Within-Firm Pay Inequality*

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Abstract

Financial regulators and investors alike have expressed concerns about high pay inequality *within* firms. Using a proprietary data set of public and private firms, this paper shows that firms with higher pay inequality—relative wage differentials between top- and bottom-level jobs—are larger and have higher valuations, better operating performance, and higher equity returns. High-inequality firms also exhibit larger earnings surprises, consistent with the argument that pay inequality is not fully priced by the market. Overall, our results support the notion that high pay disparities within firms are a reflection of better managerial talent.

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1 Introduction

Rising income inequality has garnered attention in the media and among policy circles.[1] The argument in the public domain is that inequality may be harmful for economic growth (Persson and Tabellini (1994), Alesina and Rodrik (1994), Easterly (2007), IMF (2014)), impair intergenerational mobility (OECD (2011), Corak (2013)), and even cause deep financial and real crises, such as the Great Depression or the Great Recession (Rajan (2010), Kumhof, Rancière, and Winant (2015)).

Interest in pay inequality extends beyond macroeconomics. Financial regulators and investors alike have recently expressed concerns about high pay inequality *within* firms: "High pay disparities inside a company can hurt employee morale and productivity, and have a negative impact on a company's overall performance" (Julie Fox Gorte, PAX World Management (2013)). In agreement, the Securities and Exchange Commission, as mandated by Section 953(b) of the Dodd-Frank Act, has adopted a new rule requiring companies to disclose the *ratio* of median employee pay to that of the chief executive officer.[2] Market participants have reacted positively to this pay ratio disclosure: "Grosvenor believes that income inequality and a shrinking middle class are real and important issues that our country needs to address. We believe transparency and disclosure such as that called for in the proposal, which disclose a "pay ratio," can be helpful in allowing investors to more accurately judge the effect of pay structure on company performance" (Michael J. Sacks, Grosvenor Capital Management (2013)).[3]

This study examines how pay inequality varies across firms, how it relates to firms' operating performance and valuations, and whether it is priced by the market. From a

[1] See, for instance, Alan Krueger's (2012) speech as Chairman of the Council of Economic Advisers on the "The Rise and Consequences of Inequality," as well as debates in the media and academic circles ignited by Thomas Piketty's (2014) book "Capital in the Twenty-First Century."

[2] The rule is effective October 17, 2015. Firms must comply by the fiscal year beginning on or after January 1, 2017. The pay ratio disclosure applies to all firms except emerging growth companies, smaller reporting companies, and foreign private issuers.

[3] Similarly, Anne Simpson (2013) from CalPERS concludes: "We believe that pay ratio disclosure, required by Section 953(b) of Dodd-Frank, will provide important supplementary information on the financial incentives that drive performance throughout the company, vertically, as well as horizontally, across markets [...] Companies should use this disclosure as an opportunity to provide insights on the role effective management of human capital plays with regard to value creation."

theoretical perspective, pay inequality may vary across firms for a number of reasons.[4] It could, for example, reflect differences in managerial talent, provision of incentives, or managerial rent extraction. While our main results are consistent with pay inequality being a reflection of managerial talent or incentive provision, they are inconsistent with rent extraction. Additional tests suggest that managerial talent is a key driver of pay disparities within firms.

Empirical investigation of pay inequality within firms is challenging due to lack of publicly available data. To address this challenge, we employ a proprietary data set of UK firms in which employee pay is observed at the firm-job title-year level. Job titles are grouped into nine hierarchy levels, allowing us to measure how pay disparities between hierarchy levels vary across firms. For instance, level 1, our lowest hierarchy level, includes work that "requires basic literacy and numeracy skills and the ability to perform a few straightforward and short-term tasks to instructions under immediate supervision." Typical job titles are cleaner, labourer, and unskilled worker. Level 5, in the middle of the hierarchy, includes work that "requires a vocational qualification and sufficient relevant specialist experience to be able to manage a section or operate with self-contained expertise in a specialist discipline or activity." Typical job titles are engineer, marketing junior manager, and warehouse supervisor. And level 9, the highest hierarchy level, includes "very senior executive roles with substantial experience in, and leadership of, a specialist function, including some input to the organisation's overall strategy." Typical job titles are finance director, HR director, and lawyer/head of legal.

To obtain measures of within-firm pay inequality, we construct *pay ratios* comparing the pay across different hierarchy levels within the same firm and year. For example, "pay ratio 19" compares the pay of top-level executives, such as finance and HR directors, with the pay of unskilled workers or cleaners at the bottom of the firm's hierarchy. There are nine hierarchy levels, leaving us with $(9 \times 8)/2 = 36$ pay ratios.

We find that larger firms exhibit significantly more pay inequality. This result is

[4] As in the macro- and labor economics literature, we refer to pay inequality as the disparity in pay between top- and bottom-level jobs. This is different from pay *discrimination*, which pertains to unequal pay (e.g., for men and women) for the same job.

entirely driven by hierarchy levels where managerial talent is important (levels 6 to 9). By contrast, pay ratios comparing lower hierarchy levels to one another (levels 1 to 5) are largely invariant with respect to firm size. Accordingly, an HR director's pay (level 9) increases relative to the pay of an unskilled worker (level 1) as firm size increases. However, the pay of an ordinary HR/Personnel officer (level 4) does not increase relative to the pay of an unskilled worker. The effect of firm size on pay inequality is economically large. Moving from the 25th to the 75th percentile of the firm-size distribution—an increase in firm size of 1,565%—raises the pay associated with hierarchy level 9 by 280.1% relative to the pay associated with hierarchy level 1. By comparison, the pay associated with hierarchy level 6 increases only by 59.7% relative to the pay associated with hierarchy level 1. Consequently, an increase in firm size has a roughly five times bigger impact on pay ratio 19 than it has on pay ratio 16.

While firm size plays a key role for theories emphasizing the efficient assignment of managerial talent, our size results are also potentially consistent with either incentive provision or rent extraction. To distinguish between rent extraction and the other two hypotheses, we examine how pay inequality is related to firms' operating performance and valuations. If pay inequality is primarily a reflection of managerial talent or the provision of incentives, we would expect firms with more inequality to have better operating performance and higher valuations. By contrast, if pay inequality is merely a reflection of managerial rent extraction, we would expect firms with more inequality to exhibit worse operating performance and lower valuations. Regardless of whether we consider the firm's return on assets or Tobin's Q, we find that high-inequality firms are better performers and have higher valuations.

In additional tests, we seek to distinguish between talent assignment and incentive provision. The underlying idea is that if moral hazard is the key channel, we should see stronger results in environments where moral hazard is potentially more severe, e.g., in less competitive industries or among firms with weaker governance. On the other hand, if talent assignment is the key channel, our results should be stronger in more competitive industries, since there is more competition for managerial talent. If better governance results in a better assignment of managerial talent, our results should also be stronger among better governed firms. We employ various measures of industry concentration and firm-level governance. Regardless of which measure we use, we find that our results are stronger in more competitive industries and among better governed firms, although the differences between low- and high-competition industries, or between weak- and strong-governance firms, are not always significant. Overall, our results suggest that managerial talent is a key driver of pay disparities within firms.

The final part of our study examines whether within-firm pay inequality is priced by the market. To examine the relation between pay inequality and stock returns, we form a hedge portfolio that is long in high-inequality firms and short in low-inequality firms. Regardless of whether we use the market model or the Carhart (1997) four-factor model, and regardless of whether we consider value- or equal-weighted returns, we find that the inequality hedge portfolio yields a positive and significant alpha. An important concern is that pay inequality may be correlated with firm characteristics that have been shown to affect stock returns. To address this concern, we estimate Fama-MacBeth regressions allowing us to include a wide array of control variables. We again find that firms with higher pay inequality earn significant abnormal returns, suggesting that our results are not simply driven by pay inequality being correlated with firm characteristics that have been shown to be correlated with returns.

Our return results are consistent with the view that high-inequality firms attract better managerial talent, and this is not fully captured by the market. Indeed, Edmans (2011) finds that the market does not fully capture intangibles (specifically, employee satisfaction), while Lilienfeld-Toal and Ruenzi (2014) and Groen-Xu, Huang, and Lu (2016) find that the market does not fully price CEO stock ownership and CEO salary changes, respectively. In our case, the scope for mispricing is especially large, since our within-firm pay-level data are not publicly available. To provide further evidence on mispricing, we study earnings surprises. Using analysts' earnings forecasts to proxy for investors' expectations, we find that high-inequality firms exhibit significantly larger analysts' forecast errors. Thus, the market is indeed surprised by the earnings of high-inequality firms, consistent with a mispricing channel.

Having presented our main results, let us briefly come back to the debate surrounding

Section 953(b) of the Dodd-Frank Act, which served as a partial motivation for our empirical study. In this debate, a key concern is that "high pay disparities inside a company can hurt employee morale and productivity, and have a negative impact on a company's overall performance" (see above). Our results suggest a more balanced view: while pay inequality may affect employee morale, it may also reflect managerial talent or the provision of incentives.[5] Indeed, we find that, *on average*, pay inequality is positively associated with firms' operating and stock market performance.

Our paper contributes to the literature seeking to understand pay structures within firms. Much of this literature focuses on CEO pay.[6] Some researchers argue that CEO pay is excessive and driven by CEOs' ability to extract rents (Bebchuk and Fried (2004), Bebchuk, Cremers, and Peyer (2011)). Others argue that high CEO pay is a reward for scarce managerial talent based on the competitive assignment of CEOs in market equilibrium (Terviö (2008), Gabaix and Landier (2008), Edmans, Gabaix, and Landier (2009), Edmans and Gabaix (2011)). Consistent with the second argument, CEO pay is strongly correlated with firm size, both in the cross-section and time-series (Gabaix and Landier (2008), Gabaix Landier, and Sauvagnat (2014)). Kaplan and Rauh (2010, 2013) provide further evidence in support of the "scarce talent view" by looking at other professions, such as investment bankers, corporate lawyers, and professional athletes. Our paper adds to this literature by studying wages across *all* hierarchy levels. Our findings are consistent with pay disparities between top- and bottom-level jobs being a reflection of scarce managerial talent.

Several recent papers study the role of firm- and worker-level heterogeneity for the rise in aggregate income inequality using administrative data sets from the United States (Barth et al. (2016), Song et al. (2016)), Germany (Card, Heining, and Kline (2013)), and Brazil (Alvarez, Engbom, and Moser (2015)). While our paper shares with this literature

[5] In a randomized field experiment with Indian manufacturing workers, Breza, Kaur, and Shamdasani (2016) find that pay inequality results in lower output and lower attendance. However, when workers learn that pay inequality is a reflection of productivity differences, there is *no* discernable effect on either output or attendance.

[6] Frydman and Jenter (2010), Murphy (2013), and Edmans and Gabaix (2016) provide comprehensive surveys of the CEO pay literature.

the focus on firms, our primary aim is to understand *what* types of firms have more pay inequality and, eventually, *why* some firms may exhibit more pay inequality than others. We find that high-inequality firms are larger and have better operating performance and higher valuations. We also find that they earn significant abnormal returns, suggesting that pay inequality is not fully priced by the market.

The remainder of this paper is organized as follows. Section 2 describes the data and summary statistics. Section 3 discusses alternative hypotheses. Section 4 examines the relation between pay inequality and firm size. Section 5 considers firms' valuations and operating performance. Section 6 presents sample splits based on industry concentration and firm-level governance. Section 7 examines the relation between pay inequality and stock returns. Section 8 studies earnings surprises. Section 9 concludes.

2 Data and Summary Statistics

2.1 Pay-Level Data

We have comprehensive firm-level data on employee pay for a broad cross-section of UK firms for the years 2004 to 2013. Our data include "basic" employee pay—they do not include any premiums for overtime, bonus, or incentive pay. The data are provided by Income Data Services (IDS), an independent research and publishing company specializing in the field of employment. IDS was established in 1966 and acquired by Thomson Reuters (Professional) UK Limited in 2005. It is the leading organization carrying out detailed monitoring of firm-level pay trends in the UK, providing its data to various public entities, such as the UK Office for National Statistics (ONS) and the European Union.

IDS gathers information on employee pay associated with various job titles within a firm. Important for our purposes, employers are asked to group job titles into broader hierarchy levels based on managerial responsibility and skill requirements. Thus, if a given job title has different meanings at different firms (e.g., different managerial responsibility), it is assigned to different hierarchy levels. There are ten hierarchy levels. To increase the sample size in some of our regressions, we combine the lowest two hierarchy levels into a single level, meaning we have nine hierarchy levels altogether.[7]

Table 1 provides descriptions of all nine hierarchy levels along with examples of job titles. For instance, level 1, our lowest hierarchy level, includes work that "requires basic literacy and numeracy skills and the ability to perform a few straightforward and short-term tasks to instructions under immediate supervision." Typical job titles are cleaner, labourer, and unskilled worker. Level 5, in the middle of the hierarchy, includes work that "requires a vocational qualification and sufficient relevant specialist experience to be able to manage a section or operate with self-contained expertise in a specialist discipline or activity." Typical job titles are engineer, marketing junior manager, and warehouse supervisor. Finally, level 9, the highest hierarchy level, includes "very senior executive roles with substantial experience in, and leadership of, a specialist function, including some input to the organisation's overall strategy." Typical job titles are finance director, HR director, and lawyer/head of legal.

A strength of our data relative to others (e.g., the U.S. Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) data set) is that we can observe employee pay at the firm-hierarchy level. That being said, a weakness of our data is that we only observe the average pay associated with a given hierarchy level in a given firm and year. Thus, our unit of observation is at the firm-hierarchy-year level.

2.2 Sampling and Bias

IDS collects information on employee pay by surveying employers. Thus, all our wage data are survey-based. Surveys can take one of two forms: i) IDS is contracted by client firms to provide guidance on their internal pay policies, and ii) IDS conducts market-wide studies of firms' pay policies, often pertaining to specific job tasks or labor market segments. These studies are then offered to subscribers for a fee.

Whether the surveys are initiated by client firms or by IDS, they usually cover specific segments of a firm's labor force. In particular, top-level executive jobs are underrep-

[7] Results based on the original ten hierarchy levels are virtually identical. The only difference is the smaller sample size in regressions involving the original hierarchy levels 1 and 2.

resented in our sample, as witnessed by the relatively smaller number of observations associated with hierarchy level 9, our highest hierarchy level (cf. Table 2). At that level, IDS competes with specialized executive compensation consulting firms, and potential clients may favor these firms over IDS. Indeed, none of our pay-level data associated with hierarchy level 9 come from client-initiated surveys—they all come from surveys initiated by IDS. Also, there are only relatively few instances where IDS surveys both hierarchy level 9 and lower hierarchy levels (i.e., levels 1, 2, or 3) within the *same* firm and year, as evidenced by the relatively smaller number of firm-year observations associated with pay ratios 19, 29, and 39 (cf. Table 3).

Firms may be sampled multiple times. The average firm in our sample is surveyed 3.7 times, or about every third year. However, there is substantial heterogeneity across firms with respect to sampling frequency: firms at the 25th percentile of the sampling distribution are sampled twice, those at the 50th percentile are sampled three times, and those at the 75th percentile are sampled five times.

An important concern with survey data is that it may be biased. In our case, the specific type of bias may depend on whether the survey is initiated by the client firm or by IDS. As for IDS-initiated surveys, a bias may arise from the selection of firms that are part of the survey as well as from firms' responses to the survey. With regard to selection bias, IDS uses the results from its own surveys to advise clients on their wages in client-initiated surveys. If IDS were to pick firms for its surveys in a biased manner to skew wages higher or lower, this could result in the loss of future business if clients became aware that they are either over-paying their workers or losing key talent due to under-payment. IDS is fully qualified to identify benchmark firms to be included in the survey and interpret firm-specific job titles in a way that is meaningful across firms. At the time of data acquisition, IDS employed 34 research staff with specialized skills in employment law, pensions, pay and HR practices.

A bias could also arise from firms with abnormally high or low wages refusing to participate in the survey. In order to entice firms to participate, IDS offers a free summary of the survey to all participants as well as the option to purchase the detailed survey for a discount. IDS takes care to ensure that no firms can be identified in the survey results, mitigating any concerns that participation could reveal internal pay policies or trade secrets. However, it is possible that some firms do not participate in the survey out of concern associated with the time required to fill out the questionnaire.

With regard to client-initiated surveys, we must consider any bias that may arise due to the types of firms that choose to hire IDS for their internal surveys and which jobs are selected for these surveys. Guidance from IDS states that the client firm and IDS must together agree on which jobs will be covered. One of the reasons IDS may be brought into a firm is to ensure that different jobs with different requirements comply with the s.1(5) of the Equal Pay Act. As such, the selection of "benchmark" jobs may be subject to judicial review. Furthermore, there was no expectation by firms that any of this data was to be made publicly available. As such, there would appear to be limited motivation to intentionally skew the coverage of jobs in the data base.

It may be useful to compare our data to aggregated wage data for the UK from the Annual Survey of Hours and Earnings (ASHE). ASHE data are based on a 1% sample of employee jobs drawn from HM Revenue and Customs Pay As You Earn (PAYE) records. To allow a comparison with our data, we use gross pay per full-time worker during 2004-2013 and deflate it by the consumer price index (CPI) provided by the UK Office for National Statistics (ONS). The results show that wages in our sample are slightly higher than the national average, and they are also more right-skewed: while the median (mean) wage in the ASHE data is 22,500 (27,911) GBP per year, the median (mean) wage in our sample is 24,670 (34,206) GBP per year. That wages in our sample are somewhat above the national average can be explained by the fact that our sample firms are larger (cf. Section 2.3), bearing in mind that larger firms tend to pay higher wages on average (cf. Section 4.2). That being said, the wage-firm size *elasticity* in our data is almost identical to that reported in other studies (see, again, Section 4.2).

2.3 Firm Size

To obtain measures of firm size, we match the IDS firm names to Bureau van Dijk's Amadeus database. Amadeus provides financial information about public and private firms in the UK and other European countries. That Amadeus includes private firms is important for us, since 40% of our sample firms are private. All matches have been checked by IDS employees who are familiar with the sample firms. Our final sample consists of 880 firms.

Our main measure of firm size is the number of employees. However, our results are similar if we use either firms' sales or assets in lieu of the number of employees (cf. Appendix Tables A1 and A2). Sales are deflated using the consumer price index (CPI) provided by the UK Office for National Statistics (ONS). As is typical of samples that include both private and public firms, the firm-size distribution is heavily right-skewed due to the presence of some very large public firms. To avoid that outliers drive our results, we winsorize firm size at the 5% level. However, our results are similar if we winsorize firm size at the 1%, 2.5%, or 10% level.[8]

The average firm in our sample is 32 years old, has 10,014 employees, book assets of 1,890 million GBP, and sales of 1,610 million GBP. There is substantial heterogeneity in firm size. For example, moving from the 25th percentile (381 employees) to the median (1,705 employees) of the firm-size distribution involves an increase of 348%. Moving from the median to the 75th percentile (6,345 employees) involves a further increase of 272%. Firms are also widely dispersed across industries. The five largest industry categories in our sample are manufacturing (SIC 20-39, 29.8% of firms), services (SIC 70-89, 23.1% of firms), transportation, communication, electric, gas, and sanitary services (SIC 40-49, 16.6% of firms), finance, insurance, and real estate (SIC 60-67, 14.9% of firms), and wholesale and retail trade (SIC 50-59, 12.2% of firms).

2.4 Descriptive Statistics

Table 2 shows the distribution of wages separately for each hierarchy level based on all firm-year observations. Wages are deflated using the consumer price index (CPI) provided

[8]See Appendix Table A4. The non-winsorized firm-size distribution has a median of 1,705 employees, mean of 12,606 employees, maximum of 508,714 employees, and skewness of 7.19. With 1% winsorizing, the distribution remains heavily right-skewed: mean of 11,844 employees, maximum of 273,024 employees, and skewness of 5.21. The 5% winsorized distribution has a mean of 10,014 employees, maximum of 97,300 employees, and skewness of 3.03.

by the UK Office for National Statistics (ONS) and winsorized at the 1% level. As can be seen, wages are increasing with hierarchy levels. For instance, the average wage in hierarchy level 1 is 13,778 GBP, the average wage in hierarchy level 5 is 29,352 GBP, and the average wage in hierarchy level 9 is 110,693 GBP. Moving up one level raises the average wage per hierarchy level by 29.8% on average, albeit the size of this differential varies. In particular, at lower hierarchy levels (1 to 3), moving up one level involves a smaller wage increase (between 16.3% and 20.8%) than does moving up at medium and higher hierarchy levels (4 to 8)(between 28.7% and 60.5%). Hence, while wages are increasing with hierarchy levels, the rate of increase is largest at medium and higher hierarchy levels.

To obtain measures of within-firm pay inequality, we compute for all $(9 \times 8)/2 = 36$ hierarchy-level pairs the corresponding ratio of wages within a given firm and year ("pay ratio"). Thus, a given firm-year observation implies that we observe wages for both hierarchy levels within the same firm and year. For ease of comparison, we divide wages associated with higher hierarchy levels by wages associated with lower hierarchy levels, e.g., "pay ratio 12" means that we divide the wage associated with hierarchy level 2 by the wage associated with hierarchy level 1.

Table 3 shows the distribution of pay ratios for all 36 possible hierarchy-level pairs. As one might expect, pay ratios are increasing with the distance between hierarchy levels. For instance, pay ratio 12 is lower than pay ratio 13, which is lower than pay ratio 14. Moreover, holding the distance between hierarchy levels fixed, pay ratios are larger when both hierarchy levels are higher. For instance, pay ratio 13 is lower than pay ratio 24, which is lower than pay ratio 35.

Table 3 also shows the percentage of firm-year observations for which a given pay ratio is greater than one. This percentage is always close or equal to 100%, confirming that employee pay is closely linked to hierarchy levels. Indeed, only 2.2% of firm-year observations exhibit pay ratios that are less than one. Dropping these observations does not affect our results.[9]

[9]That some firm-year observations have pay ratios that are less than one suggests that hierarchy levels are an important, but not the only, determinant of employee pay.

3 Hypothesis Development

Our paper studies how pay inequality varies across firms and, in particular, how it relates to firm size and operating performance. From a theoretical perspective, pay inequality may vary across firms for a variety of reasons. Below we list some of the main reasons and their predictions regarding the relation between pay inequality and either firm size or operating performance.

Talent Assignment. Efficient assignment of managerial talent implies that more talented managers should match with larger firms (Terviö (2008), Gabaix and Landier (2008)). The underlying idea, which goes back to Rosen (1981, 1982), is that the value created by a match is multiplicative in talent and firm size: "Intuition suggests that the economic impact of a manager's decisions depends on the amount of resources under his control" (Terviö (2008, p. 642)).[10] Accordingly, larger firms should have more talented managers. If managers are paid according to their marginal product, this implies that pay disparities between top- and bottom-level jobs should be greater at larger firms.

Firm size plays an important role for talent assignment, perhaps more than for any of the other theories discussed below. Indeed, talent assignment predicts not only that within-firm pay disparities should increase with firm size, but also that the increase be driven by hierarchy levels for which managerial talent is particularly important. In contrast, pay ratios that compare lower hierarchy levels to one another (e.g., 12, 23, 34) should be invariant with respect to firm size. Intuitively, lower-level employees' marginal product is unlikely to rise with firm size, given that their actions are less scalable across the firm. Finally, if pay inequality is a reflection of better managerial talent, we would expect firms with more inequality to also have better operating performance.

Incentives. Incentive provision within firms may also give rise to pay inequality. There are several variants of this argument, all of which yield similar predictions regarding the

[10] See also Rosen (1982, p. 311): "Assigning persons of superior talent to top positions increases productivity by more than the increments of their abilities because greater talent filters through the entire firm by a recursive chain of command technology. These multiplicative effects support enormous rewards for top level management in large organizations."

relation between pay inequality and either firm size or operating performance:

Tournaments. In tournament models (Lazear and Rosen (1981)), managerial incentives are provided through pay differentials between higher- and lower-level managerial jobs. Larger firms have more contestants and thus require greater pay differentials, implying higher within-firm pay inequality at these firms (McLaughlin (1988)).

Synergies. In Edmans, Goldstein, and Zhu (2013), an agent's effort reduces other agents' marginal cost of effort ("synergy"). Higher-level managers have more synergy potential and are thus (in equilibrium) paid more to produce synergies. Larger firms have more synergies, implying that pay inequality increases with firm size.

(Plain) Moral Hazard. If moral hazard is more pronounced at higher hierarchy levels (e.g., due to larger private benefits), higher-level managers must be paid more (in equilibrium) to work hard. Larger firms exhibit greater scope for moral hazard (Gayle and Miller (2009)), implying higher within-firm pay inequality at these firms.

In some of the above theories, pay comes in the form of incentive pay. Our data, on the other hand, only include "basic" employee pay—they do not include any premiums for overtime, bonus, or incentive pay. That being said, incentives may be provided through simple wages in conjunction with the threat of firing (Shapiro and Stiglitz (1984)) or dynamically through the promise of higher future wages (Lazear (1979, 1981)). This is especially true for jobs below the very top executive level. Second, many of the above theories are particularly relevant for managerial jobs. Consequently, as in the talent assignment story, pay ratios comparing lower hierarchy levels with one another should be largely invariant with respect to firm size. Third, and again similar to the talent assignment story, if pay inequality is a reflection of managerial incentives, we should expect firms with more inequality to also have better operating performance.

Rent Extraction. Within-firm pay inequality may also arise from managers extracting rents (Bebchuk and Fried (2004), Bebchuk, Cremers, and Peyer (2011)).[11] At larger

[11] Even if managers below the C-suite cannot extract rents themselves, the firm's CEO may grant them rents in order to buy their loyalty or simply to enjoy a "quiet life" (Bertrand and Mullainathan (1999, 2003), Cronqvist et al. (2009)).

firms, there may be more rents to extract, implying higher pay inequality. Moreover, to the extent that lower-level employees cannot extract significant rents, pay ratios comparing lower hierarchy levels to one another should be invariant with respect to firm size. Importantly, the rent extraction hypothesis differs fundamentally from the talent assignment and incentive provision hypotheses with regard to its implications for operating performance: if within-firm pay inequality is a reflection of rent extraction, firms with more inequality should have worse, not better, operating performance.

In the next section, we examine the relation between within-firm pay inequality and firm size. We provide separate analyses for all 36 pay ratios, allowing us to see whether, e.g., this relation is primarily driven by upper-level hierarchy jobs. While a positive correlation between pay inequality and firm size is a key empirical prediction of the talent assignment hypothesis, it may also be consistent with either incentive provision or rent extraction. In Section 5, we turn to the relation between pay inequality and operating performance. As discussed above, this is where the rent extraction hypothesis makes different predictions from either talent assignment or incentive provision. Finally, Section 6 provides some additional tests seeking to distinguish between talent assignment and incentive provision.

4 Within-Firm Pay Inequality and Firm Size

4.1 More Pay Inequality at Larger Firms

To explore the relation between pay inequality and firm size, we perform a stringent test: we run $(9 \times 8)/2 = 36$ individual regressions—one for each pay ratio. This allows us to see whether, e.g., our results are driven by many or just few pay ratios. In particular, it allows us to see if the relation between pay inequality and firm size is primarily driven by pay ratios associated with upper-level hierarchy jobs.

Table 4 shows the results. Although we run 36 individual regressions, the results are surprisingly clear. Panel (A) includes all pay ratios in which hierarchy level 1 is compared to higher levels. Moving from the left to the right, the distance between hierarchy levels increases. As can be seen, the coefficient on firm size is initially insignificant (pay ratios 12, 13, 14, and 15). Beginning with pay ratio 16, it becomes positive and significant (pay ratios 16, 17, 18, and 19). In addition, whenever the coefficient is significant, it is also monotonically increasing in the pay ratio. For example, a one percent increase in firm size increases the pay associated with hierarchy level 6 by 0.0375% relative to the pay associated with hierarchy level 1. By comparison, the pay associated with hierarchy level 7 increases by 0.0883%, the pay associated with hierarchy level 8 increases by 0.162%, and the pay associated with hierarchy level 9 increases by 0.179%—all relative to the pay associated with hierarchy level 1. Thus, a one percent increase in firm size has a roughly five times bigger impact on pay ratio 19 than it has on pay ratio 16.

Panels (B) to (D) include all pay ratios in which hierarchy levels 2, 3, or 4 are compared to higher levels. The pattern is similar to that in Panel (A). Precisely, the coefficient on firm size is initially insignificant—or, in one case (pay ratio 23), negative and significant—and then positive and significant. Moreover, whenever the coefficient is significant, it is also monotonically increasing in the pay ratio.[12] Finally, Panels (E) to (H) include all pay ratios in which hierarchy levels 5, 6, 7, or 8 are compared to higher levels. The pattern is again similar, except that there is no region in which the coefficient on firm size is insignificant. That is, the coefficient is always positive and significant, and it is always monotonically increasing in the pay ratio.

Although we run 36 individual regressions, there appears to be a clear pattern in the data. When lower hierarchy levels (1 to 5) are compared to one another, an increase in firm size has no effect on within-firm pay inequality. In contrast, when higher hierarchy levels (6 to 9) are compared to either one another or lower hierarchy levels, an increase in firm size widens the pay gap between different hierarchy levels. The magnitude of this effect increases with the distance between hierarchy levels. For instance, moving from the 25th to the 75th percentile of the firm-size distribution—an increase in firm size of 1,565%—raises the pay associated with hierarchy level 9 by 280.1% relative to the pay associated with hierarchy level 1. By comparison, the pay associated with hierarchy level

[12] There is one exception: in Panel (D), the coefficient on firm size decreases slightly when moving from pay ratio 48 to 49.

6 increases only by 59.7% relative to the pay associated with hierarchy level 1.

Overall, we conclude that larger firms exhibit more pay inequality, as measured by wage differentials between hierarchy levels ("pay ratios"). However, not all pay ratios increase with firm size, but only those involving hierarchy levels where managerial talent is particularly important (levels 6 to 9). By contrast, pay ratios comparing lower hierarchy levels to one another (levels 1 to 5) are invariant with respect to firm size. Consequently, an HR director's pay (level 9) increases relative to the pay of an unskilled worker (level 1) as firm size increases. However, the pay of an ordinary HR/Personnel officer (level 4) does not increase relative to that of an unskilled worker.

Our results are not driven by industry composition effects. As is shown in Appendix Table A3, all our results hold if we focus exclusively on within-industry variation. Our results are also similar if we measure firm size using either firms' sales or assets in lieu of the number of employees (cf. Appendix Tables A1 and A2).

In Appendix Table A4, we show that our results are not driven by our choice of winsorization. Rather than estimating 36 individual regressions—one for each pay ratio—we lump all pay ratios together in a single regression and include pay ratio (i.e., hierarchy-level pair) fixed effects. Thus, the coefficient on firm size shows the average relation between pay inequality and firm size within a given hierarchy-level pair. In our baseline specification, we winsorize wages at 1% and firm size at 5%. In Panel (A), we continue to winsorize wages at 1% but employ different winsorizations for firm size. As is shown, our results do not depend on how we winsorize firm size. Similarly, in Panel (B), we continue to winsorize firm size at 5% but employ different winsorizations for wages. As can be seen, our results do not depend on how we winsorize wages. Finally, in Panel (C), we winsorize both wages and firm size symmetrically at either 1%, 2.5%, 5%, or 10%. All results are similar to those in Panels (A) and (B).

Appendix Table A4 shows the *average* relation between pay inequality and firm size within a given hierarchy-level pair. In Appendix Table A5, we use quantile regressions (Koenker and Basset (1978), Koenker and Hallock (2001)) to examine how changes in firm size affect different deciles of the pay-ratio distribution.[13] We again include hierarchy-level pair fixed effects. Hence, the coefficients are informative about how changes in firm size affect the first, second, etc., decile of the pay-ratio distribution within a given hierarchy-level pair. (Table 3 provides summary statistics showing quartiles of the pay-ratio distribution separately for all 36 hierarchy-level pairs.) As can be seen, an increase in firm size shifts the entire distribution of pay ratios upward, as evidenced by the fact that all nine coefficients are positive and significant. However, the shift in the distribution is not uniform: the coefficients are (almost monotonically) increasing across deciles, and the coefficient associated with the ninth decile is more than three times larger than the coefficient associated with the first decile. Thus, the relation between pay inequality and firm size is mainly captured by the upper half of the pay-ratio distribution.

4.2 The Employer Size-Wage Effect Revisited

The invariance of "bottom-level" pay ratios—those comparing hierarchy levels 1 to 5 to one another—with regard to firm size raises questions. Are wages associated with lower hierarchy levels individually invariant to firm size? Or do they merely increase (or decrease) at a similar rate? To answer these questions, we shall now examine wage *levels* instead of ratios.

Table 5 presents the results. The first column, which combines all hierarchy levels, includes hierarchy level fixed effects. Thus, the comparison is between small and large firms within a given hierarchy level. As can be seen, the well documented employer size-wage effect (e.g., Brown and Medoff (1989), Oi and Idson (1999)) also holds in our data. Across all hierarchy levels, a one percent increase in firm size implies a wage increase of 0.0126% on average. This magnitude is similar to the employer size-wage effect documented in Brown and Medoff (1989, Table 1, 1b), who report a wage-firm size elasticity of 0.013% using May CPS wage data.

But not all wages increase with firm size. Indeed, as the remaining columns show, wages at lower hierarchy levels (1 to 5) do *not* increase with firm size—they are either

[13]The quantile regression can be implemented in STATA using Qreg.

invariant to firm size or, if anything, slightly decreasing. In contrast, wages at higher hierarchy levels (6 to 9) increase with firm size. For these wages, the rate of increase is larger at higher hierarchy levels, which explains why "top-level" pay ratios, such as 78, 79, or 89, are all increasing in firm size.

Table 5 establishes two main results. First, while the employer size-wage effect also holds in our data—wages are increasing with firm size on average—it is entirely driven by the upper tail of the wage distribution. Second, and equally important, the invariance of "bottom-level" pay ratios with respect to firm size is not driven by wages in the numerator and denominator both increasing (or decreasing) at a similar rate. Rather, both wages are individually invariant with respect to firm size.

4.3 Pay Inequality and Firm Growth

We already mentioned that our results hold if we focus exclusively on within-industry variation (cf. Appendix Table A3). In what follows, we focus on within-firm variation, thus accounting for any unobserved time-invariant heterogeneity across firms.

Our ability to include firm fixed effects is limited by sample size considerations. As mentioned earlier, IDS samples firms multiple times. The average sampling frequency is 3.7 times, and the median is three times. However, not every sampling includes all hierarchy levels within a given firm. As a consequence, some pay ratios have relatively few within-firm repeat observations. Given this limitation, we form two broad groups of pay ratios. One consists of "top-bottom" (e.g., 17, 18, 19, 27, 28, etc.) and "top-level" (e.g., 67, 78, 89, etc.) pay ratios. These are the pay ratios that are *significantly* related to firm size in Table 4. The other group consists of "bottom-level" (e.g., 12, 23, 34, etc.) pay ratios, i.e., pay ratios that compare lower hierarchy levels to one another. These pay ratios are *not* significantly related to firm size in Table 4. Together, both groups span all possible 36 pay ratios.

The question of interest is whether our main results continue to hold if we include firm fixed effects. That is, does "top-bottom" and "top-level" pay inequality—but not "bottom-level" pay inequality—become larger as firms grow over time? Given that we form broad groups of pay ratios, we can include hierarchy pair fixed effects and even hierarchy pair × firm fixed effects. Thus, the coefficient on firm size provides us with the average relation between changes in pay inequality and changes in firm size over time within a given hierarchy pair and firm.

Table 6 reports the results. Columns (1), (3), and (5) show the results for "bottom-level" pay ratios, while columns (2), (4), and (6) show the results for "top-bottom" and "top-level" pay ratios. Columns (1) and (2) include firm fixed effects, columns (3) and (4) include hierarchy pair and firm fixed effects, and columns (5) and (6) include hierarchy pair × firm fixed effects. As in Table 4, all regressions include year fixed effects. As can be seen, the coefficient on firm size is insignificant for "bottom-level" pay ratios. By contrast, it is significant for "top-bottom" and "top-level" pay ratios even after including hierarchy pair × firm fixed effects. Together, these results suggest that pay disparities between top and bottom hierarchy levels—but also between different top hierarchy levels—become larger as firms grow over time. Equally important, the results confirm that our main results are not driven by unobserved time-invariant heterogeneity across firms.

5 Operating Performance and Firm Value

If pay inequality is primarily a reflection of managerial talent or incentive provision, we would expect firms with more inequality to have better operating performance and higher valuations. By contrast, if pay inequality is merely a reflection of managerial rent extraction, we would expect firms with more inequality to have *worse* operating performance and *lower* valuations.

Given our previous results showing that pay inequality is positively related to firm size, we want to make sure that we are not simply picking up correlations between firm size and operating performance or firm value. For this reason, we run all regressions both with and without firm-size controls. To see what this means conceptually, consider the talent assignment hypothesis. If firm size was a perfect proxy for managerial talent, we should see no variation in pay inequality among firms of similar size. However, firm size may not be the only determinant of talent assignment. That is, firm size may be a proxy for talent—consistent with our results in Section 4—but an imperfect one, and so firms of the same size may hire managers of different talent.[14] Those hiring more talented managers exhibit greater pay inequality. Thus, pay inequality may proxy for talent even after controlling for firm size.[15] In the data, there is much variation in pay inequality among firms of similar size, consistent with the above argument.

To obtain a measure of pay inequality at the firm level, we compute for each firm-pay ratio-year observation its percentile rank within the pay-ratio sample distribution in the same year. (For example, pay ratio 19 at firm X in year Y lies at the Zth percentile across all observations associated with pay ratio 19 in that year.) We then aggregate this information at the firm level by computing the average percentile rank for each firm in a given year.[16] Lower average percentile ranks mean lower pay inequality. We lag our measure of pay inequality by one year in all regressions.

Panel (A) of Table 7 examines the relation between within-firm pay inequality and the firm's return on assets (ROA). Column (1) shows that this relation is positive and significant. In column (2), we control for firm size. As can be seen, the point estimate is slightly smaller, and the result is statistically weaker. In columns (3) and 4), we use industry-adjusted ROA as our dependent variable. Industry adjustments are done by subtracting the industry median across all firms in Amadeus in the same 3-digit SIC industry and year. As is shown, the results largely mirror those in columns (1) and (2): there is a positive and significant relation between pay inequality and ROA, while controlling for firm size lowers the point estimates and raises the standard errors.[17]

[14] A manager's marginal product may be increasing in several factors, firm size being (only) one of them. For instance, in Edmans and Gabaix (2011), managerial talent is assigned based on firm size as well as firm risk. Similarly, in Eisfeldt and Kuhnen (2013), firms and managers form matches based on multiple characteristics.

[15] Even if firm size was a perfect proxy for managerial talent, we would see variation in pay inequality among firms of similar size if some firms were acting suboptimally, paying either too much or too little relative to what is optimal. We thank an anonymous referee for pointing this out.

[16] Assigning equal weight to all 36 pay ratios may lead to situations in which firms with large "top-bottom" pay ratios (e.g., 18, 29)—high-inequality firms by any sensible standards—are (mis-)classified as low-inequality firms only because they have compressed "mid-level" (e.g., 34, 45) or "bottom-level" (e.g., 12, 23) pay ratios. For this reason, we only use "top-bottom" pay ratios when computing our firm-level measure of pay inequality.

[17] Appendix Table A6 suggests that this result is mainly driven by stronger sales.

Panel (B) considers the relation between pay inequality and firm value (Tobin's Q). Tobin's Q is the market value of assets divided by the book value of assets, where the market value of assets is the book value of assets plus the market value of common stock minus the sum of the book value of common stock and balance sheet deferred taxes. Given that Amadeus does not provide estimates of market values, we must limit ourselves to publicly traded firms in the UK and construct measures of firm value using Datastream. The results largely mirror those in Panel (A). In particular, there is a positive and significant association between pay inequality and firm value, which holds even after controlling for firm size and industry-adjusting Tobin's Q.

In sum, the results in Table 7 suggest that high pay-inequality firms are not worse performers. On the contrary, they appear to have better operating performance and higher Tobin's Q.

6 Competition and Governance

The results in Section 5 are inconsistent with managerial rent extraction. By contrast, all the results so far are consistent with both talent assignment and incentive provision. In principle, both hypotheses could be in operation, given that they are not mutually exclusive. In the following, we present additional evidence trying to distinguish between the two hypotheses. The underlying idea is that if moral hazard is the key channel, we should see stronger results in environments where moral hazard is potentially more severe, e.g., in less competitive industries (Giroud and Mueller (2010, 2011)) or among firms with weaker governance. On the other hand, if talent assignment is the key channel, our results should be stronger in *more* competitive industries, since there is more competition for managerial talent. If better governance results in a better assignment of managerial talent, our results should also be stronger among better governed firms.[18]

Table 8 examines whether our results are stronger in less or more competitive industries, or among firms with weaker or better governance. Our measures of industry concentration are the Herfindahl-Hirschmann Index (HHI), the Lerner Index, and the

[18] We are grateful to an anonymous referee for suggesting the empirical tests in this section.

Top 5 concentration ratio. The HHI is defined as the sum of squared market shares in a given industry and year. Industries are based on 3-digit SIC codes. Market shares are based on firms' sales using all firms in Amadeus. The Lerner Index is computed as in Aghion et al. (2005). It is the average price-cost margin across all firms in Amadeus in a given 3-digit SIC industry and year. At the firm-year level, the price-cost margin is computed as operating profits minus depreciation, provisions, and financial costs divided by sales. The Top 5 concentration ratio is the sum of market shares of the largest five firms in a given 3-digit SIC industry and year. Market shares are based on firms' sales using all firms in Amadeus. Our measures of firm-level governance are board independence and blockholder ownership. Board independence is the ratio of the number of independent directors to total board size using data from BoardEx UK. Blockholder ownership is total direct ownership by all blockholders of a firm with an ownership stake of 5% or more using data from the Osiris database.

In Panels (A) to (C), we examine whether our results are stronger in less or more competitive industries. Sample splits are based on industry medians, i.e., "low" refers to industries with below-median values of the HHI, Lerner Index, and Top 5 concentration ratio, respectively ("competitive industries"). Columns (1) to (4) consider the relation between pay inequality and the firm's return on assets (ROA) based on the empirical specification used in Table 7. Columns (5) and (6) consider the relation between pay inequality and firm size based on the empirical specification used in Table 6. In Panel (A), industry concentration is measured using the HHI. As is shown, our results are much stronger in competitive industries. Indeed, the coefficients are only significant in those industries. That being said, the coefficients in competitive and concentrated industries are not always significantly different from each other. While the difference is significant in the ROA regressions (p-values of 0.031 and 0.037, respectively), it is not significant in the firm-size regressions (p-value of 0.156). A similar picture emerges in Panel (B), where industry concentration is measured using the Lerner Index, and in Panel (C), where it is measured using the Top 5 concentration ratio.

In Panels (D) and (E), we examine whether our results are stronger among firms with weaker or better governance. Regardless of whether we consider board independence or blockholder ownership, we find that our results are stronger among better governed firms. Similar to above, however, the coefficients associated with weak- and strong-governance firms may not be significantly different from each other.

Overall, the results in Table 8 provide support for the talent assignment hypothesis. Using different measures of industry concentration and firm-level governance, we find that our results are stronger in more competitive industries and among better governed firms, albeit the differences between low- and high-competition industries, or between weak- and strong-governance firms, are not always significant.

7 Is Pay Inequality Priced by the Market?

This section examines if within-firm pay inequality is priced by the market. To study the relation between pay inequality and equity returns, we form a hedge portfolio that is long in high-inequality firms and short in low-inequality firms. Our stock price data are from Datastream. Our measure of pay inequality is the same as in Section 5. To reflect changes in pay inequality over time, we rebalance portfolios at the beginning of each year. We compute both equal- and value-weighted portfolio returns. Portfolio weights are constructed using firms' end-of-year market capitalizations. A firm is classified as "high inequality" in year t if its pay inequality measure in year $t-1$ lies in the top tercile across all firms in our sample. Similarly, a firm is classified as "low inequality" in year t if its pay inequality measure in year $t-1$ lies in the bottom tercile of the sample distribution. The sample period is from 1/2006 to 9/2014 (105 months). Excess returns are computed by subtracting 3-month UK Treasury bill returns from raw returns.

Table 9 reports results from time-series regressions of monthly excess returns. For brevity, the table only displays the intercept, or alpha (α), of each regression. Panel (A) shows results for the inequality hedge portfolio. Panels (B) and (C) show results separately for the high- and low-inequality portfolio. In all three panels, columns (1) and (2) show results for value-weighted portfolios, while columns (3) and (4) show results for equal-weighted portfolios. Factors for the UK are obtained from the XFi Centre for

Finance and Investment at the University of Exeter.[19]

Columns (1) and (3) show results from regressions of monthly excess returns on an intercept and the market factor (RMRF). As can be seen, the alpha associated with the inequality hedge portfolio is positive and significant. In both value- and equal-weighted regressions, the alpha associated with the high-inequality portfolio is positive, while the alpha associated with the low-inequality portfolio is negative. Notably, the alpha associated with the high-inequality portfolio is small relative to that associated with the low-inequality portfolio. Hence, most of the abnormal return associated with the hedge portfolio is driven by the low-inequality portfolio. Columns (2) and (4) show results from estimating the Carhart (1997) four-factor model, which includes, besides the intercept and RMRF, the book-to-market factor (HML), size factor (SMB), and momentum factor (UMD). The results mirror those obtained from using the market model. In both value- and equal-weighted regressions, the alpha associated with the inequality hedge portfolio is positive and significant. And again, most of the abnormal return associated with the hedge portfolio is driven by the low-inequality portfolio.

What accounts for the positive alpha associated with the inequality hedge portfolio? One interpretation, which is consistent with our previous results, is that high-inequality firms attract better managerial talent, and this is not fully captured by the market. This interpretation is consistent with Edmans (2011), who finds that the market does not fully capture intangibles (specifically, employee satisfaction). In our case, the scope for mispricing is especially large, since our within-firm pay-level data are not publicly available. Alternatively, there is the possibility that pay inequality may be correlated with firm characteristics that have been shown to affect stock returns. To explore this possibility, we now turn to Fama-MacBeth regressions, allowing us to include a wide array of control variables.

Table 10 reports Fama-MacBeth coefficients from monthly cross-sectional regressions of individual stock returns on a "high inequality" dummy and control variables. The dummy is equal to one if a firm's pay inequality measure in year $t-1$ lies in the top

[19] See Gregory, Tharyan, and Christidis (2013) for a description of the data.

tercile of the sample distribution and zero if it lies in the bottom tercile. The sample is restricted to firms in the top and bottom terciles. Our measure of pay inequality is the same as in Table 9. Hence, firms classified as "high inequality" are the same firms that make up the high-inequality portfolio in our time-series regressions. Control variables include size (market equity), book-to-market, dividend yield, trading volume, and stock price, all lagged, as well as compound returns from months t-3 to t-2 (Ret2-3), t-6 to t-4 (Ret4-6), and t-12 to t-7 (Ret7-12). These controls are standard in Fama-MacBeth regressions of this sort (e.g., Brennan, Chordia, and Subrahmanyam (1998), Gompers, Ishii, and Metrick (2003), Giroud and Mueller (2011), Edmans (2011)).

The results in Table 10 broadly confirm those in Table 9. As Gompers, Ishii, and Metrick (2003) point out, the dummy coefficient in the Fama-MacBeth regression can be interpreted as an abnormal return. In column (1), which does not include any controls, the abnormal return is similar to what we found previously in Table 9. In column (2), which includes size and book-to-market as controls, the abnormal return in slightly lower. Lastly, in column (3), which includes the full set of controls, the abnormal return to high-inequality firms (relative to low-inequality firms) is 0.954% and significant at the 5% level. Thus, we may conclude that the explanatory power of pay inequality for equity returns does not simply arise because pay inequality is correlated with firm characteristics that have been shown to be correlated with returns.

8 Earnings Surprises

Our results in Section 7 are consistent with the view that high-inequality firms attract better managerial talent, and this is not fully captured by the market. To provide further evidence on mispricing, we now study earnings surprises. Under a mispricing channel, investors do not fully anticipate the earnings by high-inequality firms. That is, investors are (positively) surprised.

Following Core, Guay, and Rusticus (2006), Giroud and Mueller (2011), and Edmans (2011), we use analysts' earnings forecasts to proxy for investors' expectations. Data on analysts' earnings forecasts are obtained from the Institutional Brokers' Estimate System

(I/B/E/S). Analysts' forecast error (or "earnings surprise") is the firm's actual earnings per share at the fiscal year-end minus the (mean or median) I/B/E/S consensus forecast of earnings per share, scaled down by the firm's stock price two months prior. We use the I/B/E/S consensus forecast eight months before the fiscal year-end to ensure that analysts know the previous year's earnings when making their forecasts. To mitigate the effect of outliers, we drop observations for which the forecast error is larger than 10% of the stock price in the month of the forecast (e.g., Lim (2001), Teoh and Wong (2002)). Finally, we require that a company be followed by at least five analysts to ensure that consensus forecasts constitute reliable proxies of market expectations (e.g., Easterwood and Nutt (1999), Loha and Mianc (2006)).

Table 11 presents the results. Columns (1) to (3) consider analysts' forecast errors based on mean I/B/E/S consensus forecasts, while columns (4) to (6) consider analysts' forecast errors based on median I/B/E/S consensus forecasts. Pay inequality is the same (lagged) measure as in Section 5, where we studied the relation between pay inequality and firms' earnings. Control variables include size (market equity) and book-to-market. As can be seen, regardless of which controls we include, and regardless of whether we consider mean or median I/B/E/S consensus forecasts, firms with higher pay inequality exhibit significantly larger earnings surprises. Thus, the market is indeed surprised by the earnings of high-inequality firms, consistent with a mispricing channel.

9 Concluding Remarks

Using a proprietary data set of public and private firms in the UK, we study how within-firm pay inequality varies across firms, how it relates to firms' operating performance and valuations, and whether it is priced by the market. We find that high-inequality firms are larger, consistent with theories emphasizing the efficient assignment of managerial talent. In addition, we find that high-inequality firms have higher valuations, better operating performance, and higher equity returns. The latter result suggests that managerial talent is not fully priced by the market, consistent with our findings that high-inequality firms exhibit significantly larger earnings surprises.

Aggregate income inequality has risen steadily over the past decades.[20] While this is arguably speculative, our results suggest that some of this rise may be related to firm growth.[21] Between 1986 and 2010, average employment by the 50 (100) largest firms in the U.S. has risen by 55.8% (53.0%). Likewise, over the same time period, average employment by the 50 (100) largest firms in the UK has risen by 51.3% (43.5%). In untabulated results, we explore the relation between firm growth by the largest firms in a country and aggregate income inequality, as measured by the log 90/10 wage differential, based on a sample of 16 developed countries. Irrespective of whether we consider the 50 or 100 largest firms in a country, we find a positive and significant association between firm growth and aggregate income inequality at the country level. Thus, part of what may be perceived as a global trend toward more wage inequality may be driven by an increase in employment by the largest firms in the economy.

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[20] See Atkinson, Piketty, and Saez (2011) for a review of the literature.

[21] Section 4.1 shows that larger firms exhibit more within-firm pay inequality. Section 4.3 shows that within-firm pay inequality increases over time as firms grow larger.

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Table 1
Hierarchy Levels

Hierarchy Level	Examples of Job Titles	IDS Description
1	Cleaner, Labourer, Unskilled Worker	Work requires basic literacy and numeracy skills and the ability to perform a few straightforward and short-term tasks to instructions under immediate supervision. Previous experience is not necessary (IDS Level 1). Work requires developed literacy and numeracy skills and the ability to perform some routine tasks within procedures that may include keyboard and practical skills and initial contact with customers. Some previous experience is required (IDS Level 2).
2	Administrative Assistant, Driver, Operator	Work requires specific administrative, practical, craft or technical skills gained by previous experience and qualifications to carry out a range of less routine work and to provide specialist support, and could include closer contact with the public/customers (IDS Level 3).
3	Technician, Craftsman, Skilled Worker	Work requires broad and deep administrative, technical or craft skills and experience to carry out a wider range of activities including staff supervision, undertaking specialist routines and procedures and providing some advice (IDS Level 4).
4	Craftsman - Multiskilled, HR/Personnel Officer, Retail Manager	Work requires detailed experience and possibly some level of vocational qualification to be able to oversee the operation of an important procedure or to provide specialist advice and services, involving applied knowledge of internal systems and procedures (IDS Level 5).
5	Engineer, Marketing Junior Manager, Warehouse Supervisor	Work requires a vocational qualification and sufficient relevant specialist experience to be able to manage a section or operate with self-contained expertise in a specialist discipline or activity (IDS Level 6).
6	Area Sales/Account Manager, Engineer - Senior, Manager - Middle	Work is concerned with the provision of professional services and requires an experienced and qualified professional to provide expertise and advice and operate independently. Also includes operational managers responsible for service delivery (IDS Level 7).
7	Engineering Manager, Lawyer -Senior, Operations Manager	Work requires deep professional experience and qualifications in a specific discipline to be able to carry out a range of specialist technical or scientific activities, which may include the management of a team or services. May also include specialist management roles responsible for delivery of a major service (IDS Level 8).
8	Finance Function Head, IT Function Head, Sales Function Head	Senior managerial roles involved in managing an important activity or providing authoritative expertise, also contributing to the organisation as a whole through significant experience (IDS Level 9).
9	Finance Director, HR Director, Lawyer - Head of Legal	Very senior executive roles with substantial experience in, and leadership of, a specialist function, including some input to the organisation's overall strategy (IDS Level 10).

Table 2
Distribution of Wages by Hierarchy Level

This table shows the distribution of wages for each hierarchy level across all firm-year observations. Wages are in GBP. Hierarchy levels are described in Table 1. The sample period is from 2004 to 2013.

Hierarchy Level	Obs.	Avg. Wage	25%	50%	75%
1	696	13,778	11,090	13,413	16,001
2	890	16,248	13,122	16,354	18,731
3	852	19,621	16,471	19,715	22,371
4	1,034	22,815	19,662	22,562	25,344
5	955	29,352	24,783	28,496	32,901
6	868	38,878	31,961	36,806	43,330
7	696	52,977	40,632	48,793	60,587
8	461	85,014	57,967	74,236	100,813
9	240	110,693	77,844	101,494	131,004

Table 3
Pay Ratios

This table shows the distribution of pay ratios for all 36 hierarchy-level pairs. Pay ratio is the ratio of wages associated with a hierarchy-level pair in a given firm and year. Hierarchy levels are described in Table 1. Ratio > 1 (%) denotes the percentage of firm-year observations for which the pay ratio exceeds one. The sample period is from 2004 to 2013.

Hierarchy-Level Pair	Obs.	Avg. Pay Ratio	25%	50%	75%	Ratio > 1 (%)
12	559	1.171	1.083	1.154	1.234	96
13	474	1.364	1.217	1.332	1.474	98
14	449	1.635	1.371	1.579	1.791	100
15	383	1.959	1.620	1.875	2.204	100
16	295	2.517	1.964	2.342	2.928	100
17	193	3.376	2.500	3.084	3.954	100
18	74	5.920	3.616	4.742	6.817	100
19	23	8.286	4.798	7.429	9.820	100
23	660	1.208	1.108	1.173	1.281	95
24	597	1.417	1.222	1.365	1.548	97
25	511	1.728	1.430	1.652	1.907	99
26	415	2.225	1.814	2.122	2.506	100
27	251	2.899	2.208	2.683	3.364	100
28	99	4.981	2.986	3.962	6.006	100
29	36	7.301	5.064	6.379	9.383	100
34	631	1.208	1.083	1.177	1.292	90
35	542	1.496	1.264	1.428	1.634	98
36	436	1.928	1.582	1.853	2.190	100
37	275	2.507	1.909	2.260	2.904	100
38	109	4.384	2.600	3.472	5.310	100
39	46	6.515	4.212	5.735	8.670	100
45	648	1.295	1.129	1.249	1.406	94
46	542	1.655	1.383	1.575	1.846	99
47	399	2.230	1.755	2.090	2.551	100
48	202	3.547	2.493	3.237	4.157	100
49	112	5.442	3.979	4.970	6.398	100

Table 4
More Pay Inequality at Larger Firms

The dependent variable is the pay ratio (in logs) associated with a given hierarchy-level pair. Firm size (lg_emp) is the number of employees (in logs). All regressions include year fixed effects. Standard errors (in parentheses) are clustered at the firm level. The sample period is from 2004 to 2013. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Panel (A):

Pay Ratio	12	13	14	15	16	17	18	19
lg_empl	-0.001	-0.005	0.008	0.009	0.038***	0.088***	0.162***	0.179***
	(0.004)	(0.005)	(0.007)	(0.009)	(0.012)	(0.015)	(0.026)	(0.039)
Constant	0.171***	0.373***	0.462***	0.626***	0.568***	0.445**	-0.232	0.372
	(0.030)	(0.049)	(0.066)	(0.093)	(0.133)	(0.213)	(0.195)	(0.252)
Observations	559	474	449	383	295	193	74	23
R-squared	0.024	0.040	0.070	0.050	0.147	0.377	0.505	0.740

Panel (B):

Pay Ratio	23	24	25	26	27	28	29
lg_empl	-0.011***	-0.005	-0.009	0.006	0.061***	0.133***	0.152***
	(0.004)	(0.005)	(0.007)	(0.009)	(0.012)	(0.026)	(0.038)
Constant	0.268***	0.391***	0.632***	0.662***	0.482***	0.198	0.714**
	(0.034)	(0.051)	(0.068)	(0.083)	(0.123)	(0.196)	(0.326)
Observations	660	597	511	415	251	99	36
R-squared	0.037	0.029	0.061	0.027	0.209	0.398	0.361

Panel (C):

Pay Ratio	34	35	36	37	38	39
lg_empl	0.004	0.007	0.019*	0.072***	0.147***	0.159***
	(0.005)	(0.008)	(0.010)	(0.015)	(0.029)	(0.037)
Constant	0.147***	0.320***	0.396***	0.246	0.476***	0.247
	(0.045)	(0.067)	(0.085)	(0.154)	(0.166)	(0.284)
Observations	631	542	436	275	109	46
R-squared	0.024	0.027	0.044	0.239	0.347	0.407

Panel (D):

Pay Ratio	45	46	47	48	49
lg_empl	-0.001	0.021***	0.057***	0.105***	0.102***
	(0.005)	(0.007)	(0.008)	(0.013)	(0.019)
Constant	0.207***	0.271***	0.147	0.330***	0.888***
	(0.042)	(0.057)	(0.094)	(0.072)	(0.257)
Observations	648	542	399	202	112
R-squared	0.023	0.061	0.195	0.323	0.266

Table 4 (continued)

Panel (E):

Pay Ratio	56	57	58	59
lg_empl	0.020***	0.041***	0.089***	0.091***
	(0.005)	(0.006)	(0.011)	(0.013)
Constant	0.087*	0.092	0.276***	0.742***
	(0.047)	(0.070)	(0.063)	(0.143)
Observations	693	557	346	193
R-squared	0.071	0.160	0.272	0.221

Panel (F):

Pay Ratio	67	68	69
lg_empl	0.018***	0.056***	0.062***
	(0.004)	(0.009)	(0.012)
Constant	0.049	0.119**	0.602***
	(0.041)	(0.053)	(0.137)
Observations	576	391	214
R-squared	0.059	0.166	0.131

Panel (G):

Pay Ratio	78	79
lg_empl	0.033***	0.046***
	(0.008)	(0.010)
Constant	0.031	0.361***
	(0.047)	(0.079)
Observations	397	213
R-squared	0.101	0.106

Panel (H):

Pay Ratio	89
lg_empl	0.024***
	(0.009)
Constant	0.272***
	(0.092)
Observations	201
R-squared	0.050

Table 5
The Employer Size-Wage Effect Revisited

The dependent variable is the wage (in logs) associated with a given hierarchy level. Firm size (lg_emp) is the number of employees (in logs). All regressions include year fixed effects. The regression in column "All" additionally includes hierarchy-level fixed effects. Standard errors (in parentheses) are clustered at the firm level. The sample period is from 2004 to 2013. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Hierarchy Level	All	1	2	3	4
lg_empl	0.013***	-0.021***	-0.006	-0.011	0.001
	(0.005)	(0.006)	(0.007)	(0.007)	(0.005)
Constant	4.789***	5.020***	5.123***	5.361***	5.470***
	(0.036)	(0.053)	(0.056)	(0.055)	(0.043)
Observations	6,692	696	890	852	1034
R-squared	0.825	0.079	0.013	0.036	0.027

Hierarchy Level	5	6	7	8	9
lg_empl	0.0004	0.026***	0.054***	0.088***	0.104***
	(0.006)	(0.006)	(0.007)	(0.013)	(0.014)
Constant	5.631***	5.656***	5.701***	6.001***	6.089***
	(0.049)	(0.050)	(0.089)	(0.075)	(0.110)
Observations	955	868	696	461	240
R-squared	0.041	0.061	0.151	0.223	0.227

Table 6
Pay Inequality and Firm Growth

The dependent variable is the pay ratio (in logs) associated with a given hierarchy-level pair. The sample in columns (1), (3), and (5) consists of all "bottom-level" pay ratios: 12, 13, 14, 15, 23, 24, 25, 34, 35, and 45. The sample in columns (2), (4), and (6) consists of all "top-bottom" and "top-level" pay ratios: 16, 17, 18, 19, 26, 27, 28, 29, 36, 37, 38, 39, 46, 47, 48, 49, 56, 57, 58, 59, 67, 68, 69, 78, 79, and 89. Firm size (lg_emp) is the number of employees (in logs). Columns (1) and (2) include firm fixed effects, columns (3) and (4) include hierarchy-level pair and firm fixed effects, and columns (5) and (6) include hierarchy-level pair × firm fixed effects. All regressions additionally include year fixed effects. The sample consists of all firm-hierarchy-level pairs with at least one repeat observation. Standard errors (in parentheses) are clustered at the firm level. The sample period is from 2004 to 2013. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Pay Ratios	(1)	(2)	(3)	(4)	(5)	(6)
lg_empl	-0.005	0.061**	0.004	0.061***	0.005	0.075***
	(0.015)	(0.025)	(0.013)	(0.022)	(0.014)	(0.029)
Constant	0.362***	0.148	0.141	-0.162	0.289**	0.071
	(0.119)	(0.208)	(0.103)	(0.182)	(0.114)	(0.239)
Observations	3,960	4,305	3,960	4,305	3,960	4,305
R-squared	0.235	0.291	0.612	0.792	0.795	0.888

Table 7
Operating Performance and Firm Value

In Panel (A), the dependent variable is the firm's return on assets (ROA). ROA is EBITDA divided by the book value of assets. In columns (2) and (4), firm size (lg_emp) is the number of employees (in logs). In columns (3) and (4), ROA is industry-adjusted by subtracting the industry median across all firms in Amadeus in the same 3-digit SIC industry and year. Pay Inequality at the firm level is lagged by one year and described in Section 5. Panel (B) is analogous to Panel (A), except that the dependent variable is Tobin's Q, the sample is restricted to publicly traded UK firms in Datastream, and industry-adjustments are based on all firms in Datastream in the same 3-digit SIC industry and year. Tobin's Q is the market value of assets divided by the book value of assets, where the market value of assets is the book value of assets plus the market value of common stock minus the sum of the book value of common stock and balance sheet deferred taxes. Standard errors (in parentheses) are clustered at both the firm and year level. The sample period is from 2004 to 2013. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Panel (A): Return on Assets

	ROA		Ind.-Adj. ROA	
	(1)	(2)	(3)	(4)
Pay Inequality	0.0490**	0.0471*	0.0560**	0.0464*
	(0.0232)	(0.0271)	(0.0217)	(0.0266)
lg_empl		0.000454		0.00174
		(0.00300)		(0.00297)
Constant	0.0341**	0.0347*	-0.0182*	-0.0258
	(0.0138)	(0.0210)	(0.0107)	(0.0206)
Observations	634	583	622	573
R-squared	0.013	0.013	0.018	0.016

Panel (B): Tobin's Q

	Tobin's Q		Ind.-Adj. Tobin's Q	
	(1)	(2)	(3)	(4)
Pay Inequality	0.446**	0.433**	0.470**	0.468**
	(0.196)	(0.204)	(0.214)	(0.234)
lg_empl		0.0974**		0.0897**
		(0.0397)		(0.0440)
Constant	1.188***	1.108***	0.0894	-0.635*
	(0.0961)	(0.328)	(0.182)	(0.385)
Observations	395	344	388	337
R-squared	0.025	0.047	0.017	0.040

Table 8
Competition and Governance

This table presents sample splits based on various measures of industry concentration (Panels (A) to (C)) and firm-level governance (Panels (D) and (E)). Columns (1) to (4) consider the relation between the firm's return on assets (ROA) and pay inequality based on the specification in Table 7. Columns (5) and (6) consider the relation between pay inequality and firm size based on the specification in Table 6. In Panels (A) to (C), sample splits are based on industry medians, i.e., "low" refers to industries with below-median values of the HHI, Lerner Index, and Top 5 concentration ratio, respectively. In Panels (D) and (E), sample splits are based on firm-level medians, i.e., "low" refers to firms with below-median values of board independence and blockholder ownership, respectively. HHI, Lerner Index, Top 5 concentration ratio, board independence, and blockholder ownership are described in Section 6. In all panels, the last row shows the *p*-value associated with the Wald chi-square test measuring whether the coefficients in the below- and above-median groups are significantly different from each other. The sample period is from 2004 to 2013. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Panel (A): HHI Index

	ROA					Pay Inequality	
	Low	High	Low	High		Low	High
	(1)	(2)	(3)	(4)		(5)	(6)
Pay Inequality	0.0764***	0.00357	0.0779***	-0.00301	lg_empl	0.0664***	0.0171
	(0.0227)	(0.0204)	(0.0298)	(0.0267)		(0.0230)	(0.0268)
lg_empl			-0.000868	0.00261			
			(0.00414)	(0.00291)			
Constant	0.00877	0.0595***	0.0154	0.0413**	Constant	-0.416**	0.0225
	(0.00968)	(0.00930)	(0.0320)	(0.0207)		(0.175)	(0.227)
Observations	303	319	268	305	Observations	3,868	4,153
R-squared	0.058	0.030	0.062	0.034	R-squared	0.767	0.811
Difference in Coefficients (*p*- value)	0.031		0.037		Difference in Coefficients (*p*- value)	0.156	

Table 8 (continued)

Panel (B): Lerner Index

	ROA					Pay Inequality	
	Low	High	Low	High		Low	High
	(1)	(2)	(3)	(4)		(5)	(6)
Pay Inequality	0.0874***	0.00799	0.0708**	0.0129	lg_empl	0.0407**	0.0111
	(0.0275)	(0.0282)	(0.0325)	(0.0352)		(0.0207)	(0.0333)
lg_empl			0.00166	0.000403			
			(0.00542)	(0.00346)			
Constant	-0.0525***	0.0601***	0.00129	0.0545***	Constant	-0.153	0.0593
	(0.0131)	(0.00724)	(0.0360)	(0.0104)		(0.173)	(0.270)
Observations	305	317	269	304	Observations	3,757	4,264
R-squared	0.053	0.015	0.061	0.015	R-squared	0.777	0.795
Difference in Coefficients (p-value)	0.065		0.235		Difference in Coefficients (p-value)	0.437	

Table 8 (continued)

Panel (C): Top 5 Concentration Ratio

	ROA					Pay Inequality	
	Low	High	Low	High		Low	High
	(1)	(2)	(3)	(4)		(5)	(6)
Pay Inequality	0.0773***	0.00177	0.0765**	-0.00138	lg_empl	0.0243***	0.00180
	(0.0246)	(0.0206)	(0.0296)	(0.0278)		(0.00923)	(0.0103)
lg_empl			0.00103	0.00120			
			(0.00350)	(0.00305)			
Constant	0.0214**	0.0623***	0.0148	0.0538***	Constant	0.173**	0.372***
	(0.00980)	(0.0106)	(0.0189)	(0.0204)		(0.0771)	(0.0971)
Observations	306	316	271	302	Observations	4,048	3,973
R-squared	0.061	0.025	0.067	0.025	R-squared	0.109	0.201
Difference in Coefficients (p-value)	0.024		0.044		Difference in Coefficients (p-value)	0.092	

Table 8 (continued)

Panel (D): Board Independence

	ROA					Pay Inequality	
	High	Low	High	Low		High	Low
	(1)	(2)	(3)	(4)		(5)	(6)
Pay Inequality	0.0826**	0.013	0.0675**	-0.00463	lg_empl	0.0349**	0.0162
	(0.0383)	(0.0458)	(0.0311)	(0.0466)		(0.0141)	(0.00976)
lg_empl			0.0130***	0.00596			
			(0.00424)	(0.00528)			
Constant	0.0359	0.0592	-0.0136	0.00460	Constant	-0.243	-0.0350
	(0.0367)	(0.0514)	(0.0446)	(0.0602)		(0.159)	(0.109)
Observations	110	122	107	112	Observations	996	1,007
R-squared	0.161	0.046	0.237	0.14	R-squared	0.841	0.793
Difference in Coefficients (p-value)	0.209		0.173		Difference in Coefficients (p-value)	0.095	

Table 8 (continued)

Panel (E): Blockholder Ownership

	ROA					Pay Inequality	
	High	Low	High	Low		High	Low
	(1)	(2)	(3)	(4)		(5)	(6)
Pay Inequality	0.137***	0.0696*	0.0917**	0.0596*	lg_empl	0.0633**	-0.0131
	(0.0464)	(0.0417)	(0.0437)	(0.0337)		(0.0269)	(0.0552)
lg_empl			0.00556	-0.00532			
			(0.00984)	(0.00782)			
Constant	-0.137***	0.0123	-0.170*	0.0667	Constant	0.0632	0.621
	(0.0312)	(0.0252)	(0.0961)	(0.0620)		(0.320)	(0.516)
Observations	103	80	90	74	Observations	794	815
R-squared	0.227	0.096	0.235	0.167	R-squared	0.250	0.260
Difference in Coefficients (p-value)	0.298		0.614		Difference in Coefficients (p-value)	0.196	

Table 9
Time-Series Regressions of Monthly Excess Returns

This table reports alphas (α) from time-series regressions of monthly excess returns. Excess returns are computed by subtracting 3-month UK Treasury bill returns from raw returns. Panel (A) shows results for a hedge portfolio that is long in high-inequality firms and short in low-inequality firms. A firm is classified as "high inequality" in year *t* if its pay inequality measure in year *t-1* lies in the top tercile across all firms in the sample. Similarly, a firm is classified as "low inequality" in year *t* if its pay inequality measure in year *t-1* lies in the bottom tercile of the sample distribution. Pay Inequality at the firm level is described in Section 5. Portfolios are rebalanced at the beginning of each year. Panels (B) and (C) show results separately for the high- and low-inequality portfolio, respectively. Columns (1) and (3) include the intercept (α) and market factor (RMRF). Columns (2) and (4) include the intercept (α), market factor (RMRF), book-to-market factor (HML), size factor (SMB), and momentum factor (UMD). Columns (1) and (2) show results for value-weighted portfolios. Columns (3) and (4) show results for equal-weighted portfolios. Standard errors are in parentheses. The sample period is from 1/2006 to 9/2014 (105 months). *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Panel (A): Inequality Hedge Portfolio

	Value-weighted		Equal-weighted	
	(1)	(2)	(3)	(4)
alpha	1.417**	1.412**	1.613***	1.442**
	(0.570)	(0.551)	(0.540)	(0.584)

Panel (B): High-Inequality Portfolio

	Value-weighted		Equal-weighted	
	(1)	(2)	(3)	(4)
alpha	0.205	0.180	0.459	0.376
	(0.282)	(0.302)	(0.299)	(0.310)

Panel (C): Low-Inequality Portfolio

	Value-weighted		Equal-weighted	
	(1)	(2)	(3)	(4)
alpha	-1.211**	-1.232**	-1.155**	-1.066**
	(0.496)	(0.485)	(0.488)	(0.465)

Table 10
Fama-MacBeth Return Regressions

This table reports Fama-MacBeth coefficients from monthly cross-sectional regressions of individual stock returns on a "high inequality" dummy and control variables. The dummy is equal to one if a firm's pay inequality measure in year *t-1* lies in the top tercile of the sample distribution and zero if it lies in the bottom tercile. The sample is restricted to firms in the top and bottom terciles. Pay Inequality at the firm level is described in Section 5. Control variables include size (market equity), book-to-market (BM), dividend yield, trading volume, and stock price, all lagged, as well as compound returns from months t-3 to t-2 (Ret2-3), t-6 to t-4 (Ret4-6), and t-12 to t-7 (Ret7-12). The sample period is from 1/2006 to 9/2014 (105 months). Standard errors are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
High Inequality	1.516***	1.333***	0.954**
	(0.495)	(0.452)	(0.480)
Size		-0.109	-0.392
		(0.122)	(0.639)
BM		-1.377*	-0.153
		(0.706)	(0.778)
Div. Yield			1.213
			(6.557)
Volume			0.126
			(0.517)
Stock Price			0.00171
			(0.00245)
Ret2-3			0.0412
			(0.0655)
Ret4-6			0.0345
			(0.0413)
Ret7-12			-0.0152
			(0.0399)
Constant	-0.598	1.065	-0.248
	(0.593)	(1.109)	(2.718)
Observations	2,232	2,184	2,008
R-squared	0.003	0.001	0.006

Table 11
Earnings Surprises

The dependent variable is analysts' forecast error ("earnings surprise"), which is the firm's actual earnings per share at the fiscal year-end minus the I/B/E/S consensus forecast of earnings per share, scaled down by the firm's stock price two months prior. In columns (1) to (3), we use the mean I/B/E/S consensus forecast. In columns (4) to (6), we use the median I/B/E/S consensus forecast. The I/B/E/S consensus forecast is taken eight months prior to the fiscal year-end. Pay Inequality at the firm level is described in Section 5. Control variables include size (market equity) and book-to-market (BM). All regressions include month and end-of-forecast year fixed effects. Standard errors (in parentheses) are clustered at both the firm and year level. The sample period is from 2004 to 2013. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

	Mean Forecast Error			Median Forecast Error		
	(1)	(2)	(3)	(4)	(5)	(6)
Pay Inequality	0.0801***	0.0740***	0.0685***	0.0788***	0.0730***	0.0673***
	(0.0281)	(0.0213)	(0.0240)	(0.0283)	(0.0221)	(0.0243)
BM		-0.0457	-0.0405		-0.0427	-0.0374
		(0.0431)	(0.0426)		(0.0432)	(0.0427)
Size			0.0146*			0.0150*
			(0.00775)			(0.00788)
Constant	-0.0450	-0.00915	-0.146**	-0.0435	-0.00991	-0.151**
	(0.0300)	(0.0135)	(0.0726)	(0.0299)	(0.0125)	(0.0739)
Observations	303	274	274	303	274	274
R-squared	0.067	0.091	0.098	0.067	0.089	0.097

Appendix

Table A1
Measuring Firm Size Using Firms' Sales

This table presents variants of the regressions in Table 4 in which firm size is measured using firms' sales (in logs). All regressions include year fixed effects. Standard errors (in parentheses) are clustered at the firm level. The sample period is from 2004 to 2013. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Pay Ratio	12	13	14	15	16	17	18	19
lg_sales	-0.001	-0.007	0.002	0.001	0.025**	0.077***	0.133***	0.150***
	(0.003)	(0.004)	(0.006)	(0.008)	(0.010)	(0.015)	(0.028)	(0.035)
Constant	0.166***	0.435***	0.484***	0.668***	0.503***	-0.003	-0.330	-0.729
	(0.043)	(0.070)	(0.094)	(0.134)	(0.183)	(0.298)	(0.379)	(0.575)
Observations	580	490	462	394	302	198	78	26
R-squared	0.024	0.050	0.072	0.042	0.109	0.312	0.417	0.618

Pay Ratio	23	24	25	26	27	28	29
lg_sales	-0.014***	-0.012**	-0.016**	-0.005	0.047***	0.110***	0.110***
	(0.003)	(0.005)	(0.007)	(0.008)	(0.010)	(0.024)	(0.037)
Constant	0.405***	0.537***	0.812***	0.780***	0.242	-0.527	0.245
	(0.047)	(0.077)	(0.106)	(0.127)	(0.173)	(0.372)	(0.572)
Observations	686	618	532	432	261	104	40
R-squared	0.066	0.049	0.078	0.024	0.156	0.369	0.249

Pay Ratio	34	35	36	37	38	39
lg_sales	-0.002	-0.003	0.009	0.059***	0.111***	0.137***
	(0.005)	(0.007)	(0.009)	(0.014)	(0.029)	(0.034)
Constant	0.214***	0.424***	0.402***	-0.090	-0.099	-1.101*
	(0.073)	(0.108)	(0.140)	(0.239)	(0.373)	(0.551)
Observations	648	557	445	280	112	48
R-squared	0.021	0.022	0.026	0.193	0.287	0.368

Pay Ratio	45	46	47	48	49
lg_sales	-0.005	0.017***	0.050***	0.096***	0.101***
	(0.004)	(0.006)	(0.008)	(0.014)	(0.019)
Constant	0.279***	0.170*	-0.203	-0.530**	0.147
	(0.072)	(0.097)	(0.135)	(0.266)	(0.331)
Observations	666	557	412	209	115
R-squared	0.032	0.053	0.183	0.308	0.275

Table A1 (continued)

Pay Ratio	56	57	58	59
lg_sales	0.013***	0.036***	0.068***	0.079***
	(0.004)	(0.005)	(0.011)	(0.013)
Constant	0.038	-0.165*	-0.324	0.149
	(0.068)	(0.099)	(0.230)	(0.206)
Observations	716	577	361	203
R-squared	0.051	0.150	0.212	0.204

Pay Ratio	67	68	69
lg_sales	0.015***	0.042***	0.051***
	(0.004)	(0.008)	(0.011)
Constant	-0.049	-0.094	0.130
	(0.059)	(0.107)	(0.175)
Observations	598	407	225
R-squared	0.055	0.133	0.119

Pay Ratio	78	79
lg_sales	0.030***	0.038***
	(0.007)	(0.010)
Constant	-0.154	0.109
	(0.104)	(0.164)
Observations	415	224
R-squared	0.091	0.098

Pay Ratio	89
lg_sales	0.026***
	(0.008)
Constant	0.067
	(0.126)
Observations	212
R-squared	0.068

Table A2
Measuring Firm Size Using Firms' Assets

This table presents variants of the regressions in Table 4 in which firm size is measured using firms' assets (in logs). All regressions include year fixed effects. Standard errors (in parentheses) are clustered at the firm level. The sample period is from 2004 to 2013. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Pay Ratio	12	13	14	15	16	17	18	19
lg_asset	-0.001	-0.004	0.003	0.002	0.021***	0.060***	0.103***	0.134***
	(0.002)	(0.004)	(0.005)	(0.007)	(0.008)	(0.013)	(0.027)	(0.035)
Constant	0.183***	0.414***	0.470***	0.654***	0.458**	0.056	-1.072*	-0.774
	(0.048)	(0.076)	(0.101)	(0.145)	(0.183)	(0.316)	(0.548)	(0.643)
Observations	675	538	500	450	338	223	88	31
R-squared	0.024	0.049	0.077	0.044	0.109	0.251	0.296	0.472

Pay Ratio	23	24	25	26	27	28	29
lg_asset	-0.010***	-0.008**	-0.007	-0.004	0.033***	0.080***	0.085**
	(0.003)	(0.004)	(0.005)	(0.007)	(0.009)	(0.027)	(0.038)
Constant	0.388***	0.530***	0.703***	0.797***	0.307	-0.446	-0.304
	(0.052)	(0.080)	(0.106)	(0.151)	(0.211)	(0.568)	(0.793)
Observations	765	684	601	486	293	120	49
R-squared	0.043	0.039	0.042	0.023	0.109	0.227	0.186

Pay Ratio	34	35	36	37	38	39
lg_asset	-0.004	-0.004	-0.0001	0.035***	0.075***	0.099***
	(0.004)	(0.005)	(0.007)	(0.013)	(0.024)	(0.033)
Constant	0.256***	0.468***	0.543***	0.117	0.057	-0.693
	(0.074)	(0.105)	(0.150)	(0.278)	(0.410)	(0.619)
Observations	712	603	485	301	125	54
R-squared	0.020	0.021	0.018	0.116	0.169	0.255

Pay Ratio	45	46	47	48	49
lg_asset	-0.003	0.008	0.031***	0.060***	0.065***
	(0.004)	(0.006)	(0.008)	(0.014)	(0.022)
Constant	0.274***	0.275**	-0.073	-0.337	0.394
	(0.075)	(0.110)	(0.170)	(0.335)	(0.473)
Observations	729	612	456	240	138
R-squared	0.019	0.038	0.117	0.190	0.133

Table A2 (continued)

Pay Ratio	56	57	58	59
lg_asset	0.007**	0.023***	0.042***	0.047***
	(0.003)	(0.005)	(0.009)	(0.012)
Constant	0.103	-0.068	-0.171	0.400
	(0.076)	(0.108)	(0.252)	(0.258)
Observations	794	643	413	237
R-squared	0.035	0.104	0.132	0.117

Pay Ratio	67	68	69
lg_asset	0.008***	0.026***	0.031***
	(0.003)	(0.007)	(0.010)
Constant	0.017	0.009	0.300
	(0.061)	(0.121)	(0.216)
Observations	672	465	254
R-squared	0.032	0.078	0.064

Pay Ratio	78	79
lg_asset	0.015**	0.024**
	(0.006)	(0.010)
Constant	-0.018	0.215
	(0.119)	(0.210)
Observations	472	257
R-squared	0.056	0.049

Pay Ratio	89
lg_asset	0.020***
	(0.007)
Constant	-0.155
	(0.143)
Observations	243
R-squared	0.058

Table A3
Within-Industry Analysis

This table presents variants of the regressions in Table 4 which include, in addition to year fixed effects, 2-digit SIC industry fixed effects. Standard errors (in parentheses) are clustered at the firm level. The sample period is from 2004 to 2013. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Pay Ratio	12	13	14	15	16	17	18	19
lg_empl	-0.003	-0.009	-0.013	-0.012	0.018	0.049***	0.107**	0.185*
	(0.004)	(0.008)	(0.010)	(0.009)	(0.013)	(0.016)	(0.041)	(0.099)
Constant	0.280***	0.125*	0.515***	0.860***	0.951***	0.736***	0.592**	-0.104
	(0.034)	(0.065)	(0.085)	(0.095)	(0.113)	(0.235)	(0.289)	(1.217)
Observations	552	468	442	377	291	190	73	22
R-squared	0.155	0.178	0.287	0.336	0.380	0.588	0.680	0.949

Pay Ratio	23	24	25	26	27	28	29
lg_empl	-0.015***	-0.021***	-0.017**	-0.010	0.031**	0.082**	0.224**
	(0.005)	(0.006)	(0.007)	(0.009)	(0.013)	(0.032)	(0.104)
Constant	0.577***	0.739***	0.953***	0.581***	0.402***	-0.462	-0.648
	(0.031)	(0.078)	(0.059)	(0.070)	(0.134)	(0.511)	(1.225)
Observations	652	589	506	412	249	99	36
R-squared	0.194	0.289	0.347	0.351	0.443	0.607	0.859

Pay Ratio	34	35	36	37	38	39
lg_empl	-0.003	0.0003	0.007	0.042***	0.110***	0.095
	(0.005)	(0.006)	(0.009)	(0.012)	(0.029)	(0.057)
Constant	0.385***	0.700***	0.394***	0.514***	-0.088	0.212
	(0.038)	(0.047)	(0.062)	(0.195)	(0.401)	(0.703)
Observations	622	537	434	274	109	46
R-squared	0.265	0.283	0.319	0.432	0.596	0.790

Pay Ratio	45	46	47	48	49
lg_empl	0.0065	0.023***	0.052***	0.091***	0.111***
	(0.005)	(0.007)	(0.010)	(0.017)	(0.029)
Constant	0.323***	0.188**	-0.031	0.248	0.402*
	(0.043)	(0.095)	(0.138)	(0.246)	(0.232)
Observations	642	539	397	201	111
R-squared	0.150	0.227	0.335	0.510	0.565

Table A3 (continued)

Pay Ratio	56	57	58	59
lg_empl	0.016***	0.035***	0.078***	0.089***
	(0.005)	(0.006)	(0.014)	(0.019)
Constant	0.048	0.114*	0.342	0.954***
	(0.039)	(0.059)	(0.323)	(0.209)
Observations	689	554	344	192
R-squared	0.212	0.309	0.430	0.493

Pay Ratio	67	68	69
lg_empl	0.014**	0.049***	0.043**
	(0.005)	(0.012)	(0.018)
Constant	0.129***	-0.171	1.205***
	(0.043)	(0.200)	(0.228)
Observations	572	388	213
R-squared	0.161	0.290	0.364

Pay Ratio	78	79
lg_empl	0.031***	0.047***
	(0.009)	(0.014)
Constant	-0.159	0.191
	(0.153)	(0.150)
Observations	395	212
R-squared	0.298	0.370

Pay Ratio	89
lg_empl	0.015
	(0.012)
Constant	0.724***
	(0.163)
Observations	200
R-squared	0.288

Table A4
Winsorizing Firm Size and Wages

This table presents variants of the regressions in Table 4 in which different winsorizations of firm size and wages are employed. Rather than estimating 36 individual regressions, all pay ratios are lumped together in a single regression that includes pay ratio (i.e., hierarchy-level pair) fixed effects in addition to year fixed effects. Firm size (lg_emp) is the number of employees (in logs). In our baseline specification in Table 4, wages are winsorized at 1% and firm size is winsorized at 5%. In Panel (A), wages are winsorized at 1%, while firm size is winsorized at either 1%, 2.5%, 5%., or 10%. In Panel (B), firm size is winsorized at 5%, while wages are winsorized at either 1%, 2.5%, 5%., or 10%. In Panel (C), wages and firm size are symmetrically winsorized at either 1%, 2.5%, 5%, or 10%. Standard errors (in parentheses) are clustered at the firm level. The sample period is from 2004 to 2013. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Panel (A): Winsorizing Firm Size (Wages Fixed at 1%)

	1%	2.50%	5%	10%
	(1)	(2)	(3)	(4)
lg_empl	0.0207***	0.0209***	0.0221***	0.0230***
	(0.00541)	(0.00565)	(0.00585)	(0.00622)
Constant	0.332***	0.331***	0.320***	0.313***
	(0.0459)	(0.0476)	(0.0491)	(0.0516)
Observations	8,265	8,265	8,265	8,265
R-squared	0.698	0.698	0.698	0.698

Panel (B): Winsorizing Wages (Firm Size Fixed at 5%)

	1%	2.5%	5%	10%
	(1)	(2)	(3)	(4)
lg_empl	0.0221***	0.0217***	0.0211***	0.0203***
	(0.00585)	(0.00580)	(0.00549)	(0.00491)
Constant	0.320***	0.324***	0.327***	0.332***
	(0.0491)	(0.0487)	(0.0464)	(0.0421)
Observations	8,265	8,265	8,265	8,265
R-squared	0.698	0.711	0.730	0.767

Table A4 (continued)

Panel (C): Winsorizing Firm Size and Wages Symmetrically

	1%	2.5%	5%	10%
	(1)	(2)	(3)	(4)
lg_empl	0.0207***	0.0204***	0.0211***	0.0212***
	(0.00541)	(0.00561)	(0.00549)	(0.00523)
Constant	0.332***	0.334***	0.327***	0.325***
	(0.0459)	(0.0472)	(0.0464)	(0.0442)
Observations	8,265	8,265	8,265	8,265
R-squared	0.698	0.711	0.730	0.766

Table A5
Quantile Regression

This table presents a quantile regression based on the baseline specification in Table A4 (wages and firm size winsorized at 1% and 5%, respectively). As in Table A4, the regression includes pay ratio (i.e., hierarchy-level pair) fixed effects and year fixed effects. Firm size (lg_emp) is the number of employees (in logs). Standard errors (in parentheses) are clustered at the firm level. The sample period is from 2004 to 2013. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Wage Quantile	10th	20th	30th	40th	50th	60th	70th	80th	90th
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
lg_empl	0.00702*	0.00776**	0.00938***	0.0101***	0.0115***	0.0145***	0.0138**	0.0169**	0.0223***
	(0.00392)	(0.00340)	(0.00358)	(0.00384)	(0.00400)	(0.00482)	(0.00591)	(0.00797)	(0.00737)
Constant	1.548***	1.584***	1.556***	1.543***	1.637***	1.605***	1.920***	1.910***	2.098***
	(0.0577)	(0.0369)	(0.0380)	(0.0535)	(0.0725)	(0.0685)	(0.0806)	(0.0832)	(0.0729)
Observations	8,265	8,265	8,265	8,265	8,265	8,265	8,265	8,265	8,265
R-squared	0.678	0.686	0.691	0.692	0.694	0.695	0.694	0.692	0.691

Table A6
Decomposing ROA

This table presents variants of the regression in column (2) of Table 7. In column (1), the dependent variable is sales divided by the book value of assets. In column (2), the dependent variable is total cost (EBITDA minus sales) divided by the book value of assets. In column (3), the dependent variable is operating cost divided by the book value of assets. Standard errors (in parentheses) are clustered at both the firm and year level. The sample period is from 2004 to 2013. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

	Sales	Total Cost	Operating Cost
	(1)	(2)	(3)
Pay Inequality	0.451*	0.372	0.413
	(0.259)	(0.268)	(0.269)
lg_empl	-0.0537	-0.0537	-0.0655*
	(0.0348)	(0.0366)	(0.0354)
Constant	1.653***	1.647***	1.716***
	(0.235)	(0.240)	(0.239)
Observations	583	583	578
R-squared	0.013	0.009	0.015