47	1.07	3.59	2.10	0.38	3.17	2.25	1.44	0.44	0.55	5.69	1.95	0.93
7	34	34	0.54	1.42	0.41	0.90	0.30	-0.48	1.73	-2.69	1.25	-1.52	5.22	-2.97	0.01	0.02	0.98
7	33	33	0.53	1.39	0.50	1.17	0.35	-0.64	1.85	-0.64	0.37	-0.92	2.26	-0.30	-0.30	-0.20	0.94
7	41	41	0.53	1.38	0.52	1.21	0.82	0.14	0.66	-1.97	1.45	0.32	0.93	-1.55	0.96	1.06	0.86
7	46	46	0.52	1.36	0.33	0.69	1.08	1.05	-0.12	0.61	6.00	8.54	-0.08	-1.70	2.13	8.30	1.00
7	15	15	0.52	1.35	0.73	2.16	0.40	0.56	0.89	-2.38	0.20	0.51	0.62	-0.68	0.96	0.38	0.84
7	646	646	0.52	1.35	0.00	0.00	-0.17	-0.16	-0.08	-0.05	-2.19	-2.67	-0.66	-0.17	-0.33	-2.08	0.95
7	14	14	0.51	1.33	-0.20	-0.41	0.55	0.31	1.05	0.73	0.34	0.25	0.34	0.15	0.86	0.37	0.55
7	47	47	0.51	1.31	0.06	0.64	1.90	-0.37	0.00	0.63	3.25	-1.24	0.00	0.50	1.53	2.14	0.97
7	27	27	0.50	1.30	-0.11	-0.23	-1.00	1.69	0.29	-2.35	-3.14	10.67	1.89	-4.56	0.69	2.25	1.00
7	17	17	0.49	1.25	0.19	0.38	0.61	0.30	1.50	-1.86	1.24	0.79	3.44	-1.64	0.91	1.17	0.98
7	13	13	0.49	1.24	-0.72	-2.07	-2.54	2.26	-1.08	0.56	-0.86	0.91	-0.51	0.10	-0.28	-0.06	0.95
7	63	63	0.47	1.20	-0.14	-0.29	-0.42	0.43	1.07	-1.29	-0.49	0.68	1.03	-0.38	0.01	0.01	0.91
7	85	85	0.47	1.18	0.43	0.96	0.01	-0.28	1.09	0.67	0.01	-0.41	0.72	0.15	-0.27	-0.14	0.90
7	00	00	0.45	1.11	-0.74	-2.18	-0.54	-0.10	0.20	0.50	-1.72	-0.44	0.46	0.35	-0.64	-1.31	0.88
7	19	19	0.44	1.10	-0.46	-1.03	0.96	1.03	1.13	-5.03	-2.16	3.27	4.56	-5.89	1.98	2.79	1.00
7	10	10	0.44	1.08	-0.78	-2.50	-5.10	0.41	-0.38	7.95	-0.71	0.11	-0.12	0.81	-4.69	-0.46	0.79
7	69	69	0.42	1.04	-0.10	-0.20	-0.58	-2.48	1.20	12.14	-0.30	-0.89	1.11	0.64	-3.05	-1.33	0.87
7	36	36	0.42	1.03	-0.34	-0.73	-0.26	0.23	-0.76	0.15	-1.39	1.93	-2.82	-0.52	-0.03	-0.10	0.94
7	18	18	0.41	1.01	-0.78	-2.47	-0.78	0.43	0.76	-2.52	-0.18	0.16	0.64	-0.31	-0.36	-0.05	0.81
7	918	918	0.41	1.00	0.53	1.24	0.12	-0.15	-0.03	-1.01	3.62	-5.88	-0.58	-9.93	-0.03	-0.56	1.00
7	127	127	0.39	0.96	0.22	0.46	1.37	-0.53	2.19	-1.56	1.97	-1.00	3.99	-1.05	0.84	0.77	0.98
7	25	25	0.38	0.93	-0.74	-2.21	-0.57	0.13	0.23	0.63	-0.87	0.31	0.29	0.30	-0.43	-0.46	0.85
7	14	14	0.38	0.93	0.36	0.78	0.25	-0.84	2.33	-2.61	0.53	-2.31	5.52	-2.38	-0.59	-0.80	0.99
7	13	13	0.38	0.91	0.88	3.65	0.55	-0.32	0.73	-1.04	1.59	-1.27	1.52	-1.00	0.23	0.42	0.93
7	181	181	0.37	0.90	0.11	0.22	1.10	0.88	1.18	-2.46	0.60	0.62	0.54	-0.65	1.98	0.67	0.52
7	60	60	0.37	0.88	0.37	0.81	-2.58	-4.59	3.42	0.76	-1.62	-1.77	1.94	0.77	-7.17	-1.79	0.85
7	71	71	0.36	0.80	-0.17	-0.34	-2.34	-1.29	1.86	2.49	-0.88	-0.51	1.11	0.14	-3.63	-1.08	0.86
7	7	7	0.34	0.80	0.37	0.79	-0.05	-1.04	1.86	-5.93	-0.34	-3.33	18.35	20.13	-1.09	-4.77	1.00
7	33	33	0.32	0.76	-0.86	-3.42	-2.38	0.60	-0.17	0.62	-0.64	0.27	-0.09	0.11	-1.78	-0.32	0.70
7	55	55	0.31	0.73	0.08	0.16	0.42	-0.13	1.60	-3.53	0.67	-0.27	2.48	-1.65	0.29	0.29	0.94
7	133	133	0.29	0.68	-0.14	-0.28	-3.16	0.80	2.56	-15.71	-10.86	4.11	10.87	-9.37	-2.36	-5.72	1.00
7	10	10	0.26	0.61	0.40	0.87	-4.11	-1.81	3.41	4.00	-0.22	-0.52	0.90	0.41	-2.92	-0.38	0.89
7	116	116	0.09	0.20	0.41	0.89	0.90	0.57	-0.01	-0.97	1.77	1.37	-0.02	-0.80	1.46	1.77	0.89

Exhibit 2  
Apple

Job Title	Section 1		Section 2				Section 3					Section 4				Section 5		Section 6
	Years of Data	Total Emp-Years	Level Correlation		Change Correlation		Regression Coefficients					Regression T-Stats				Net Effect		r2
			Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat		
	7	29	0.08	-0.18	0.33	0.70	0.04	0.09	1.00	-2.10	0.04	0.12	-0.78	-0.64	0.13	0.08	0.73	
	7	117	0.04	0.06	0.26	0.55	-0.56	1.36	-6.15	1.05	-1.15	3.45	-3.63	0.97	0.80	1.44	0.96	
	7	26	-0.04	-0.08	0.21	0.43	-0.76	0.43	1.14	-2.09	-0.93	0.73	1.69	-1.20	-0.34	-0.26	0.99	
	7	22	-0.04	-0.10	0.17	0.34	4.02	1.91	-5.35	23.44	2.41	1.95	-2.23	2.84	5.94	2.26	0.97	
	7	31	-0.07	-0.16	0.29	0.62	-0.47	-1.28	2.00	-1.97	-0.26	-0.93	1.01	-0.32	-1.74	-0.61	0.64	
	7	11	-0.27	-0.63	0.23	0.48	0.75	0.14	0.01	-0.87	0.25	0.05	0.00	-0.37	0.89	0.17	0.21	
	7	46	-0.28	-0.65	0.02	0.03	2.17	-1.69	6.88	-6.27	1.76	-1.10	1.77	-1.60	0.48	0.21	0.82	
	7	52	-0.36	-0.87	0.37	0.79	1.19	0.84	-0.81	-2.05	2.75	2.07	-1.17	-2.10	2.04	2.78	0.95	
	7	50	-0.43	-1.05	-0.96	-6.86	-0.30	0.05	-0.07	-0.09	-6.12	1.64	-0.80	-0.54	-0.24	-3.24	0.99	
	7	49	-0.48	-1.23	0.27	0.57	-0.03	-0.11	-0.46	1.13	-0.06	-0.26	-0.43	0.48	-0.14	-0.18	0.55	
	7	164	-0.49	-1.25	-0.44	-0.97	-0.12	0.34	-0.76	0.70	-1.22	3.94	-3.94	2.00	0.22	1.43	0.86	
	7	36	-0.50	-1.29	0.05	0.10	1.28	3.22	-5.96	6.31	0.99	1.06	-0.97	1.00	4.50	1.10	0.61	
	7	21	-0.54	-1.42	0.80	2.66	1.42	0.35	-0.68	-1.28	6.57	1.85	-1.97	-2.37	1.77	4.71	0.99	
	7	59	-0.62	-1.79	0.31	0.65	0.43	0.52	-0.51	0.18	0.46	0.58	-0.70	0.24	0.94	0.59	0.48	
	7	40	-0.65	-1.92	0.35	0.74	0.75	0.85	-0.63	-0.30	0.43	0.46	-0.41	-0.22	1.61	0.50	0.92	
	6	16	0.98	9.32	0.93	4.31												
	6	19	0.96	7.34	0.85	2.85												
	6	54	0.95	7.16	0.89	3.46												
	6	48	0.93	4.91	0.94	4.62												
	6	44	0.87	3.58	0.64	1.18												
	6	20	0.87	3.48	0.45	0.72												
	6	73	0.85	3.24	-0.41	-0.78												
	6	19	0.77	2.41	0.51	1.03												
	6	6	0.76	2.35	-0.46	-0.91												
	6	15	0.75	2.31	0.90	3.40												
	6	24	0.75	2.27	0.08	0.12												
	6	6	0.75	2.26	0.53	1.07												
	6	57	0.73	2.13	-0.47	-0.92												
	6	8	0.72	2.05	0.36	0.85												
	6	10	0.71	2.04	0.55	1.14												
	6	6	0.67	1.81	0.59	1.26												
	6	6	0.63	1.61	0.81	1.95												
	6	8	0.63	1.61	0.82	2.00												
	6	11	0.60	1.49	0.83	2.59												
	6	19	0.59	1.45	0.05	0.08												
	6	12	0.48	1.08	-0.06	-0.09												
	6	19	0.47	1.07	0.04	0.07												
	6	18	0.42	0.93	-0.61	-1.09												
	6	166	0.42	0.92	-0.55	-1.14												
	6	16	0.41	0.89	0.60	1.07												
	6	53	0.38	0.82	-0.32	-0.58												
	6	13	0.36	0.78	-0.14	-0.24												
	6	39	0.34	0.73	0.87	3.11												
	6	18	0.27	0.55	-0.84	-2.21												
	6	8	0.27	0.55	0.78	1.77												
	6	10	0.13	0.27	0.10	0.14												
	6	28	0.13	0.27	0.83	2.58												
	6	12	0.11	0.22	-0.61	-1.10												
	6	24	0.08	0.17	0.12	0.22												
	6	114	0.08	0.16	0.94	4.93												
	6	22	0.04	0.08	0.58	1.22												
	6	6	0.04	0.07	0.90	3.64												
	6	90	-0.01	-0.02	0.26	0.47												
	6	87	-0.11	-0.23	-0.44	-0.84												

Exhibit 2  
Apple

Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years of Data	Total Emp-Years	Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect		r2
			Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	
	6	17	-0.16	-0.32	-0.07	-0.13											
	6	16	-0.29	-0.60	-0.78	-2.16											
	6	6	-0.30	-0.60	-0.55	-1.13											
	5	40	-0.31	-0.65	-0.11	-0.19											
	6	6	-0.45	-1.02	0.80	2.27											
	6	1206	-0.65	-1.70	0.32	0.59											
	6	13	-0.76	-2.35	-0.93	-4.48											
	6	15	-0.85	-3.22	-0.43	-0.83											

Exhibit 2  
Google

Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years of Data	Total Emp-Years	Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect		r2
			Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	
	0.94	3.15	0.89	3.63	0.08	0.07	1.36	-2.10	0.45	0.26	3.49	-3.85	0.15	0.37	0.98		
	0.91	8.58	-0.88	-5.21	-0.26	0.10	0.73	-0.87	1.01	0.27	1.53	-1.29	0.36	0.62	0.91		
	0.91	6.51	0.83	4.27	0.80	0.26	0.48	-1.30	0.87	0.13	0.35	-0.64	1.06	0.37	0.88		
	0.86	5.00	0.76	3.30	0.16	0.08	0.70	-1.49	0.40	0.14	0.85	-1.15	0.24	0.26	0.75		
	0.82	4.29	0.82	4.05	-0.08	-3.78	2.60	0.26	-0.11	-1.70	2.30	0.15	-1.86	-1.10	0.89		
	0.79	3.89	0.78	3.55	-0.21	-1.40	2.46	-2.14	-0.56	-0.52	4.01	-2.41	-1.63	-1.80	0.94		
	0.79	3.88	0.75	3.22	0.45	0.57	0.45	-2.87	0.99	0.55	0.79	-1.95	1.02	0.69	0.77		
	0.79	3.83	0.61	2.21	-0.27	-0.71	2.24	-3.07	-0.83	-1.34	4.09	-3.87	-0.98	-1.19	0.95		
	0.79	3.82	0.84	4.31	0.61	0.50	0.12	-1.31	1.49	0.56	0.20	-1.16	1.11	0.87	0.79		
	0.78	3.75	0.82	4.01	0.38	0.24	0.53	-2.31	1.00	0.27	0.99	-1.54	0.62	0.50	0.80		
	0.74	3.33	0.75	3.24	0.64	0.88	-0.45	-0.85	2.02	1.79	-1.17	-0.82	1.52	2.14	0.74		
	0.71	3.05	0.72	2.91	-0.30	-2.66	3.51	-1.03	-0.32	-1.73	2.31	-0.42	-2.97	-1.23	0.86		
	0.71	3.01	0.83	4.25	0.68	0.53	0.03	-1.25	1.35	0.47	0.04	-0.83	1.21	0.75	0.78		
	0.70	2.90	0.70	2.78	-0.29	-3.04	1.65	-1.88	-0.93	-2.14	2.97	-1.92	-1.33	-1.73	0.84		
	0.67	2.68	0.50	1.64	-0.72	-1.63	2.56	-3.79	-2.59	-3.56	4.96	-5.62	-2.35	-3.28	0.91		
	0.62	2.39	0.47	1.52	0.27	0.41	0.37	-1.40	0.48	0.50	0.37	-0.72	0.68	0.51	0.59		
	0.59	2.20	0.55	1.84	-1.63	-4.30	5.16	-4.24	-1.47	-2.51	2.86	-4.61	-6.13	-2.16	0.82		
	0.56	2.05	0.53	1.77	-2.49	-7.13	7.79	-5.04	-2.28	-3.94	4.41	-1.94	-9.62	-3.40	0.91		
	0.51	1.78	0.29	0.66	-1.01	-3.63	2.56	-2.55	-1.52	-1.63	2.14	-3.56	-2.64	-1.62	0.68		
	0.48	1.63	0.39	1.21	-0.98	-2.45	3.07	-5.23	-0.85	-1.26	1.94	-2.93	-3.43	-1.12	0.83		
	0.27	0.84	-0.02	-0.05	0.15	0.67	0.31	-4.53	0.32	0.91	0.40	-3.20	0.82	0.70	0.75		
	0.81	3.90	0.77	3.21	0.35	0.43	0.23	-2.15	1.13	0.64	0.53	-1.75	0.78	0.81	0.77		
	0.80	3.75	0.72	2.51	-0.11	-0.45	1.71	-3.16	-0.14	-0.24	1.71	-2.76	-0.56	-0.21	0.90		
	0.75	3.16	0.85	4.29	1.58	2.53	-1.92	-2.75	3.14	2.44	-2.19	-1.43	4.11	3.77	0.92		
	0.71	2.82	0.47	1.42	1.78	3.60	-2.30	0.40	2.18	2.42	-1.61	0.12	5.38	2.41	0.86		
	0.66	2.47	0.50	1.53	1.25	1.78	-1.19	1.94	3.31	3.15	-1.67	1.23	3.03	3.39	0.89		
	0.52	1.74	0.62	2.09	0.46	0.10	0.22	1.96	0.71	0.09	0.15	1.13	0.56	0.33	0.63		
	0.32	0.95	0.68	2.45	1.20	1.43	-0.38	-1.13	1.21	0.71	-0.24	-1.47	2.62	0.89	0.77		
	0.84	4.08	0.62	3.45	1.37	2.09	-0.38	-0.78	4.96	3.54	-0.84	-0.51	3.46	4.07	0.97		
	0.78	3.27	0.77	2.94	0.96	1.43	-0.46	1.25	5.78	3.93	-1.70	1.37	2.40	4.80	0.96		
	0.73	2.80	0.80	3.23	1.06	1.36	-0.75	0.45	2.63	1.44	-1.12	0.29	2.42	1.86	0.82		
	0.71	2.63	0.70	2.43	1.73	2.75	-2.01	1.05	7.82	6.48	-5.33	0.90	4.48	7.35	0.97		
	0.67	2.38	0.71	2.45	0.80	0.83	-0.13	0.74	2.41	1.03	-0.21	0.54	1.82	1.47	0.93		
	0.64	2.18	0.60	1.84	0.28	0.10	0.34	-0.24	0.63	0.10	0.55	-0.18	0.38	0.27	0.80		
	0.56	1.79	0.83	3.70	0.12	0.02	1.64	-0.59	0.18	0.03	1.22	-0.27	0.14	0.11	0.92		
	0.44	1.28	0.63	2.00	2.00	0.63	0.47	0.85	0.89	0.16	0.13	0.07	2.63	6.45	0.77		
	0.34	0.95	0.18	0.48	1.05	1.92	-0.72	-0.01	1.31	1.32	-0.55	0.00	2.97	1.39	0.63		
	0.31	0.86	0.54	1.58	-0.17	-0.39	2.01	1.80	-0.23	-0.39	1.39	0.70	-0.56	-0.34	0.85		
	0.26	0.72	0.45	1.12	0.44	0.25	-0.04	1.69	0.59	0.24	-0.03	0.85	0.69	0.39	0.60		
	0.22	0.59	0.30	0.77	-0.23	-1.16	2.30	-0.22	-0.78	-2.06	4.60	-0.12	-1.39	-1.72	0.97		
	0.09	0.23	-0.11	-0.27	0.35	0.55	0.79	2.64	1.22	1.12	0.93	1.48	0.91	1.23	0.74		
	0.06	0.17	-0.01	0.02	0.56	1.41	-0.72	-1.11	1.04	1.55	-0.68	-0.37	1.96	1.43	0.74		
	-0.15	-0.40	-0.25	-0.64	-2.18	-3.28	3.77	-6.75	-1.31	-1.20	1.38	-0.72	-5.46	-1.31	0.58		
	-0.24	-0.66	-0.10	-0.24	-1.80	-3.72	4.55	-2.91	-2.13	-2.64	3.35	-0.63	-5.52	-2.58	0.88		
	-0.54	-1.69	0.22	-0.55	-0.63	-4.27	2.21	-4.20	-1.34	-1.50	2.05	-0.46	-1.90	-1.52	0.70		
	0.78	3.05	0.71	2.38	1.10	1.74	0.04	3.10	0.75	0.51	0.02	0.24	2.84	0.58	0.85		
	0.78	3.04	0.92	3.42	1.88	2.60	-2.06	-3.37	3.56	1.63	-1.79	-3.79	4.48	2.23	0.96		
	0.71	2.50	0.70	2.21	0.75	1.66	0.17	-3.81	2.83	2.60	0.37	-3.67	2.41	2.73	0.96		
	0.69	2.34	0.76	2.58	0.56	0.45	0.11	1.61	1.59	0.57	0.16	1.11	1.01	0.92	0.87		
	0.64	2.08	0.76	2.69	1.02	1.13	-0.62	2.14	3.30	1.62	-1.01	1.81	2.15	2.18	0.96		
	0.55	1.60	0.65	3.66	1.26	-0.55	1.38	2.37	0.69	-0.15	0.40	0.32	0.71	0.14	0.87		
	0.51	1.45	0.34	0.81	0.53	0.15	1.09	0.81	0.40	0.05	0.45	0.30	0.68	0.17	0.96		
	0.39	1.03	0.49	1.26	0.46	0.80	0.61	0.32	0.75	0.80	0.43	0.22	1.26	0.79	0.95		
	0.37	0.97	0.63	1.81	0.32	0.51	1.07	-0.52	0.57	0.58	0.97	-0.59	0.83	0.58	1.00		
	0.35	0.91	0.29	0.68	-1.44	-4.65	5.64	-5.81	-0.38	-0.58	0.75	0.48	-6.10	-0.52	0.92		
	0.30	0.76	0.38	0.92	-0.60	-2.22	3.62	4.53	-0.29	-0.54	0.77	0.24	-2.82	-0.47	0.68		
	0.21	0.52	-0.24	0.55	1.32	3.39	-0.83	6.66	0.97	0.50	-0.31	1.46	2.71	0.67	0.78		
	0.20	0.50	-0.11	-0.25	0.76	1.14	0.60	3.34	0.68	0.56	0.33	0.78	1.90	0.61	0.91		
	0.17	0.42	0.82	1.36	-0.08	-0.37	1.79	-0.64	0.56	-0.67	2.41	-0.70	-0.45	-0.53	0.97		

Exhibit 2  
Google

Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years of Data	Total Emp-Years	Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect		r2
			Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	
			0.11	0.26	0.05	0.12	1.78	4.82	-3.95	-8.75	0.53	0.77	-0.50	-0.38	6.61	0.72	0.69
			0.10	0.25	0.40	0.98	-0.64	-1.19	2.95	-1.74	-0.96	-1.01	2.17	-0.88	-1.83	-1.01	0.98
			0.09	0.22	0.47	1.20	-0.22	-0.67	2.13	-1.85	-0.22	-0.39	1.04	-0.85	-0.89	-0.33	0.36
			0.08	0.19	0.61	1.74	-0.11	-0.73	1.64	0.18	-0.35	-1.28	2.37	0.16	-0.84	-0.97	0.92
			0.00	0.00	0.54	1.44	-0.19	-1.04	2.39	4.19	-0.27	-0.75	1.17	1.85	-1.24	-0.59	0.95
			-0.19	-0.47	0.56	0.87	-0.44	-1.21	2.37	-2.43	-0.85	-1.21	2.05	-1.36	-1.66	-1.10	0.94
			0.94	6.31	0.98	10.15	0.92	0.44	0.15	1.14	1.80	0.34	0.13	0.94	1.36	0.70	0.99
			0.88	4.22	0.98	9.86	1.71	1.08	-1.17	1.74	2.76	0.95	-0.85	1.42	2.78	1.63	0.99
			0.81	3.05	0.93	5.04	2.09	1.73	-1.40	4.09	11.51	5.52	-4.20	10.69	3.82	7.88	1.00
			0.80	2.97	0.89	3.87	1.89	2.59	-2.38	-0.19	1.24	0.96	-0.73	-0.07	4.48	1.07	0.91
			0.78	2.79	0.92	4.85	-0.04	-1.56	2.30	0.05	-0.07	-1.45	2.12	0.04	-1.60	-0.99	0.99
			0.77	2.68	0.87	3.50	-0.01	-0.93	1.40	1.72	-0.03	-1.46	2.31	2.49	-0.94	-1.01	0.99
			0.76	2.60	0.79	2.55	-2.08	-3.14	6.08	-2.19	-1.36	-1.38	1.95	0.97	-5.22	-1.38	0.98
			0.73	2.36	0.77	2.38	-0.48	-1.11	2.62	0.84	-6.23	-8.70	18.00	7.53	-1.59	-7.81	1.00
			0.72	2.31	0.73	2.15	-2.48	-6.19	6.26	-2.27	-3.18	-3.57	4.53	-2.61	-8.67	-3.46	1.00
			0.70	2.22	0.77	2.40	-0.76	-1.84	3.07	-1.89	9.88	-12.40	19.74	-11.61	-2.62	-11.63	1.00
			0.69	2.14	0.75	2.28	-0.69	-2.40	3.41	-7.95	-0.25	-0.42	0.61	-1.33	-3.09	-0.37	0.93
			0.67	2.00	0.86	3.38	1.48	1.36	-0.94	2.69	0.97	0.51	-0.33	0.73	2.85	0.69	0.94
			0.64	1.87	0.87	3.48	-0.04	-0.79	1.30	0.83	-0.15	-1.63	2.67	1.56	-0.83	-1.15	0.99
			0.63	1.80	0.55	1.14	0.39	-0.10	2.24	12.58							
			0.62	1.76	0.63	1.61	-0.92	-2.25	3.15	-0.31	-4.54	-5.33	8.35	-0.79	-3.17	-5.10	1.00
			0.61	1.74	0.68	1.83	0.01	-0.21	1.26	0.28	0.02	-0.15	0.74	0.18	-0.20	-0.09	0.89
			0.60	1.68	0.64	1.66	-0.89	-1.99	3.14	-0.82	-5.88	-6.81	10.24	2.59	-2.88	-6.54	1.00
			0.60	1.67	0.75	2.29	0.41	0.22	0.58	1.15	0.65	0.25	0.60	1.23	0.64	0.47	0.99
			0.57	1.56	0.90	4.02	0.15	-0.71	1.44	1.90	0.22	-0.40	1.27	1.40	-0.56	-0.26	0.97
			0.56	1.52	0.76	2.33	0.78	0.82	-0.11	0.71	1.67	0.94	-0.12	0.79	1.80	1.20	0.99
			0.50	1.29	0.39	0.83	4.23	8.54	-8.63	-7.90	1.16	1.18	-1.07	-1.13	12.77	1.17	0.85
			0.49	1.26	0.67	1.78	1.37	-4.14	4.70	24.13	0.11	-0.20	0.22	0.91	-2.77	-5.08	0.84
			0.47	1.20	0.38	0.82	-0.89	-1.63	2.83	-2.19	-3.13	-3.15	6.13	-4.50	-2.43	-3.16	0.99
			0.44	1.11	0.37	0.81	-1.66	-2.94	4.48	-8.60	-0.97	-0.89	1.31	-1.73	-4.59	-0.92	0.93
			0.44	1.09	0.42	0.92	-0.82	-1.60	2.92	-2.97	-0.73	0.68	1.34	-1.06	-2.42	-0.70	0.88
			0.43	1.06	0.46	0.99	-0.65	-1.18	2.15	-1.97	-0.59	-0.57	0.99	-0.91	-1.83	-0.58	0.98
			0.41	1.02	0.49	0.79	1.37	2.80	-2.02	0.00							
			0.40	0.97	0.54	1.36	-5.72	-13.34	10.00	5.70	-1.24	-1.20	1.52	1.11	-10.06	-1.27	0.94
			0.23	0.53	0.45	1.01	0.28	0.43	0.82	0.22	0.38	0.26	0.38	0.10	0.71	0.50	1.00
			0.22	0.51	0.16	0.22	2.66	4.65	-1.97	0.00							
			0.21	0.49	0.41	0.90	-0.83	-3.92	4.02	7.39	-2.91	-5.34	6.73	2.49	-4.76	-4.89	0.99
			0.16	0.41	0.31	0.66	-0.20	-0.67	2.19	2.39	-0.92	-1.76	4.10	1.40	-0.87	-1.55	0.98
			0.13	0.29	0.00	-0.01	-0.36	-0.84	1.88	-1.39	-1.32	-1.38	3.83	-0.58	-1.20	-1.43	0.99
			-0.30	-0.69	-0.11	-0.22	3.76	6.86	-6.03	2.52	6.36	5.97	-5.30	2.11	10.62	0.34	1.00
			-0.30	-0.69	-0.60	-1.51	-1.75	-2.91	2.70	-1.26	-2.35	-2.34	2.92	-1.03	-4.05	-2.36	0.94
			0.94	5.52	0.96	5.88											
			0.82	2.84	0.88	3.25											
			0.81	2.78	0.92	4.09											
			0.79	2.55	0.82	2.51											
			0.78	2.53	0.98	9.30											
			0.74	2.19	0.84	2.71											
			0.71	2.02	0.79	2.22											
			0.70	1.99	0.75	1.95											
			0.68	1.86	0.97	6.88											
			0.63	1.62	0.84	2.71											
			0.59	1.45	0.55	1.13											
			0.58	1.44	0.63	1.41											
			0.57	1.40	0.51	1.02											
			0.56	1.37	0.63	1.40											
			0.54	1.30	0.56	1.17											
			0.54	1.27	0.75	1.95											
			0.52	1.21	0.78	2.19											
			0.47	1.06	0.48												

Exhibit 2  
Google

Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years of Data	Total Emp-Years	Level Correlation Coeff	Level Correlation T-Stat	Change Correlation Coeff	Change Correlation T-Stat	Regression Coefficients				Regression T-Stats				Net Effect		r2
							Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	
			0.44	0.99	0.00	1.32											
			0.42	0.93	-0.50	0.99											
			0.28	0.83	0.42	0.81											
			0.35	0.74	0.27	0.49											
			0.34	0.72	0.64	1.45											
			0.30	0.63	0.05	-3.20											
			0.20	0.64	0.18	0.32											
			0.29	0.61	0.17	-0.10											
			0.25	0.51	0.18	0.32											
			0.22	0.45	-0.08	-0.14											
			0.19	0.39	-0.55	-1.13											
			0.15	0.31	0.30	0.45											
			0.14	0.29	0.57	0.69											
			0.12	0.23	0.15	0.27											
			0.10	0.20	-0.58	-1.24											
			0.09	0.18	0.01	0.01											
			0.07	0.13	0.07	0.12											
			-0.04	-0.09	-0.37	-0.69											
			-0.05	-0.11	-0.28	-0.51											
			-0.24	-0.48	-0.00	-1.31											

Exhibit 2  
Intel

Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years of Data	Total Emp-Years	Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect		r2
			Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	
11 432	0.96	10.82	0.95	8.41	-2.03	-0.51	0.64	-0.34	6.11	-0.78	1.25	-0.76	1.52	1.78	0.95		
11 1501	0.96	9.78	0.94	7.56	1.56	0.20	0.32	-0.54	6.76	0.36	0.73	-1.63	1.86	-2.07	0.95		
11 233	0.94	8.46	0.91	6.14	1.47	1.33	-0.23	-0.59	4.71	0.74	-0.25	-0.15	2.80	1.46	0.92		
11 3042	0.94	8.03	0.89	5.67	0.61	-0.39	-0.20	0.31	7.76	2.09	-1.33	1.93	1.00	4.39	0.95		
11 5042	0.92	7.30	0.91	6.21	0.81	2.22	-0.06	-0.63	3.59	2.93	-0.23	-2.53	3.03	4.40	0.96		
11 293	0.91	6.73	0.89	5.46	2.30	0.95	-0.19	-0.45	4.05	0.63	-0.18	-0.54	3.25	1.88	0.88		
11 724	0.88	5.65	0.94	8.07	1.43	0.58	0.19	-0.55	1.48	0.38	0.39	-1.04	2.00	2.26	0.91		
11 59	0.88	5.56	0.73	2.91	1.12	0.73	0.22	-0.33	2.35	0.84	0.37	-0.49	1.85	1.54	0.81		
11 394	0.88	5.52	0.88	5.34	0.63	0.35	-0.13	0.06	4.97	1.77	-0.54	0.30	0.98	3.77	0.87		
11 3991	0.88	5.51	0.96	9.32	1.21	0.07	0.45	-0.45	5.45	0.12	2.00	-1.73	1.28	2.52	0.97		
11 715	0.86	4.96	0.96	9.29	1.41	-0.28	0.49	-0.32	4.26	-0.51	1.00	-0.87	1.13	2.18	0.95		
11 437	0.85	4.85	0.84	4.41	0.76	0.75	0.30	-0.49	4.90	1.85	1.46	-2.05	1.51	5.13	0.95		
11 6082	0.85	4.85	0.94	7.51	0.81	0.45	0.34	-0.48	6.95	1.58	2.34	-2.61	1.27	4.17	0.97		
11 912	0.85	4.76	0.94	7.60	0.95	0.69	0.20	-0.59	3.95	1.52	0.76	-1.49	1.64	3.53	0.94		
11 31	0.84	4.74	0.82	4.00	0.59	0.35	0.44	-0.13	3.17	0.95	1.78	-0.52	0.94	2.06	0.91		
11 216	0.83	4.50	0.83	4.23	0.66	0.62	0.09	0.03	4.10	2.02	0.34	0.08	1.28	3.57	0.93		
11 1681	0.83	4.45	0.92	6.69	0.78	0.39	0.30	-0.37	5.05	1.16	1.00	-1.38	1.17	3.20	0.96		
11 103	0.81	4.17	0.87	4.91	0.76	0.70	0.09	-0.30	4.60	2.74	0.41	-1.11	1.46	4.40	0.93		
11 2903	0.81	4.12	0.95	8.50	0.92	0.20	0.32	-0.30	8.74	0.80	2.51	-1.67	1.12	4.24	0.98		
11 413	0.81	4.11	0.95	8.85	0.88	0.38	0.07	-0.09	3.34	1.23	0.34	-0.31	1.26	3.91	0.95		
11 1438	0.81	4.08	0.93	7.04	0.96	0.63	0.02	-0.19	3.97	1.40	0.08	-0.43	1.58	3.38	0.92		
11 2235	0.80	4.01	0.80	5.55	0.73	0.22	0.42	-0.36	7.48	1.12	3.34	-2.29	0.95	4.04	0.96		
11 4821	0.80	4.00	0.96	9.45	0.80	0.19	0.27	-0.26	12.44	1.28	3.21	-2.23	1.00	5.90	0.99		
11 638	0.80	3.98	0.91	6.09	0.77	0.53	0.13	-0.22	4.39	1.74	0.59	-0.74	1.31	3.65	0.94		
11 760	0.80	3.97	0.93	7.45	0.94	0.34	0.23	-0.29	5.66	1.03	1.16	-1.11	1.28	3.47	0.96		
11 501	0.79	3.91	0.88	5.24	0.75	0.24	0.46	-0.50	4.67	0.68	2.22	-1.90	0.99	2.42	0.96		
11 1538	0.79	3.90	0.91	6.15	0.78	0.20	0.22	-0.05	3.77	0.59	0.79	-0.17	0.98	2.32	0.90		
11 292	0.79	3.89	0.82	4.10	0.70	0.83	0.05	-0.23	3.30	2.23	0.16	-0.52	1.53	3.43	0.85		
11 528	0.79	3.81	0.75	3.23	0.84	1.07	0.36	-0.95	4.51	2.41	1.37	-3.86	1.91	3.58	0.93		
11 75	0.78	3.80	0.81	3.88	2.04	0.36	0.21	-0.24	3.00	0.25	0.19	-0.23	2.40	1.22	0.83		
11 244	0.78	3.78	0.90	5.76	0.68	0.61	0.06	-0.23	0.04	4.38	0.55	-1.62	1.29	7.24	0.97		
11 5735	0.78	3.75	0.91	6.32	0.76	0.29	0.30	-0.31	6.40	1.23	2.00	-1.53	1.06	3.83	0.97		
11 2100	0.78	3.72	0.95	9.08	0.74	0.29	0.11	-0.08	11.59	2.62	1.25	-0.67	1.03	7.72	0.99		
11 328	0.77	3.66	0.77	3.41	0.75	0.71	0.38	-0.88	4.32	2.20	1.67	-3.46	1.46	3.53	0.93		
11 1011	0.77	3.64	0.91	6.37	0.74	0.36	-0.06	0.16	6.31	1.72	-0.35	0.66	1.09	4.25	0.95		
11 811	0.77	3.62	0.84	4.31	0.67	0.44	0.10	-0.20	3.33	1.31	0.35	-0.63	1.11	2.49	0.81		
11 262	0.77	3.61	0.91	6.02	0.75	0.54	0.02	-0.17	4.38	2.21	0.07	-0.64	1.26	4.18	0.92		
11 1332	0.77	3.61	0.92	6.65	0.79	0.51	0.18	-0.35	4.64	1.69	0.85	-1.17	1.30	3.57	0.94		
11 104	0.77	3.57	0.84	4.35	0.53	0.19	0.54	-0.50	4.55	0.98	3.37	-2.61	0.72	2.80	0.96		
11 91	0.76	3.52	0.80	5.55	1.09	0.23	-0.37	0.29	3.84	0.37	-0.82	0.50	1.32	2.15	0.83		
11 127	0.75	3.44	0.90	6.00	0.35	0.00	0.00	0.68	3.84	0.02	0.00	0.63	0.35	1.75	0.86		
11 1525	0.75	3.43	0.89	5.20	0.78	0.45	-0.05	0.15	5.52	1.98	-0.25	0.54	1.24	4.20	0.95		
11 9515	0.75	3.39	0.86	4.86	0.89	0.85	-0.21	0.02	4.12	2.74	0.75	0.06	1.74	4.39	0.91		
11 369	0.74	3.35	0.97	10.62	0.80	0.28	0.13	-0.19	12.18	2.90	1.51	-1.69	1.08	8.85	0.99		
11 6476	0.74	3.31	0.97	10.88	0.88	0.17	0.11	-0.05	9.63	1.06	0.97	-0.28	1.05	5.69	0.98		
11 73	0.74	3.27	0.54	1.83	0.69	1.21	-0.10	-0.26	3.46	4.54	-0.32	-0.91	1.91	5.11	0.90		
11 1580	0.74	3.26	0.93	7.07	0.83	0.46	0.21	-0.44	4.96	1.46	1.03	-1.57	1.30	3.58	0.95		
11 165	0.73	3.24	0.94	7.74	0.74	0.42	0.07	-0.14	12.31	4.81	0.79	-1.28	1.16	10.29	0.99		
11 573	0.73	3.18	0.97	11.28	0.74	0.18	-0.01	0.68	10.93	1.79	-0.09	0.67	0.92	7.00	0.98		
11 155	0.72	3.15	0.91	6.37	1.26	-0.07	0.62	-0.88	3.47	-0.14	1.57	-2.13	1.20	1.99	0.92		
11 598	0.72	3.14	0.89	5.39	0.65	0.32	0.32	-0.39	5.41	1.65	2.06	-1.93	0.97	3.95	0.97		
11 548	0.72	3.11	0.82	4.03	0.60	0.45	0.46	-0.71	2.24	0.98	1.36	-1.45	1.05	1.88	0.88		
11 1676	0.72	3.08	0.94	7.83	0.64	0.29	-0.03	0.09	12.56	3.94	-0.39	1.04	0.93	9.19	0.99		
11 473	0.72	3.07	0.93	7.05	0.78	0.23	0.24	-0.21	11.30	1.86	2.72	-1.66	1.00	6.68	0.99		
11 402	0.71	3.06	0.88	5.17	0.60	0.22	0.25	-0.11	4.23	1.02	1.29	-0.47	0.82	2.88	0.94		
11 373	0.71	3.04	0.89	5.60	0.86	0.10	0.41	-0.58	3.15	0.26	1.26	-1.61	0.96	1.92	0.89		



Exhibit 2  
Intel

Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years of Data	Total Emp-Years	Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect		r2
			Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	
11 1906	0.71	3.04	0.97	10.58	0.85	0.22	0.13	-0.14	9.03	1.52	1.05	-0.83	1.07	-0.07	0.98		
11 3531	0.71	3.03	0.89	5.61	-0.72	0.21	0.33	-0.26	7.95	1.32	2.79	-1.66	0.93	4.71	0.98		
11 934	0.71	3.03	0.92	6.73	0.72	0.36	0.04	-0.02	7.71	2.74	0.33	-0.10	1.08	-0.22	0.98		
11 1873	0.71	3.02	0.96	9.25	0.85	-0.36	0.21	-0.43	9.91	2.60	2.01	-2.80	1.21	7.24	0.99		
11 130	0.71	2.99	0.90	5.77	0.86	0.03	0.42	-0.38	3.38	0.07	1.28	-0.96	0.89	1.59	0.89		
11 2037	0.70	2.98	0.92	6.42	0.63	0.23	0.18	-0.11	6.43	1.93	1.78	-0.85	0.86	5.50	0.98		
11 88	0.70	2.98	0.91	6.08	0.69	0.06	0.27	-0.13	3.97	-0.21	1.20	-0.54	0.75	2.06	0.91		
11 366	0.70	2.95	0.95	8.65	0.67	0.18	0.16	-0.11	13.19	2.16	2.20	-1.16	0.85	8.03	0.99		
11 137	0.70	2.94	0.67	2.53	0.71	0.37	0.76	-0.67	3.37	1.01	2.72	-2.35	1.08	2.16	0.96		
11 828	0.70	2.92	0.93	7.12	0.63	0.27	-0.10	0.06	5.89	1.78	-0.60	0.37	0.89	4.25	0.92		
11 969	0.70	2.91	0.91	6.08	0.66	0.35	-0.18	0.26	6.39	2.57	-1.14	1.47	1.01	5.16	0.94		
11 87	0.69	2.89	0.75	3.25	0.92	1.57	-0.16	-0.84	4.41	3.84	-0.58	-2.69	2.49	5.00	0.93		
11 179	0.69	2.87	0.87	5.06	0.64	0.05	0.57	-0.77	5.02	0.28	3.39	-4.03	0.69	2.74	0.96		
11 8083	0.69	2.87	0.96	9.77	0.78	0.25	-0.03	0.09	12.24	2.56	-0.35	0.73	1.03	8.27	0.99		
11 934	0.69	2.86	0.95	10.05	0.83	0.15	0.12	-0.04	12.79	1.57	1.42	-0.31	0.98	8.03	0.99		
11 1049	0.69	2.85	0.89	5.67	0.68	0.28	0.49	-0.60	4.91	1.15	2.29	-2.62	0.96	3.24	0.96		
11 146	0.69	2.84	0.65	2.41	0.39	0.43	0.29	-0.16	1.82	1.34	1.00	-0.52	0.82	1.81	0.84		
11 509	0.69	2.84	0.89	5.51	0.70	0.18	0.30	-0.17	4.88	0.78	1.58	-0.74	0.88	2.97	0.95		
11 1402	0.69	2.83	0.94	7.53	0.77	0.19	0.26	-0.54	4.41	0.81	1.16	-1.27	0.96	-3.11	0.94		
11 2097	0.68	2.81	0.97	11.60	0.78	0.15	0.07	-0.02	13.52	1.65	0.91	-0.15	0.83	8.04	0.99		
11 288	0.68	2.77	0.95	8.82	0.83	0.00	0.24	-0.10	7.42	-0.01	1.66	-0.55	0.83	3.85	0.97		
11 546	0.68	2.76	0.94	7.55	0.72	0.29	0.07	-0.04	10.66	2.99	0.76	-0.29	1.01	7.77	0.99		
11 12094	0.68	2.75	0.95	8.95	0.76	0.28	-0.02	0.07	16.18	-4.10	-0.24	0.81	1.04	11.59	0.99		
11 577	0.67	2.74	0.96	9.51	0.82	0.18	0.02	0.02	6.42	1.06	0.12	0.08	1.00	4.25	0.95		
11 59	0.67	2.72	0.45	1.42	1.17	0.66	0.28	-0.65	1.34	0.35	0.19	-0.47	1.83	0.73	0.66		
11 358	0.67	2.72	0.85	4.50	0.58	0.40	-0.23	0.30	4.89	2.47	-1.27	1.51	0.96	4.17	0.90		
11 753	0.67	2.70	0.97	11.28	0.91	0.20	-0.12	0.25	18.00	2.81	-1.70	2.54	1.11	11.93	0.99		
11 517	0.67	2.69	0.84	4.39	0.49	0.28	0.06	0.02	3.39	1.48	0.26	0.07	0.77	2.76	0.87		
11 547	0.67	2.68	0.95	9.06	0.78	0.29	0.08	-0.16	9.05	2.41	0.68	-1.08	1.07	6.51	0.98		
11 834	0.66	2.67	0.94	7.57	0.81	0.02	0.36	-0.27	8.80	0.16	3.17	-1.75	0.83	4.89	0.99		
11 556	0.66	2.66	0.89	5.49	0.73	0.28	-0.05	0.02	3.34	1.08	-0.15	0.07	1.00	2.64	0.84		
11 361	0.66	2.65	0.55	1.88	1.08	1.40	-0.82	0.92	4.01	3.26	-2.79	2.83	2.48	3.84	0.79		
11 955	0.66	2.65	0.95	8.72	0.67	0.22	-0.09	0.12	6.90	1.62	-0.68	0.72	0.89	4.72	0.95		
11 188	0.66	2.64	0.88	5.23	0.67	0.43	-0.06	0.11	7.43	3.15	-0.46	0.60	1.09	5.97	0.97		
11 169	0.66	2.63	0.92	6.63	0.78	-0.01	0.43	-0.54	4.71	-0.04	2.09	-1.30	0.77	2.49	0.96		
11 91	0.66	2.62	0.84	4.34	1.85	0.51	0.49	-0.64	3.26	0.37	0.49	-0.66	2.36	1.55	0.91		
11 94	0.66	2.60	0.84	4.32	0.61	0.00	0.79	-0.89	1.50	0.00	1.68	-1.45	0.61	0.89	0.87		
11 59	0.65	2.59	0.81	3.93	0.97	0.78	-0.29	0.10	2.52	1.75	-0.57	0.15	1.75	2.67	0.82		
11 537	0.65	2.59	0.97	11.61	0.81	0.20	0.12	-0.17	12.42	2.35	1.33	-1.54	1.01	8.04	0.99		
11 249	0.65	2.59	0.78	3.47	0.69	0.54	-0.26	0.23	3.24	1.77	-0.82	0.62	1.23	2.81	0.77		
11 557	0.65	2.58	0.90	5.76	0.61	0.06	0.35	-0.26	4.22	0.27	1.84	-1.16	0.67	2.34	0.94		
11 1504	0.65	2.54	0.90	5.83	0.64	0.19	0.22	-0.12	4.79	1.02	1.19	-0.54	0.82	3.28	0.95		
11 159	0.64	2.53	0.85	4.66	0.60	0.38	0.23	-0.42	3.11	1.51	0.77	-1.05	0.97	2.75	0.87		
11 629	0.64	2.51	0.94	7.72	0.84	0.25	-0.04	0.15	6.63	1.51	-0.25	0.67	1.09	4.72	0.96		
11 427	0.64	2.50	0.87	5.03	0.58	0.23	0.07	0.02	3.76	1.03	0.32	0.07	0.81	2.57	0.88		
11 498	0.64	2.49	0.91	6.15	0.51	0.13	0.12	-0.02	4.81	0.92	0.74	-0.12	0.64	3.09	0.93		
11 465	0.64	2.49	0.92	6.44	0.72	0.14	0.13	-0.04	4.33	0.57	0.55	-0.16	0.86	2.54	0.91		
11 7219	0.64	2.47	0.93	7.41	0.70	0.15	-0.07	0.21	6.35	0.90	-0.43	1.00	0.85	3.70	0.94		
11 641	0.64	2.47	0.97	10.80	0.70	0.06	0.07	0.09	21.05	1.36	1.47	1.02	0.76	11.66	1.00		
11 1354	0.63	2.45	0.95	8.60	0.84	0.26	-0.09	0.15	7.62	1.56	-0.57	0.63	1.10	5.05	0.96		
11 117	0.63	2.44	0.86	4.68	0.68	0.34	0.73	-1.36	1.62	0.75	1.47	-1.93	1.00	1.57	0.87		
11 3942	0.63	2.42	0.97	10.47	0.80	0.17	0.06	-0.07	7.41	1.11	0.37	-0.39	0.97	4.63	0.96		
11 198	0.63	2.42	0.75	3.16	0.68	0.59	0.33	-0.81	1.45	0.87	0.99	-1.25	1.26	1.42	0.78		
11 9310	0.63	2.40	0.93	7.13	0.67	0.26	-0.11	0.23	12.47	3.48	-1.33	2.29	0.93	8.81	0.99		
11 910	0.62	2.40	0.94	7.87	0.72	0.22	0.02	0.05	6.85	1.61	0.13	0.28	0.94	4.81	0.96		
11 1690	0.62	2.39	0.96	10.06	0.63	0.21	-0.01	-0.03	9.53	2.25	-0.08	-0.26	0.84	6.39	0.97		

Exhibit 2  
Intel

Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years of Data	Total Emp-Years	Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect		r2
			Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	
11 283	0.62	2.37	0.94	7.52	0.65	0.05	0.30	-1.25	7.48	0.42	2.54	-1.81	0.71	4.13	0.98		
11 142	0.62	2.37	0.83	4.28	0.72	0.31	0.18	-4.06	8.01	2.32	1.46	-0.33	1.03	5.73	0.99		
11 2959	0.62	2.36	0.92	6.75	0.72	0.20	0.13	-0.05	8.49	1.69	1.16	-0.35	0.92	5.64	0.98		
11 880	0.62	2.36	0.93	7.34	0.70	0.32	-0.11	0.18	16.35	5.74	-1.75	2.20	1.03	12.77	0.99		
11 202	0.61	2.34	0.85	4.49	0.77	0.28	0.22	-0.61	5.44	1.53	1.16	-2.88	1.05	3.95	0.94		
11 1662	0.61	2.32	0.91	6.38	0.61	0.23	0.05	0.04	6.83	1.91	0.38	0.23	0.85	4.89	0.97		
11 731	0.61	2.29	0.94	7.46	0.95	0.31	-0.11	0.18	5.47	1.49	-0.46	0.60	1.26	4.15	0.94		
11 2905	0.61	2.29	0.68	2.63	0.68	0.79	-0.41	0.54	4.01	2.68	-2.34	2.66	1.47	3.36	0.81		
11 2086	0.61	2.29	0.95	8.39	0.76	0.23	0.10	-0.10	11.64	2.61	1.13	-0.81	0.99	8.19	0.99		
11 1156	0.61	2.29	0.71	2.86	0.74	0.86	-0.51	0.62	6.12	4.08	-4.06	4.03	1.60	5.14	0.91		
11 91	0.61	2.29	0.64	2.33	0.90	1.18	0.26	-1.23	-2.02	1.38	0.41	-2.07	2.07	1.92	0.87		
11 1393	0.60	2.26	0.84	4.44	0.72	0.19	0.02	0.05	2.62	0.50	0.06	0.13	0.90	1.70	0.74		
11 96	0.60	2.26	0.84	4.38	0.60	0.15	0.30	-0.21	2.16	0.44	0.84	-0.51	0.75	1.50	0.84		
11 281	0.60	2.25	0.80	3.74	0.73	0.65	-0.11	-0.15	3.57	2.18	-0.38	-0.43	1.37	3.32	0.84		
11 128	0.60	2.24	0.94	7.89	0.75	0.26	-0.11	0.04	6.10	1.57	-0.60	0.20	1.01	4.27	0.93		
11 601	0.60	2.23	0.91	6.20	0.57	0.17	0.08	0.04	7.66	1.70	0.72	0.46	0.74	5.09	0.97		
11 303	0.60	2.23	0.95	1.87	0.48	0.48	0.59	-0.82	1.84	1.14	1.74	-2.12	0.96	1.62	0.90		
11 147	0.59	2.21	0.85	4.64	0.47	0.12	0.26	-0.16	5.01	0.93	2.02	-1.06	0.59	3.12	0.96		
11 281	0.59	2.20	0.68	2.60	0.63	0.93	0.49	-1.91	1.52	1.85	1.07	-3.78	1.56	2.22	0.93		
11 282	0.59	2.19	0.68	2.59	0.54	0.63	-0.41	0.42	-4.24	3.97	-1.95	1.85	1.18	4.79	0.89		
11 223	0.59	2.18	0.88	5.13	0.59	0.14	0.15	-0.09	2.98	0.53	0.52	-0.31	0.72	1.93	0.83		
11 5107	0.59	2.18	0.95	8.21	0.84	0.24	0.15	-0.28	5.52	1.16	0.75	-1.03	1.08	3.87	0.95		
11 213	0.59	2.18	0.82	4.07	0.45	0.03	0.45	-0.36	2.95	0.14	2.19	-1.50	0.48	1.57	0.92		
11 347	0.58	2.15	0.93	6.90	0.76	0.02	0.21	-0.24	3.83	0.98	0.78	-0.66	0.79	1.98	0.88		
11 135	0.58	2.15	0.76	3.34	0.38	0.13	0.15	0.03	2.29	0.56	0.61	0.13	0.50	1.49	0.80		
11 1471	0.58	2.13	0.93	7.06	0.65	0.32	-0.21	0.23	8.65	3.35	-1.84	1.76	0.97	6.81	0.96		
11 2090	0.58	2.13	0.95	9.03	0.60	0.18	0.03	-0.01	8.79	1.97	0.27	-0.07	0.79	5.91	0.97		
11 197	0.58	2.13	0.91	6.18	0.77	0.16	0.05	-0.05	3.57	0.62	0.15	-0.13	0.94	2.36	0.86		
11 35	0.58	2.12	0.76	3.32	0.76	0.57	0.11	-0.36	1.09	0.86	0.14	-0.34	1.33	1.21	0.72		
11 159	0.57	2.11	0.85	4.48	0.98	0.74	-0.47	0.30	4.51	2.97	-1.57	0.79	1.72	4.57	0.90		
11 126	0.57	2.10	0.69	2.71	1.14	1.07	-0.90	0.54	4.38	3.53	-2.14	1.07	2.21	4.76	0.86		
11 223	0.57	2.09	0.95	8.28	0.68	0.18	0.13	-0.18	6.80	1.40	0.96	-1.01	0.86	4.66	0.97		
11 934	0.57	2.08	0.91	6.20	0.82	0.33	-0.01	0.06	6.86	2.24	-0.05	0.28	1.15	5.30	0.97		
11 403	0.57	2.07	0.87	4.91	0.55	0.13	0.29	-0.30	3.25	0.58	1.23	-1.05	0.68	2.07	0.89		
11 1801	0.57	2.06	0.96	9.45	0.70	0.22	0.06	-0.09	13.13	3.09	0.78	-0.93	0.91	9.09	0.99		
11 400	0.57	2.06	0.85	4.49	0.67	0.45	-0.41	0.40	5.67	2.89	-2.06	1.68	1.11	4.91	0.90		
11 390	0.57	2.06	0.88	5.26	0.57	0.16	0.17	-0.11	3.80	0.78	0.81	-0.43	0.73	2.48	0.91		
11 115	0.56	2.04	0.57	1.97	0.29	0.30	0.31	-0.21	1.24	0.60	0.89	-0.54	0.49	1.00	0.64		
11 556	0.56	2.03	0.95	8.49	0.65	0.18	0.00	0.02	6.90	1.45	0.01	0.13	0.84	4.56	0.95		
11 120	0.56	2.03	0.62	2.25	0.48	0.36	0.00	-0.07	1.78	0.90	0.00	-0.15	0.83	1.46	0.50		
11 5274	0.56	2.02	0.92	6.52	0.60	0.23	-0.29	0.32	6.74	1.85	-2.08	2.13	0.83	4.59	0.93		
11 1349	0.56	2.01	0.85	4.53	0.74	0.46	-0.15	-0.10	4.78	2.27	-0.65	-0.40	1.20	4.06	0.88		
11 29	0.56	2.01	0.50	2.04	0.58	0.34	0.51	-0.46	0.98	0.40	0.67	-0.50	0.93	0.76	0.66		
11 83	0.56	2.00	0.61	2.18	1.56	1.26	-1.03	0.95	2.13	0.97	-0.99	0.70	2.82	1.62	0.49		
11 120	0.54	1.91	0.70	2.80	0.45	0.23	0.24	-0.29	1.75	0.70	0.55	-0.58	0.68	1.36	0.66		
11 107	0.54	1.91	0.47	1.53	0.64	1.07	0.19	-0.58	1.25	1.71	0.23	-0.65	1.71	1.82	0.62		
11 379	0.53	1.90	0.85	4.56	0.43	0.14	0.20	-0.18	3.10	0.78	0.93	-0.77	0.57	2.13	0.86		
11 164	0.53	1.89	0.89	5.65	0.64	0.30	-0.11	0.09	4.61	1.67	-0.52	0.35	0.94	3.52	0.89		
11 57	0.52	1.89	0.23	0.68	0.06	0.28	0.22	0.10	0.35	1.17	0.89	0.36	0.33	0.94	0.77		
11 2080	0.53	1.89	0.91	6.07	0.62	0.33	-0.32	0.36	9.83	4.08	-3.13	3.14	0.95	7.84	0.97		
11 92	0.53	1.89	0.86	4.78	1.23	-0.01	0.01	-0.02	-2.89	-0.01	0.02	-0.03	1.22	1.16	0.74		
11 225	0.53	1.88	0.19	0.56	2.13	5.05	-3.95	3.09	1.46	2.76	-3.11	1.66	7.18	2.51	0.81		
11 1020	0.53	1.88	0.96	9.33	0.69	0.06	0.14	-0.06	9.28	0.99	1.33	-0.47	0.75	5.24	0.98		
11 209	0.52	1.85	0.90	5.89	0.93	0.43	-0.28	0.07	5.65	2.15	-1.20	0.29	1.36	4.54	0.91		
11 732	0.52	1.82	0.88	5.35	0.66	0.43	-0.28	0.18	7.75	3.94	-3.08	1.18	1.08	6.67	0.95		
11 567	0.51	1.79	0.84	4.34	0.55	0.25	0.04	-0.15	3.28	1.11	0.17	-0.53	0.81	2.41	0.81		

Exhibit 2  
Intel

Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years of Data	Total Emp-Years	Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect		r2
			Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	
11 147	0.51	1.75	0.54	1.81	1.24	1.41	-0.21	0.81	1.90	1.20	-0.23	0.75	2.66	1.76	0.77		
11 86	0.51	1.77	0.79	3.65	1.01	0.67	-0.58	0.49	3.20	1.85	-1.27	1.00	1.68	-2.97	0.78		
11 102	0.50	1.75	0.81	3.91	0.54	0.33	0.22	-0.52	3.49	1.69	0.97	-1.88	0.87	-2.97	0.90		
11 4897	0.50	1.75	0.98	12.47	0.61	-0.16	-0.13	0.18	23.02	4.67	-3.16	3.88	0.77	14.83	0.99		
11 1283	0.50	1.74	0.96	9.47	0.92	0.32	-0.18	0.20	11.04	3.34	-1.57	1.40	1.24	8.41	0.98		
11 54	0.50	1.74	0.57	1.94	0.57	-0.03	0.42	-0.12	0.99	-0.03	0.60	-0.17	0.54	0.38	0.54		
11 222	0.49	1.67	0.70	2.76	0.62	0.56	-0.36	0.29	2.67	1.82	-0.99	0.69	1.18	2.61	0.70		
11 43	0.48	1.66	0.60	2.11	0.79	1.05	-0.64	0.46	2.16	2.61	-1.17	0.66	1.84	2.77	0.79		
11 56	0.47	1.62	0.76	3.30	0.53	0.16	0.41	0.70	1.48	0.37	0.91	-1.23	0.70	1.05	0.81		
11 536	0.46	1.56	0.88	5.16	0.70	-0.04	0.16	-0.24	3.19	-0.13	0.51	-0.82	0.66	1.60	0.81		
11 7841	0.46	1.55	0.94	7.67	0.82	0.32	-0.37	0.32	9.49	2.99	-2.82	2.15	1.14	7.10	0.96		
11 325	0.46	1.55	0.68	2.65	0.21	-0.18	0.74	-0.69	1.37	-0.86	3.29	-2.77	0.04	0.12	0.89		
11 249	0.46	1.54	0.53	1.79	1.23	1.07	-0.31	0.93	1.91	0.98	-0.36	0.84	2.29	1.50	0.62		
11 666	0.46	1.54	0.96	9.70	0.68	0.13	-0.01	-0.03	6.56	1.02	-0.06	-0.15	0.81	4.14	0.94		
11 150	0.46	1.54	0.91	6.38	0.52	0.03	0.28	-0.35	6.29	0.24	2.44	-2.80	0.55	-3.42	0.96		
11 106	0.44	1.49	0.78	3.50	0.66	0.55	-0.14	-0.07	2.86	2.01	-0.44	-0.16	1.19	2.82	0.87		
11 101	0.44	1.46	0.72	2.94	0.57	0.04	0.50	-0.56	1.39	0.07	0.93	-0.89	0.62	0.76	0.76		
11 1976	0.44	1.46	0.83	4.10	0.68	0.48	-0.47	0.38	6.73	3.82	-2.95	2.20	1.16	5.99	0.92		
11 353	0.43	1.43	0.82	4.00	0.71	0.26	-0.25	0.20	2.97	0.92	-0.68	0.53	0.99	2.16	0.72		
11 56	0.43	1.42	0.49	1.57	1.04	1.39	-0.40	-0.48	1.87	1.86	-0.52	-0.57	2.43	2.24	0.67		
11 137	0.43	1.42	0.87	4.89	0.81	0.36	-0.30	0.35	3.47	1.33	-0.87	0.85	1.18	2.78	0.83		
11 105	0.42	1.38	0.86	4.75	0.84	0.39	-0.31	0.05	6.05	2.44	-1.50	0.24	1.23	4.84	0.92		
11 125	0.41	1.34	0.58	2.03	0.57	0.70	-0.34	0.12	2.36	2.39	-0.99	0.34	1.27	2.77	0.77		
11 117	0.41	1.33	0.58	2.03	0.53	-0.23	0.87	-1.07	0.83	-0.25	1.07	-1.28	0.30	0.24	0.67		
11 65	0.40	1.32	-0.02	-0.07	0.48	1.30	-0.35	0.08	1.01	2.07	-0.47	0.10	1.78	1.85	0.59		
11 156	0.38	1.22	0.74	3.13	0.60	0.32	-0.49	0.61	3.02	1.23	-1.54	1.64	0.92	2.34	0.73		
11 35	0.35	1.14	0.50	2.06	0.13	-0.31	0.80	-0.34	0.31	-0.61	1.51	-0.55	-0.18	-0.23	0.62		
11 98	0.35	1.12	0.57	1.97	0.63	0.55	-0.53	0.51	1.92	1.28	-1.03	0.93	1.18	1.83	0.50		
11 225	0.34	1.10	0.71	2.82	0.58	-0.08	0.58	-0.82	1.30	-0.14	0.92	-1.07	0.50	0.59	0.67		
11 171	0.34	1.08	0.80	3.76	0.70	0.12	-0.43	0.34	2.96	0.49	-1.54	1.13	0.82	2.35	0.78		
11 45	0.34	1.08	0.50	1.62	0.09	-0.43	1.15	-1.06	0.44	-1.56	3.87	-3.50	-0.34	-0.82	0.87		
11 533	0.34	1.07	0.41	1.28	1.15	1.12	-0.12	1.23	1.70	1.00	-0.13	1.01	2.27	1.42	0.66		
11 243	0.33	1.05	0.86	4.84	0.61	0.24	-0.31	0.42	4.09	1.26	-1.28	1.53	0.85	2.92	0.85		
11 774	0.33	1.04	0.83	4.27	0.45	0.16	-0.02	0.16	3.29	0.89	-0.08	0.75	0.60	2.26	0.86		
11 47	0.29	0.92	0.73	3.05	0.47	-0.13	0.47	-0.46	1.38	-0.30	1.06	-0.98	0.34	0.53	0.69		
11 199	0.27	0.84	0.60	2.10	0.44	0.37	-0.19	0.36	1.43	0.96	-0.38	0.55	0.81	1.32	0.68		
11 111	0.25	0.76	0.48	1.56	0.31	0.18	0.21	-0.29	1.00	0.46	0.51	-0.68	0.49	0.81	0.53		
11 30	0.21	0.64	0.09	0.25	0.14	0.54	-0.12	0.12	0.33	0.99	-0.19	0.19	0.68	0.80	0.43		
11 31	0.17	0.52	0.66	2.46	0.23	-0.65	0.88	-1.73	0.98	-1.97	2.75	-2.07	-0.42	-0.85	0.79		
11 361	0.12	0.38	0.79	3.70	0.59	0.11	-0.24	0.14	3.26	0.46	-0.90	0.50	0.70	1.96	0.71		
11 734	-0.03	-0.08	0.47	1.51	0.66	-0.02	0.22	-0.63	3.20	-0.07	0.77	-2.03	0.63	1.49	0.84		
10 901	0.92	6.51	0.96	9.10	1.00	1.35	0.01	-0.46	15.91	4.71	0.11	-2.98	2.35	7.74	0.99		
10 102	0.91	6.40	0.96	8.44	0.74	0.98	0.53	-0.89	3.30	2.03	1.81	-2.45	1.72	3.81	0.98		
10 1266	0.90	5.74	0.83	3.66	1.53	0.26	0.50	-0.39	4.28	0.19	0.67	-0.91	1.78	1.16	0.96		
10 952	0.88	5.29	0.92	6.33	1.18	0.77	-0.03	0.15	5.46	1.56	-0.11	0.39	1.95	3.84	0.96		
10 529	0.84	4.30	0.94	7.21	0.69	0.27	0.27	-0.19	6.57	1.38	1.92	-1.09	0.97	4.10	0.97		
10 186	0.84	4.30	0.98	12.18	0.58	0.14	0.08	-0.07	11.57	1.62	1.10	-0.83	0.72	6.46	0.98		
10 262	0.82	4.10	0.82	3.73	0.59	0.48	-0.14	0.23	3.88	1.95	-0.45	0.61	1.07	3.34	0.86		
10 391	0.81	3.94	0.91	5.67	0.77	0.74	0.20	-0.66	5.36	3.11	1.24	-0.25	1.51	5.96	0.98		
10 1514	0.79	3.64	0.97	9.92	0.76	0.29	0.13	-0.09	8.76	2.15	1.07	-0.58	1.05	6.44	0.98		
10 30	0.78	3.53	0.77	2.94	0.81	-0.01	0.72	-0.73	2.23	-0.01	1.42	-1.61	0.80	0.80	0.90		
10 794	0.76	3.31	0.88	4.88	0.54	0.32	0.04	0.00	3.95	1.57	0.20	0.02	0.86	3.10	0.88		
10 25	0.75	3.21	0.69	2.31	0.65	0.88	0.44	-0.76	1.86	2.05	0.80	-0.99	1.73	2.23	0.93		
10 1794	0.74	3.12	0.96	9.71	0.68	0.20	0.15	-0.09	10.13	1.90	1.56	-0.78	0.88	6.55	0.98		
10 50	0.72	2.97	0.65	1.62	0.85	0.33	0.16	-0.42	1.54	0.42	0.26	-0.75	1.18	0.95	0.73		
10 189	0.71	2.89	0.39	1.04	0.20	0.58	0.07	-0.14	6.57	1.23	0.16	-0.27	0.78	1.17	0.77		

Exhibit 2  
Intel

Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years of Data	Total Emp-Years	Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect		r2
			Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	
	10	149	0.67	2.70	0.84	3.75	0.24	1.11	0.15	-1.83	0.32	2.13	0.30	-1.34	1.35	1.70	0.92
	10	1401	0.68	2.61	0.96	9.53	-0.72	-0.27	0.06	-4.09	9.38	2.52	0.50	-0.62	0.99	6.88	0.98
	10	81	0.68	2.61	0.75	2.95	1.20	1.12	0.39	0.27	2.19	1.58	-0.57	0.35	2.31	2.29	0.76
	10	1872	0.63	2.29	0.95	8.08	0.69	-0.29	-0.05	0.06	8.10	2.53	-0.42	0.42	0.98	6.08	0.97
	10	53	0.62	2.36	0.46	1.25	0.68	-0.75	0.23	-0.32	5.31	4.85	1.71	-1.26	1.42	5.75	0.97
	10	31	0.61	2.20	0.94	7.06	1.28	-0.42	0.82	-1.13	5.65	-1.31	2.71	-3.26	0.85	2.03	0.98
	10	40	0.60	2.09	0.89	5.10	1.03	0.47	0.29	-0.81	2.39	0.97	0.62	-1.30	1.50	2.17	0.90
	10	951	0.59	2.05	0.93	6.70	0.62	0.30	-0.24	0.25	10.29	3.72	-2.57	2.31	0.92	7.78	0.97
	10	20	0.58	2.04	0.56	1.66	0.30	-0.27	0.47	0.38	1.05	-0.68	1.35	-0.78	0.03	0.04	0.87
	10	37	0.58	2.04	0.89	4.84	1.29	0.23	0.09	0.05	2.39	0.41	0.19	0.08	1.51	2.05	0.90
	10	113	0.57	1.98	0.73	2.61	0.21	0.27	0.20	0.09	0.34	0.52	0.37	0.15	0.46	0.52	0.81
	10	464	0.57	1.97	0.82	3.86	0.84	0.93	0.34	-0.18	1.89	1.44	0.72	-0.27	1.77	2.36	0.95
	10	86	0.55	1.88	0.56	1.64	1.20	2.76	0.18	-0.29	2.28	1.80	0.22	-0.34	4.05	2.12	0.73
	10	29	0.48	1.55	0.90	5.35	0.63	0.27	0.06	-0.22	4.22	1.40	0.28	-0.76	0.90	3.16	0.90
	10	107	0.48	1.54	0.78	3.31	0.67	0.81	0.22	-0.33	3.00	3.30	0.89	-0.77	1.48	4.16	0.98
	10	878	0.47	1.52	0.92	6.24	0.96	0.40	-0.12	0.15	4.86	1.53	-0.43	0.32	1.37	3.79	0.93
	10	42	0.46	1.45	0.87	4.28	0.72	0.53	0.35	-0.76	0.50	0.79	0.45	-1.06	1.24	0.73	0.95
	10	281	0.45	1.42	0.66	2.34	0.30	0.20	0.23	-0.09	1.79	0.88	0.85	-0.28	0.50	1.48	0.78
	10	49	0.37	1.13	0.94	7.27	0.64	-0.15	0.13	-0.28	5.60	-0.83	0.83	-1.38	0.49	2.03	0.93
	10	340	0.34	1.02	0.92	6.08	0.52	0.16	0.11	-0.21	6.64	1.52	0.93	-1.61	0.68	4.43	0.96
	10	44	0.26	0.78	0.91	5.82	1.04	-0.03	0.32	-0.06	3.33	-0.08	0.84	-0.10	1.01	1.83	0.91
	10	42	0.26	0.76	0.79	3.13	3.52	1.88	-0.54	1.64	6.75	2.12	-0.70	1.94	5.21	4.68	0.97
	10	157	0.23	0.68	0.40	1.17	0.28	0.30	0.16	-0.07	0.52	0.43	0.22	-0.09	0.58	0.54	0.43
	10	20	-0.28	-0.83	-0.32	-0.88	0.07	0.37	0.13	-1.18	0.16	0.68	0.21	-1.75	0.44	0.52	0.68
	10	40	-0.34	-1.02	-0.46	-1.45	-0.16	0.35	-0.16	-1.00	-0.30	0.52	-0.25	-1.38	0.17	0.16	0.68
	9	72	0.84	4.12	0.73	2.59	2.09	0.76	0.09	-1.59	1.57	0.30	0.04	-0.56	2.86	0.82	0.81
	9	46	0.78	3.34	0.77	2.94	1.06	0.67	0.54	-0.76	1.37	0.24	0.90	-0.43	1.73	0.56	0.81
	9	105	0.78	3.31	0.79	3.13	1.15	0.86	0.01	0.49	16.00	9.29	0.16	3.20	2.02	14.45	0.99
	9	18	0.77	3.16	0.75	2.57	0.57	0.15	0.76	-0.64	0.99	0.19	1.43	-0.64	0.72	0.80	0.89
	9	50	0.75	3.01	0.85	3.89	0.77	0.92	0.37	-1.82	0.50	0.82	0.35	-0.91	1.69	0.90	0.87
	9	64	0.75	2.98	0.92	4.79	3.72	0.33	-1.05	1.80	1.60	0.23	-0.69	0.79	4.05	1.76	0.92
	9	172	0.72	2.73	0.85	3.92	0.82	0.28	0.19	-0.33	1.36	0.33	0.19	-0.26	1.10	0.91	0.75
	9	56	0.61	2.03	0.70	2.19	0.92	0.94	-0.21	0.16	3.01	1.38	-0.40	0.26	1.86	2.00	0.97
	9	67	0.43	1.26	0.21	0.49	0.05	-0.30	0.88	-0.96	0.13	-0.54	1.61	-1.59	-0.26	-0.31	0.71
	9	17	0.36	1.01	0.55	1.31	5.91	3.81	-2.42	0.48	2.49	2.36	-2.09	0.41	9.72	3.51	0.96
	9	13	0.17	0.46	0.58	1.41	0.10	-0.15	0.52	-0.29	0.10	-0.12	0.49	-0.29	-0.05	-0.02	0.79
	9	52	0.06	0.22	0.60	1.81	1.09	0.34	0.38	-0.65	3.50	1.05	1.09	-0.99	1.43	2.58	0.65
	8	283	0.99	17.90	0.97	9.74	0.86	-0.01	0.14	-0.01	6.72	-0.02	1.05	-0.05	0.86	1.38	0.97
	8	864	0.98	12.28	0.98	9.96	0.78	0.36	0.18	-0.24	12.01	1.90	2.63	-1.88	1.12	5.69	0.99
	8	1526	0.98	11.20	0.96	7.28	0.74	-0.02	0.19	-0.29	4.74	-0.04	1.16	-0.93	0.72	1.51	0.95
	8	50	0.97	10.69	0.96	7.81	0.91	0.17	-0.09	-0.12	4.85	0.29	-0.41	-0.31	1.08	1.69	0.94
	8	420	0.97	10.36	0.97	8.73	0.74	0.26	0.09	-0.37	14.77	1.66	1.63	-3.65	1.00	6.01	1.00
	8	288	0.97	9.49	0.94	6.39	0.61	-0.04	0.04	-0.20	3.39	-0.12	0.20	-0.59	0.56	1.27	0.91
	8	1097	0.96	8.48	0.93	5.58	0.33	0.09	0.08	-0.19	6.90	1.22	1.57	-2.02	0.42	4.05	0.98
	8	92	0.96	8.30	0.89	4.29	0.96	0.07	0.18	0.08	2.47	0.07	0.45	0.10	1.04	0.95	0.83
	8	1185	0.96	8.16	0.87	4.03	-0.83	1.18	0.23	-0.63	6.14	1.86	1.17	-2.32	2.01	3.07	0.98
	8	119	0.95	7.73	0.95	6.85	2.48	0.75	-0.22	-0.28	10.75	1.97	-0.77	-0.58	3.23	6.38	0.99
	8	51	0.94	7.02	0.78	2.77	1.06	-0.02	0.37	-1.71	1.74	-0.02	0.46	-1.30	1.04	0.65	0.87
	8	355	0.94	6.66	0.83	3.30	0.43	0.46	0.05	-0.18	6.58	3.98	0.68	-1.37	0.89	5.85	0.97
	8	52	0.93	6.35	0.93	4.25	0.95	1.33	-0.16	-0.76					2.27		1.00
	8	34	0.93	6.18	0.79	2.87	1.11	1.33	0.17	-0.44	5.31	2.15	0.87	-1.46	2.44	3.08	0.97
	8	503	0.92	5.98	0.93	5.53	0.90	0.61	0.24	-0.11	2.37	0.56	0.68	-0.16	1.52	1.58	0.93
	8	258	0.92	5.71	0.90	4.56	0.79	0.15	0.00	-0.13	2.48	0.24	0.01	-0.20	0.94	1.20	0.82
	8	143	0.92	5.70	0.92	5.17	1.24	0.94	0.02	0.19	3.82	1.16	0.06	0.30	2.18	2.45	0.93
	8	24	0.91	5.51	0.96	7.81	1.50	-0.86	1.10	-1.27	6.40	-2.06	3.94	-4.57	0.64	1.47	0.89
	8	612	0.91	5.50	0.81	3.09	0.44	-0.08	0.40	-0.43	2.85	-0.31	2.41	-1.42	0.36	1.01	0.93

Exhibit 2  
Intel

Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years of Data	Total Emp-Years	Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect		r2
			Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	
8 359	0.91	5.42	0.84	3.53	0.59	-0.10	0.50	-0.47	4.45	-0.38	3.44	-1.76	0.49	1.50	0.07		
8 152	0.91	5.32	0.67	2.01	0.43	0.75	0.12	-0.29	3.08	3.03	0.66	-1.03	1.18	3.60	0.92		
8 98	0.90	5.00	0.94	6.09	1.44	0.21	0.34	-0.88	2.61	0.25	0.71	-0.98	1.65	2.00	0.94		
8 374	0.90	4.94	0.70	2.19	0.58	0.04	0.53	-0.61	1.66	0.04	1.49	-1.07	0.62	0.51	0.92		
8 689	0.90	4.92	0.94	6.39	0.87	1.50	0.11	-0.83	1.67	1.34	0.30	-1.87	2.37	3.38	0.99		
8 203	0.88	4.53	0.95	6.80	2.06	0.25	0.42	-0.73	43.99	2.43	7.04	-9.31	2.32	23.84	1.00		
8 291	0.87	4.41	0.94	6.05	0.64	0.46	0.13	-0.17	7.62	3.81	1.42	-1.07	1.10	7.90	0.99		
8 65	0.86	4.07	0.65	1.90	1.50	0.76	-1.51	1.81	3.06	1.28	-1.46	3.42	2.26	5.65	0.95		
8 318	0.84	3.77	0.91	4.83	0.65	0.35	0.12	-0.06	4.53	1.09	0.46	-0.15	1.00	2.51	0.98		
8 24	0.83	3.68	0.74	2.49	0.68	2.29	-0.04	-3.04	1.06	2.31	-0.04	-1.88	2.97	2.25	0.94		
8 217	0.82	3.50	0.96	7.70	0.63	0.17	-0.21	0.27	32.69	6.94	-8.81	6.75	0.80	22.98	1.00		
8 201	0.82	3.49	0.84	3.43	0.54	0.30	-0.04	0.29	3.35	1.40	-0.22	0.89	0.84	2.75	0.88		
8 214	0.81	3.36	0.94	6.24	0.62	0.24	-0.01	-0.06	5.00	1.47	-0.07	-0.25	0.86	3.82	0.96		
8 304	0.81	3.36	0.52	1.37	0.23	-0.07	0.37	-0.43	0.84	-0.18	1.44	-0.91	0.16	0.25	0.72		
8 296	0.80	3.32	0.91	4.94	0.48	-0.43	0.41	-0.06	4.05	-1.36	2.10	-0.27	0.66	0.12	0.98		
8 116	0.80	3.30	0.91	4.95	0.62	0.34	0.34	-0.76	6.72	2.40	3.96	-4.87	0.95	6.30	0.99		
8 180	0.78	3.03	0.88	4.13	0.40	0.16	0.13	0.04	2.75	0.51	0.48	0.12	0.56	1.37	0.94		
8 1077	0.77	2.97	0.92	5.43	0.57	0.26	0.09	-0.20	5.81	2.02	0.83	-1.08	0.83	4.79	0.98		
8 155	0.77	2.92	0.95	6.98	0.93	0.43	0.15	0.20	9.92	4.50	1.94	1.44	1.36	12.17	1.00		
8 57	0.76	2.91	0.54	1.45	1.12	1.05	-0.14	1.02	2.78	1.85	-0.43	1.65	2.17	2.40	0.80		
8 48	0.76	2.90	0.40	0.99	0.70	0.73	0.12	0.95	4.75	3.51	0.65	3.27	1.44	4.65	0.95		
8 64	0.76	2.90	0.56	1.52	0.80	1.22	-0.14	0.05	1.51	1.36	-0.12	0.04	2.02	1.58	0.70		
8 246	0.76	2.87	0.93	5.66	0.99	-0.13	-0.37	0.25	6.76	-0.56	-2.17	0.84	0.86	3.16	0.97		
8 157	0.75	2.81	0.88	4.13	0.60	0.45	0.59	-0.51	1.01	0.65	1.45	-0.67	1.06	1.60	0.94		
8 33	0.75	2.81	0.83	3.26	2.33	0.41	-1.63	0.25	2.80	0.74	-3.32	0.78	2.74	6.78	0.98		
8 41	0.75	2.81	0.39	0.95	0.84	0.76	0.40	0.84	2.52	1.52	1.13	1.30	1.60	2.23	0.90		
8 67	0.75	2.79	0.11	0.24	0.77	1.02	0.04	0.44	1.60	1.67	0.10	0.68	1.79	1.75	0.62		
8 62	0.75	2.77	0.94	6.08	0.71	0.47	0.37	-0.27	85.90	58.69	59.28	-22.97	1.17	129.23	1.00		
8 72	0.75	2.75	0.37	0.89	0.42	0.15	0.43	-0.35	0.63	0.13	0.81	-0.32	0.57	0.33	0.67		
8 69	0.72	2.56	0.20	0.46	0.04	0.06	0.24	-0.32	0.34	0.35	1.65	-1.25	0.10	0.41	0.76		
8 10	0.72	2.51	0.15	0.34	0.79	1.77	-0.84	0.75	0.58	1.22	-0.48	0.26	2.50	1.06	0.64		
8 460	0.71	2.50	0.91	5.04	0.53	0.31	0.03	-0.20	8.28	3.96	0.37	-1.66	0.84	7.81	0.99		
8 28	0.71	2.44	0.29	0.67	0.18	0.87	0.37	-1.00	0.59	1.92	1.14	-1.66	1.06	1.65	0.93		
8 53	0.70	2.38	0.41	1.00	0.47	0.78	0.27	0.65	0.89	1.19	0.45	0.62	1.25	1.31	0.74		
8 102	0.69	2.34	0.66	1.76	1.06	2.22	-0.21	-0.04	3.56	2.14	-0.18	-0.03	3.26	2.68	0.95		
8 33	0.69	2.32	0.74	2.47	1.60	0.84	-1.27	1.94	8.75	5.92	-5.09	5.55	2.44	10.41	0.99		
8 324	0.67	2.23	0.56	1.60	0.29	0.18	0.23	0.05	2.30	1.15	1.57	0.20	0.47	2.02	0.90		
8 14	0.67	2.20	0.55	1.48	1.25	0.61	0.13	1.89	6.47	2.56	0.58	4.51	1.86	5.42	0.98		
8 132	0.65	2.11	0.94	5.98	0.89	0.41	-0.13	-0.37	5.32	2.31	-0.80	-1.43	1.30	5.86	0.98		
8 34	0.65	2.10	0.52	1.38	0.59	0.38	0.09	0.89	10.55	5.92	1.33	7.48	0.96	10.05	0.99		
8 79	0.65	2.08	0.85	3.63	0.62	-0.05	0.89	-1.07	1.95	-0.11	1.98	-1.94	0.57	1.11	0.95		
8 730	0.65	1.65	0.64	1.86	0.68	0.64	-0.30	0.87	5.55	5.21	-1.91	3.72	1.32	6.73	0.97		
8 1281	0.55	1.60	0.61	1.71	0.53	0.64	-0.17	0.62	3.75	4.51	-0.97	2.35	1.17	5.18	0.96		
8 355	0.52	1.51	0.79	2.88	0.72	0.44	-0.25	0.06	1.72	1.02	-0.51	0.08	1.16	1.83	0.76		
8 206	0.48	1.33	0.76	2.39	0.64	0.48	-0.37	0.49	3.56	2.52	-1.65	1.38	1.13	3.80	0.90		
8 4110	0.47	1.30	0.91	4.91	1.00	0.51	-0.33	0.45	5.46	3.02	-1.71	1.44	1.52	5.74	0.97		
8 644	0.46	1.26	0.88	4.20	0.58	0.31	-0.10	0.24	6.08	3.00	-0.98	1.35	0.87	5.57	0.97		
8 108	0.45	1.24	-0.42	-1.03	0.73	0.61	0.36	0.72	0.39	0.34	0.25	0.27	1.34	0.39	0.74		
8 64	0.45	1.24	0.74	2.44	0.77	0.88	-0.32	0.58	2.46	3.63	-0.96	1.22	1.65	3.75	0.95		
8 23	0.44	1.19	0.47	1.18	0.54	0.53	0.02	0.79	1.33	1.22	0.03	0.97	1.07	1.56	0.75		
8 82	0.43	1.18	0.31	0.72	0.42	0.30	0.30	0.17	0.65	0.36	0.44	0.13	0.72	0.57	0.47		
8 412	0.39	1.04	-0.03	-0.07	0.18	0.64	-0.14	0.58	1.06	3.52	-0.61	1.70	0.82	2.81	0.91		
8 334	0.37	0.98	0.91	5.06	0.62	0.30	-0.01	-0.13	4.92	2.26	-0.08	-0.59	0.91	4.64	0.97		
8 97	0.26	0.65	0.13	0.30	0.31	0.33	0.16	0.99	2.27	2.30	0.93	3.30	0.65	2.74	0.97		
8 41	0.19	0.48	0.43	1.08	1.06	-0.70	1.54	-0.85	0.70	-0.30	0.82	-0.31	0.36	0.11	0.76		
8 151	0.10	0.24	-0.46	-1.15	-0.41	-0.50	0.48	-0.43	-2.83	-3.01	3.66	-1.77	-0.91	-3.25	0.90		

Exhibit 2  
Intel

Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years of Data	Total Emp-Years	Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect		r2
			Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	
	8	17	0.09	0.23	0.04	0.10	-0.56	-0.38	1.10	-1.61	-0.55	-0.23	-0.50	-0.80	-0.94	-0.37	0.70
	7	104	0.99	14.44	0.82	2.85	1.14	1.18	-0.09	-0.01	1.48	1.03	-0.25	-0.01	2.32	1.59	0.86
	7	163	0.99	13.23	0.85	3.20	0.57	0.15	0.26	-0.17	170.84	47.89	194.68	-80.66	0.71	117.74	1.00
	7	283	0.98	10.30	0.90	4.19	0.89	0.35	0.05	-0.14	2.34	1.14	0.35	-0.51	1.24	1.91	0.97
	7	245	0.97	9.67	0.79	2.57	1.32	0.61	-0.15	0.49	3.19	2.10	-0.84	1.67	1.94	2.94	0.95
	7	236	0.97	8.77	0.68	1.87	1.14	0.88	-0.17	0.10	17.95	15.90	-6.89	2.33	2.02	18.15	1.00
	7	18	0.96	8.21	0.38	0.82	-0.14	0.87	-0.01	-0.31	-0.12	1.14	-0.02	-0.36	0.75	0.49	0.87
	7	43	0.95	7.10	0.23	0.47	0.31	0.93	0.23	-0.25	0.21	0.95	0.33	-0.22	1.24	0.59	0.60
	7	26	0.95	6.90	0.26	0.53	-0.70	0.15	0.73	-1.01	-0.49	0.12	1.14	-1.09	-0.55	-0.21	0.84
	7	116	0.95	6.82	0.67	1.83	0.38	0.04	0.24	-0.10	2.45	0.44	4.00	-1.02	0.42	1.74	0.99
	7	38	0.95	6.61	0.71	2.03	0.38	0.23	0.56	-0.87	0.16	0.16	0.55	-0.48	0.61	0.19	0.77
	7	118	0.94	6.35	0.25	0.52	0.97	1.19	0.03	-0.07	3.95	6.27	0.33	-0.46	2.16	5.16	0.99
	7	331	0.94	6.31	0.74	2.23	0.48	1.24	0.22	0.07	0.32	0.76	0.30	0.05	1.72	0.69	0.87
	7	23	0.94	6.28	0.30	0.64	1.69	1.01	-0.35	1.06	8.89	8.16	-3.65	7.14	2.70	0.52	0.99
	7	47	0.94	6.16	-0.04	-0.08	0.69	0.12	-0.28	1.02	4.52	0.77	-3.15	7.38	0.81	3.08	0.99
	7	58	0.94	6.02	0.84	3.08	0.65	0.16	0.42	-0.70	0.37	0.12	0.54	-0.54	0.81	0.32	0.84
	7	389	0.93	5.80	0.98	1.41	0.81	0.37	-0.06	0.32	1.48	1.15	-0.25	0.87	1.19	1.41	0.83
	7	114	0.92	5.11	0.86	3.44	0.98	1.26	-0.50	0.28	9.71	4.95	-2.37	1.04	2.24	7.23	0.99
	7	78	0.91	4.78	0.84	3.06	0.64	0.46	0.57	-0.63	3.30	1.03	1.65	-1.35	1.10	1.96	0.98
	7	11	0.91	4.77	0.56	1.36	0.52	0.56	0.59	-0.99	0.18	0.33	0.46	-0.38	1.09	0.28	0.74
	7	10	0.90	4.64	-0.21	-0.43	-0.52	0.03	0.29	0.55	-0.13	0.02	0.15	0.17	-0.48	-0.09	0.38
	7	154	0.90	4.59	0.80	3.86	0.70	-0.35	0.38	-0.27	0.72	-0.53	0.94	-0.44	0.34	0.22	0.92
	7	38	0.89	4.28	0.91	4.34	-2.43	1.12	-0.12	0.31	1.55	1.02	-0.19	0.28	3.56	1.80	0.95
	7	57	0.88	4.22	-0.01	-0.03	0.30	1.33	0.01	0.44	0.14	0.80	0.01	0.23	1.63	0.45	0.68
	7	14	0.88	4.19	0.79	2.56	1.41	1.63	-0.08	0.17	3.38	1.26	-0.13	0.20	3.04	1.94	0.96
	7	93	0.88	4.10	0.51	1.17	0.39	0.53	0.14	-0.10	0.19	0.43	0.15	-0.07	0.91	0.31	0.54
	7	12	0.87	3.95	-0.28	-0.30	1.73	1.98	0.09	0.02	155.52	275.61	-0.38	3.81	3.72	205.65	1.00
	7	61	0.86	3.80	0.51	1.18	-2.12	-1.62	1.89	-2.71	-2.11	-1.70	3.49	-4.25	-3.75	-1.93	0.99
	7	40	0.86	3.75	0.46	1.03	0.91	0.00	-0.55	0.22	0.56	0.00	-0.99	0.23	0.91	0.33	0.75
	7	70	0.86	3.74	0.39	0.84	-0.20	-0.03	0.30	-1.19	-0.15	-0.03	0.05	-1.40	-0.23	-0.11	0.92
	7	81	0.86	3.72	0.78	2.53	-1.55	-1.09	1.49	-0.68	2.23	-2.74	5.13	-1.23	0.46	0.53	1.00
	7	45	0.86	3.70	0.69	1.91	1.92	1.03	-0.04	0.46	1.64	1.63	-0.07	0.53	2.95	1.79	0.93
	7	35	0.85	3.68	0.64	1.86	-0.36	-0.35	0.80	-1.47	-0.46	-0.60	2.23	-2.45	-0.71	-0.54	0.97
	7	8	0.85	3.62	0.43	0.95	-3.96	-4.09	3.34	-7.26	-2.93	-3.93	4.56	-5.07	-8.05	-3.88	0.98
	7	99	0.85	3.55	0.67	1.79	1.34	0.61	-0.07	0.26	6.07	6.89	-0.77	1.70	1.94	5.87	0.99
	7	82	0.84	3.43	0.15	0.31	2.16	1.13	-0.81	1.24	2.08	1.99	-1.91	1.82	3.29	2.12	0.85
	7	31	0.84	3.40	0.72	2.00	1.23	1.76	-0.59	0.20	0.98	0.50	-0.27	0.13	2.99	0.65	0.75
	7	569	0.83	3.32	0.32	0.67	0.93	0.64	-0.26	0.11	1.39	1.68	-0.95	0.23	1.57	1.55	0.89
	7	15	0.82	3.24	0.74	2.23	2.26	1.27	-0.47	0.09	0.83	0.48	-0.55	0.07	3.53	0.67	0.78
	7	17	0.82	3.23	-0.32	-0.69	0.87	2.52	-0.26	1.72	0.39	1.54	-0.33	0.81	3.38	0.89	0.95
	7	39	0.82	3.22	0.14	0.27	-5.32	-2.53	3.26	-4.08	-1.61	-1.16	1.98	-1.77	-7.85	-1.51	0.91
	7	83	0.80	3.02	0.86	3.43	2.81	0.85	-0.20	0.69	2.06	1.02	-0.32	0.68	3.67	1.84	0.94
	7	123	0.80	2.98	0.53	1.26	0.33	0.33	0.45	-0.39	0.17	0.30	0.53	-0.27	0.66	0.23	0.78
	7	32	0.78	2.78	0.28	0.58	1.45	2.36	-0.44	-0.57	0.39	0.82	-0.23	-0.22	3.81	0.58	0.96
	7	351	0.77	2.72	0.64	1.69	-0.31	-0.68	1.13	-1.28	-0.19	-0.62	1.51	-1.12	-0.99	-0.39	0.93
	7	10	0.76	2.61	0.96	6.79	1.00	1.04	0.13	0.47	1.14	1.18	0.27	0.52	2.04	2.97	0.97
	7	47	0.73	2.42	0.35	0.75	2.28	1.32	-0.60	0.97	7.20	8.06	-4.27	4.23	3.60	7.82	0.99
	7	252	0.73	2.41	0.47	1.06	-0.88	-0.61	0.51	-1.11	-1.10	-1.37	1.79	-2.35	-1.48	-1.22	0.90
	7	162	0.72	2.40	0.90	1.15	-0.33	0.19	0.32	-0.52	0.31	0.32	0.72	-0.67	0.53	0.33	0.89
	7	59	0.73	2.38	0.53	1.26	-0.14	-0.74	1.35	-0.76	-0.11	-0.86	2.25	-0.88	-0.88	-0.44	0.97
	7	196	0.71	2.27	0.48	1.09	1.52	0.71	-0.41	0.47	0.89	0.77	-0.57	0.38	2.23	0.88	0.97
	7	38	0.71	2.27	0.31	0.65	-13.06	-9.42	3.60	-2.98	-0.77	-0.79	0.82	-0.84	-22.47	-0.78	0.48
	7	17	0.71	2.22	0.37	0.81	-0.94	0.91	0.53	0.09	0.82	1.05	0.72	0.05	1.45	1.22	0.87
	7	15	0.67	2.03	0.22	0.40	-0.74	-0.05	2.31	-3.50							
	7	100	0.61	1.75	-0.14	-0.27	-0.53	-0.77	2.84	-3.35	-0.91	-0.63	1.41	-1.40	-1.29	-0.77	0.90
	7	34	0.61	1.73	-0.05	-0.09	2.16	1.40	-1.80	0.84	3.65	4.04	-7.06	1.98	3.56	3.92	0.99

Exhibit 2  
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Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years of Data	Total Emp-Years	Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect		r2
			Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	
	7	12	0.60	1.69	0.69	1.89	1.46	4.18	-1.01	-5.31	-1.14	1.33	-0.55	-2.46	5.64	1.53	0.99
	7	18	0.60	1.67	0.68	1.85	0.81	0.54	0.75	0.35	0.11	0.15	0.24	0.07	1.35	0.14	0.82
	7	224	0.59	1.64	0.33	0.70	1.58	0.63	-0.86	0.91	1.44	1.03	-2.22	1.42	2.21	1.32	0.87
	7	27	0.59	1.62	-0.59	-1.47	-2.44	0.08	0.44	-1.28	-0.37	0.02	0.24	-0.25	-2.36	-0.24	0.75
	7	52	0.58	1.59	-0.79	-2.62	-0.26	0.23	-0.06	-0.07	-0.49	0.88	-0.33	-0.20	-0.03	-0.04	0.92
	7	31	0.54	1.45	0.67	1.83	2.56	0.74	0.13	0.92	0.54	0.30	0.06	0.26	3.30	0.50	0.76
	7	878	0.50	1.31	0.59	1.48	1.85	0.75	-0.70	0.51	46.85	35.03	-45.73	19.62	2.60	43.87	1.00
	7	88	-0.49	1.27	-0.79	-2.57	-0.24	0.32	-0.37	0.19	-2.49	6.95	-11.05	3.14	6.08	0.54	1.00
	7	9	0.49	1.26	0.61	1.34	2.99	-4.04	3.39	-3.51							
	7	14	0.42	1.04	0.60	1.48	5.60	3.82	-2.25	1.36	2.90	2.25	-2.54	0.88	9.42	3.07	0.96
	7	15	0.39	0.95	0.62	1.59	7.30	2.86	-2.56	3.35	-3.09	4.58	-3.84	3.05	10.16	5.44	0.97
	7	68	0.38	0.91	-0.51	-1.17	-4.24	-1.54	1.33	-1.91	-0.76	-0.62	0.88	-0.79	-5.88	-0.72	0.64
	7	34	0.36	0.85	-0.62	-1.57	-0.33	0.65	-0.02	0.24	-0.27	1.18	-0.05	0.27	0.32	0.19	0.93
	7	11	0.34	0.81	-0.14	-0.27	3.17	2.67	-1.80	1.00	0.34	0.63	-0.44	0.15	5.84	0.45	0.55
	7	12	0.31	0.74	0.60	1.29	-8.09	-11.14	12.08	-6.51							
	7	47	0.24	0.55	0.29	0.61	2.29	1.15	-0.73	0.52	0.65	0.61	-0.66	0.29	3.44	0.65	0.46
	7	24	0.12	0.26	0.09	0.17	4.06	2.08	-1.49	2.58	18.07	20.25	-14.21	15.65	6.14	19.43	1.00
	7	14	0.06	0.17	0.24	0.50	0.71	-0.45	0.92	0.61	0.43	-0.54	1.27	0.70	0.27	0.11	0.95
	7	187	-0.08	-0.17	0.37	0.78	-0.10	-0.08	0.12	-0.62	-0.08	-0.12	0.24	-0.97	-0.18	-0.10	0.77
	7	10	-0.18	-0.42	0.29	0.62	15.96	30.79	-17.07	35.69	5.13	4.95	-4.84	5.17	46.74	5.01	0.98
	7	15	-0.22	-0.50	0.53	1.26	1.02	-0.23	0.62	-0.63	0.20	-0.09	0.27	-0.16	0.79	0.10	0.58
	7	17	-0.43	-1.07	0.48	1.10	5.55	2.37	-2.37	1.63	3.35	2.98	-3.45	1.37	7.92	3.33	0.96
	6	201	0.97	7.68	0.99	3.51											
	6	98	0.96	7.13	0.97	6.67											
	6	8	0.96	6.83	0.92	4.03											
	6	222	0.95	5.98	0.92	4.00											
	6	8	0.95	5.93	0.72	1.48											
	6	28	0.93	5.17	0.69	0.15											
	6	72	0.92	4.75	0.48	0.95											
	6	17	0.92	4.72	0.83	2.13											
	6	25	0.91	4.36	0.24	0.35											
	6	131	0.91	4.26	0.61	3.08											
	6	12	0.90	4.06	0.78	1.78											
	6	18	0.90	4.03	0.86	2.35											
	6	402	0.89	3.99	0.79	2.26											
	6	41	0.89	3.96	0.90	2.05											
	6	77	0.89	3.95	0.77	3.12											
	6	12	0.88	3.76	0.76	1.68											
	6	36	0.88	3.74	-0.03	-0.05											
	6	8	0.87	3.57	0.13	0.22											
	6	93	0.87	3.55	0.56	1.16											
	6	23	0.87	3.50	0.91	3.87											
	6	31	0.85	3.28	0.68	1.61											
	6	53	0.84	3.09	-0.14	-0.25											
	6	485	0.84	3.07	0.76	2.02											
	6	12	0.84	3.06	0.62	1.37											
	6	44	0.83	3.00	0.56	1.17											
	6	7	0.83	2.96	0.68	1.62											
	6	21	0.82	2.89	0.38	0.59											
	6	15	0.82	2.89	0.70	1.39											
	6	6	0.78	2.52	0.68	1.32											
	6	8	0.78	2.48	0.97	5.92											
	6	22	0.77	2.45	0.61	1.34											
	6	14	0.75	2.25	0.43	0.84											
	6	20	0.75	2.24	1.00	19.25											
	6	18	0.73	2.16	-0.06	-0.10											

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Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years of Data	Total Emp-Years	Level Correlation Coeff	Level Correlation T-Stat	Change Correlation Coeff	Change Correlation T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	r2
	6	149	0.71	2.03	0.98	7.11											
	8	22	0.68	1.86	0.36	0.63											
	8	10	0.61	1.56	0.98	8.07											
	6	8	0.55	1.32	-0.12	-0.18											
	6	14	0.52	1.20	0.93	2.98											
	6	10	0.51	1.19	-0.65	-1.47											
	6	34	0.51	1.18	-0.76	-1.67											
	6	15	0.49	1.14	0.50	0.99											
	6	9	0.42	0.93	0.35	0.52											
	6	51	0.41	0.90	0.16	0.16											
	6	12	0.27	0.55	-0.80	-2.34											
	6	8	0.24	0.49	-0.33	-0.61											
	6	13	0.23	0.41	0.80	2.81											
	6	10	0.21	0.42	0.67	1.28											
	6	40	0.18	0.37	0.60	1.29											
	6	24	0.09	0.18	0.42	0.65											
	6	11	-0.02	-0.04	0.98	1.23											
	6	10	-0.41	-0.90	-0.20	-0.20											
	6	170	-0.14	-2.21	0.06	0.10											



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Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years of Data	Total Emp-Years	Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect		r2
			Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	
	11	2581	0.60	2.26	0.97	12.05	1.50	1.01	-0.26	-0.34	10.44	2.21	-1.05	-1.42	2.51	4.97	0.99
	11	997	0.59	2.16	0.95	8.57	1.13	1.33	-0.48	-0.04	8.97	3.99	-3.14	-0.29	2.46	5.57	0.96
	11	293	-0.54	1.91	0.97	11.05	1.50	1.17	-0.49	-0.08	5.38	2.13	-1.04	-0.29	2.67	3.97	0.97
	11	150	0.40	1.29	0.76	3.31	2.01	1.70	-0.80	-0.27	4.41	1.72	-1.21	-0.33	3.71	2.77	0.87
	11	140	0.26	0.81	-0.05	-0.12	0.69	1.28	-0.43	1.77	1.41	3.27	-0.74	2.01	1.97	2.14	0.71
	10	170	-0.78	-3.55	0.98	10.93	1.08	-0.18	0.15	0.12	4.91	-0.37	0.47	0.23	0.89	1.50	0.97
	10	1571	-0.55	1.85	0.79	3.16	1.34	1.01	-0.36	0.02	13.75	6.15	-3.76	0.14	2.35	11.01	0.99
	10	69	0.49	1.00	-0.30	-0.78	-0.19	0.68	-0.18	0.15	-0.28	1.47	-0.42	0.17	0.50	0.57	0.52
	10	194	0.40	1.25	0.70	2.85	1.39	1.36	-0.33	-0.44	1.89	0.78	-0.27	-0.43	2.75	1.12	0.94
	9	57	0.67	2.39	0.08	0.21	0.62	0.82	-0.05	0.38	0.53	0.91	-0.07	0.24	1.44	0.92	0.40
	9	1073	0.64	2.22	0.89	2.34	1.15	0.25	0.30	-0.41	5.94	0.88	1.77	-0.85	1.40	2.74	0.89
	9	94	-0.59	1.94	0.57	1.56	1.10	0.36	0.01	1.56	2.52	0.28	0.01	2.86	1.47	1.11	0.80
	9	81	-0.54	1.70	0.77	2.94	1.63	1.09	-0.15	0.23	4.23	1.86	-0.49	0.46	2.71	4.12	0.92
	9	758	0.53	1.67	0.08	2.05	0.34	-0.90	0.56	-0.09	0.33	-0.28	0.37	-0.02	-0.56	-0.14	0.51
	9	46	0.17	0.46	0.74	2.70	2.01	0.71	-0.11	0.23	2.20	0.66	-0.16	-0.18	2.73	2.07	0.75
	9	485	-0.01	-0.02	0.46	1.28	1.34	1.60	-0.55	0.31	4.91	3.62	-2.13	0.90	2.94	4.97	0.94
	8	113	0.80	3.25	0.91	4.90	0.44	0.22	1.21	-2.04	1.78	0.33	2.25	-5.15	0.66	0.73	1.00
	8	24	0.68	2.25	0.72	2.32	1.52	2.13	-0.81	-0.39	0.39	0.24	-0.10	-0.06	3.65	0.29	0.83
	8	29	0.61	1.87	0.76	2.62	2.07	2.81	-1.72	0.60	1.19	0.79	-0.53	0.22	4.88	0.93	0.83
	8	114	0.46	1.25	0.81	3.08	1.40	1.62	-1.07	0.50	0.84	0.48	-0.34	0.17	3.01	0.61	0.74
	8	22	0.33	0.87	-0.04	-0.10	0.37	0.68	0.51	-1.04	0.95	0.84	0.41	-0.53	1.05	0.99	0.97
	8	177	0.33	0.85	0.94	5.94	2.15	2.42	-2.11	1.22	2.70	1.46	-1.39	0.96	4.57	1.88	0.95
	8	203	-0.63	-2.00	0.13	0.30	1.48	5.00	-4.14	2.16	1.84	1.56	-1.55	1.36	7.08	1.74	0.93
	7	48	0.82	3.26	0.65	1.73	2.10	0.32	-0.98	3.09	6.73	1.26	-4.45	4.93	2.42	8.37	0.90
	7	22	0.74	2.48	0.87	3.60	2.05	1.38	-0.10	0.31	1.40	1.17	-0.13	0.20	3.43	2.57	0.93
	7	7	-0.72	-2.33	0.86	3.41	3.15	0.40	0.59	-0.24	1.69	0.08	0.14	-0.08	3.54	0.77	0.95
	7	43	0.70	2.17	0.54	1.28	0.89	1.50	-0.51	-0.15	2.01	1.58	-1.42	-0.52	2.39	1.78	0.82
	7	354	0.65	1.93	0.70	2.61	1.31	2.39	-0.84	0.14	6.24	3.53	-3.28	0.44	3.70	5.12	0.96
	7	58	0.62	1.75	0.71	2.01	0.76	3.57	-1.38	2.21	0.73	1.19	-0.94	1.30	4.33	1.71	0.87
	7	110	0.31	0.72	-0.45	-1.01	-0.86	1.35	-0.69	2.45	-2.20	2.04	-1.87	3.56	0.49	0.54	0.99
	7	143	0.21	0.48	0.90	4.19	1.05	-0.28	0.30	-0.40	5.44	-0.61	1.27	-1.51	0.77	1.34	0.98
	7	26	0.04	0.10	-0.21	-0.43	1.11	1.49	-0.29	-2.38	0.35	0.28	-0.06	-0.55	2.60	0.31	0.83
	7	136	-0.10	-0.23	-0.09	-0.18	1.45	2.95	-1.25	-0.62	2.56	3.71	-3.39	-1.23	4.41	3.45	0.93
	7	16	-0.33	-0.78	0.12	0.25	-0.39	1.05	-1.03	0.90	-0.83	1.32	-2.01	2.15	0.66	0.61	0.96
	7	378	-0.55	-1.49	0.73	2.11	1.15	-4.61	-3.16	-0.29	1.93	1.31	-1.27	-0.30	5.76	1.58	0.86
	7	25	-0.73	-2.36	0.14	0.28	-0.19	0.70	-0.18	-0.23	-0.04	0.23	-0.07	-0.03	0.50	0.08	0.62
	7	15	-0.83	-3.37	0.60	1.52	0.27	0.93	-0.52	2.08	0.62	1.93	-1.36	4.48	1.20	1.59	0.98
	6	16	0.95	6.25	0.98	8.84											
	6	180	0.93	5.09	0.93	4.44											
	6	17	0.93	4.88	0.98	8.53											
	6	120	0.92	4.71	0.71	1.74											
	6	26	0.90	4.15	0.92	4.10											
	6	14	0.89	3.88	0.96	6.19											
	6	145	0.86	3.33	0.62	1.36											
	6	90	0.84	3.14	0.57	1.20											
	6	377	0.84	3.05	0.92	4.14											
	6	167	0.84	3.04	0.96	5.81											
	6	268	0.83	3.02	0.98	9.39											
	6	203	0.81	2.81	0.42	0.81											
	6	31	0.81	2.77	0.91	3.70											
	6	19	0.80	2.65	0.33	0.61											
	6	53	0.78	2.46	0.83	2.55											
	6	118	0.75	2.28	0.85	2.83											
	6	146	0.75	2.27	0.88	3.28											
	6	39	0.74	2.22	0.93	4.32											

Exhibit 2  
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Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years of Data	Total Emp-Years	Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect		r2
			Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	
	6	96	0.71	2.02	0.95	5.47											
	6	39	0.71	2.01	0.74	1.93											
	6	91	0.71	2.00	0.49	0.97											
	6	8	0.69	1.92	0.68	1.62											
	6	26	0.67	1.81	0.19	0.33											
	6	26	0.58	1.41	0.28	0.51											
	6	31	0.57	1.39	0.77	2.08											
	6	9	0.54	1.27	-0.38	-0.71											
	6	8	0.52	1.22	0.78	2.14											
	6	405	0.46	1.02	0.60	1.30											
	6	230	0.43	0.96	0.69	1.63											
	6	14	0.42	0.93	0.36	0.67											
	6	23	0.41	0.91	0.09	0.15											
	6	15	0.40	0.88	0.17	0.30											
	6	8	0.38	0.82	-0.03	-0.06											
	6	12	0.38	0.81	0.44	0.85											
	6	18	0.35	0.75	0.27	0.49											
	6	78	0.33	0.70	0.38	0.70											
	6	38	0.33	0.69	0.85	2.82											
	6	115	0.29	0.60	0.09	0.15											
	6	37	0.28	0.58	0.59	1.27											
	6	102	0.23	0.48	0.63	1.51											
	6	74	0.07	0.14	-0.05	-0.09											
	6	24	0.05	0.10	0.46	0.94											
	6	338	0.01	0.01	0.43	0.82											
	6	17	0.00	-0.01	-0.30	-0.55											
	6	6	-0.05	-0.09	-0.13	-0.23											
	6	16	-0.09	-0.17	-0.15	-0.26											
	6	54	-0.12	-0.25	-0.93	-4.33											
	6	98	-0.13	-0.27	0.81	2.40											
	6	179	-0.24	-0.50	0.34	0.63											
	6	23	-0.26	-0.54	0.09	0.16											
	6	19	-0.29	-0.61	0.07	0.13											
	6	35	-0.36	-0.78	0.83	2.61											
	6	18	-0.38	-0.83	0.22	0.40											
	6	15	-0.40	-0.87	0.53	1.08											
	6	16	-0.46	-1.02	0.80	2.29											
	6	10	-0.47	-1.06	0.69	1.36											
	6	38	-0.85	-3.22	-0.92	-3.98											

Exhibit 2  
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Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years of Data	Total Emp-Years	Level Correlation Coeff	T-Stat	Change Correlation Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	r2
TECHNICAL_DIRECTOR	11	1872	0.94	8.31	0.80	5.65	0.55	0.31	0.03	-0.02	3.08	0.63	0.60	-0.06	0.86	1.32	0.82
ARTIST_SKETCH	11	141	0.91	6.64	0.82	4.06	1.29	1.53	-0.12	0.18	7.17	4.44	-1.77	0.40	2.82	6.78	0.94
ENGINEER_SOFTWARE	11	503	0.91	6.41	0.93	7.25	0.95	0.70	0.01	-0.25	6.38	1.64	0.14	-0.62	1.65	3.78	0.91
ANIMATOR_SUPERVISING	11	70	0.82	4.35	0.80	5.41	0.23	2.42	-0.22	2.26	0.18	1.94	-1.16	1.85	-2.65	5.34	0.89
ANIMATOR	14	772	0.81	4.21	0.78	-3.53	0.55	0.46	0.06	-0.82	5.27	1.97	1.47	-3.57	1.03	3.32	0.92
ANIMATOR_DIRECTING	11	44	0.77	3.57	0.80	5.59	-1.79	3.71	0.06	2.65	-1.16	2.92	0.44	2.22	1.92	3.94	0.92
LAYOUT_ARTIST	11	129	0.75	3.37	0.79	3.68	0.91	1.27	0.15	3.47	3.97	3.23	1.90	0.79	2.18	5.50	0.92
ENGINEER_SR_SOFTWARE	11	53	0.74	3.31	0.79	3.59	0.70	1.61	0.00	0.79	1.75	2.89	0.03	1.11	2.32	5.27	0.89
DESIGNER_PRODUCTION	11	62	0.73	3.20	0.85	4.85	-0.52	2.50	-0.22	3.16	-0.22	1.55	-0.97	1.44	1.98	2.14	0.85
ANIMATOR_FIX	11	73	0.72	3.10	0.75	3.21	0.53	1.60	-0.05	0.10	0.86	2.81	-0.33	0.10	2.12	4.47	0.83
ART_DIRECTOR	11	70	0.70	2.95	0.74	3.26	1.18	0.70	-0.04	1.55	4.33	1.74	-0.33	1.81	1.89	3.36	0.83
ENGINEER_QUALITY_ASSURANCE	11	54	0.58	2.16	0.82	4.06	0.72	1.11	0.24	-0.86	1.07	1.77	1.00	-0.75	1.83	3.79	0.80
SYSTEMS_ADMINISTRATOR_SR	14	91	0.56	2.04	0.81	3.97	1.07	0.56	0.12	0.70	5.49	2.03	1.65	1.48	1.63	4.81	0.90
ARTIST_STORY	11	247	0.55	1.98	0.46	1.48	1.27	1.09	0.01	0.41	2.96	2.26	0.07	0.43	2.36	2.98	0.70
MGR_DESKTOP_SYSTEMS	11	11	0.51	1.79	0.81	3.69	1.08	0.42	0.01	1.19	4.76	1.69	0.09	1.88	1.90	4.24	0.86
SYSTEMS_ADMINISTRATOR	11	133	0.50	1.75	0.29	0.86	0.74	1.15	0.06	-0.16	1.93	2.43	0.51	-0.20	1.89	2.50	0.62
SCIENTIST_SR	11	62	0.50	1.74	0.39	1.21	1.06	1.26	-0.09	0.07	2.05	2.72	-0.49	0.06	2.31	2.91	0.68
TECH_DIRECTOR_SUPERVISING	11	70	0.49	1.67	0.72	2.95	1.91	0.66	-0.15	3.54	4.54	1.97	-0.89	3.08	2.56	4.81	0.87
MGR_FINANCIAL_SYSTEMS	11	11	0.43	1.41	0.84	4.41	0.91	0.34	0.00	0.90	5.48	1.95	0.03	2.05	1.24	4.99	0.88
ENGINEERING_MANAGER	11	11	0.42	1.38	0.83	4.20	0.88	0.24	0.06	0.56	4.82	1.10	1.22	1.12	1.12	3.60	0.86
ENGINEER_ASSOCIATE	14	11	0.42	1.38	0.88	5.34	0.84	0.21	0.04	0.53	5.76	1.20	0.67	1.39	1.05	4.31	0.88
ARTIST_GRAPHIC	11	42	0.42	1.37	0.63	2.20	1.15	0.84	0.08	1.67	3.63	2.51	0.76	1.85	1.98	3.68	0.79
ADMINISTRATOR_TECH_DEPT	11	24	0.38	1.22	0.80	4.72	0.60	0.02	0.00	-0.13	4.06	0.10	1.73	-0.36	0.62	2.11	0.84
TECH_DIRECTOR_LEAD_CRTV_SVCS	11	11	0.34	1.09	0.84	4.35	0.95	0.24	0.06	0.73	4.89	1.21	0.87	1.37	1.19	4.01	0.86
DEVELOPER_RENDERMAN_PRODUCTS	11	11	0.21	0.63	0.79	3.66	1.01	0.25	0.03	1.20	4.52	1.44	0.40	2.01	1.25	4.30	0.85
TECH_DIRECTOR_CRTV_SVCS	11	44	0.19	0.59	0.26	0.75	0.57	0.92	0.18	-1.39	2.12	3.91	1.80	-1.63	1.49	3.88	0.85
SCULPTOR	11	22	0.17	0.52	0.41	1.29	0.84	0.35	0.07	1.70	4.85	2.20	1.10	4.11	1.19	4.57	0.92
ENGINEER_PRODUCTION_SUPPORT	11	35	0.12	0.36	0.12	0.35	0.77	0.92	0.01	-1.08	1.17	1.57	0.04	-0.60	1.69	1.58	0.39
PROJECT_MGR_STUDIO_TOOLS	10	35	0.50	1.62	0.71	2.65	1.47	0.68	0.03	-4.53	2.67	2.62	0.15	-2.98	2.15	3.58	0.85
MGR_SYSTEMS_OPERATIONS	10	10	0.41	1.28	0.74	2.66	1.03	0.40	-0.20	2.10	3.42	1.19	-0.93	1.93	1.44	2.70	0.81
ENGINEER_RENDERMAN_SUPPORT	10	15	0.28	0.83	0.68	2.45	1.10	0.40	0.02	-0.34	2.08	1.33	0.06	-0.13	1.99	2.68	0.67
VP_SOFTWARE_ENGINEERING	10	12	0.26	0.76	0.56	1.79	3.29	0.66	0.72	-9.33	2.20	1.19	1.18	-2.35	3.95	2.37	0.89
USER_INTERFACE_DESIGNER	10	20	-0.14	0.40	0.66	2.35	0.65	0.35	0.02	0.43	1.94	1.17	0.19	0.35	0.99	2.17	0.61
DIR_RENDERMAN_PRODUCT_DEV	9	9	0.34	0.95	0.78	3.01	1.66	0.14	0.12	2.32	3.77	0.40	0.55	1.91	1.80	3.41	0.88
DESIGNER_ENVIRONMENTAL	9	15	0.17	0.45	0.43	-1.07	1.85	1.06	0.30	-1.74	5.03	12.17	6.25	-4.55	2.92	7.02	0.99
ARTIST_AFTER_EFFECTS	8	25	0.58	1.73	0.73	2.36	-0.34	1.69	0.31	-2.68	-0.22	2.03	0.66	-1.00	1.35	1.15	0.85
TECHNICAL_WRITER	8	13	0.35	0.92	0.63	1.60	0.56	0.06	0.85	-6.04	11.18	17.44	10.07	16.87	1.52	20.27	1.00
TECHNICAL_LEAD_RENDERING	8	8	0.34	0.80	0.81	3.05	1.03	0.02	0.22	2.32	6.00	0.08	2.32	3.35	1.05	3.89	0.97
ARTIST_STORY_DEVELOPMENT	8	20	0.27	0.70	-0.03	-0.06	-0.05	-0.57	0.11	-1.05	-0.10	2.80	0.91	-0.20	0.52	0.30	0.86
ARCHITECT_SYSTEM	7	11	0.98	10.74	0.85	3.29	1.66	0.21	-0.06	2.78	0.99	0.19	-0.21	0.75	1.87	1.13	0.83
TECHNICAL_LEAD_BACKUP_GROUP	7	8	0.96	7.73	0.90	4.22	-0.83	4.13	-0.40	2.52	-0.40	1.31	-1.32	1.09	3.30	2.38	0.93
ART_DIRECTOR_SHADING	7	22	0.95	6.70	0.78	2.52	0.55	1.40	0.06	0.28	1.35	1.81	0.93	0.23	1.95	2.38	0.94
TECHNICAL_DIRECTOR_LEAD	7	115	0.92	5.28	0.79	2.25	1.04	1.77	-0.06	-0.58							
ENGINEER	7	7	0.85	3.60	0.76	2.31	1.18	0.74	0.09	-0.79	5.27	3.52	3.33	-1.49	1.92	5.57	0.98
DIR_STUDIO_TOOLS	7	7	0.82	3.21	0.96	7.09	2.09	0.29	0.07	5.04	0.89	0.21	0.16	0.96	2.38	1.63	0.97
MGR_MEDIA_SYSTEMS	7	9	0.78	2.79	0.86	3.41	2.94	0.52	0.05	-1.45	4.09	0.72	0.45	-0.50	3.45	4.23	0.97
ENGINEER_SR_MEDIA_SYSTEM	7	12	0.76	2.65	0.18	0.36	1.90	1.47	0.15	-1.79	7.78	8.33	11.24	-5.53	3.37	8.20	0.99
MGR_TOOLS_WORKFLOW	7	7	0.56	1.50	0.77	2.39	1.06	1.29	-0.21	-9.01	0.65	3.32	-0.40	-3.41	2.35	1.54	0.98
ENGINEER_MEDIA_SYSTEMS	7	16	0.43	1.07	0.26	0.54	0.71	0.69	0.07	2.87	-0.61	0.72	0.31	0.72	-0.02	-0.02	0.80
MGR_QUALITY_ASSURANCE	7	7	0.25	0.57	0.61	1.53	1.05	0.53	0.16	-0.85	18.35	16.92	22.03	-6.19	1.58	21.97	1.00
ENGINEER_PIPELINE	7	10	0.06	0.14	0.70	1.96	2.22	0.86	0.07	-0.01	2.35	3.50	0.68	-0.01	3.09	3.38	0.97
ENGINEER_RECORDING	7	7	0.02	0.05	0.92	4.69	0.97	0.26	0.01	0.02	509.00	279.12	44.62	3.82	1.22	620.48	1.00
HR_APPLICATION_DEVELOPER	7	7	-0.03	-0.06	-0.06	-0.11	0.09	1.52	0.90	-0.48	0.03	0.99	0.65	-0.07	1.61	0.50	0.53
RENDER_PIPELINE_SPECIALIST	7	19	-0.14	-0.32	0.55	1.33	1.06	0.37	0.26	0.00	6.82	5.52	15.44	0.01	1.43	7.54	1.00

Exhibit 2  
Pixar

Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years of Data	Total Emp-Years	Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect		r2
			Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	
ENGINEER_SOFTWARE_TECHSUPPORT	7	7	-0.85	-3.77	0.01	-0.03	-0.51	0.02	-0.01	2.20	-0.03	0.07	-0.03	1.07	-0.40	-0.55	0.58
ENGINEER_IMAGE_MASTERING	6	8	0.92	4.74	0.54	1.13											
TECHNICAL_LEAD_TBLECOM	6	6	0.92	4.65	0.75	1.97											
ENGINEER_SCREENING_ROOM	6	6	0.88	3.76	0.79	2.24											
MGR_IMAGE_MASTERING	6	6	0.88	3.60	0.78	2.18											
CGI_PAINTER	6	60	0.74	2.20	0.53	1.07											
DESIGNER_CAMERA	6	6	0.60	1.50	0.76	2.00											
ENGINEER_APPLICATIONS	6	6	0.52	1.22	0.57	0.98											
FINANCIAL_APPS_DEVELOPER	6	6	0.46	1.03	0.80	2.11											
MGR_SR_PROJECT_STUDIO_TOOLS	6	6	0.46	1.03	0.21	0.31											
LAYOUT_ARTIST_LEAD	6	6	0.42	0.93	0.27	0.40											
MEDIA_SYSTEMS_COORDINATOR	6	8	0.12	0.24	-0.35	-0.66											