

Pay, Productivity and Management

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Abstract:

Combining confidential Census matched employer-employee earnings data and firm employment and sales data, we find four key results. First, employees at more productive firms have higher pay across *all* percentiles of the earnings distribution. Second, the magnitude of this relationship varies substantially across workers, with the elasticity of pay on revenue productivity doubling from 7% for the median paid employee to 15% for the top paid employee; this means that more productive firms have higher within-firm inequality. These different magnitudes appear causal, with similar results when we instrument productivity with market conditions, and are particularly strong at large publicly-traded firms. Third, these patterns are consistent with more productive firms adopting more aggressive performance-based pay schemes for top executives: top workers at more productive firms have higher pay volatility, and we find similar relationships between a firm's management practices (which include use of incentives) and workers' pay. Finally, these results imply that rising productivity can account for a share of rising within-firm inequality, but this share is modest. Instead, rising returns in the aggregate stock market can account for a larger share of rising inequality, consistent with managers increasingly being paid based on the state of the macroeconomy rather than their firms' performance.

JEL Codes: J24, J30, J31

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1. Introduction

The dramatic rise in U.S. wage inequality since the 1970s has been well documented. An enormous body of theoretical and empirical research has been conducted over the past two decades attempting to understand the causes of this trend (e.g., Katz and Autor (1999), Acemoglu (2002), Autor, Katz and Kearney (2008), and Acemoglu and Autor (2011)). Much of this research has focused on CEO and executive pay. For example, Piketty (2013) (p. 315) notes that “*the primary reason for increased income inequality in recent decades is the rise of the super-manager.*” He adds (p. 332) that “*wage inequalities increased rapidly in the United States and Britain because U.S. and British corporations became much more tolerant of extremely generous pay packages after 1970.*”

While much has been learned from these analyses, several major questions remain unanswered. An important set of open questions concerns the link between within-firm wage dispersion on the worker side to trends in the behavior, performance, and management practices of the firms themselves. A major difficulty with studying questions of this sort has been the lack of a comprehensive, matched employer-employee data set in the United States that contains information on both employee pay and firm performance.¹

To help address these questions this paper combines confidential microdata from three major programs at the U.S. Census Bureau. We use detailed quarterly labor earnings data from 2003 to 2015 for over 100 million US employees, matched to their employers, from the Longitudinal Employer-Household Dynamics (LEHD) program. We match this data to employment and revenue information for firms across the US from the Longitudinal Business Database (LBD). Finally, we incorporate information about firms’ use of structured management practices relating to performance monitoring, targeting, and incentive setting from the Managerial and Organizational Practices Survey (MOPS), a supplement to the Annual Survey of Manufactures for 2010 and 2015.

Utilizing the combined data from these three programs yields four major findings. First, employees at more productive firms and firms with more structured management practices have substantially

¹ For example, Davis and Haltiwanger (1991) address the issue of within and between firm wage dispersion in the manufacturing sector by linking the predecessor of the Longitudinal Business Database to household responses to the Current Population Survey (CPS).

higher pay across *all* percentiles of the earnings distribution. Not only are executive earnings higher but so are earnings at every level, from the 1st percentile upwards.

Second, this increase in earnings is greater at higher pay levels. Thus, higher productivity and more structured management practices are also associated with higher levels of pay dispersion within firms (as well as higher pay levels as noted above). This is particularly notable at the very top end of the earnings ranks. For example, while the firm's top earner sees a pay increase of 11% for the doubling of productivity, the 5th, 25th and 50th ranked managers see only 9.0%, 7.1% and 6.5% respectively. These results are robust to the inclusion of firm controls, including firm fixed effects, and we use an instrumental variable approach to show that workers' pay behaves similarly when productivity is higher due to "lucky" macroeconomic conditions.

This pay-performance link holds in both public and private firms, although it is almost twice as strong in public firms for the highest paid workers. The highest paid worker (likely the CEO) sees a 16.4% pay increase in public firms but only a 9.4% pay increase in private firms for a doubling a productivity. Lower ranks, in particular employees outside the top 50 highest paid, display similar performance-pay relationships in public and private firms.

Third, top-earner pay *volatility* is also strongly related to productivity and structured managed practices. One explanation is that more productive firms adopt more aggressive management practices – more intensive monitoring and aggressive performance pay schemes – which leads to both higher levels of pay but also higher volatility of pay.

Finally, we conduct back-of-the-envelope analyses to assess to what degree rising productivity accounts for rising within-firm pay inequality. While higher productivity implies higher within-firm pay inequality in the cross-section, increases in productivity over time in our sample generate only a modest increase in inequality when compared to the actual increase; productivity gains are not large enough to explain rising inequality. We conclude that there must be alternative sources of top earners' pay increasing more than lower earners. We present suggestive evidence consistent with one alternative story: rising pay for the very top managers, especially at publicly-traded firms, may be linked to executive pay contracts effectively rewarding workers for the state of macroeconomy.

We document that S&P500 returns predicting higher pay for top earners, and the increase in these returns over time predict increases in inequality that align closer with the actual increases.

This paper is linked to four key literatures. The first is the general literature on earnings inequality, which examines the rise in inequality in the US (and globally) over the last forty years, building on classic papers like Piketty and Saez (2003) and Autor, Katz and Kearney (2008).

The second is the literature connecting inequality to firms. A growing body of work documents that the variance of firm earnings or wages explains an increasing share of total inequality in a range of countries, including the United States (Barth et al. (2016), Abowd et al. (2018), and Song et al. (2019)), the United Kingdom (Faggio et al. (2010) and Mueller et al. (2017)), Germany (Card et al. (2013)), Sweden (Hakanson, Lindqvist and Vlachos (2015)), and Brazil (Helpman et al. (2017), Alvarez et al. (2018)). Our paper shows that this increase in the variance in earnings may arise from productivity and profit growth since higher-earning individuals in firms appear to have a stronger pay-performance link.

Third, the paper connects to the literature looking at CEO pay. A large literature has asked to what extent rising CEO pay is due to improved performance, firm size, and/or rent extraction; see, for example, Frydman and Jenter (2010) and Edmans and Gabaix (2016) for broad discussions and Gabaix and Landier (2008), Tosi et al. (2000), Bivens and Mishel (2013) for arguments for CEO pay increases being driven by performance, firm size, and rent extraction, respectively.^{2,3} One reason for the focus on CEO pay in the literature is its connection with overall inequality, as a popular hypothesis is that inequality at the very top of firms' pay distributions is a driving force leading to an increase in overall inequality (e.g., Piketty (2013) and Mishel and Sabadish (2014)). Other

² Kaplan (2013) also finds evidence of CEO pay related to performance rather than rent extraction, in particularly arguing that, while CEOs of public firms are highly paid, so too are other professional groups who should not have similar rent extraction opportunities. Similarly, Kaplan and Rauh (2013) argue that because the top earners whose earnings have increased span many occupations, rising inequality is consistent with an increasing market value for talent, rather than increasing managerial power.

³ There is a related broad literature studying the behavior of CEOs and managers and the subsequent implications for firms' productivity and performance. See, for instance, Bertrand and Schoar (2003), Malmendier and Tate (2005), Bennedsen et al. (2007), Malmendier and Tate (2009), Kaplan et al. (2012), Lazear et al. (2015), Mullins and Schoar (2016), Hoffman and Tadelis (2017), Bandiera et al. (2018), Bandiera et al. (2020), Antón et al. (2021), and Kaplan and Sorensen (2021).

research by Smith et al. (2019) has looked at the role of business owners' business income but does not connect it to the earnings of other employees at that firm. By leveraging granular LEHD data on employees beyond the CEO, our paper demonstrates both the *absolute* and *relative* connection between pay and firm productivity for earners across the income distribution. Furthermore, we compare our results to the pay-productivity relationship for executives at large publicly-traded firms in Compustat Execucomp, who are the focus of many papers on executive pay. We find similar relationships between pay and productivity for Execucomp executives and for top earners at publicly-traded companies but weaker pay-productivity relationships for top earners at privately-held companies; we interpret these patterns as consistent with performance-based executive pay, which may be more relevant for executives at publicly-traded firms.

Finally, the paper links to the literature on the large firm pay premium, which has long shown that large firms pay higher wages, even after controlling for a full range of firm and employee attributes (e.g. Moore (1911), Brown and Medoff (1989), Oi and Idson (1999) and Bloom et al. 2018). The prior literature offers several potential explanations for this. One is that larger firms may be more unpleasant to work in and hence pay compensating differentials. Another explanation is that larger firms may face challenges in monitoring their workers, and hence pay higher wages to solve personnel problems. Finally, another hypothesis has been that larger firms may earn higher rents and share some of these rents with their workers, because of perceptions of fairness or bargaining considerations. Our paper showing how more productive firms, which are typically larger, pay higher wages across the wage distribution is perhaps more supportive of the rents explanation, given that compensation and monitoring explanations would likely not be common to all employees.

The paper is organized as follows. Section 2 discusses our core datasets, while Section 3 reviews our main results on pay and firm performance, with Section 4 concluding.

2. Data

We link data from several programs at the U.S. Census Bureau. These data allow us to measure the relationships between workers' earnings and their employers' labor productivity and management structure.

2.1 Longitudinal Employer Household Dynamics (LEHD)

We measure individuals' earnings and their relative earnings positions within their firms using data from the Longitudinal Employer-Household Dynamics (LEHD) program, the most comprehensive matched employer-employee data for the United States. We also use information from the LEHD on individuals' demographics, including date of birth, sex, and education, to control for the demographic composition of firms.⁴

The earnings data in the LEHD is based on firm-side state unemployment insurance (UI) records and contains quarterly employment and earnings information for most individuals working in each state.⁵ We focus on LEHD data from 2003 through 2015, resulting in a balanced panel of all 50 states plus Washington, D.C. The data covers almost all non-farm sectors of the economy, effectively containing all workers covered by the UI system (namely, workers who could claim UI benefits after an eligible dismissal from their employer).⁶

The earnings reported in the LEHD data include salaries and wages as well as bonuses, stock options, and other cash pay, allowing us to study the pay of top earners, such as CEOs, with reasonable accuracy.⁷ The data contain both longitudinal person and longitudinal firm identifiers,⁸ which allow us to study all workers within a firm and follow firms and workers over time.

⁴ The LEHD sources this demographic information from several government sources, including the Decennial Census and the Social Security Administration's Numident file. Some of the demographic characteristics are imputed for some individuals, due to incomplete coverage of the data sources and imperfect linkages; at the extreme, education is imputed for 88% of individuals (Vilhuber (2018)). Throughout, we use only the non-imputed values, and then replace missing values with a constant and include controls for the fact that the values were missing. We define an individual's age in a given year as the difference between that year and their year of birth, such that their age is the age they turn in that year.

⁵ For an overview of the data sources for and contents of the LEHD infrastructure files, see Abowd et al. (2009).

⁶ In 1994, the employment in the LEHD reflected about 96% of national employment and 92.5% of wages and salaries BLS (1997). Due to the nature of the UI system, the data does not include small non-profits, self-employed workers, some agricultural workers, and federal government worker. For details, see Kornfeld and Bloom (1999, pg. 173), BLS (1997, pg. 43), and <http://workforcesecurity.doleta.gov/unemploy/pdf/uilawcompar/2012/coverage.pdf>.

⁷ Stock options are typically reported when they are awarded to employees.

⁸ Note that the LEHD employment information is organized at the State Employer Identification Number (SEIN) level, which is a collection of establishments in the same firm in the same state and detailed NAICS code. We pool across SEINs to get to the firm-level using a mapping available in the LEHD.

Within each firm, in each year, after we impose several sample restrictions described below in Section 2.6, we specify individual workers' relative pay positions in two ways. First, we identify a worker's within-firm **percentile bin**, spanning from 1 to 100, where bin 100 contains the highest earners.⁹ Second, we identify a worker's within-firm **rank**, where the top earner (e.g., CEO) takes rank 1, etc.

2.2 Longitudinal Business Database (LBD)

We measure firm-level national revenue and employment using the LBD, which allows us to construct one of our key measures: firm-level labor productivity. We additionally source rich firm-level industry codes (6-digit NAICS) from the LBD.

The LBD consolidates annual information on sales and employment at the firm level for all non-farm industries beginning in 1997.¹⁰ More granular data on business outcomes are less general than these measures. For example, other studies measure total factor productivity at the establishment level for the manufacturing sector using rich data from the Census of Manufactures, which covers all manufacturing firms in the Economic Census years (years ending in 2 or 7), or the Annual Survey of Manufactures (ASM), which surveys manufacturing establishments in all other years.¹¹ Establishment data in sectors other than manufacturing are generally available only in Economic Census years and lack the detailed input data captured for the manufacturing sector. The revenue data in the LBD is not comprehensive of all firms in the U.S., and its coverage is biased towards older, more stable firms. The impact of this limitation on our analyses is minimal, as we restrict our analysis to relatively large firms; see Section 2.6 for details.

⁹ We calculate these bins as follows: $\text{bin} = \text{floor}(\text{reverse rank within firm} * 100 / (\text{firm employment} + 1)) + 1$; where "reverse rank" means that we rank individuals such that the lowest earner is rank 1, etc. Firm employment is the total number of workers at the firm in the sample (i.e., the number of people to be put in bins). Due to indivisibility, most firms will have slightly unequal number of workers in each bin.

¹⁰ See Haltiwanger et al. (2017) for general details. This data is available to researchers on approved projects through the Federal Statistical Research Data Center (FSRDC) network, where additional documentation is available (Haltiwanger et al. (2019)).

¹¹ For more information on measuring total factor productivity at the establishment level for the manufacturing sector, see Cunningham et al. (2018).

Our measure of revenue labor productivity, henceforth called productivity, is $\log(\text{real revenue}/\text{employment})$.¹² While we do not adjust this measure directly for industry variation, we control for industry in our analyses below.

2.3 Management and Organizational Practices Survey (MOPS)

We measure the firm's use of structured management practices using the MOPS. We use these measures to aid in the interpretation of the relationship between productivity and within-firm earnings dispersion.

The MOPS was issued as a supplement to ASM for survey years 2010 and 2015. All establishments that were included in the ASM samples for those years were also sent the MOPS.¹³ In both survey waves, the MOPS asks plant managers 16 questions about the management practices at their establishments. In particular, respondents are asked questions regarding their practices relating to performance monitoring, target setting, and incentivization of workers. Following Bloom et al. (2019), we score responses to each question between 0 and 1, where zero corresponds to the least structured practices (practices that are less explicit, formal, frequent, or specific) and one corresponds to the most structured practices (practices that are more explicit, formal, frequent, or specific). We then compute an establishment's overall structured management score as the simple mean of the scores of all completed questions.¹⁴ The resulting management score is itself bounded between 0 and 1, where we interpret an establishment with a larger value as having more structured management practices. Bloom et al. (2019) find that establishments with higher structured management scores also tend to be more productive. We aggregate across establishments to the firm-level by taking employment-weighted averages of the management scores across establishments.

2.4 Compustat Bridge (CSB)

¹² We deflate nominal revenue to 2010 dollars using the PCE deflator.

¹³ For details see Buffington et al. (2017) or <https://www.census.gov/programs-surveys/mops/about.html>. The management questions on the MOPS are based on those in the World Management Survey (Bloom and Van Reenen (2007)).

¹⁴ We do not consider the management practices of establishments having missing responses to six or more questions.

In addition to the three core Census programs discussed above, we also use the Compustat bridge to identify publicly-traded firms in each year in order to examine whether the relationship between productivity and within-firm inequality depends on the governance structure of a firm. The CSB maps the identifiers in Compustat (gvkey) to Census firm identifiers (FIRMID), by year (Tello-Trillo and Streiff (2020)). We label firms that appear in the CSB in a given year as “publicly-traded.”

2.5 Compustat and Compustat Execucomp

We supplement our Census analysis based on the Compustat bridge by running analogous analyses outside of the Census system using the Compustat annual fundamentals data on employment and revenue (and thus productivity) and the Compustat Execucomp data on top executives’ earnings at large publicly-traded firms.

2.6 Samples

We consider three samples in this paper.

Main Sample: In our main sample, we study firms that have employees in the LEHD in any year between 2003 and 2015 and that have revenue (and therefore productivity) information in the LBD. We make several additional sample restrictions.

In each year, we restrict the sample to firms with at least 100 full-year workers¹⁵ in the LEHD for that year. An individual is a full-year, or “6-quarter sandwich,” worker if they earn above the minimum wage¹⁶ in the fourth quarter of the previous year, all four quarters of the current year, and the first quarter of the following year. We make this restriction in order to avoid mislabeling a worker who moves jobs in the middle of a quarter as a low paid worker. Because the LEHD does not have information on hours for most states, we use this restriction to reach a sample of individuals for whom the current year’s earnings likely reflect their full-time complete earnings at the firm. We restrict to firms that have at least 100 of these workers in order to have a balanced sample when we consider earnings percentiles within firms. In our instrumental variable (IV) analysis, we focus on

¹⁵ Here, a worker is a person-SEIN pair, i.e., equivalent to a person-firm-industry-state pair.

¹⁶ We say that a worker earns above the minimum wage at an SEIN in a given quarter if her real earnings are at least \$3,298 (i.e., \$7.25/hour * 35 hours/week * (52 weeks/4 quarters), rounded down). We use the CPI-U to deflate earnings measures to 2010 dollars.

the top 100 workers at firms belonging to industries covered by the instruments developed in Alfaro et al. (Forthcoming); see below for details.

For this sample of firms, we classify a firm as publicly-traded (i.e., “public”) in a given year if that firm appears in the Compustat Bridge in that year. We classify a firm as privately-held (i.e., “private”) if it does not appear in the Compustat Bridge in that year.

Table 1 presents several descriptive statistics for our main sample, as well as for the subsamples of firms that are privately-held and publicly-traded. Our main sample, by definition, consists of large firms – the mean firm has almost 1,500 employees nationwide on March 12 of a given year according to the LBD. A smaller number of employees are full-year workers, with the mean firm employing around 750 full-year workers. Within-firm earnings inequality is large within these firms. At the mean firm, workers at the 90th percentile of earnings (amongst full-year workers) earn 3.5 times more ($3.5 = \exp(1.253)$) than workers at the 10th percentile. This gap widens dramatically when we consider earnings gaps between the 99th percentile or the top earner and the 10th percentile: at the mean firm, the workers at the 99th percentile earn almost 9 times more than workers at the 10th percentile ($8.7 = \exp(2.164)$), while the top earner earns over 16 times more than workers at the 10th percentile.

When we split our main sample into firms that are privately-held vs. publicly-traded in Columns (3)-(6) of Table 1, we see that public firms, as expected, tend to be larger, higher paying, and more productive than their private counterparts. Additionally, public firms exhibit higher within-firm earnings inequality on average.

Execucomp sample: When we study the relationship between a firm’s productivity and its workers’ pay, we compare our findings to the results from analogous analyses performed on a set of firms in Compustat Execucomp. We use Compustat employment and revenue and Execucomp executive pay information from 2006 through 2016. We make similar sample restrictions as in our main sample: we restrict to firms at which the top five executives are full-year workers and which have non-

missing productivity.¹⁷ These restrictions result in a sample of 4,681 firms. Because Execucomp covers larger firms within Compustat, firms in the Execucomp sample are larger (the mean firm has 16,094 employees) and more productive (the mean firm has productivity value of 12.84) on average than the set of public firms in our main sample.

Management sample: When we study the relationship between a firm's management structure and its workers' pay, we restrict our main sample to firms for which we can obtain management information from the MOPS. We use both the 2010 and 2015 MOPS, such that this sample consists of all firms in 2010 and 2015 that have at least one establishment that appears in the same-year MOPS. Note that, while the MOPS covers manufacturing establishments, we still consider all workers at each firm (who satisfy the main sample's restrictions), including those at non-manufacturing establishments (SEINs).

In Columns (7) and (8) of Table 1, we present summary statistics for this management sample. Compared to our main sample, firms in our management sample tend to be larger, higher paying, and more productive. The average firm in our management sample also has higher within-firm earnings inequality.

3. Results: Pay and productivity

We begin our empirical analysis by documenting that more productive firms tend to have both higher average pay *and* higher within-firm earnings inequality. We then leverage the richness of the LEHD to document in greater detail how top earners at firms tend to have higher pay, and this pay is more tightly linked to productivity for top paid individuals, especially those at publicly-traded firms.

¹⁷ We begin our Execucomp sample in 2006 because the coverage of Execucomp varies before 2006 and the definition of pay changes in 2006 (Mishel and Sabadish (2013)). Following Mishel and Sabadish (2013), we measure annual earnings as the combined value of an individual's salary, bonus, stock awards, option exercises, and non-equity incentive plan earnings, in 2010 dollars (values deflated by the CPI-U). An individual is a full-year worker in Execucomp if they earn above minimum wage (\$13,195, i.e., \$7.25/hour * 35 hours/week * 52 weeks) in the previous, current, and following year at the same firm, where we track an individual across years using their name and firms across years using their gvkey. We rank executives according to the executive rank provided by Compustat Execucomp, which ranks executives based on their salary and bonus. We require all top-5 ranked executives to be full-year workers. Productivity is log real revenue per worker, where we deflate revenue to 2010 dollars using the PCE.

3.1 Productivity and within-firm earnings inequality

We begin by documenting aggregate patterns of firm productivity and pay for our main sample. We estimate several models of the following form:

$$y_{j,n,t} = \alpha + \beta \text{Productivity}_{j,t} + \mathbf{X}_{j,t} \delta + \gamma_t + \gamma_n + \epsilon_{j,n,t}, \quad (1)$$

where $y_{j,n,t}$ is an outcome of firm j in industry n in year t , such as mean log annual earnings. The key right-hand-side variable is $\text{Productivity}_{j,t}$, the revenue labor productivity of firm j in year t . The coefficient of interest is β , which captures the relationship between a firm's productivity and the outcome.

The model also controls for other characteristics of firms that may be related to both y and productivity. These include a vector of controls $\mathbf{X}_{j,t}$ describing workers' demographics¹⁸ as well as year t and industry n fixed effects. $\epsilon_{j,n,t}$ is a residual. By including demographic controls, we aim to account for selection: for instance, by controlling for the share of workers who are female, we aim to measure the relationships between productivity and pay and within-firm inequality net of the female share, which itself may account for earnings differences and may be correlated with productivity. Similarly, we include industry fixed effects, since productivity and pay may vary dramatically across industries, and we do not want our estimates to be conflated by cross-industry patterns.

Table 2 presents the estimates of model (1) for several outcomes and shows that more productive firms tend to both pay more on average and have higher within-firm earnings inequality. As Column (1) shows, a 10% increase in productivity is associated with a 0.7% increase in mean pay. This increase is not equally distributed across workers at the firm: more productive firms also tend to have higher inequality, as Columns (2)-(5) show for several measures of within-firm pay inequality. For example, in Column (5), a 10% increase in productivity predicts a widening of the gap between the pay of the top earner – likely the Chief Executive Officer (CEO) – and the median worker's pay

¹⁸ This vector is a quadratic expansion (i.e., linear, quadratic, and interactions) of the following firm-year-level variables: share of workers who are female; shares of workers whose highest-attained education level is less than high school, high school, some college, or college or more; and shares of workers who are between the ages of 16 and 25, 26 and 35, 36 and 45, 46 and 55, and 56 and 55. The vector also contains the share of workers whose above demographics were missing.

by 0.8%.¹⁹ In terms of the aggregate distribution of productivity, these patterns are economically large. Moving from the 10th to the 90th percentile in the distribution of productivity in our main sample, these estimates predict an increase in average pay of 20% and an increase in the gap between the top earners and median worker's pay of 26%.

In the next section, we explore these patterns in greater detail by measuring the relationship between firm productivity and the earnings of workers across the within-firm pay distribution.

3.2 Productivity and pay across the within-firm earnings distribution

Given that firms with higher productivity also tend to have both higher average pay and higher inequality, we explore in greater detail how the earnings for workers across the pay distribution are related to productivity.

3.2.1 Specifications

To address this question, we estimate models similar to (1) in which we disaggregate firm-level pay outcomes into the pay outcomes of individuals across the pay distribution:

$$y_{g,j,n,t} = \alpha + \beta Productivity_{j,t} + \mathbf{X}_{j,t}\delta + \gamma_t + \gamma_n + \epsilon_{g,j,n,t}, \quad (2)$$

where $y_{g,j,n,t}$ is an outcome for group g (an earnings percentile bin or rank) at firm j in industry n in year t , such as mean log annual earnings. The key right-hand-side variable is $Productivity_{j,t}$, the revenue labor productivity of firm j in period t . β is the coefficient of interest, capturing the relationship between group g 's outcome and the firm's productivity.

As in Section 3.1, this model also controls for other characteristics of firms that may be related to both y and productivity. These include a vector of controls $\mathbf{X}_{j,t}$ describing workers' demographics as well as year t and industry n fixed effects. $\epsilon_{g,j,n,t}$ is a residual.

3.2.2 Productivity and pay

¹⁹ We calculate this 0.8% from the coefficient on productivity (0.0876) in Column (5). Specifically, a 10% increase in productivity predicts a widening of the gap between the pay of the top earner and the median worker's pay by $(1.1^{0.0876}-1) * 100 = 0.8$ percent.

We begin by considering how the earnings of workers across the whole within-firm earnings distribution (of full-year workers) varies with the firm's productivity. Figure 1a presents the point estimates of model (2), where the outcome is the mean log earnings of workers within a firm earnings percentile. The figure shows three striking patterns. First, all the coefficients on the y-axis are positive, showing that workers at higher-productivity firms tend to earn more across the entire earnings distribution, consistent with the higher average pay in Column (1) of Table 2. Second, consistent with Columns (2)-(5) of Table 2, this positive relationship is not equal across the earnings distribution. Instead, the upwards slope shows that the pay of higher earners is more positively correlated with productivity than the pay of lower earners. For example, a 10% increase in productivity predicts a 0.82% increase in pay for earners at the 90th percentile (the 0.086 coefficient for the 90th percentile in Figure 1) but only a 0.51% increase in pay for earners at the 10th percentile (the 0.053 coefficient for the 10th percentile in Figure 1). Third, this upward slope in the correlation between pay and productivity across the earnings percentiles is particularly large across the top percentiles: the difference in coefficients between the 100th percentile and the 90th percentile is larger than the difference in the coefficients between the 90th percentile and the 10th percentile. This pattern suggests that the pay-performance link is increasingly strong rising up pay percentiles.

Because the differences in the relationship between productivity and pay are particularly dramatic, we next focus on the top earners by earnings rank. Figure 1b presents the point estimates of model (2), where the outcome is the log earnings of the workers at the top ranks within firms, where the top paid employee is often the Chief Executive Officer (CEO), the second top is often the Chief Financial Officer (CFO), with other senior managers typically rounding out ranks 3 to 10.²⁰ Even among these very top earners, we see an increasing correlation between pay and productivity across the ranks. For the top earners at firms, a 10% increase in productivity predicts a 1.5% increase in pay. Meanwhile, for the fifth highest earner, the predicted increase in pay is only 1.2%.

3.2.3 Robustness and causality of productivity-pay relationship

²⁰ For example, in Execucomp 81% of CEOs have the highest total pay (where pay=salary and bonus and stock grants and stock options and non-equity incentives) in the firm-year, and 92% have the highest salary and bonus pay in that firm-year. Both statistics are for all firms reporting the pay of 5 or more executives in that firm-year. In private firms, where stock grants and stock grants are a much smaller component of salary, CEOs are particularly likely to be the highest-paid employees in a firm-year.

While we have shown that, cross-sectionally, workers at more productive firms earn more, particularly if they are top managers, we argue that these relationships are robust and at least partially causal. Here, we discuss additional robustness tests as well as an instrumental variables approach.

First, our results are robust to including worker demographics and firm controls, as well as restricting our analysis to particular sectors or firm ages. One explanation for these relationships might be variations in individual characteristics, so as noted above every regression is saturated with a quadratic expansion of education, age, gender and year individually and in cross product. This attempts to control for broad variations in these characteristics across employees with a flexible functional form, which is possible because of the large size of our regression sample. We also include a full set of 6-digit industry fixed effects to control for differences in pay levels across industries. In Appendix Figure A3 we go further by including a full set of firm fixed effects, so coefficients are entirely identified by changes in firm performance and individual pay, and find a similar result.²¹ This relationship also turns out to be incredibly robust in multiple dimensions. For example, Appendix Figure A1 breaks this down into all 18 two-digit NAICS sectors revealing a similar positive, rising convex relationship between pay and performance rising up earnings ranks. Appendix Figure A2 breaks this down by firm age and again shows very similar results by different age categories.

Second, while we have demonstrated above that top earners' pay is disproportionately and robustly correlated with firm performance, a natural question for these relationships is to what extent is firm performance causally driving individually employee pay, rather than say reflecting a selection story or reflecting some other change not captured by our controls. To investigate this, Table 3 uses instrumental variables from Alfaro et al. (Forthcoming), which are the industry-level exposures to the seven major international currencies for the US, oil prices, and economic policy uncertainty.

This identification strategy exploits the fact that industries have different responses to common shocks. For example, oil companies' revenues are positively correlated with oil prices, while retailers' revenues are approximately neutral and airlines' revenues are negatively correlated. Alfaro

²¹ Note that while the firm (by definition) stays the same over time, the top earners may change; that is, the top earner at a firm in 2010 need not be the same individual as the top earner at that firm in 2015.

et al. (Forthcoming) estimate these exposures by industry year using a 10-year rolling windows of daily stock returns firms in that industry regressed on daily changes in currencies, oil prices, and the policy uncertainty index.

We estimate the causal relationship between productivity and pay by estimating 2SLS regressions, instrumenting productivity with the instruments described above. To do this analysis, we focus on the top 100 paid sandwich workers²² at each firm in each year, for firms belonging to industries for which we have instruments. We estimate both OLS and 2SLS versions of

$$y_{g,j,n,t} = \alpha + \beta_1 Productivity_{j,t} + \beta_2 Rank_g \times Productivity_{j,t} + \gamma_g + \gamma_t + \gamma_n + \epsilon_{g,j,n,t}, \quad (3)$$

where $y_{g,j,n,t}$ is log annual earnings for group g (an earnings rank) at firm j in industry n in year t . We estimate both the relationship between earnings and productivity (captured by β_1) and the how this relationship varies (linearly) with rank (captured by β_2). We include rank, year, and industry fixed effects.²³

In our 2SLS specification of model (3), we instrument productivity (both on its own and interacted with rank) with the Alfaro et al. (Forthcoming) instruments. We interpret the 2SLS results as indicating the causal relationship between pay and productivity; namely, the results capture how pay varies when firms are more or less “lucky” in their performance, based on exposure to common shocks.

Table 3 columns (1) and (2) report the basic OLS, showing that log earnings is correlated with productivity, confirming the OLS results on the IV sample. In column (1), we exclude the interaction term and demonstrate that earnings tend to be higher at more productive firms. Importantly, in column (2) this has a significant negative interaction with rank, reflecting the results in Figures 1 to 3 that higher earning (smaller rank value) employees’ pay is more sensitive to firm performance.

²² Focusing on the top 100 workers for each firm-year pair allows to equally weight all firms within the same year.

²³ In unreported results, we confirm our 2SLS results are similar if we include the worker characteristics controls, as in model (2).

As shown in columns (3) and (4), our instrumental variables approach produces broadly similar results to the OLS.²⁴ When productivity is higher because of “lucky” exposure to common shocks, workers have higher earnings, and this is particularly true for workers at the top. These results are consistent with productivity causally affected workers’ pay.

3.2.4 Role of ownership: publicly-traded vs. privately-held firms

One reason top earners’ pay may be particularly correlated with productivity is that these workers may be disproportionately subject to performance-based pay (see for example Gao and Li, 2015). If this is true, then we may expect the pattern in Figure 1 to be stronger for publicly-traded firms, where top earners may be more incentivized to increase productivity, than for privately-held ones.

Figure 2a replicates Figure 1 but breaks out the coefficient on productivity by the trading status of the firms (and controls for the trading status). Figure 2a presents specifications similar to Figure 1b, estimating the relationship between pay and productivity at different earnings ranks, depending on public status. Within our main (Census) sample, the pay of top earners at publicly-traded firms is more correlated with productivity than the pay for top earners at privately-held firms. For example, for the top-paid employee, which might typically be the CEO, we see the pay-productivity coefficient in public firms is 0.22 and is 0.13 in private firms.²⁵

Furthermore, the slope in the pay-productivity correlation *across* top earners is also stronger for public firms. For example, for public firms, a 10% increase in productivity predicts a 2.1% increase in pay for the top earner and a 1.4% increase in pay for the fifth earner, such that the coefficient for the top earner is 1.5 times that for the fifth earner at public firms. Meanwhile, for private firms, a 10% increase in productivity predicts a 1.2% increase in pay for the top earner and a 1.0% increase in pay for the fifth earner, such that the coefficient for the top earner is only 1.2 times that for the fifth earner at private firms.

²⁴ Appendix Table 1 adds the 1st stage results to Table 3. In both 1st stage specifications, F-statistics are approximately 3.

²⁵ This pattern is consistent with findings by Gao and Li (2015), who show that CEO pay at public firms is more closely correlated with firm accounting performance than CEO pay at private firms.

Both the coefficient level and slope differences for public and private firms are largest amongst the very top earners. Once we consider, e.g., the 25th top earner or the 50th top earner, the gaps are much smaller. This suggests that the difference in the relationship between productivity and pay, at least for large firms, may be relatively small and concentrated at the very top of the earnings distribution.

Figure 2a also compares these pay-productivity correlations with those for the set of top executives at large publicly-traded firms in our Execucomp sample.²⁶ As the figure shows, the relationship between pay and productivity for top executives in Execucomp is very similar to the relationship between pay and productivity for top earners at publicly-traded firms in the LEHD. This finding provides support of our interpretation that the top earners at firms in the LEHD likely include executives. This comparison also demonstrates the benefits of using the LEHD to analyze pay within firms: within the LEHD, we can consider the pay of non-executives (i.e., lower ranks) and can study a much broader set of firms, leading to higher precision (i.e., much smaller confidence intervals) and results that capture a broader scope of the labor market.

One explanation for the stronger relationship in public firms is these are on average larger than private firms. To address this, the Figure 2b presents analogous results but reweights public firms by ventiles of employment to have the same size distribution as private firms and still find a much stronger relationship between pay and performance in public firms.²⁷ We also re-estimate these results including controls for log(employment) at the firm level and again find very similar results,

²⁶ For our Execucomp sample, we estimate regressions of the log annual earnings of one of the top 5 executives on productivity and year and 6-digit industry fixed effects; within Compustat, we do not have information on the worker compositions of firms, and so we cannot include the worker composition controls in the regressions.

²⁷ Unlike in Figure 2a, Figure 2b is based on weighted regressions, where the weights are chosen to match the employment distribution of public firms to that of private firms. As Table 1 shows, publicly-traded firms are larger on average than privately-held firms. This means that estimates of model (2) broken out by trading status may hinder interpretation, since comparing the pay-productivity correlation of the, e.g., 50th top earner at a large public firm to the 50th top earner at a smaller private firm may be misleading. Additionally, some top earners of smaller private companies may be compensated in equity, which may not be captured in their LEHD earnings; by weighting the regressions to match the employment distributions, we compare publicly-traded firms to privately-held firms whose top earners' compensation should be captured by the LEHD and may equally be related to firm performance. Private firms are given weight 1, while public firms are given weights equal to the share of private firms with similar employment divided by the share of public firms with similar employment (where similar employment is based on binning all firms into ventiles of employment).

suggesting public firms have a stronger pay-performance relationship that is not primarily explained by their larger firm size.

4. Mechanisms: Performance-based pay

A major question around the convex relationship between pay and performance across managerial ranks is what is the underlying mechanism driving this. In this section, we present two sets of patterns consistent with performance pay incentives for more senior managers being a contributing factor. We start by showing that higher productivity also predicts higher within-worker pay volatility, particularly for top paid workers, suggesting a role for incentive-based pay. Then, we directly study the role of managerial policies by leveraging the MOPS data and show that firms with more structured management practices (including incentive-based pay) have similar pay patterns.

4.1. Pay volatility and productivity

A possible implication of more performance-based pay for top earners is that top earners should experience more within-year pay volatility at more productive firms, for instance because a larger share of their income may come through bonuses.

We investigate this by estimating model (2) where the outcome is the within-year pay volatility for the top earners at firms. We measure within-year pay volatility as the standard deviation in quarterly log earnings, within a given year. Figure 3 presents these estimates. Consistent with performance-based pay, earners at more productive firms are more likely to have higher within-year pay volatility, and this is particularly true for the very top earners.²⁸ Because our sample restricts to full-year workers, we do not believe that the within-year pay volatility, or the relationship between volatility and productivity, is driven by top earners at more productive firms being more likely to leave the firm. Rather, because these workers are consistently employed at the firm, these patterns reflect real within-job pay variation, which may be particularly driven by the sizes of their bonuses.

Senior managers have a stronger relationship between pay volatility and performance, with this getting rapidly stronger heading towards the top-paid executives. One natural explanation is that more productive firms have more aggressive performance pay, leading to greater pay volatility.

²⁸ As Figure A4 shows, pay volatility is generally higher at higher pay percentiles.

4.2. Pay and management structure

We further explore the role of performance-based pay by considering a correlate of productivity: management practices. We turn to our management sample, for which we have a measure of the degree to which a firm utilizes structured management practices. The measure incorporates both how organized the firm's production process is and how it incentivizes workers.

First, we document how management relates to average pay and within-firm inequality. Table 5 presents estimates of versions of model (1) in which we replace productivity with the firm's management score as the key explanatory variable; this table is analogous to Table 2. Recall that management scores are normalized between 0 and 1, with a mean value of 0.67 in our sample (Table 1). As Table 5 shows, the patterns we see between productivity and pay in Table 2 are also present for management and pay. Firms with more structured management tend to have higher average pay and larger inequality. In terms of the aggregate distribution of management, these patterns are economically large. Moving from the 10th to the 90th percentile in the distribution of management is associated with an increase in average pay of 6.3% and an increase in the gap between the top earner's pay and the median worker's pay of 26%.²⁹

Second, as we did for productivity, we consider how pay across the firm earnings distribution correlates with management. Analogous to Figure 1, Figure 4 presents the point estimates of version of model (2), where we replace productivity with management as the key explanatory variable. While the standard errors are relatively large – the management sample contains only 2.5% of the observations from the main sample – we see similar patterns. Workers across the earnings distribution at firms with more structured management tend to have higher earnings, and these correlations generally increase across the distribution, with workers in the top percentile experiencing the largest correlation.

²⁹ The relationship between management and within-firm earnings inequality may be driven by how firms incentivize their workers. For example, the predicted increase in the pay gap between the 99th and 10th percentile workers with a higher management score is entirely driven by whether firms incentivize their workers with performance-based pay and promotions. If we re-estimate Column (3) of Table 3 and break out the management score into a score based on questions on monitoring and a score based on questions on incentives, the coefficients (standard errors) are -0.086 (0.041) and 0.141 (0.032), respectively.

This matches a story of more productive better managed firms providing increasingly aggressive performance pay systems for senior managers, increasingly overall pay levels and also pay volatility. Since this relationship between pay and performance is increasingly steep for employees higher up in the earnings rank it is also associated with growing levels of within firm inequality. Thus, it appears that firms adopting more aggressive performance pay see improved productivity and higher pay, but at the expense of higher pay volatility and within-firm pay inequality.

5. Aggregate inequality implications

We have documented that workers at more productive firms are paid more, and this is particularly true for the top workers at firms, possibly because more productive firms use more performance-based pay schemes to incentivize senior managers. In the cross-section, these patterns mean that more productive firms exhibit higher within-firm earnings inequality, which we summarize below. Given that, can rising productivity account for rising within-firm earnings inequality over time? We show that slowly rising productivity can only account for a modest share of the increase in top paid workers' earnings relative to lower workers; instead, we speculate that rising managerial earnings may be accounted for by the tight link between managerial earnings and the macroeconomy, particularly the stock market.

5.1. Cross-sectional within-firm earnings inequality

To take stock of the pay-performance relationship in the cross-section, Table 4 examines the relationship in regression form and provides an angle to get a handle on the overall magnitude of these relationships. We estimate regressions relating pay to productivity for a sample of the top 100 paid sandwich earners at each firm in each year; we estimate models similar to model (3) and include as controls year, industry, and rank fixed effects and log total LEHD employment at each firm in each year.

In column (1), we see earnings is highly correlated with productivity, with the coefficient implying every 10% increase in productivity is associated with a 1.6% increase in earnings. This is low in relation to estimates from the rent sharing literature, for example Kline et al. (2019) who often find pass throughs of closer to 0.2 to 0.4. We should note these regressions all include a full set of industry

controls, log(employment) and rank fixed-effects, and in this specification are not instrumented, so this complicates the comparison of these magnitudes.

In column (2), we include a control for public ownership of the ultimate parent and find this is associated with a 29% higher level of pay, but with the pay-performance relationship remaining extremely similar to column (1). In column (3) we include an interaction of rank and productivity with a coefficient of -0.0006 on a base for productivity of 0.1866. This implies the pass through from a 10% increase in productivity is approximately 0.19 for the top paid employee but only 0.13 for the 100th ranked employee.³⁰ These specifications summarize the main cross-sectional fact of this paper: more productive firms exhibit higher within-firm pay inequality.

5.2. Trends in within-firm earnings inequality

Given that more productive firms exhibit higher within-firm pay inequality *and* within-firm pay inequality has increased over time (Song et al. (2019)), can the increase in inequality be explained by rising productivity?

We conduct a simple back-of-the-envelope calculation to answer this question. In our sample, productivity increased by 7.7% from 2005 to 2013.³¹ We multiply this trend by the coefficients presented in Figure 1b, resulting in predicted increases in earnings for different earning ranks, which we then compare to the actual increase in earnings at each rank.³²

Between 2003 and 2015, the average top earners' pay increased by 14%. Meanwhile, the average 50th ranked earners' pay increased by only 6%. Because productivity increased over this time period, we *expect* some increase in inequality; but, the implied changes for these ranks' pay is modest compared to the actual increase. The increase in productivity predicts that the top earners' pay should

³⁰ Table 4 also includes a column (4) that summarizes that top paid workers at publicly-traded firms disproportionately earn more than top paid workers at privately-held firms.

³¹ We estimate a linear time trend of productivity, conditional on our standard set of controls, and then multiply that time trend by 13 (the number of years in our sample). For example, we estimate a time trend of 0.0057 for the pooled sample of all firms; this implies an increase in revenue/employment of 7.7% from 2003 to 2015 (adjusted for worker demographics and industry composition changes).

³² To estimate the actual increase in level earnings, we take the exponent of the difference between mean log earnings at a given rank in 2015 vs. 2003 and subtract 1.

have only increased by 1%, while the 50th ranked earners' pay should have only increased by 0.7%. Clearly, productivity is not the only source of pay changes, and the rise in productivity underpredicts all workers' pay increases. But more importantly, the rise in productivity cannot account for the increasing gap between top and lower paid workers' pay.

The fact that productivity increases do not largely predict the rise in within-firm earnings inequality is particularly stark for publicly-traded firms, where the top paid workers' pay doubled between 2005 and 2013, while the 50th ranked workers' pay only increased by 43%. Publicly-traded firms experienced a larger productivity increase over the time period (10%), but this increase still only predicts a fraction of the rise in earnings. The rise in productivity predicts that top paid workers' pay should have increased by only 1.5% and the 50th ranked workers' pay by 0.5%.

This back-of-the-envelope is very simple, yet it conveys a simple message: productivity has not increased enough to account for the majority of the rise in within-firm earnings inequality. Our measures of productivity increases may be conservative, but even if we consider the aggregate productivity increases of 2% per year measured by FRED, pay for workers at the top disproportionately increased more than lower paid workers in a way that is difficult to explain with rising productivity.

We conclude from this analysis that *something else* has driven the rise in top paid workers' pay relative to their lower paid coworkers. To conclude, we briefly provide speculative evidence consistent with another story: top paid workers' pay is disproportionately predicted by the state of the macroeconomy, specifically the stock market, and rising stock returns can predict a larger share of the increase in pay over time.

We investigate this by dividing these into size groups and studying the relationship between pay and S&P500 returns by replacing productivity with annual S&P500 returns in model (2).³³ We study this to examine the response to an external factor – the overall stock-market performance – in individual

³³ It is important to note that, because we use annual S&P500 returns, we can no longer include year fixed effects in this model. This means that this specification is particularly subject to possible omitted variable bias, such that we interpret these findings with caution.

executive pay. We consider three size groups: medium sized firms with 100 to 249 employees, larger firms with 250 to 999 employees, and mega firms with 1000+ employees.³⁴ We see two clear results. First, public firms within each size category display a distinctly stronger relationship to the S&P500, with this typically about twice as strong for public as private firms; but, notably the coefficients are still positive for private firms, none of whom are part of the index. Second, as firms grow in size, the relationship between the S&P500 and individual employee pay increases, with the coefficient on returns rising for example for the top paid employees in public firms from 0.006 in medium firms, to 0.015 in larger firms to 0.023 in mega firms. This size pattern may reflect that larger firms tend to have stronger and more structured performance management systems for performance pay and bonuses (e.g. see Bloom et al. 2019 and Scur et al. 2021).

What do these patterns mean? Top paid workers' pay, especially for those at large publicly-traded firms, is disproportionately predicted by aggregate stock market returns. The connection between pay and aggregate stock market returns, which may be uncorrelated with a firm's productivity, may reflect executive pay policies that effectively reward executives for the market's performance. Just as we calculated how rising productivity accounts for rising within-firm earnings inequality, we can similarly analyze rising S&P500 returns. Compared to increasing productivity, the increasing trend in S&P500 returns from 2003 to 2015 predicts a sizable share of the actual increase in earnings. For example, the increase in the S&P500 return predicts that the average top earners' pay should have increased by 11%, while it actually increased by 14%; the increase in return predicts that the 50th ranked earner's pay should have increased by 6.1%, while it actually increased by 6.2%.³⁵ Again, this calculation is simple but demonstrates that market conditions, especially if they increasingly affect top managerial pay, may better account for rising within-firm earnings increases than rising productivity.

6. Conclusion

We use confidential Census matched employer-employee earnings data to study the relationships between pay, productivity, and management practices. We find that employees at more productive

³⁴ The requirement to have 100+ continuing (sandwich) employees in each firm means we do not include any genuinely smaller firms in our study.

³⁵ These numbers are likely inflated due to omitted variable bias in the regressions of earnings on annual S&P500 returns, given that year effects are omitted.

firms and firms with more structured management practices have substantially higher pay, both on average and across every percentile of the pay distribution. This pay-performance relationship is particularly strong amongst top paid executives, with a doubling of firm productivity associated with 11% more pay for the highest-paid employee (likely the CEO) compared to 4.7% for the median worker. This pay-performance link holds in public and private firms, although is almost twice as strong in public firms for the highest paid executives. Top-executive pay *volatility* is also strongly related to productivity, and pay inequality is strongly related to management practices, suggesting this performance-pay relationship arises from more aggressive monitoring and incentive practices amongst top executives.

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Table 1. Summary Statistics

Statistic	Main Sample		Main Sample, Private Firms		Main Sample, Public Firms		Management Sample	
	(1) Mean	(2) Std Dev	(3) Mean	(4) Std Dev	(5) Mean	(6) Std Dev	(7) Mean	(8) Std Dev
Mean log pay	10.95	0.483	10.92	0.469	11.26	0.545	11.01	0.421
90-10 Gap	1.253	0.395	1.234	0.391	1.492	0.364	1.228	0.359
99-10 Gap	2.164	0.632	2.134	0.627	2.526	0.579	2.241	0.575
Top Earner-10 Gap	2.796	0.965	2.705	0.88	3.919	1.232	3.113	1.098
Top Earner-50 Gap	2.287	0.914	2.205	0.836	3.304	1.188	2.631	1.027
Sample employment (full-year workers)	745.9	5500	491.7	3421	3890	15780	1501	12260
Total Employment	1448	10450	937.6	6596	7763	29630	2350	21070
Productivity (log revenue/employment)	5.006	1.147	4.958	1.138	5.598	1.082	5.630	0.848
Management							0.673	0.118
N (firm-year pairs)	443,000	443,000	410,000	410,000	33,000	33,000	11,000	11,000
Number of underlying worker-year pairs	330,400,000	330,400,000	201,500,000	201,500,000	128,900,000	128,900,000	16,440,000	16,440,000
Number of unique firms	73,000	73,000	69,500	69,500	5,400	5,400	8,000	8,000

Notes: Pay measures are based on full-year workers at firms in each year and include the mean log annual earnings, the 90th-10th percentile and 99th-10th percentile log annual earnings gaps, and the gaps between the top earner and the 10th and 50th percentiles. Percentiles and ranks are based on full-year workers. Total employment includes all workers, not only full-year workers. Productivity is log revenue per worker. Management is the overall management score and is normalized between 0 and 1. In Columns (1) and (2), the sample includes all firms in our main sample from 2003-2015; Columns (3) and (4) and Columns (5) and (6) split this sample into privately vs. publicly traded firms, respectively. In Columns (7) and (8), the sample includes firms in our management sample from 2010 and 2015. Observation-level is the firm-year; statistics are unweighted.

Table 2. Pay Levels and Inequality are Correlated with Productivity

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	Mean Pay	90-10 Gap	99-10 Gap	Top Earner-10 Gap	Top Earner-50 Gap
Productivity	0.0684*** (0.0006)	0.0332*** (0.0005)	0.0637*** (0.0010)	0.1000*** (0.0016)	0.0876*** (0.0015)
% rise from 10 th to 90 th productivity percentile	18.0	8.7	16.8	26.3	23.1
N	443,000	443,000	443,000	443,000	443,000

Notes: * Significant at the 10% level, ** 5% level, *** 1% level. All columns present regressions of measures of pay based on full-year workers. In Column (1), the dependent variable is the mean log annual earnings at a firm in a year. In Columns (2), the dependent variable is the difference between the within-firm 90th and 10th percentiles of log annual earnings; in Column (3), the dependent variable is the gap between the 99th and 10th percentiles. In Column (4), the dependent variable is the difference between the log annual earnings of the top earner and the 10th percentile; in Column (5), the dependent variable is the gap between the top earner and the 50th percentile. Productivity is log revenue per worker; 10th percentile of productivity is 3.73, while 90th percentile is 6.36. Controls include a quadratic expansion of workers' demographics, including education, age, and sex, and year and 6-digit industry fixed effects. The sample includes all firms in our main sample from 2003-2015; each firm appears in every regression. Observation-level is the firm-year; regressions are unweighted.

Table 3. Productivity Increases Cause Higher Pay and Higher Pay Inequality

	OLS (1)	OLS (2)	2SLS, 2 nd Stage (3)	2SLS, 2 nd Stage (4)
Dependent Variable:	Log Annual Earnings			
Productivity	0.1499*** (0.01475)	0.1771*** (0.01633)	0.1467* (0.08290)	0.2198** (0.1023)
Rank X Productivity [^]		-0.5390*** (0.1452)		-1.447** (0.6320)
N	37,770,000	37,770,000	37,770,000	37,770,000
JointF-stat	103.3	59.36	3.133	2.905

Notes: * Significant at the 10% level, ** 5% level, *** 1% level. This table presents several regression estimates for our main sample, where we reshape the sample to be at the firm-year-rank level; we restrict to the top 100 paid employees in each firm-year pair. Each column describes a separate regression of earnings on productivity instrumented by lagged instruments from Alfaro, Bloom, and Lin, including currency price changes (CAD, Euro, JPY, AUD, SEK, CHF, and GBP), oil price changes, and economic policy uncertainty changes (EPU); we restrict to firms in industries covered by these instruments. Each regression includes the following controls: year, RE-LBD NAICS6 industry, and rank fixed effects. Standard errors are clustered at the SIC2 level. See Appendix Table 1 for first stages. [^] denotes that for presentation purpose the point-estimate and standard errors for the Rank X Productivity results have both been scaled up by 1000.

Table 4: log earnings on productivity, public status, and rank

Dependent Variable:	(1)	(2)	(3)	(4)
	Log Annual Earnings			
Productivity	0.1643*** (0.000093)	0.1554*** (0.000093)	0.1866*** (0.000147)	0.1554*** (0.000093)
Public		0.2943*** (0.000338)	0.2943*** (0.000337)	0.3781*** (0.000602)
Rank X Productivity			-0.000619*** (0.000002)	
Rank X Public				-0.001659*** (0.000010)
N	44300000	44300000	44300000	44300000

Notes: * Significant at the 10% level, ** 5% level, *** 1% level. This table presents several regression estimates for our main sample, where we reshape the sample to be at the firm-year-rank level; we restrict to the top 100 paid employees in each firm-year pair. Each column describes a separate regression of log annual earnings on various RHS variables. Each regression includes the following controls: year, RE-LBD NAICS6 industry, and rank fixed effects and log total LEHD employment.

Table 5. Pay levels and inequality are correlated with Management Practices

Dependent Variable:	(1) Mean Pay	(2) 90-10 Gap	(3) 99-10 Gap	(4) Top Earner-10 Gap	(5) Top Earner-50 Gap
Management	0.2078*** (0.0296)	0.0732*** (0.0253)	0.1199*** (0.0456)	0.8133*** (0.0849)	0.7842*** (0.0812)
% rise from 10 th to 90 th management percentile	6.1	2.1	3.5	23.8	23.0
N	11,000	11,000	11,000	11,000	11,000

Notes: * Significant at the 10% level, ** 5% level, *** 1% level. All columns present regressions of measures of pay based on full-year workers. In Column (1), the dependent variable is the mean log annual earnings at a firm in a year. In Columns (2), the dependent variable is the difference between the within-firm 90th and 10th percentiles of log annual earnings; in Column (3), the dependent variable is the gap between the 99th and 10th percentiles. In Column (4), the dependent variable is the difference between the log annual earnings of the top earner and the 10th percentile; in Column (5), the dependent variable is the gap between the top earner and the 50th percentile. Management in the overall management score and takes on values between 0 and 1; 10th percentile of management is 0.51, while 90th percentile is 0.81. Controls include a quadratic expansion of workers' demographics, including education, age, and sex, and year and 6-digit industry fixed effects. The sample includes all firms in our management sample from 2010 and 2015; each firm appears in every regression. Observation-level is the firm-year; regressions are unweighted.

Appendix Table 1. Productivity Increases Cause Higher Pay and Higher Pay Inequality, with 1st Stages

Dependent Variable:	OLS (1) Log Annual Earnings	OLS (2) Log Annual Earnings	2SLS, 1 st (3) Productivity	2SLS, 2 nd (4) Log Annual Earnings	2SLS, 1 st (5) Productivity	2SLS, 1 st (6) Rank X Productivity	2SLS, 2 nd (7) Log Annual Earnings
Productivity	0.1499*** (0.01475)	0.1771*** (0.01633)		0.1467* (0.08290)			0.2198** (0.1023)
Rank X Productivity		-0.0005390*** (0.0001452)					-0.001447** (0.0006320)
IV CAD			1.506 (1.080)		1.506 (1.080)	-529.1* (294.7)	
IV Euro			-0.04002 (0.4951)		-0.04002 (0.4951)	-135.1 (351.8)	
IV JPY			-0.2250 (0.4965)		-0.2250 (0.4965)	265.4 (377.7)	
IV AUD			0.5603 (0.6970)		0.5603 (0.6970)	-225.0 (284.2)	
IV SEK			0.6418 (0.3853)		0.6418 (0.3853)	131.5 (168.5)	
IV CHF			-0.4541 (0.5310)		-0.4541 (0.5310)	-621.7* (360.4)	
IV GBP			-1.215 (1.235)		-1.215 (1.235)	-495.3** (216.5)	
IV Oil			0.7483* (0.3931)		0.7483* (0.3931)	-8.451 (250.1)	
IV EPU			775.2** (382.3)		775.2** (382.3)	-223900** (104700)	
Rank X IV CAD						11.98** (5.750)	
Rank X IV Euro						2.636 (6.743)	
Rank X IV JPY						-5.481 (7.509)	
Rank X IV AUD						5.015 (5.232)	
Rank X IV SEK						-1.962 (3.301)	
Rank X IV CHF						11.86* (7.093)	
Rank X IV GBP						8.594** (3.584)	
Rank X IV Oil						0.9157 (4.854)	
Rank X IV EPU						5209** (2405)	
N	37770000	37770000	37770000	37770000	37770000	37770000	37770000
JointF-stat	103.3	59.36	2.723	3.133	2.723	6.719	2.905

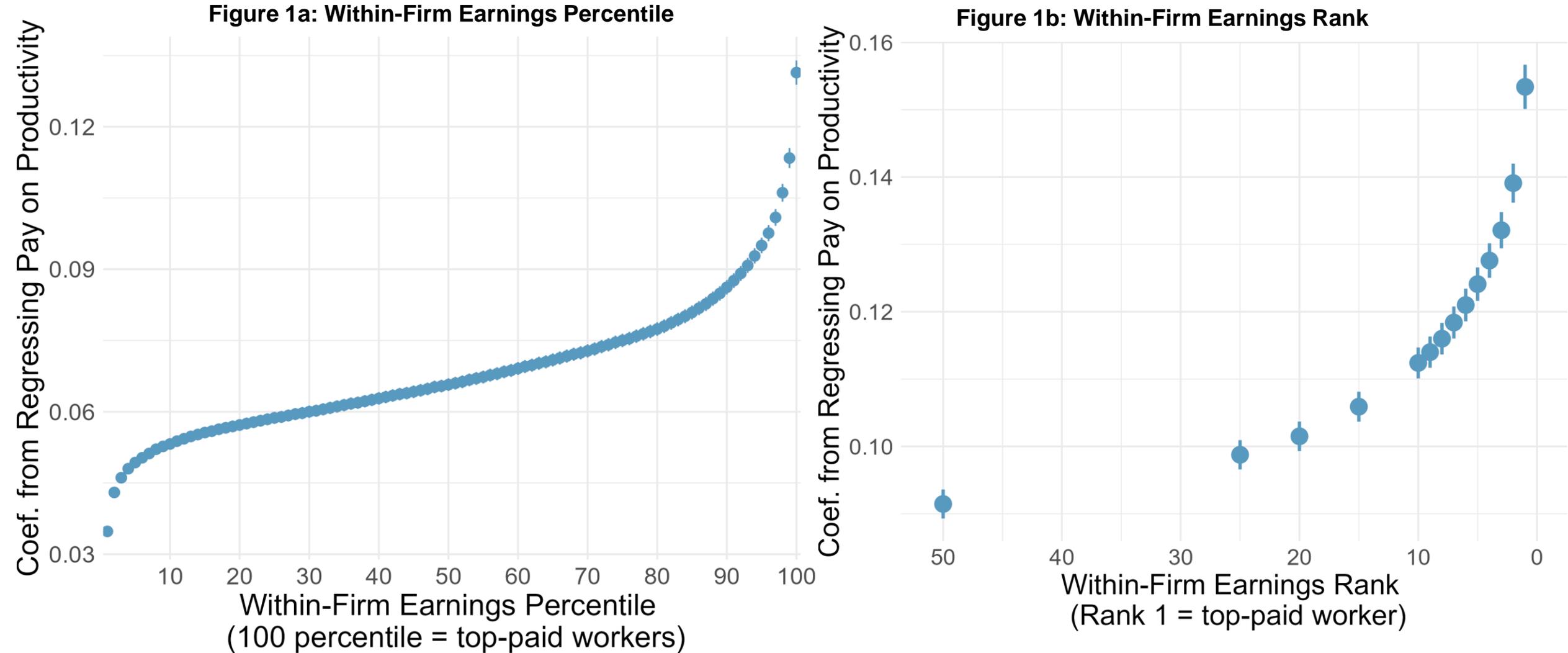
Notes: * Significant at the 10% level, ** 5% level, *** 1% level. This table presents several regression estimates for Sample 9. Each column describes a separate regression of earnings on productivity instrumented by lagged instruments from Alfaro, Bloom, and Lin, including currency price changes (CAD, Euro, JPY, AUD, SEK, CHF, and GBP), oil price changes, and economic policy uncertainty changes (EPU). Each regression includes the following controls: year, RE-LBD NAICS6 industry, and rank fixed effects. Standard errors are clustered at the SIC2 level.

Appendix Table 2: log earnings on productivity, public status, and rank

Dependent Variable:	(1)	(2)	(3)
	Sandwich Worker Next Year		
Productivity Next Year	0.01762*** (0.000075)		0.009929*** (0.000119)
Rank		-0.000656*** (0.000002)	
Rank X Productivity Next Year			0.000152*** (0.000002)
N	41860000	41860000	41860000
RankFEs			x

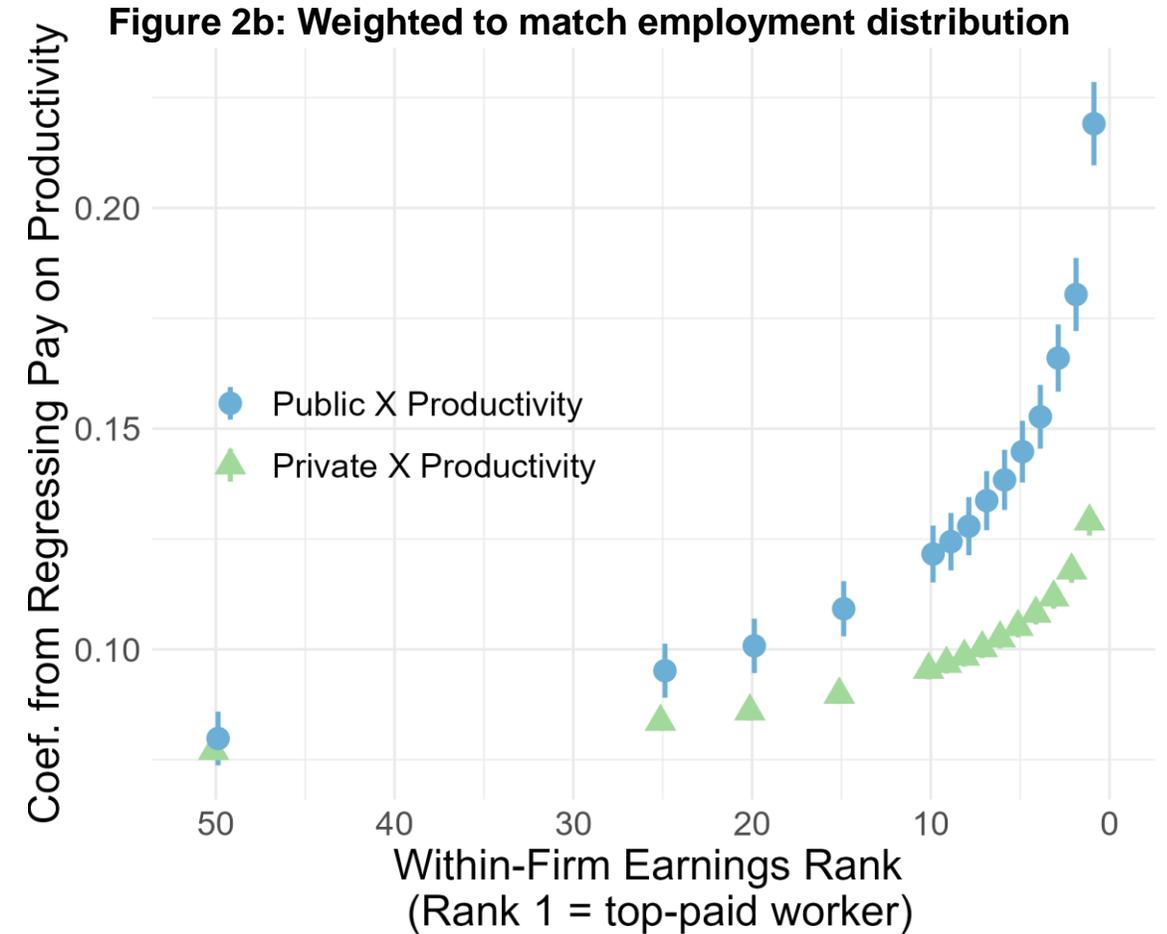
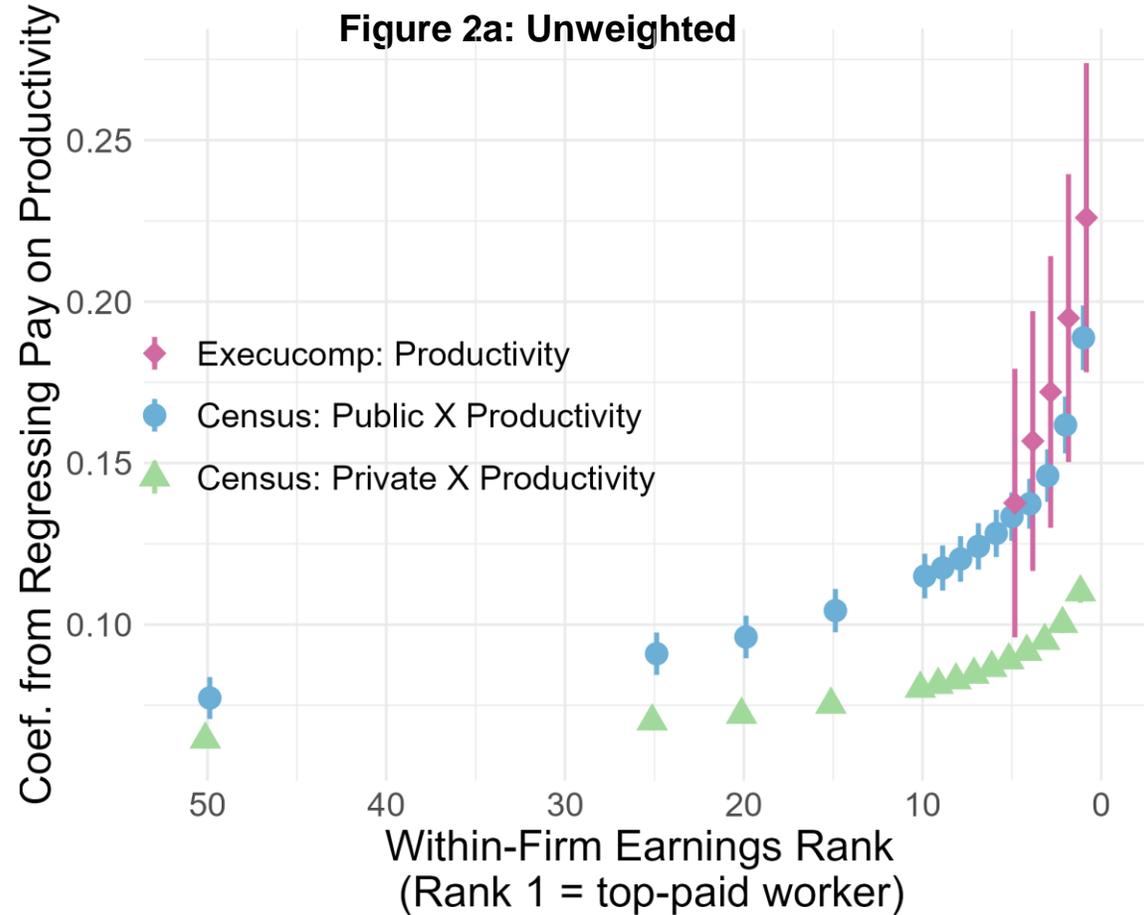
Notes: * Significant at the 10% level, ** 5% level, *** 1% level. This table presents several regression estimates for our main sample, where we reshape the sample to be at the firm-year-rank level; we restrict to the top 100 paid employees in each firm-year pair. We restrict to firms with productivity information in the subsequent year. Each column describes a separate regression of whether a top 100 worker this year is a sandwich worker at the firm in the next year, i.e., whether an individual is still employed at the firm for all four quarters next year and for Q1 in the following year. Each regression includes the following controls: year, RE-LBD NAICS6 industry, and rank fixed effect (where noted in the footer).

Figure 1: Pay levels are more correlated with productivity for top managers



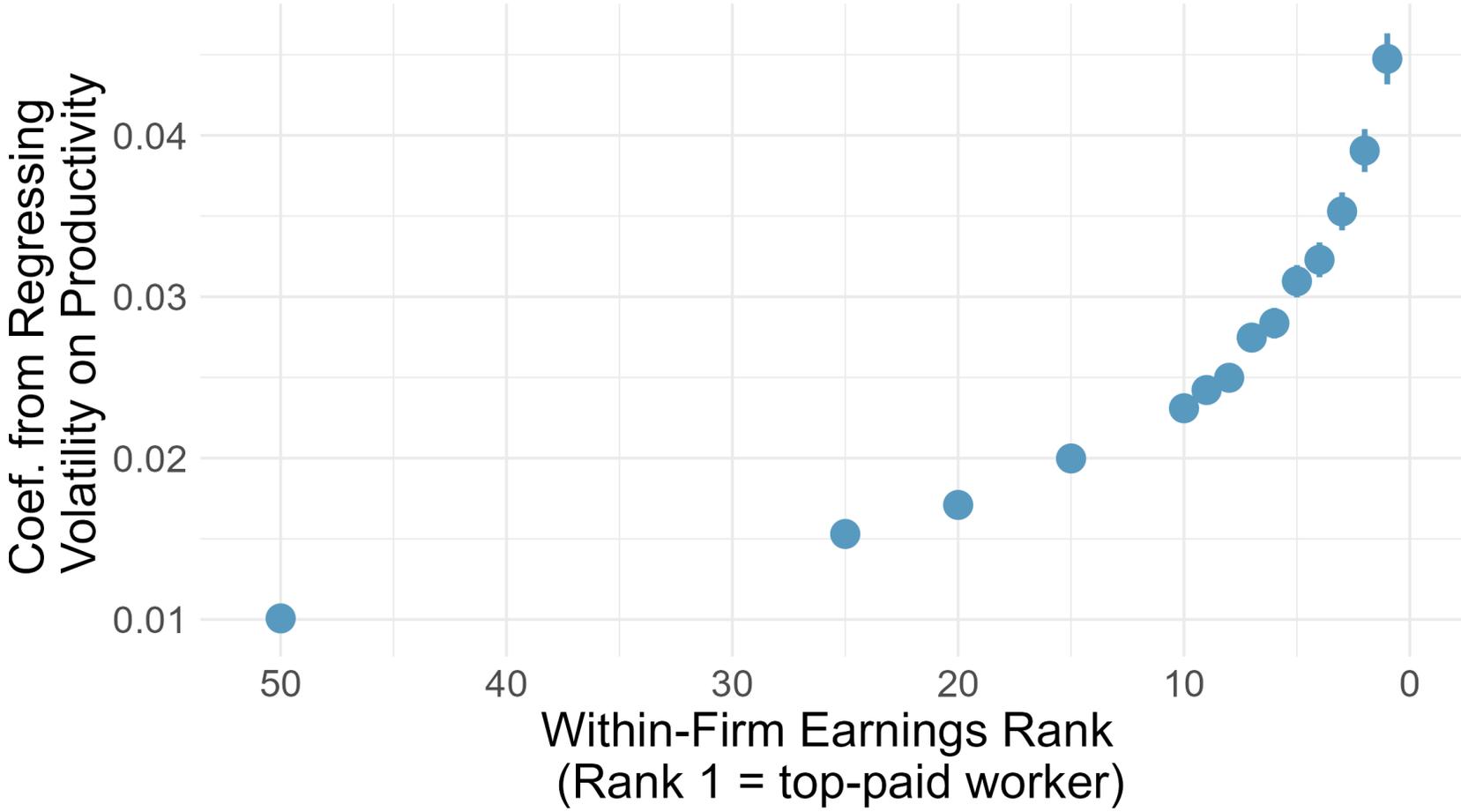
Notes: Each value represents the coefficient (and 95% confidence interval) on productivity from a regression of the mean log annual earnings, within a given within-firm earnings percentile (Figure 1a) or for a given within-firm earnings rank (Figure 1b), on productivity and controls that include a quadratic expansion of workers' demographics, including education, age, and sex, and year and 6-digit industry fixed effects. To place workers into percentiles (Figure 1a) or rank (Figure 1b), within each firm in each year, full-year workers are ranked by annual earnings (creating the ranks, with rank 1 being the top-paid worker) and separated into 100 equally-sized (up to rounding) bins (creating the percentiles, where percentile bin 100 contains the top-paid workers). Productivity is log revenue per worker. The sample includes all firms in our main sample from 2003-2015; each firm appears in every regression. Observation-level is the firm-year; regressions are unweighted. N = 443,000.

Figure 2: Pay levels are particularly strongly correlated with productivity for top managers in public firms



Notes: In both subfigures, each pair of the blue (circle) and green (triangle) values represent the coefficients (and 95% confidence intervals) on productivity interacted with the trading status of the firm (public vs. private) from a regression of log annual earnings, of a given within-firm earnings rank, on the interactions and controls from Figure 1 and an indicator for being publicly traded. In Figure 2a, each pink (diamond) value represents the coefficient (and 95% confidence intervals) on productivity from a regression of log annual earnings of one of the top 5 executives in Compustat Execucomp on productivity and year and 6-digit industry fixed effects. The Compustat Execucomp sample includes all firms in our Execucomp sample from 2007-2015. Observation-level is the firm-year. Within each sample, each firm appears in every regression. In Figure 2a, regressions are unweighted (i.e., firm-year-weighted). In Figure 2b, regressions are weighted to match the employment distributions of public firms to private firms in our Census sample in order to make the firms more comparable; private firms are given weight 1, while public firms are given weights equal to the share of private firms with similar employment divided by the share of public firms with similar employment (where similar employment is based on binning all firms into ventiles of employment). Census N = 443,000. (410,000 firm-years are private; 33,000 are public.) Compustat Execucomp N = 4,681.

Figure 3: Pay volatility is more correlated with productivity for top managers



Notes: Each value represents the coefficient (and 95% confidence interval) on productivity from a regression of the within-year pay volatility, of a given within-firm earnings rank, on productivity and controls from Figure 1. Pay volatility is the standard deviation of log quarterly earnings, within a year (i.e., the standard deviation of (log Q1 earnings, log Q2 earnings, log Q3 earnings, log Q4 earnings)). The sample includes all firms in our main sample from 2003-2015; each firm appears in every regression. Observation-level is the firm-year; regressions are unweighted. N = 443,000.

Figure 4: Pay levels and pay volatility are more correlated with structured management at higher pay levels

Figure 4a: Pay Levels

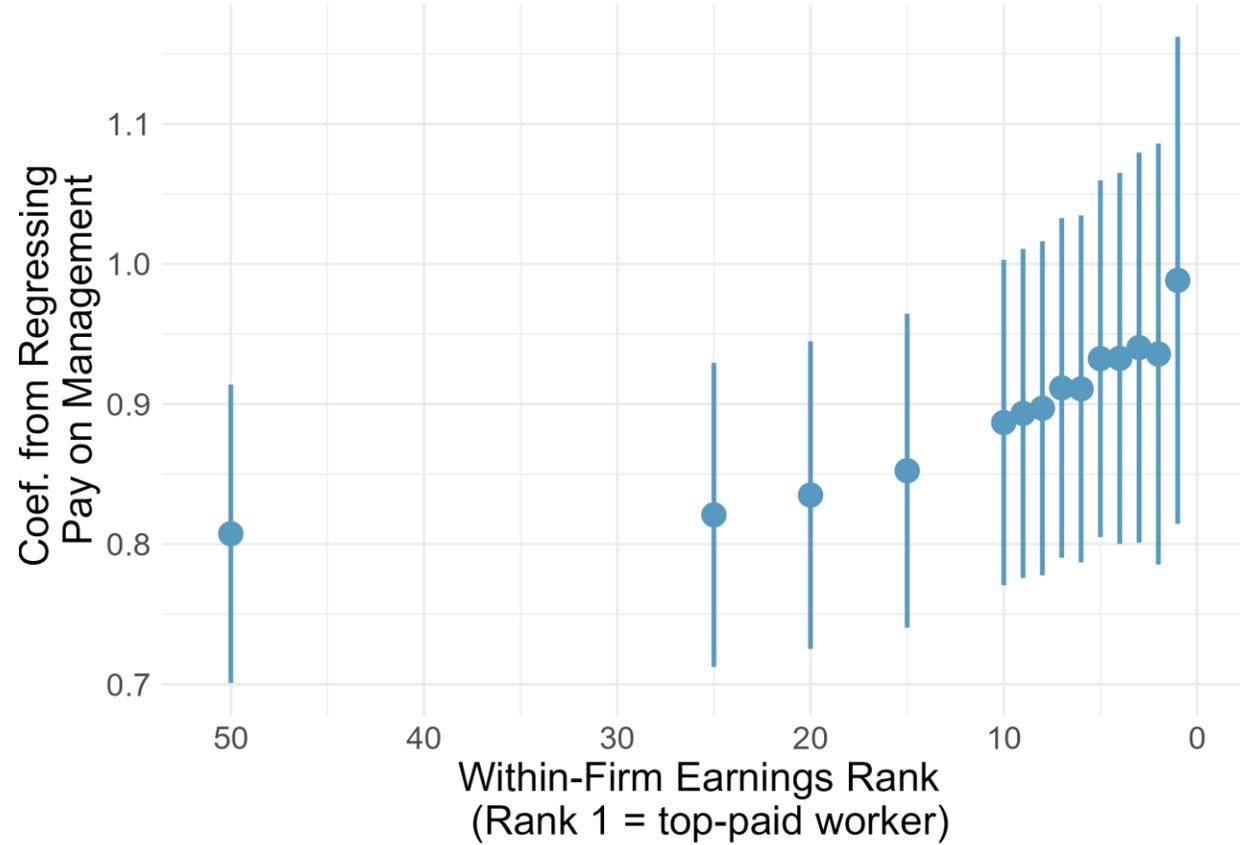
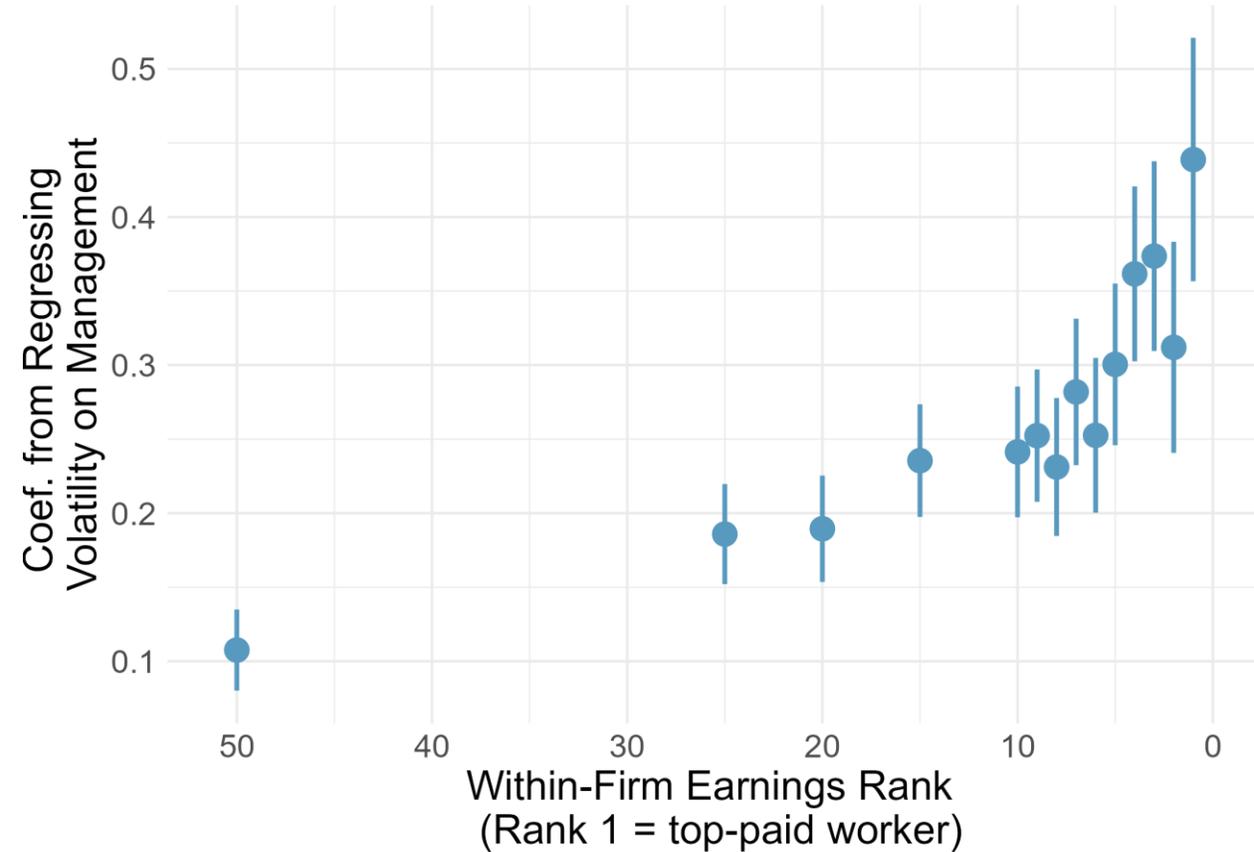
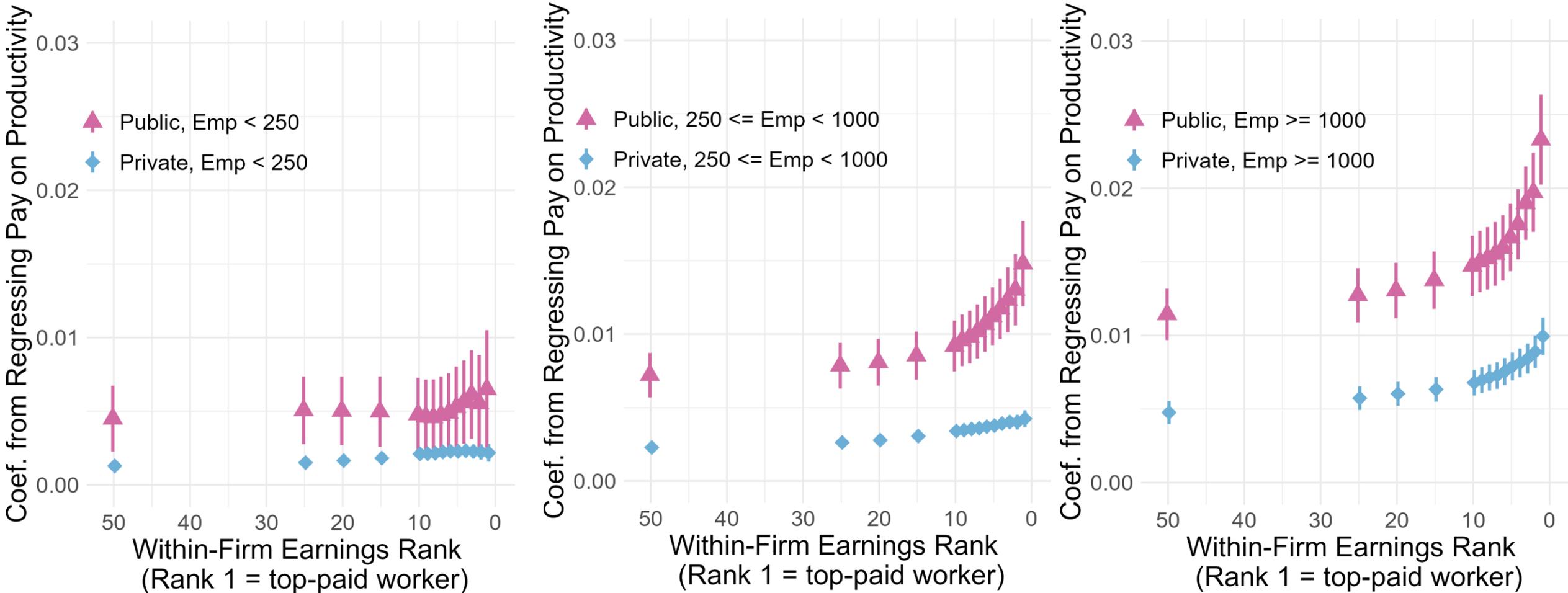


Figure 4b: Within-Year Pay Volatility



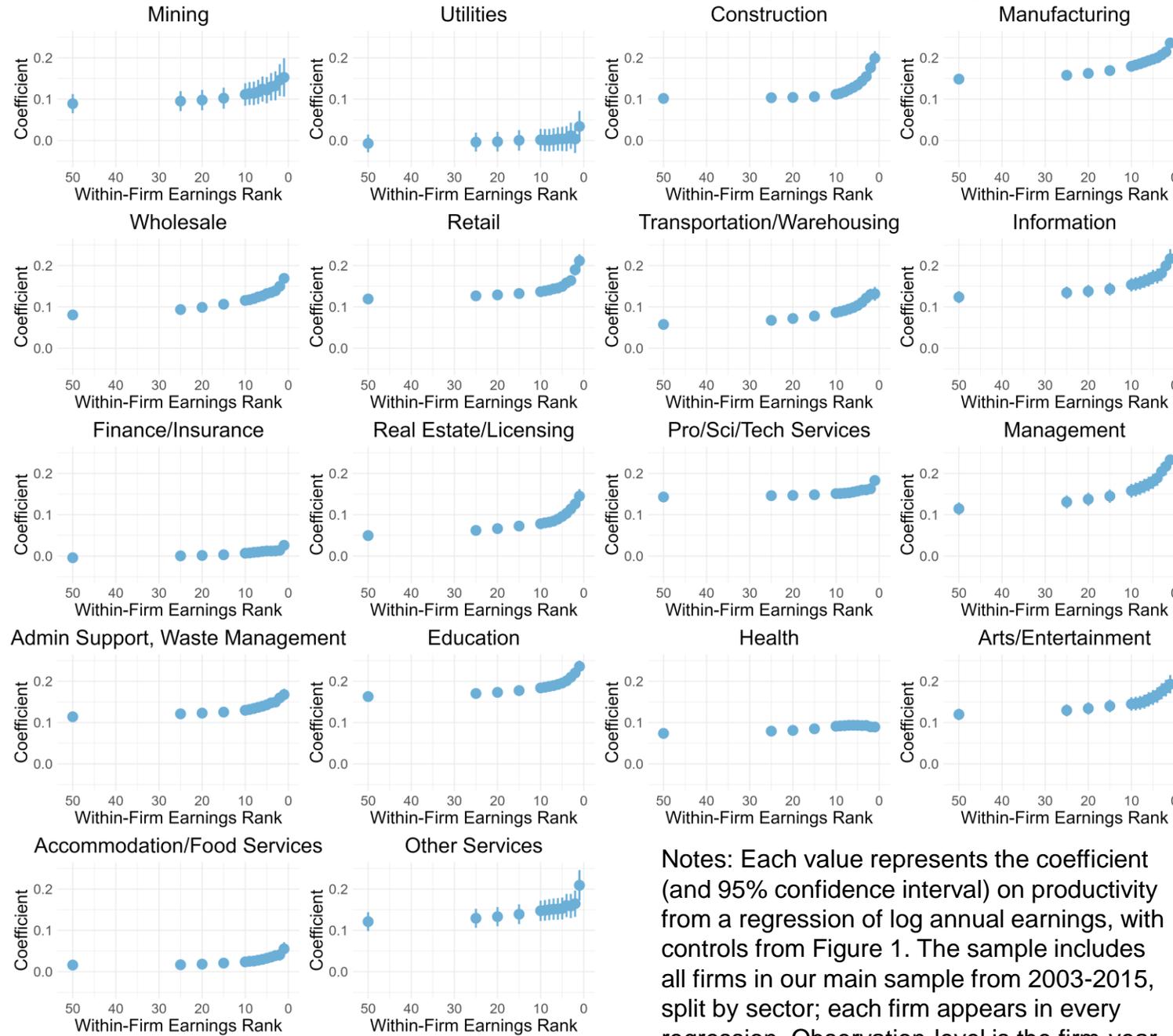
Notes: Each value represents the coefficient (and 95% confidence interval) on managements score from a regression of the log annual earnings, of a given within-firm earnings rank, on management score and controls from Figure 1. The sample includes all firms in our management sample from 2010 and 2015; each firm appears in every regression. Observation-level is the firm-year; regressions are unweighted. N = 11,000.

Figure 5: Pay levels are particularly correlated with the S&P500 return for top managers in larger firms and public firms



Notes: Each value represents the coefficient (and 95% confidence interval) on productivity from a regression of log annual earnings, with controls from Figure 1. The samples presented include all firms in our main sample from 2003-2015, which we restrict to publicly-traded or privately-held firms and split by LBD employment; within-sample, each firm appears in every regression. Observation-level is the firm-year; regressions are unweighted. N(Public, Emp < 250) = 4,000. N(Public, 250 <= Emp < 1000) = 10,500. N(Public, Emp >= 1000) = 19,000. N(Private, Emp < 250) = 158,000. N(Private, 250 <= Emp < 1000) = 189,000. N(Private, Emp >= 1000) = 62,000.

Figure A1: Productivity-pay correlations rising with pay rank, by industry



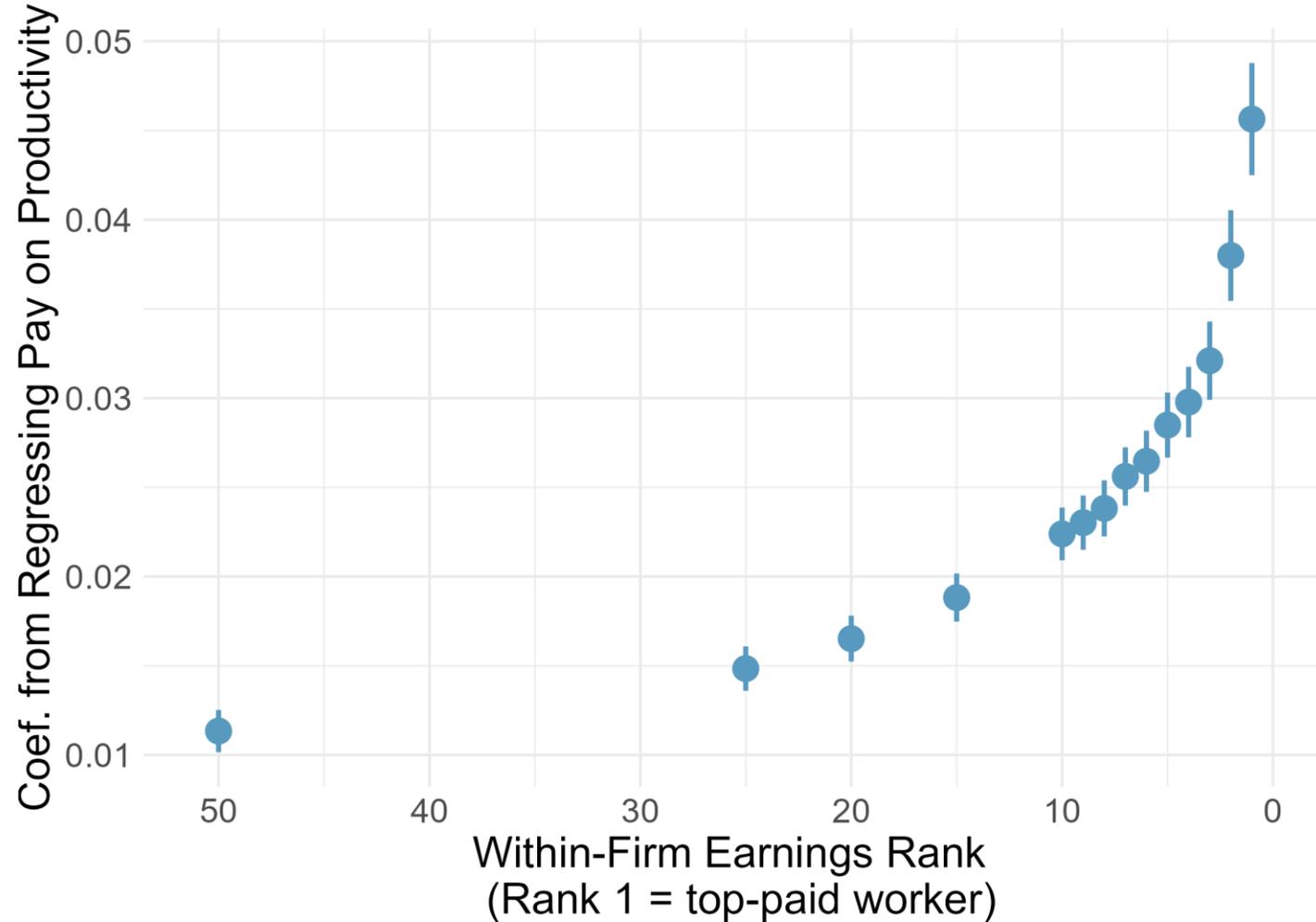
Notes: Each value represents the coefficient (and 95% confidence interval) on productivity from a regression of log annual earnings, with controls from Figure 1. The sample includes all firms in our main sample from 2003-2015, split by sector; each firm appears in every regression. Observation-level is the firm-year.

Figure A2: Pay levels correlations rising with pay rank in all firm ages



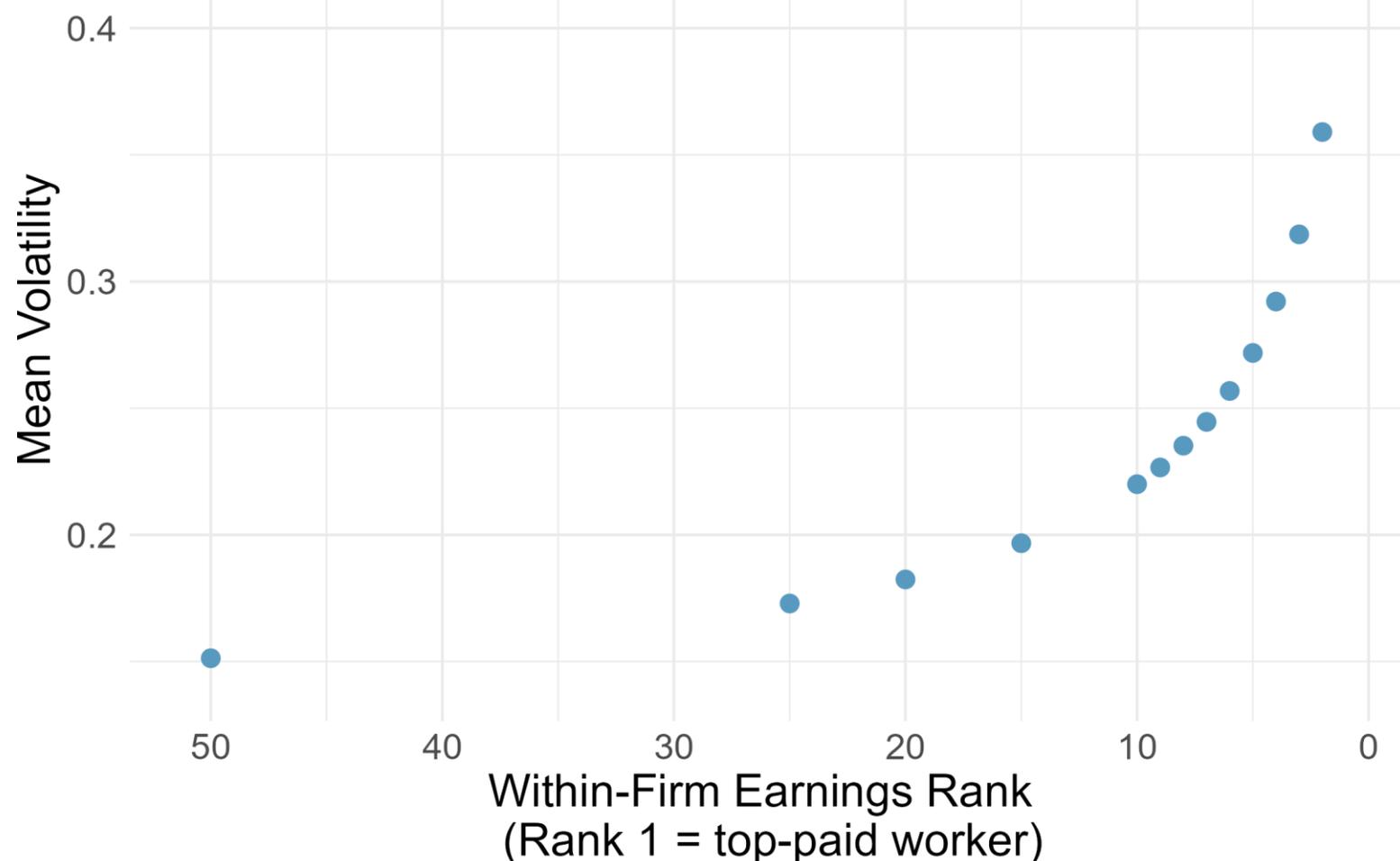
Notes: Each value represents the coefficient (and 95% confidence interval) on productivity from a regression of the log annual earnings, with controls from Figure 1. The sample includes all firms in our main sample from 2003-2015, which we split by LBD firm age; within-sample, each firm appears in every regression. Observation-level is the firm-year; regressions are unweighted. N(Age < 10) = 37,5000. N(10 <= Age < 25) = 98,000. N(Age >= 25) = 301,000.

Figure A3: The correlation of *increases in pay* with *increases in productivity* are rising with pay rank



Notes: Each value represents the coefficient (and 95% confidence interval) on productivity from a regression of log annual earnings, with controls from Figure 1. The sample includes all firms in our main sample from 2003-2015; each firm appears in every regression. Observation-level is the firm-year; regressions are unweighted. N = 443,000.

Figure A4: Pay volatility is at higher pay levels



Notes: Each value represents the mean pay volatility, of a given within-firm earnings rank. Pay volatility is the standard deviation of log quarterly earnings, within a year (i.e., the standard deviation of (log Q1 earnings, log Q2 earnings, log Q3 earnings, log Q4 earnings)). The sample includes all firms in our main sample from 2003-2015; each firm appears in every mean. Observation-level is the firm-year; means are unweighted. N = 443,000.