Within-Firm Pay Inequality

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Financial regulators and investors 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 and stronger operating performance. Moreover, firms with higher pay inequality exhibit larger equity returns and greater earnings surprises, suggesting that pay inequality is not fully priced by the market. Our results support the notion that differences in pay inequality across firms are a reflection of differences in managerial talent. (*JEL* G13, G14, J31, L25, M52)

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Rising income inequality has garnered attention in the media and among policy circles.[1] What is perhaps less well known is that financial regulators and stock market investors have recently joined the debate by expressing concerns about high income 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). In agreement, the Securities and Exchange Commission, as mandated by Section 953(b) of the Dodd-Frank Act, adopted a new rule in August 2015 requiring companies to disclose the ratio of median employee pay to that of the chief executive officer. Market participants have reacted positively to this pay

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1 See, for example, 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 ignited by Thomas Piketty's (2014) book "Capital in the Twenty-First Century."

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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).

Other countries are currently still debating whether to introduce pay ratio disclosure. For instance, UK Prime Minister Theresa May recently announced plans to introduce a pay ratio disclosure rule much like the one adopted in the United States. The UK Trade Union Congress supports these plans, arguing that "the publication of pay ratios would play a useful role in focussing the attention [...] on the need for fair pay across the company as a whole."[2] Likewise, UK stock market investors have positively reacted to the possible introduction of pay ratio disclosure: "We believe that the inequality faced by many employees has a material impact on society. [...] LGIM wants companies to publish the ratio between the CEO's total pay (the 'single figure') and that of the median employee" (Angeli Benham, Legal & General Investment Management).[3]

The debate surrounding the introduction of pay ratio disclosure raises several questions. What justification is there for "shaming" firms with high pay inequality, thus possibly dissuading investors from investing in these firms? Do these firms have worse performance or lower valuations? Should investors be concerned about investing in firms with high pay inequality, that is, do these firms have lower equity returns? These are some of the questions our study is trying to answer.

Empirical investigation of pay inequality within firms is challenging due to lack of publicly available data. To address this challenge, we use 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 broad 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. By contrast, level 9, our 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 head of legal. To obtain measures of within-firm pay inequality, we construct *pay ratios* comparing the average pay across different hierarchy

2 Testimony by the Trade Union Congress (TUC) to the UK Parliament, November 2016.

3 Some investors go beyond requiring pay ratio disclosure. BlackRock, the world's largest asset manager and stakeholder in every company listed on the FTSE 100, recently wrote a letter to the bosses of more than 300 UK companies saying it would only approve salary rises for top executives if the companies increased workers' wages by a similar amount (*Financial Times*, January 20, 2017).

levels within the same firm and year. For example, pay ratio 19 compares the average pay of top-level executives, such as finance and HR directors, with that of employees at the bottom of the firm's hierarchy, such as cleaners and unskilled workers, within the same firm and year. There are nine hierarchy levels, leaving us with $(9\times 8)/2=36$ pay ratios.

Pay inequality may vary across firms for a number of reasons. For instance, it may reflect differences in managerial talent. A key implication of the talent assignment hypothesis, which goes back to Rosen's (1981, 1982) economics of superstars, is that more talented managers should match with larger firms (Terviö 2008; Gabaix and Landier 2008). Intuitively, senior employees' talent scales with firm size—as Terviö (2008, p. 642) puts it, "the economic impact of a manager's decisions depends on the amount of resources under his control"—whereas junior employees' talent less likely scales with firm size.[4] Accordingly, if employees are paid according to their marginal product, pay disparities between top- and bottom-level jobs should increase with firm size.

When examining the relation between pay inequality and firm size, we find that pay disparities between hierarchy levels are indeed more pronounced at larger firms. Importantly, and consistent with the talent assignment hypothesis, this result is entirely driven by hierarchy levels where managerial talent is particularly important (levels 6 to 9). By contrast, pay disparities between lower hierarchy levels (levels 1 to 5) are invariant with respect to firm size. Thus, 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 economic magnitude of the firm-size effect is large. Moving from the 25th to the 75th percentile of the firm-size distribution 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. Hence, 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 the efficient assignment of managerial talent, our firm-size results are potentially also consistent with other explanations of within-firm pay inequality. For instance, higher managerial pay at larger firms may be a reflection of stronger incentive provision, or managers at these firms may simply be able to extract more rents. To assess the plausibility of the rent extraction story, we examine how pay inequality is related to firms' operating performance and valuations. If pay inequality is primarily a reflection of managerial talent or incentive provision, we would

[4] 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."

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 (ROA) or Tobin's q, we find that high-inequality firms exhibit stronger operating performance and higher valuations, which is inconsistent with managerial rent extraction. Both effects are economically significant: moving from the 25th to the 75th percentile of the pay-inequality distribution increases ROA by 1.68 percentage points (a 28.6% increase) and Tobin's q by 0.12 (a 9.0% increase).

In additional tests, we seek to distinguish between managerial talent assignment and incentive provision. The underlying idea is that if incentive provision is the key channel, then 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 corporate governance. By contrast, if talent assignment is the key channel, our results should be stronger in more competitive industries, since there is more competition for managerial talent, and they should also be stronger among better governed firms. Regardless of which measure of competition or firm-level governance we employ, we find that our results are stronger in more competitive industries and among better governed firms. Overall, these additional tests suggest that managerial talent is a key driver of pay disparities within firms.

In sum, while we are careful not to draw any causal inferences, our results are prima facie not supportive of worries that "high pay disparities inside a company […] have a negative impact on a company's overall performance." On the contrary, firms with higher pay inequality are better performers and have higher valuations. Ironically, this suggests that pay ratio disclosure, as discussed at the beginning of this section, may be *negatively* informative. Rather than publicly "shaming" firms, it may single out firms with superior performance. As for equity investors, their primary concern ought to be whether investing in firms with higher pay inequality generates alpha, regardless of whether the effect of pay inequality is causal.[5] In the second part of our paper, we therefore examine investment strategies based on pay inequality. Specifically, given the significant association between pay inequality and accounting performance, we want to see if pay inequality is (correctly) priced by the stock market.

To examine 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. Regardless of whether we use the market model or the Carhart (1997) four-factor model, we find that the inequality hedge portfolio yields a positive

[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 longer a discernable effect on either output or attendance.

and significant monthly alpha of 0.93% to 0.98%. An important concern is that pay inequality may be correlated with other firm characteristics that have been previously shown to affect stock returns. To address this concern, we estimate Fama-MacBeth regressions allowing us to include a wide array of control variables. Although including these control variables reduces the monthly abnormal return to 0.81%, it remains highly significant. Hence, our results are not simply driven by pay inequality being correlated with firm characteristics that have been shown to be correlated with stock returns.

Our equity return results are consistent with the notion that differences in managerial talent are not fully priced by the market. Indeed, Edmans (2011) finds that the market does not fully capture intangibles, 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 given that our within-firm pay-level data are not publicly available, which may explain the relatively strong abnormal return.[6] 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, which is consistent with a mispricing channel.

Our paper contributes to the literature seeking to understand pay structures within firms. Much of this literature focuses on CEO pay.[7] 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 shown to be 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 the view that differences in pay inequality across firms are a reflection of differences in scarce managerial talent.

Faleye, Reis, and Venkateswaran (2013) construct ratios of CEO pay (from ExecuComp) to average employee pay (from Compustat) and find that they are positively related to operating performance and firm value. By contrast, our paper studies pay inequality across all hierarchy levels. More important, the authors *control* for average employee pay in all their regressions. Hence, their

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6 We discuss the magnitudes of our equity return results in Section 6.

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

results are entirely identified off of variation in CEO pay, consistent with the large empirical literature that studies how CEO pay is related to firm value and performance.

Lastly, several recent papers study the role of firm- and worker-level heterogeneity for trends in aggregate income inequality using data sets from the United States (Barth et al. 2016; Song et al. 2016) Germany (Card, Heining, and Kline 2013), and Brazil (Alvarez et al. forthcoming). While our paper shares with this literature the focus on firms, our primary aim is to understand what types of firms exhibit more pay inequality and, especially, why some firms exhibit more pay inequality than do others.

1. Data and Summary Statistics

1.1 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. As a result, we are testing theories on the level of pay, not its sensitivity. 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 broad hierarchy levels based on required skills and tasks, including managerial responsibilities. Thus, if a job title has different meanings at different firms (e.g., different managerial responsibilities), 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.[8]

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

[8] 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.

Table 1
Hierarchy levels

Hierarchy level	Examples of job titles	IDS description
1	Cleaner, laborer, 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).

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, our 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 head of legal.

1.2 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: 1) IDS is contracted by client firms to provide guidance on their internal pay policies, and 2) 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 only cover particular segments of a firm's labor force. In particular, executives at the very top of the firm's hierarchy are underrepresented in our sample, as witnessed by the relatively smaller number of observations associated with hierarchy level 9 (see Table 2). At the top executive level, IDS competes with specialized executive compensation consulting firms, and potential clients may ultimately favor these firms over IDS. Indeed, none of our pay-level data associated with hierarchy level 9 are from client-initiated surveys; they all come from IDS-initiated surveys. 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 (see 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 depends on whether the survey is initiated by the client firm or 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 might result in the loss of future business if clients become aware that they are either over-paying their workers or losing key talent due to underpayment. 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. 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 arises due to the types of firms that choose to hire IDS for their internal surveys and which jobs are selected for the 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 the data would be made publicly available. As such, there would appear to be limited motivation to intentionally skew the coverage of jobs in the data.

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 higher than the national average and 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 above the national average can be explained by the fact that our sample firms are larger, bearing in mind that larger firms tend to pay higher wages on average. That being said, the wage-firm size *elasticity* in our data is almost identical to that reported in other studies (see Section 3.2).

1.3 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 especially 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 (see Tables A1 and A2 in the Online Appendix). 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 having 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.[9]

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 in firm size 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 codes 70-89, 23.1% of firms), transportation, communication, electric, gas, and sanitary services (SIC codes 40-49, 16.6% of firms), finance, insurance, and real estate (SIC codes 60-67, 14.9% of firms), and wholesale and retail trade (SIC codes50-59, 12.2% of firms).

1.4 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 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 magnitude 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, average wages are increasing and convex in 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

[9] See Table A3 in the Online Appendix. 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.

Table 2
Distribution of wages by hierarchy level

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

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.

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 would 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. The table 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.

2. Hypothesis Development

Pay inequality may vary across firms for a number of reasons. Below we list some of the main reasons and their empirical predictions regarding the relationship between pay inequality and firm size or operating performance.

2.1 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's (1981, 1982) economics of superstars, is that the value created by a manager-firm match is multiplicative in talent and firm size. Intuitively, managerial talent likely scales with firm size, given that their actions filter through the entire organization, while lower-level employees' talent is less likely scalable.[10] Consequently, larger firms should

[10] Edmans (2016) gives a nice example: "if the CEO implements a new production technology, or improves corporate culture, this can be rolled out firm-wide, and thus has a larger effect in a larger firm. 1% is $20 million in a $2 billion firm, but $200 million in a $20 billion firm. In contrast, most employees have an additive effect on firm value. Their actions are less scalable. An engineer who has the capacity to service 10 machines creates $50,000 of value regardless of whether the firm has 100 or 1,000 machines."

Table 3
Pay ratios

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
56	693	1.315	1.161	1.278	1.429	94
57	557	1.770	1.497	1.702	1.975	99
58	346	2.720	2.059	2.463	3.055	100
59	193	3.826	2.837	3.641	4.534	100
67	576	1.362	1.220	1.338	1.468	96
68	391	2.013	1.598	1.875	2.209	100
69	214	2.806	2.088	2.685	3.296	100
78	397	1.480	1.240	1.391	1.601	98
79	213	2.121	1.700	1.981	2.391	100
89	201	1.529	1.294	1.464	1.682	98

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 (%) represents the percentage of firm-year observations for which the pay ratio exceeds one. The sample period is from 2004 to 2013.

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 increasing with firm size.

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 should be largely invariant with respect to firm size. Lastly, if pay inequality is a reflection of managerial talent, we would expect firms with more inequality to have better operating performance.

2.2 Incentives

Incentive provision within firms may also give rise to pay inequality. There are many variants of this argument, all of which make similar predictions.

2.2.1 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).

2.2.2 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 paid more (in equilibrium) to produce synergies. Larger firms have more synergies, implying that pay inequality increases with firm size.

2.2.3 Moral hazard. If moral hazard is more severe at higher hierarchy levels (e.g., due to larger private benefits), then higher-level managers must be paid more (in equilibrium) to expend effort. Larger firms exhibit greater scope for moral hazard (Gayle and Miller 2009), implying higher pay inequality at these firms. Also, if effort is scalable, it will have a bigger impact not only at higher hierarchy levels but also at larger firms.[11] Again, we thus obtain the prediction that pay inequality increases with firm size.

Our data only include basic employee pay; they do not include any bonus or incentive pay. By contrast, in some of the above theories, pay comes primarily in the form of incentive pay (tournament models being an exception). That said, these theories still have implications for the *level* of pay. As noted above, managers are given more incentive pay when firms are larger. In a model with risk neutrality and limited liability, greater incentives cannot be provided by punishing more for failure (since wages are bounded by zero) and must therefore be provided by paying more for success. Thus, the level of pay goes up. In a model with risk aversion, greater incentives impose more risk on the manager, who demands a risk premium in return. Again, the level of pay goes up. Also, in some moral hazard models, incentives are provided directly through basic wages in conjunction with the threat of firing (Shapiro and Stiglitz 1984) or dynamically through the promise of higher future wages (Lazear 1979, 1981).

Many of the above theories are particularly relevant for managerial jobs. Accordingly, pay ratios comparing lower hierarchy levels with one another should be largely invariant with respect to firm size. Also, if pay inequality is a reflection of managerial incentives, we would expect firms with more inequality to have better operating performance.

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[11] See, e.g., equation (42) in Edmans and Gabaix (2016).

2.3 Rent extraction

Within-firm pay inequality may also arise from managerial rent extraction (Bebchuk and Fried 2004; Bebchuk, Cremers, and Peyer 2011).[12] At larger firms, there are 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 largely invariant with respect to firm size. The managerial rent extraction story differs fundamentally from the talent assignment and incentive provision stories with regard to its implications for operating performance: if within-firm pay inequality is a reflection of managerial rent extraction, firms with more inequality should have worse, not better, operating performance.

3. Within-Firm Pay Inequality and Firm Size

3.1 More pay inequality at larger firms

To explore the relation between pay inequality and firm size, we perform a stringent test: we estimate $(9\times 8)/2=36$ individual regressions, one for each pay ratio. This allows us to see whether, for example, our results are driven by many or just a few pay ratios. More important, it allows us to see if the relation between pay inequality and firm size is primarily driven by upper hierarchy levels, as predicted by many theories.

Table 4 shows the results. Although we estimate 36 individual regressions, our results reveal a clear pattern. Panel (A) includes all pay ratios where 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 where 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

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

Table 4
More pay inequality at larger firms

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

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

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

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

(*continued*)

increasing in the pay ratio. Finally, panels (E) to (H) include all pay ratios where 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.

Hence, despite the large number of 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 firm-size 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

Table 4
Continued

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

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

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

H

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

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 *** represent significance at the 10%, 5%, and 1% level, respectively.

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.

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

Table 5
More pay at larger firms?

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

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 *** represent significance at the 10%, 5%, and 1% level, respectively.

(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 as firm size increases.[13]

3.2 More pay at larger firms?

Are wages associated with lower hierarchy levels individually invariant to firm size, or do they merely increase (or decrease) at a similar rate? To address this question, we study wage *levels* instead of their 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, wages increase with firm size on average. The wage-firm size elasticity is 0.013%, which is identical to the elasticity in Brown and Medoff (1989, Table 1, 1b) based on 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 invariant to firm size or, if anything, slightly decreasing. Thus, the invariance of "bottom-level" pay ratios—those comparing hierarchy levels 1 to 5 to one another—to firm size in Table 4 is not driven by wages in the numerator and denominator both increasing

[13] Tables A1 to A5 in the Online Appendix contain various robustness tests. In Tables A1 and A2, we measure firm size using firms' sales and assets, respectively, in lieu of the number of employees. In Table A3, we use different winsorizations for wages and firm size. In Table A4, we focus on within-industry variation. In Table A5, we estimate 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.

Table 6
Pay inequality and firm growth

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

The dependent variable is the pay ratio (in logs) associated with a given hierarchy-level pair. The samples in Columns (1), (3), and (5) consist of all "bottom-level" pay ratios: 12, 13, 14, 15, 23, 24, 25, 34, 35, and 45. The samples in Columns (2), (4), and (6) consist 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 *** represent significance at the 10%, 5%, and 1% level, respectively.

(or decreasing) at a similar rate. Rather, both wages are individually invariant to firm size.

3.3 Pay inequality and firm growth

Does pay inequality increase as firms grow over time? To address this question, we re-examine the relation between pay inequality and firm size using firm fixed effects. We form two broad groups of pay ratios. The first group consists of "top-bottom" (e.g., 17, 18, 19, 27, 28, etc.) and "top-level" (e.g., 67, 78, 89, etc.) pay ratios. These pay ratios are *significantly* related to firm size in Table 4. The second group consists of "bottom-level" (e.g., 12, 23, 34, etc.) pay ratios. These are *not* significantly related to firm size in Table 4. Together, both groups span all 36 pay ratios. Given that we form groups of pay ratios, we can include hierarchy-level pair and even hierarchy-level pair × firm fixed effects. Thus, the coefficient on firm size shows the relation between changes in pay inequality and changes in firm size within a given hierarchy-level pair and firm.

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

4. 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 ensure that we are not simply picking up correlations between firm size and either operating performance or firm value. For this reason, we run all regressions with and without firm-size controls. To illustrate what this means, 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 managerial talent—consistent with our results in Section 3—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. Hence, pay inequality may proxy for managerial talent even after controlling for firm size. In the data, there is much variation in pay inequality among firms of similar size, consistent with this argument.[15]

To construct a sensible measure of pay inequality at the firm level, we focus on "top-bottom" pay ratios comparing higher hierarchy levels (6 to 9) to lower hierarchy levels (1 to 5).[16] For each pay ratio-firm-year observation, we compute its percentile rank within the pay-ratio sample distribution. (For example, pay ratio 19 at firm x in year t lies at the zth percentile across all observations associated with pay ratio 19 in year t.) We then aggregate this information at the firm level by computing the average percentile rank for each firm in a given year. Lower average percentile ranks imply lower pay inequality. We lag our measure of pay inequality by one year in all regressions.

Table 7 presents the results. In panel (A), we examine the relation between pay inequality and the firm's return on assets (ROA). As Column (1) shows, this relation is positive and significant.[17] In Column (2), we control for firm size. As can be seen, the coefficient on pay inequality remains significant, albeit the point estimate is slightly lower. In Columns (3) and (4), we industry-adjust

[14] For example, in Edmans and Gabaix (2011), managerial talent is assigned based on firm size as well as firm risk. Similarly, in Eisfeldt and Kuhnen (2013), manager-firm matches are formed based on multi-dimensional characteristics.

[15] Another reason why we might see variation in pay inequality among firms of similar size is that some firms are acting suboptimally.

[16] The concern is that firms with significant "top-bottom" pay ratios—high-inequality firms by any sensible standards—may be (mis-)classified as low-inequality firms only because they have compressed "bottom-level" pay ratios (comparing hierarchy levels 1 to 5 to one another) or "top-level" pay ratios (comparing hierarchy levels 6 to 9 to one another).

[17] Table A6 in the Online Appendix suggests that this result is primarily driven by stronger sales.

Table 7
Operating performance and firm value

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

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

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 three-digit SIC industry and year. *Pay inequality* at the firm level is lagged by one year and described in Section 4. Panel (B) is similar 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 three-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 *** represent significance at the 10%, 5%, and 1% level, respectively.

ROA by subtracting the industry median across all firms in Amadeus in the same three-digit SIC industry and year. As is shown, the results largely mirror those in Columns (1) and (2). In panel (B), we consider 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. As can be seen, 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, Table 7 shows that high-inequality firms are not worse performers. On the contrary, high-inequality firms exhibit stronger operating performance and higher valuations, which is inconsistent with rent extraction. Both effects are economically significant. Moving from the 25th to the 75th percentile of the pay-inequality distribution raises ROA by 1.68 percentage points (a 28.6% increase) and Tobin's q by 0.12 (a 9.0% increase).[18] Alternatively, we may express economic significance using the beta coefficients. In that case, a one-standard-deviation increase in pay inequality yields a 0.11-standard-deviation increase in ROA and a 0.07-standard-deviation increase in Tobin's q.

5. Competition and Governance

This section presents additional tests seeking to distinguish between managerial talent assignment and incentive provision. The underlying idea is that if incentive provision is the key channel, then 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 corporate governance. By contrast, if talent assignment is the key channel, our results should be stronger in *more* competitive industries, since there is more competition for managerial talent. Moreover, if better corporate governance results in a better assignment of managerial talent, our results should also be stronger among better governed firms.

To examine if our results are stronger in more competitive industries or among better governed firms, we perform sample splits based on measures of industry concentration and firm-level corporate governance. Our measures of industry concentration are the Herfindahl-Hirschmann index (HHI), Lerner index, and Top five concentration ratio. The HHI is the sum of squared market shares in a given industry and year. Industries are based on three-digit SIC codes. Market shares are based on firms' sales using all firms in Amadeus. The Lerner index is computed like in Aghion et al. (2005). It is the average price-cost margin across all firms in Amadeus in a given three-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 five concentration ratio is the sum of market shares of the largest five firms in a given three-digit SIC industry and year. Our measures of firm-level corporate 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 with an ownership stake of 5% or more based on data from Bureau van Dijk's Osiris database.

Table 8 presents the results. In panels (A) to (C), sample splits are based on industry concentration. "Low" refers to industries with below-median values

[18] In Column (1) of panel (A), the difference between the 25th and 75th percentile of the pay-inequality distribution is 0.343, and the average ROA is 5.88%. Similarly, in Column (1) of panel (B), the difference between the 25th and 75th percentile of the pay-inequality distribution is 0.277, and the average Tobin's q is 1.38.

Table 8
Competition and governance

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	

B. Lerner index

	(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	

C. Top five concentration ratio

	(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	

(*continued*)

of the HHI, Lerner index, and Top five concentration ratio ("competitive industries"). In panels (D) and (E), sample splits are based on firm-level corporate governance. "Low" refers to firms with below-median values of board independence and blockholder ownership. In each panel, Columns (1) to (4) consider the relation between pay inequality and ROA based on the empirical specification in Table 7, and Columns (5) and (6) consider the relation between pay inequality and firm size based on the empirical specification in Table 6. As can be seen, our results are much stronger in more competitive industries and among better governed firms. In fact, with few exceptions, the coefficients are only significant in those sub-samples, albeit the differences between the "low" and "high" sub-samples are not always statistically significant. Overall,

Table 8
Continued

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	

E. Blockholder ownership

	(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	

This table presents sample splits based on measures of industry concentration (panels (A) to (C)) and firm-level corporate 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; that is, "low" refers to industries with below-median values of the HHI, Lerner index, and Top five concentration ratio, respectively. In panels (D) and (E), sample splits are based on firm-level medians; that is, "low" refers to firms with below-median values of board independence and blockholder ownership, respectively. The HHI, Lerner index, Top five concentration ratio, board independence, and blockholder ownership are described in Section 5. In each panel, the last row shows the $p-$value associated with the Wald Chi-square test indicating whether the coefficients in the "low" and "high" groups are significantly different from each other. The sample period is from 2004 to 2013. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

the results in Table 8 suggest that managerial talent is a key driver of pay inequality within firms.

6. Is Pay Inequality Priced by the Market?

Should investors be concerned about investing in high-inequality firms? To address this question, we consider investment strategies based on pay inequality. Specifically, given the significant association between pay inequality and accounting performance, we want to see if pay inequality is (correctly) priced by the stock market.

To examine 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

Table 9
Time-series regressions of monthly excess returns

	Value-weighted		Equal-weighted	
	(1)	(2)	(3)	(4)
A. Inequality hedge portfolio				
alpha	0.979**	0.925**	0.962**	0.970**
	(0.427)	(0.408)	(0.427)	(0.465)
B. High-inequality portfolio				
alpha	0.122	0.057	0.190	0.151
	(0.277)	(0.295)	(0.297)	(0.310)
C. Low-inequality portfolio				
alpha	−0.857**	−0.868**	−0.771**	−0.819**
	(0.400)	(0.421)	(0.352)	(0.348)

This table reports alphas (α) from time-series regressions of monthly excess returns. Excess returns are computed by subtracting three-month UK Treasury-bill returns from raw returns. Panel (A) shows alphas associated with 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. Thus, pay inequality is lagged by one year. *Pay inequality* at the firm level is described in Section 4. Portfolios are rebalanced at the beginning of each year. Panels (B) and (C) show alphas associated with 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, and Columns (3) and (4) show results for equal-weighted portfolios. Standard errors are in parentheses. The sample period is from January 2006 to September 2014 (105 months). *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

at the firm level is the same used in Section 4. 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. Thus, pay inequality is lagged by one year. The sample period is from 1/2006 to 9/2014 (105 months). Excess returns are computed by subtracting three-month UK Treasury-bill returns from raw returns.

Table 9 shows 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 alphas associated with the inequality hedge portfolio. Panels (B) and (C) show alphas associated with the high- and low-inequality portfolio, respectively. In all three panels, Columns (1) and (2) show results for value-weighted portfolios, and Columns (3) and (4) show results for equal-weighted portfolios. UK factors are obtained from the XFi Centre for Finance and Investment at the University of Exeter.[19]

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

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 insignificant and small relative to the alpha associated with the low-inequality portfolio. Hence, most of the abnormal return associated with the inequality hedge portfolio is driven by the low-inequality portfolio. Columns (2) and (4) show results based on 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). As can be seen, the results are very similar to those in Columns (1) and (3). While the alpha associated with the inequality hedge portfolio is positive and significant, this is again largely 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 low-inequality firms have worse managerial talent, and this is not fully priced by the market. This interpretation is consistent with Edmans (2011), who finds that the market does not fully capture intangibles. In our case, the scope for mispricing is especially large given that 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 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. Thus, 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. Like in Gompers, Ishii, and Metrick (2003), we interpret the dummy coefficient in the Fama-MacBeth regression as an abnormal return. In Column (1), which does not include any controls, the abnormal return is very similar to what we found in Table 9. In Column (2), which includes size and book-to-market as controls, the

Table 10
Fama-MacBeth return regressions

	(1)	(2)	(3)
High Inequality	0.992***	0.956***	0.809**
	(0.371)	(0.356)	(0.408)
Size		−0.233**	0.423
		(0.107)	(0.686)
BM		−1.121*	−0.270
		(0.612)	(0.594)
Div. Yield			−4.615
			(5.648)
Volume			−0.588
			(0.576)
Stock Price			0.002
			(0.002)
Ret2-3			0.018
			(0.062)
Ret4-6			0.042
			(0.039)
Ret7-12			−0.004
			(0.034)
Constant	−0.092	2.365**	4.023
	(0.430)	(0.980)	(2.957)
Observations	2,218	2,170	1,996
R-squared	0.001	0.001	0.003

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 equals 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. Thus, firms classified as "high (low) inequality" are the same firms that make up the high- (low-)inequality portfolio in Table 9. *Pay inequality* at the firm level is described in Section 4. 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 January 2006 to September 2014 (105 months). Standard errors are in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

abnormal return is slightly lower. Lastly, in Column (3), which includes the full set of controls, the monthly abnormal return to high-inequality firms is 0.81% and significant at the 5% level. Hence, we 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 previously shown to be correlated with stock returns.

In Tables 9 and 10, the abnormal return to high-inequality firms ranges from 0.81% to 0.98% per month, or about 9.7% to 11.8% annually. While this is a sizable abnormal return, it is not unusually large for investment strategies based on information that is not readily publicly available. By comparison, long-short strategies based on corporate governance indices—which were not publicly available at the time of return realization—yield abnormal returns of 8.5% (Gompers, Ishii, and Metrick 2003, G-Index), 10.8% (Cremers and Nair 2005, G-Index × Top Blockholder), 17.6% (Giroud and Mueller 2011, G-Index × Top HHI), and 13.9% (Bebchuk, Cohen, and Ferrell 2009, E-Index). In contrast, investment strategies based on more easily accessible information related to corporate governance, such as CEO stock ownership (Lilienfeld-Toal and Ruenzi 2014) or CEO salary changes (Groen-Xu, Huang, and Lu 2016), tend to generate smaller abnormal returns of about 6% to 7% annually.

Table 11
Earnings surprises

	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

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 4. 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 *** represent significance at the 10%, 5%, and 1% level, respectively.

To provide further evidence on mispricing, we study earnings surprises. Under a mispricing channel, investors do not fully anticipate the higher earnings of 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). Lastly, 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, and Columns (4) to (6) consider analysts' forecast errors based on median I/B/E/S consensus forecasts. Pay inequality is the same (lagged) measure used in Section 4, where we study 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 consensus forecasts, firms with higher pay inequality exhibit larger earnings surprises. Not only are these earnings surprises statistically significant, but they are also economically significant: in Column (1), moving from the 25th to the 75th percentile of the pay-inequality distribution increases earnings surprises by 0.02. Alternatively, we may express economic significance using the beta coefficients. In that case, a one-standard-deviation increase in pay inequality is associated with a 0.09-standard-deviation increase in earnings surprises. Thus, the market is indeed surprised by the higher earnings of high-inequality firms, consistent with a mispricing channel.

7. Concluding Remarks

Using a proprietary data set of public and private firms, we have studied how within-firm pay inequality—relative wage differentials between top- and bottom-level jobs—varies across firms, how it relates to firms' operating performance and valuations, and whether it is priced by the stock market. We find that firms with higher pay inequality are larger and have higher valuations and stronger operating performance. In addition, we find that these firms exhibit higher equity returns and greater earnings surprises, consistent with a mispricing channel. Overall, our results support the notion that differences in pay inequality across firms are a reflection of differences in managerial talent.

Aggregate income inequality has steadily risen over the past decades.[20] While 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 public firms in the United States has risen by 55.8% (53.0%). Likewise, over the same time period, average employment by the 50 (100) largest public firms in the United Kingdom has risen by 51.3% (43.5%). In Mueller, Ouimet, and Simintzi (forthcoming), we explore the relation between firm growth by the largest firms in a country and aggregate income inequality—measured by the log 90/10 wage differential—based on a broad sample of developed countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Italy, Netherlands, Spain, Sweden, the United Kingdom, and the United States. Regardless of whether we consider the 50 or 100 largest public firms in a country, we find a positive and highly significant association between firm growth and aggregate income inequality at the country level. Thus, part of what is commonly perceived as a global trend toward more wage inequality may be driven by an increase in the size of the largest firms in the economy.

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20 See Acemoglu and Autor (2011) and Atkinson, Piketty, and Saez (2011) for literature reviews.

21 Section 3.1 shows that larger firms exhibit more pay inequality. Section 3.3 shows that within-firm pay inequality increases as firms grow larger over time.

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