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WITHIN-FIRM PAY INEQUALITY AND PRODUCTIVITY

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ABSTRACT

Combining confidential Census worker and firm data, we find three key results. First, employees at more productive firms earn higher pay at all earnings levels. Second, this pay-productivity relationship strengthens with seniority, doubling from an elasticity of 0.07 for pay on productivity for the median-paid employee to 0.15 for the top-paid employee. Consequently, more productive firms have higher within-firm inequality. Our data suggests this is driven by their greater adoption of aggressive performance-pay bonus and management schemes. Finally, the magnitude of this pay-performance slope suggests rising productivity can explain 40% of the rise in within-firm inequality since 1980.

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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 three 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 millions of 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 Management 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 three major findings. First, em-

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

ployees at more productive firms have substantially 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 to the 99th percentile.

Second, this increase in earnings is greater at higher pay levels. As a result, higher productivity is associated with higher levels of pay dispersion within firms. This is particularly notable at the very top end of the earnings ranks. For example, while, cross-sectionally, a firm's top earner (likely the CEO) sees a pay increase of 15% when productivity doubles, the 5th, 25th and 50th ranked earners see only 12%, 10% and 9% respectively.[2] These results are robust to the inclusion of firm controls, including firm fixed effects, and using an instrumental variable approach exploiting differential firm exposure to macroeconomic conditions. We also see similar results when we directly consider *within*-worker changes in earnings and within-firm changes in productivity: higher earning workers experience substantially larger pay increases when their firms' productivity increases.

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 sees a 19% pay increase in public firms but only an 11% 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.

Exploring the mechanism for the pay-performance patterns, we find that top earners receive proportionally larger bonuses at more productive firms. While we do not directly observe bonus pay, we use a measure of within-worker quarterly pay volatility that captures deviations from constant salaries, such as fourth quarter bonuses. We find that top-earner pay *volatility* is also strongly related to productivity. 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. Indeed, we find that greater adoption of structured management practices is associated with higher pay and pay volatility, par-

[2]See panel b of Figure 1.

ticularly for senior executives.

Finally, we conduct a quantification of our results to see how much rising productivity can explain the rise in the gap between CEO and median-worker pay from 1980 to 2013, through the lens of our pay-productivity relationships. The CEO-to-median-worker gap metric of within-firm inequality is particularly salient because the Dodd-Frank Act requires publicly-traded firms to publish it annually from 2018 onwards. Using data from Song et al. (2019), we find that increasing aggregate labor productivity from 1980 to 2013 can account for 40% of the increase in the top-to-median pay gap.

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, McKinney, and Zhao (2018), and Song et al. (2019)), the United Kingdom (Faggio, Salvanes, and Van Reenen (2010) and Mueller, Ouimet, and Simintzi (2017)), Germany (Card, Heining, and Kline (2013)) Sweden (Hakanson, Lindqvist, and Vlachos (2015)), and Brazil (Helpman et al. (2017) and 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), and Bivens and Mishel (2013) for arguments for CEO pay increases being driven by performance, firm size, and rent extraction, respectively.[3,4] 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 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 executives in Execucomp data and for top earners at publicly-traded companies in our LEHD data, 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

[3]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.

[4]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, Klebanov, and Sorensen (2012), Lazear, Shaw, and Stanton (2015), Mullins and Schoar (2016), Hoffman and Tadelis (2017), Bandiera et al. (2018), Bandiera et al. (2020), Antón et al. (2020), and Kaplan and Sorensen (2021).

higher rents and share some of these rents with their workers, because of perceptions of fairness or bargaining considerations. Our paper's demonstration of 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 proposing a key mechanism underlying these results. Section 5 presents a discussion of what our results imply for aggregate inequality. Section 6 concludes.

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 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.[5]

The earnings data in the LEHD is based on firm-side state unemployment insurance (UI)

[5]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 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.

records and contains quarterly employment and earnings information for most individuals working in each state.[6] 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).[7]

For each worker at each firm, we observe total quarterly earnings, which 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.[8] The data contain both longitudinal person and longitudinal firm identifiers,[9] which allow us to study all workers within a firm and follow firms and workers over time.

Within each firm, in each year, after we impose several sample restrictions described below in Section 2.5, 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.[10] Second, we identify a worker's within-firm **rank**, where the top earner (e.g., CEO) takes rank 1, etc.

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

[7]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 workers. For details, see Kornfeld and Bloom (1999) (pg. 173), of Labor Statistics (1997) (pg. 43), and `http://workforcesecurity.doleta.gov/unemploy/pdf/uilawcompar/2012/coverage.pdf`.

[8]Stock options and grants are typically reported when they are awarded to employees, i.e., when they are subject to UI tax; while restricted stock awards are reported when vested. Qualified stock options (also known as Incentive Stock Options) are not subject to UI tax and consequently not reported, but are capped so are not material for top earners.

[9]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.

[10]We calculate these bins as follows: bin = floor(reverse rank within firm*100/(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.

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.[11] 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.[12] 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 may be 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 2.5 for details.

Our measure of revenue labor productivity, henceforth called productivity, is real revenue per worker; in regressions below, we take the log of this measure.[13] 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 2010 and 2015 survey waves of the MOPS. We use these measures to aid in the interpretation of the relationship between productivity and within-firm earnings dispersion.

[11]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)). Throughout our analyses, we omit firms in the public administration sector, for whom sales measures are less interpretable.

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

[13]We deflate nominal revenue to 2010 dollars using the PCE deflator.

The MOPS was a periodic supplement to ASM conducted in survey years 2010, 2015, and 2021. All establishments that were included in the ASM samples for those years were also sent the MOPS.[14] We utilize 16 core questions on the MOPS asking plant managers 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.[15] 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.[16] We aggregate across establishments to the firm-level by taking employment-weighted averages of the management scores across establishments.

2.4 Compustat and Execucomp

In addition to the three core Census programs discussed above, we also use the Compustat bridge (CSB) 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 (2017)). We label firms that appear in the CSB in a given year as "publicly-traded."

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

[14]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)).

[15]Following Bloom et al. (2019), we restrict to observations with at least 10 non-missing responses to the management questions.

[16]Bloom et al. (2019) find that establishments with higher structured management scores also tend to be more productive.

and revenue (and thus productivity) and the Compustat Execucomp data on top executives' earnings at large publicly-traded firms.

2.5 Sample Selection and Characteristics

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

To ensure our analysis focuses on stable, full-time employment, we restrict our sample in each year to firms with at least 100 "6-quarter sandwich" workers in the LEHD data. These full-year sandwich workers were employed and earned above the minimum wage[17] throughout all four quarters of the current year, the fourth quarter of the previous year, and the first quarter of the following year. This definition effectively captures full-time workers who are unlikely to have switched jobs mid-year; we are confident that we capture true annual pay for these workers and consequently do not mislabel high-paid workers who join in the fourth quarter as low-paid workers, etc.[18,19] For our instrumental variable analysis, we further restrict the sample to workers in firms belonging to industries covered by the instruments developed in Alfaro, Bloom, and Lin (2024).

Table 1 summarizes key characteristics of our main sample. On average, each company employs nearly 1,500 people, with around 750 employees per company classified as full-year workers. Within these larger firms, income inequality is significant. On average, employees at the 90th percentile of earnings (among full-year workers) earn 3.5 times more than those at the 10th percentile (calculated as $e^{1.253}$). This gap widens considerably when comparing the top earners with the 10th percentile. In the average firm, employees at the 99th percentile earn almost 9 times more than

[17]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.

[18]We explore how restricting to full-year sandwich workers may interact with productivity and pay in Appendix Table A.1. We find that sandwich workers at firms that are more productive in the current year are more likely to be sandwich workers in the subsequent year, and this pattern is marginally stronger for lower-earning workers at firms.

[19]We require firms to have at least 100 of these full-year sandwich workers in order to guarantee that every firm has at least one worker in each percentile bin; this restriction eases the interpretation of our analyses involving these percentile bins.

those at the 10th percentile. Meanwhile, the highest earner within a company makes over 16 times more than someone at the 10th percentile.

Table 1 further analyzes our sample when divided into private and publicly-traded firms (columns (3)-(6)). As anticipated, public firms generally display larger size, higher wages, and higher productivity compared to private companies. Interestingly, publicly-traded firms also tend to have greater within-firm pay inequality. For example, in publicly-traded firms, the highest earners strikingly make over 27 times the earnings of the median employee and over 50 times the earnings of workers at the 10th percentile.

Execucomp sample: We use Compustat employment and revenue and Execucomp executive pay information from 2006 through 2016, making 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.[20] 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 a log productivity value of 12.84) on average than the set of publicly-traded firms in our main sample.

Management sample: For our analysis of how a firm's management structure affects worker pay, we focus on a subset of firms with at least one establishment in the 2010 or 2015 survey waves of the MOPS. While the MOPS focuses on manufacturing establishments, our analysis considers all workers within a firm with at least one establishment covered by the MOPS.

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,

[20]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.

and more productive. The average firm in our management sample also has higher within-firm earnings inequality.

3 Main 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 this inequality appears: pay is more tightly linked to productivity for top-paid individuals, especially those at publicly-traded firms.

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:

$$y_{j,n,t} = \alpha + \beta \text{Log Productivity}_{j,t} + \mathbf{X}_{j,t}\delta + \gamma_t + \gamma_n + \varepsilon_{j,n,t}, \tag{1}$$

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 Log Productivity$_{j,t}$, the log 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' demographics[21] as well as year t and 6-digit NAICS industry n fixed effects. $\varepsilon_{j,n,t}$ 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 pro-

[21] 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.

ductivity and pay may vary dramatically across industries, and we do not want our estimates to be conflated by cross-industry patterns.

Table 2 analyzes model (1) across various outcomes, demonstrating that more productive firms tend to (i) pay more on average, with column (1) showing a 10% increase in productivity is associated with a 0.7% rise in average worker pay; and (ii) exhibit greater within-firm earnings inequality, with columns (2)-(5) presenting different measures of inequality, all showing positive associations with productivity. For instance, column (4) indicates a 10% productivity increase expands the pay gap between the top earner and the median worker by 0.9%. Looking at the overall distribution of productivity, these patterns are substantial. Moving from the 10th to the 90th percentile in our main sample's productivity distribution, these estimates project an 18% increase in average pay and a 23.1% increase in the gap between the top earners and median worker's pay.

Below, 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. We also present robustness analyses to bolster our results.

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 next explore in greater detail how the earnings for workers across the pay distribution are related to productivity. We estimate models similar to model (1) in which we disaggregate firm-level pay outcomes into the pay outcomes of individuals across the pay distribution:

$$y_{g,j,n,t} = \alpha + \beta \text{Log Productivity}_{j,t} + \mathbf{X}_{j,t}\delta + \gamma_t + \gamma_n + \varepsilon_{g,j,n,t}, \tag{2}$$

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 Log Productivity$_{j,t}$, the log revenue labor productivity of firm j in year t. The coefficient of interest is β, which captures the relationship between group g's outcome and the firm's productivity.

As in model (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 above, as well as year t and industry n fixed effects.

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. Panel a of Figure 1 presents the key findings. It depicts the results of 100 separate regressions of model (2), each examining a specific percentile of the firm's earnings distribution. In each regression, the dependent variable is the average log earnings of workers within that particular percentile. The figure reveals three key patterns.

First, all the coefficients are positive. This indicates that, workers at higher-productivity firms tend to earn more than workers at lower-productivity firms, *regardless* of their position within the firm's earnings distribution. This aligns with the observation of higher average pay in column (1) of Table 2.

Second, the "benefits" of higher firm productivity are not evenly distributed across the firm's earnings distribution. This aligns with results shown in columns (2)-(5) of Table 2. The upward slope in the graph illustrates that employees with relatively higher pay see a stronger connection between their pay and the firm's productivity compared to those with lower pay. For example, a 10% increase in productivity translates to a 0.86% pay increase for workers at the 90th percentile (as indicated by the 0.086 coefficient in Figure 1). However, for workers at the 10th percentile, the same productivity increase only predicts a 0.53% pay increase.

Third, this upward trend in the pay-productivity link becomes even steeper as we move towards the top earners. The gap between the coefficients of the 100th and 90th percentiles is larger than the gap between the 90th and 80th percentiles or the gap between the 80th and 70th percentiles. This pattern suggests that the connection between pay and firm performance becomes progressively stronger for employees with higher pay levels.

Given the particularly pronounced differences in the productivity-pay relationship across the earnings spectrum, we delve deeper into the top earners. Panel b of Figure 1 showcases the results of 14 separate regressions. Each regression analyzes a specific rank within a firm, where the top-paid employee may be the Chief Executive Officer (CEO), the second top may be the Chief Financial Officer (CFO), with other senior managers typically rounding out ranks 3 to 10.[22] 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%.[23]

3.3 Robustness and causality of productivity-pay relationship

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, an instrumental variables approach, and an analysis that leverages within-worker and within-firm changes.

Additional robustness tests: 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 the firm's workers' demographics (sex, education, and age individually and interacted). We also include a full set of 6-digit NAICS industry fixed effects to control for differences in pay levels across industries. In Appendix Figure A.1 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.[24] The pay-productivity relationship also turns out to be robust in multiple dimensions of firm characteristics. For example,

[22]For example, in Execucomp 81% of CEOs have the highest total pay (where pay includes salary and bonus pay as well as stock grants, 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.

[23]To adhere to disclosure limitations, we only present coefficients for a selection of worker ranks instead of all ranks from 1 to 50. For example, the results for ranks 10 and 15 are shown, but ranks 11-14 are omitted. This approach helps us stay within acceptable disclosure statistics while still providing valuable insights.

[24]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. In an analysis later in this section, we look at year-on-year changes in earnings *within* workers, holding workers fixed.

Appendix Figure A.2 breaks this down into all 18 two-digit NAICS sectors revealing a similar positive, convex relationship between pay and performance rising up earnings ranks across nearly all sectors.[25] Appendix Figure A.3 breaks this down by firm age and again shows very similar results by different age categories.

Instrumental variables approach: 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 individual employee pay, rather than reflecting a selection story or reflecting some other change not captured by our controls. To investigate this, Table 3 uses instrumental variables from Alfaro, Bloom, and Lin (2024), 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, Bloom, and Lin (2024) 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 workers[26] at each firm in each year, for firms belonging to industries for which we have instruments. We estimate both OLS and 2SLS versions of

$$y_{g,j,n,t} = \alpha + \beta_1 \text{Log Productivity}_{j,t} + \beta_2 \text{Rank}_g \times \text{Log Productivity}_{j,t} + \gamma_g + \gamma_t + \gamma_n + \varepsilon_{g,j,n,t}, \quad (3)$$

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 how

[25]We see shallower (i.e., less convex) relationships between pay and performance in utilities, finance and insurance, and health. One possible reason for these patterns is that these sectors are highly regulated, such that the capacity for differential performance-based pay across ranks may be limited.

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

this relationship varies (linearly) with rank (captured by β_2). We include rank, year, and industry fixed effects.[27]

In our 2SLS specification of model (3), we instrument productivity (both on its own and interacted with rank) with the Alfaro, Bloom, and Lin (2024) instruments. We interpret the 2SLS results as capturing the causal relationship between pay and productivity, by rank; 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 for the IV sample. In column (1), we exclude the interaction term and demonstrate that earnings tend to be higher at more productive firms. Importantly, as shown in column (2), this pattern has a significant negative interaction with rank, reflecting the results in Figure 1 that higher earning (smaller rank value) employees' pay is more sensitive to firm performance.

As shown in columns (3) and (4), our instrumental variables approach produces broadly similar results to the OLS.[28] 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 affecting workers' pay.[29]

Within-worker and within-firm changes: Finally, we turn to explore earnings and productivity dynamics *within*-worker and *within*-firm. Our main results emphasize cross-sectional differences in firms: more productive firms tend to have higher inequality. Here, we show that these differences also appear in dynamic measures; firms that *become* more productive experience *increases* in inequality, holding fixed the set of workers.

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

[28]Appendix Table A.2 adds the 1st stage results to Table 3. In both 1st stage specifications, F-statistics are approximately 3.

[29]We provide additional evidence of causal pass-through of productivity to pay by simply lagging productivity in regressions in Appendix Table A.3, where we posit that current pay is less likely to explain past productivity (i.e., lower threat of reverse causality). We find actually slightly stronger results with lagged productivity: inequality is larger at firms that were more productive in the previous year. This test is imperfect, especially since dynamic contracting or omitted variable bias could still bias estimates, but we find the basic patter reassuring.

We analyze these within-worker, within-firm patterns by estimating regressions similar to model (2), where we adapt to study changes.

$$\Delta y_{g,j,n,t} = \alpha + \beta \Delta \text{Productivity}_{j,t} + \mathbf{X}_{j,t}\delta + \gamma_t + \gamma_n + \varepsilon_{g,j,n,t}, \tag{4}$$

where $\Delta y_{g,j,n,t}$ is the mean within-worker growth in earnings, amongst workers in group g at firm j in period t. The key right-hand-side variable is $\Delta \text{Productivity}_{j,t}$, the within-firm growth revenue labor productivity of firm j in period t.[30] We include the same controls (demographic controls and industry and year fixed effects) as before. β is the coefficient of interest, capturing the relationship between group g's mean within-worker earnings growth and the firm's productivity growth.

We estimate this model on workers with full-year earnings both in the current and previous year. Because this does not preserve their rank and percentile, we bin workers into groups g according to their annual earnings at the firm in the previous year. For example, did workers who previously earned \$100,000 experienced proportionally larger pay increases as their firm's productivity increases than workers who earned \$50,000?

Figure 2 presents striking results linking rising productivity within a firm with increasing inequality. As in the cross-sectional Figure 1, workers across all pay levels on average receive pay increases when their firm's productivity increases, but the pay increases are proportionately much larger at the top of the pay distribution. When their firm's productivity doubles, average[31] American workers earning \$45,000-\$65,000 can expect their earnings to increase 1%; meanwhile, workers earning above \$300,000 can expect their earnings to increase almost 2%.[32] These within-

[30] We measure growth using Davis, Haltiwanger, and Schuh (1996) growth rates, commonly called DHS growth rates, which for variable x measured as

$$\Delta x_t = \frac{x_t - x_{t-1}}{0.5 \times (x_t + x_{t-1})}. \tag{5}$$

[31] According to the Bureau of Labor Studies (BLS), the mean wage in 2010 was \$44,410. See `https://www.bls.gov/oes/highlight_2010.htm`.

[32] With DHS growth rates on both sides of the regression, the coefficients plotted in Figure 2 cannot be immediately interpreted as elasticities. Instead, we transform them by noting that a doubling in productivity is equivalent to a two-thirds increase in DHS productivity growth, etc. In other words, to map from DHS to traditional growth rates, note that in model (5), if $x_t = \gamma x_{t-1}$, where $(1-\gamma)$ reflects the percentage point increase in x, then $\Delta x_t = \frac{2(\gamma-1)}{\gamma+1}$.

worker within-firm differences offer additional striking evidence that higher productivity can increase within-firm inequality.

3.4 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 disproportionally subject to performance-based pay, a mechanism we explore more broadly in the next section (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 and compensated for firm performance, than for privately-held ones.

Panel a of Figure 3 replicates panel b of Figure 1 but breaks out the coefficient on productivity by the public/private status of the firms. Within our main (Census) sample, the pay of top earners at publicly-traded firms has almost twice the coefficient on productivity than for top earners at privately-held firms. For example, for the top-paid employee, we estimate a pay-productivity coefficient in publicly-traded firms of 0.22 and only 0.13 in private firms.[33]

Furthermore, the slope in the pay-productivity correlation across top earners is also stronger for publicly-traded firms. For example, for publicly-traded firms, a 10% increase in productivity predicts a 1.9% increase in pay for the top earner and a 1.3% 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 publicly-traded firms. Meanwhile, for private firms, a 10% increase in productivity predicts a 1.1% increase in pay for the top earner and a 0.9% 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.

Both the coefficient level and slope differences for public and private firms are largest amongst the very top earners. For example, for the 25th or 50th top earner, the gaps are much smaller than for the top earner. 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

[33] 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.

distribution.

Panel a of Figure 3 also compares these pay-productivity correlations with those for the set of top executives at large publicly-traded firms in our Execucomp sample.[34] 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 comparison 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., smaller confidence intervals) and a wider coverage of the labor market.

One explanation for the stronger relationship in publicly-traded firms is these are on average larger than private firms. To address this, panel b of Figure 3 presents analogous results but reweights publicly-traded firms by ventiles of employment to have the same size distribution as private firms; we still find a much stronger relationship between pay and performance in publicly-traded firms.[35] We also re-estimate these results including controls for log(employment) at the firm level and again find very similar results, suggesting publicly-traded firms have a stronger pay-performance relationship that is not wholly explained by their larger firm size.

[34]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. Appendix Table A.4 compares our sample of public firms to those in Compustat and specifically Execucomp. Top workers in our sample of public firms earn similar but lower levels than executives in Execucomp, which is unsurprising since Execucomp covers larger public firms.

[35]Unlike in panel a, panel b 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).

4 Mechanisms: Performance-based pay

Our analyses so far demonstrate two key patterns: workers at more productive firms earn higher pay at all earnings levels, but this pay-productivity relationship strengthens dramatically with seniority. Why is the relationship between pay and productivity so different for top earners? 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 (e.g., bonus pay), 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. This volatility measures deviations from flat salaries, for instance capturing variations in fourth quarter bonus pay. Figure 4 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.[36] 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

[36] As Figure A.4 shows, pay volatility is generally higher at higher pay percentiles.

by the sizes of their bonuses. We interpret these patterns between pay volatility, firm performance, and worker rank as evidence of aggressive performance pay used for senior managers that can in turn generate our main pay-performance relationships.

4.2 Pay and management structure

To further investigate the relationship between performance-based pay and productivity, we examine the role of management practices. We focus on a sample of firms for which we have data on the extent of structured management practices, as described in Section 2, and use a single metric called "structured management." This score ranges from 0 to 1, with 0 indicating firms that received the lowest scores (minimal structure in performance monitoring, targets, and incentives) and 1 representing firms that selected the highest scores (explicit emphasis on performance monitoring, detailed targets, and strong performance incentives).

As we did for productivity, we consider how pay across the firm earnings distribution correlates with management. Analogous to Figure 1, Figure 5 presents the point estimates of version of model (2), where we replace productivity with management as the key explanatory variable and focus on worker ranks. 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 both higher earnings (panel a of Figure 5) and higher within-year pay volatility (panel b of Figure 5), and these correlations generally increase across the distribution, with top-paid workers experiencing the largest correlation. This matches a story of more productive, better-managed firms providing increasingly aggressive performance pay systems for senior managers, increasing those managers' overall pay levels and also pay volatility and subsequently increasing 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. Here we turn to our third key result by considering the implications of these patterns for aggregate 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 the context of the long-run inequality growth documented in Song et al. (2019), as shown in Table 4. In 1980, the average top earner at firms in the US with at least 100 employees earned 7.6 times as much as the average median worker within firms; in 2013, this ratio grew to 8.7.[37] How much of this growing inequality is accounted for by rising productivity?

Over this time period, aggregate productivity grew at approximately 2% per year, compounding to an almost doubling of productivity from 1980 to 2013.[38] Based on our estimates of the relationships between top and median earners' pay and productivity (Figure 1), this productivity growth implies that both top and median earners' pay increased — but, because top earners' pay is more positively correlated with productivity than lower ranked workers', the productivity growth implies that top earners' pay increased *more*. Specifically, we predict that in 2013 the average top earner would earn 8 times as much as the average median worker, meaning that productivity growth accounts for 40% of the *actual* growth in inequality.

We take this simple calculations as an indication that rising productivity can account for a

[37]We arrive at these numbers by taking a weighted average of mean earnings by year and position within firms (highest-paid and median-paid workers) across firms of different sizes, based on the data underlying Figure VI in Song et al. (2019) (as well as the intermediary firm size groups not plotted). Note that this ratio captures economy-wide inequality and may be different than the average within-firm top-to-median worker gap; we focus here on the economy-wide metric in order to leverage the long time series presented in Song et al. (2019).

[38]We source productivity growth rates from FRED via `https://fred.stlouisfed.org/series/PRS85006092`, accessed February 9, 2024. From 1980 to 2013, the compounded growth rate of productivity was 96%.

sizable increase in pay inequality. Practices like performance-based pay disproportionately impact top workers, creating a pass-through from rising productivity to rising inequality.

6 Conclusion

We use confidential Census matched employer-employee earnings data to study the relationships between within-firm pay inequality and productivity. We find that employees at more productive 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 15% more pay for the highest-paid employee (likely the CEO) compared to 7% for the median worker. This pay-performance link holds in both publicly-traded and private firms, although is almost twice as strong in publicly-traded 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. Taken together, the link between productivity and pay suggests that rising productivity can account for a sizable portion of rising inequality.

Table 1: Summary statistics

	Main Sample		Main Sample, Private Firms		Main Sample, Public Firms		Management Sample	
	Mean (1)	Std Dev (2)	Mean (3)	Std Dev (4)	Mean (5)	Std Dev (6)	Mean (7)	Std Dev (8)
Mean log pay	10.95	0.483	10.92	0.469	11.26	0.545	11.01	0.421
90th Percentile-10th Percentile Gap	1.253	0.395	1.234	0.391	1.492	0.364	1.228	0.359
99th Percentile-10th Percentile Gap	2.164	0.632	2.134	0.627	2.526	0.579	2.241	0.575
Top Earner-50th Percentile Gap	2.287	0.914	2.205	0.836	3.304	1.188	2.631	1.027
Top Earner-10th Percentile Gap	2.796	0.965	2.705	0.88	3.919	1.232	3.113	1.098
Sample employment (full-year workers)	745.9	5,500	491.7	3,421	3,890	15,780	1,501	12,260
Total Employment	1,448	10,450	937.6	6,596	7,763	29,630	2,350	21,070
Log productivity (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) ('000s)	443	443	410	410	33	33	11	11
Number of underlying worker-year pairs ('000s)	330,400	330,400	201,500	201,500	128,900	128,900	16,440	16,440
Number of unique firms ('000s)	73	73	69.5	69.5	5.4	5.4	8	8

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 50th and 10th 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. Observation counts are reported in thousands.

Table 2: Pay levels and inequality are correlated with productivity

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

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: 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 50th percentile; in column (5), the dependent variable is the gap between the top earner and the 10th 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. N = 443,000.

Table 3: Productivity increases cause higher pay and higher pay inequality

Dependent Variable:	Log Annual Earnings			
	OLS		2SLS Second Stage	
	(1)	(2)	(3)	(4)
Log Productivity	0.1499***	0.1771***	0.1467*	0.2198**
	(0.01475)	(0.01633)	(0.08290)	(0.1023)
Rank × Log Productivity		-0.0005390***		-0.001447**
		(0.0001452)		(0.0006320)
Joint F-stat	103.3	59.36	3.133	2.905

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: 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 (2024), 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 A.2 for first stages. N = 37,770,000.

Table 4: Rising productivity predicts rising inequality

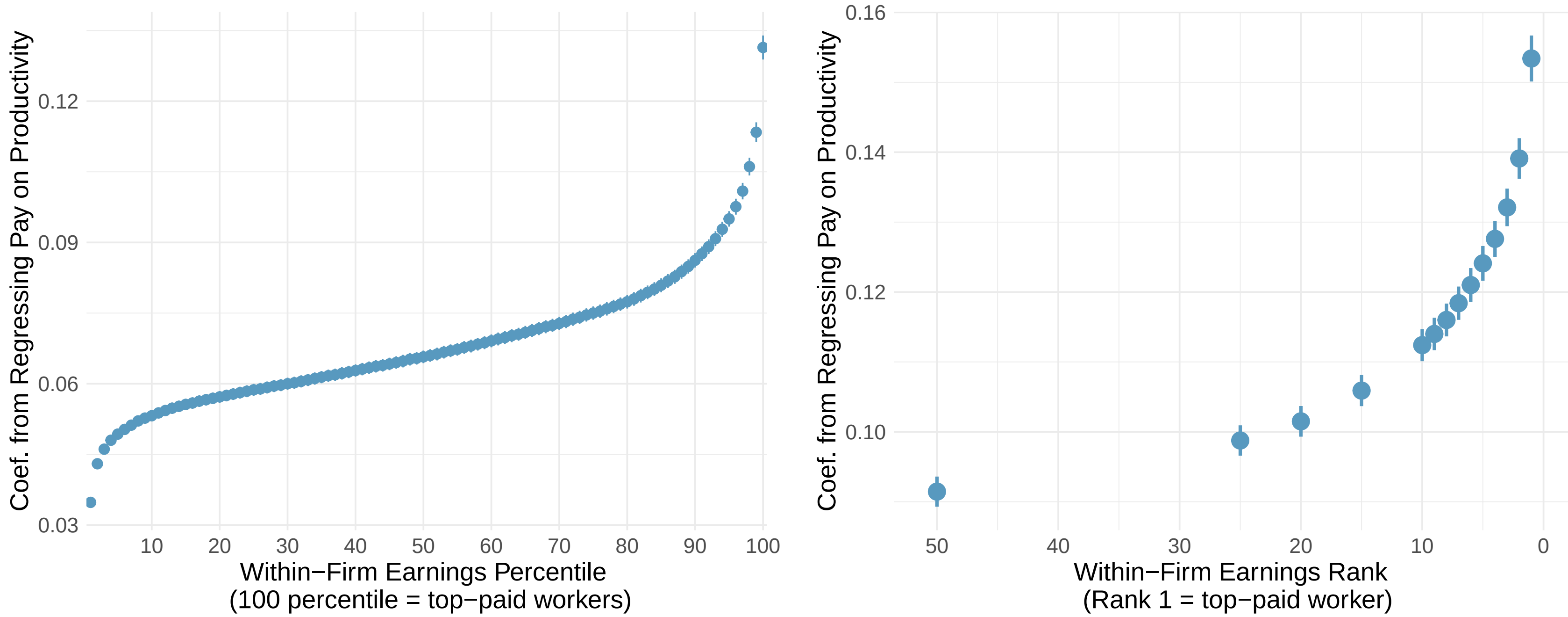
	Actual 1980 (1)	Actual 2013 (2)	Predicted 2013 (3)
Mean earnings ($)			
Top earner	202,420	301,614	224,357
Median earner	26,805	34,702	28,013
Ratio of means	7.55	8.69	8.01
Actual change in ratio ((2) - (1))		1.14	
Predicted change in ratio ((3) - (1))		0.46	
as % of actual		40.13%	

Notes: This table presents a back-of-the-envelope calculation for how rising productivity accounts for rising inequality between 1980 and 2013, according to our estimates.
Actual 1980 and 2013 geometric mean earnings for the top and median earners at firms are taken from Song et al. (2019); we take a weighted average of mean earnings by year and position within firms (highest-paid and median-paid workers) across firms of different sizes, based on the data underlying Figure VI in Song et al. (2019).
Predicted 2013 values are calculated by inflating the actual 1980 values by the predicted percent increases, according to our regression estimates for rank 1 and the 50th percentile earners as shown in Figure 1 (0.1534 for rank 1, 0.0657 for the 50th percentile) and the compounded annual growth of aggregate labor productivity from 1980 to 2013 (compounded growth = 96%; sourced from FRED via `https://fred.stlouisfed.org/series/PRS85006092`, accessed February 9, 2024). Specifically, to predict mean earnings for top earners in 2013, we multiply the 1980 mean earnings by $(1+96\%)^{0.1534}$.
We calculate ratios of the mean earnings by year (i.e., mean earnings for top earners divided by mean earnings for median earners) and show, in the bottom panel, that the predicted increase in pay gaps from 1980 to 2013 accounts for 40% of the actual increase.

Figure 1: Pay is more correlated with productivity for top earners

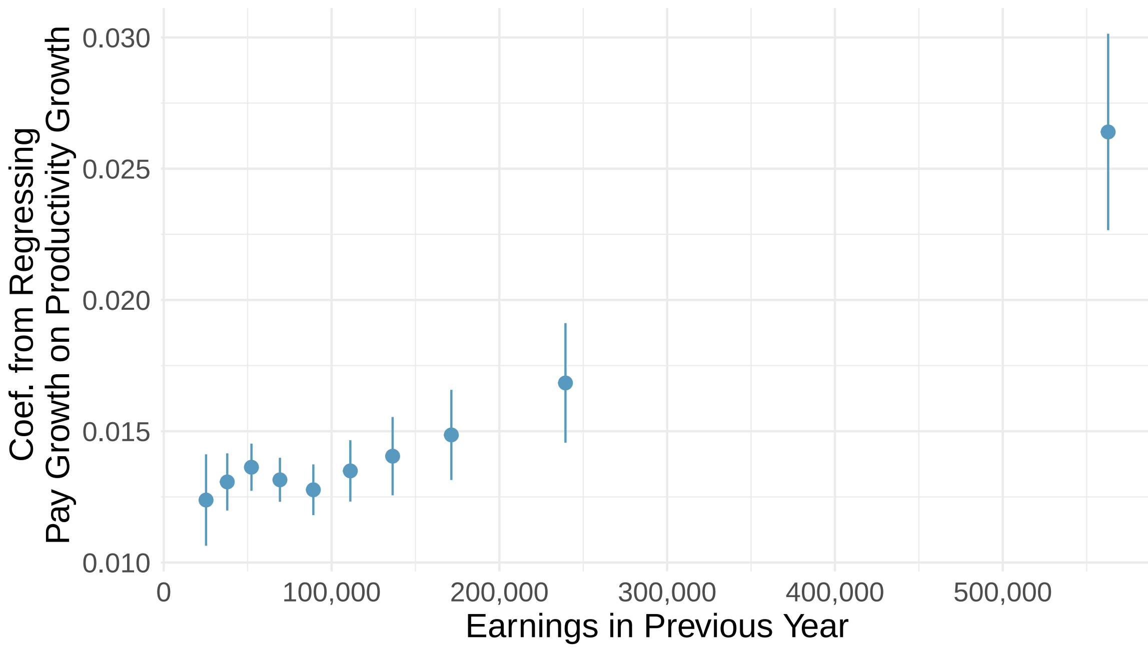
(a) Within-Firm Earnings Percentile

(b) Within-Firm Earnings Rank



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 (panel a) or for a given within-firm earnings rank (panel b), 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 (panel a) or rank (panel b), 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.

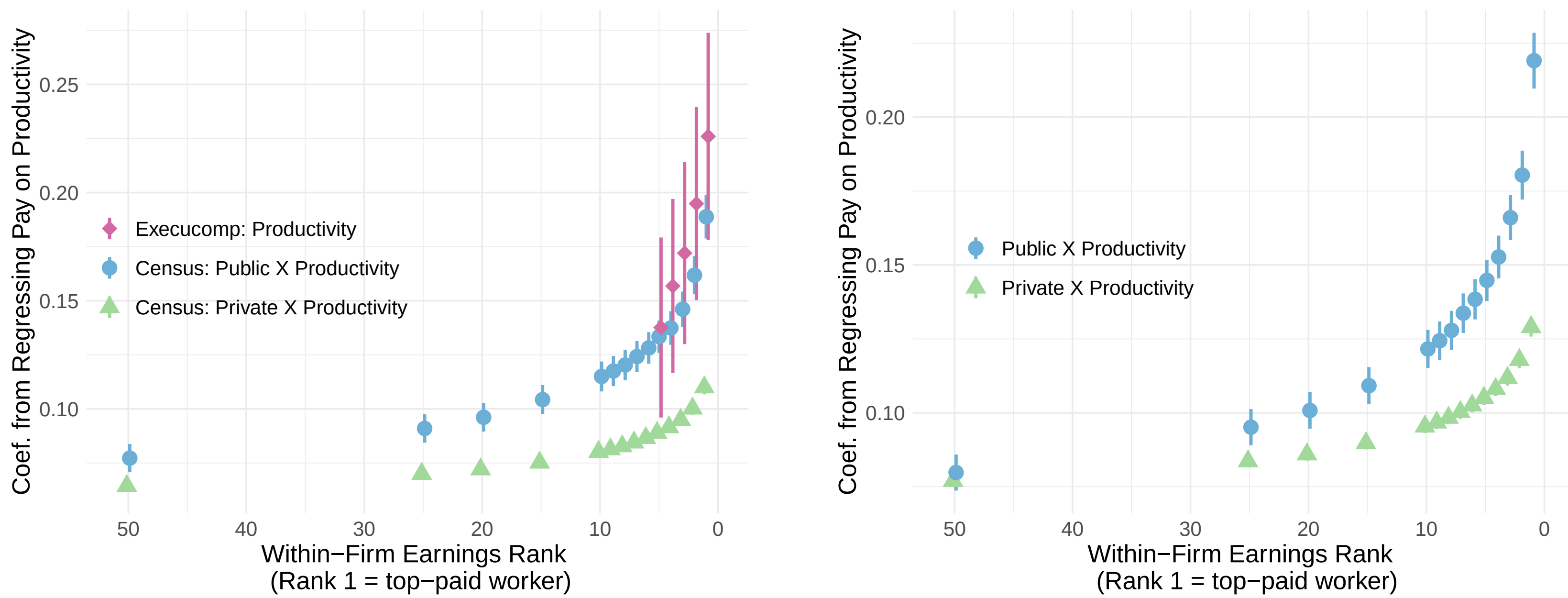
Figure 2: Pay increases are more correlated with productivity increases for top earners



Notes: Each value represents the coefficient (and 95% confidence interval) on productivity growth from a regression of the firm-level mean within-worker earnings growth, for workers in a given bin based on previous year earnings, on productivity growth and controls from Figure 1. Growth is measured as Davis, Haltiwanger, and Schuh (1996) (DHS) growth, which for variable x is given by $\frac{x_t - x_{t-1}}{0.5 \times (x_t + x_{t-1})}$. The coefficients are plotted against the mean level of earnings in the previous year within each bin. The sample restricts to firms in our main sample from 2003-2015 with at least one 10-quarter sandwich worker working in each of the following bins based on previous year earnings at the firm: \$0-\$30K, \$30-\$45K, \$45-\$60K, \$60-\$80K, \$80-\$100K, \$100-\$125K, \$125-150K, \$150-\$200K, \$200-\$300K, and \$300K+ (a 10-quarter sandwich worker is a worker with positive earnings at the firm in every quarter in both the current and previous year as well as Q4 two years in the past and Q1 in the next year; we restrict to these workers in these regressions). Each firm appears in every regression. Observation-level is the firm-year; regressions are unweighted. N = 158,000.

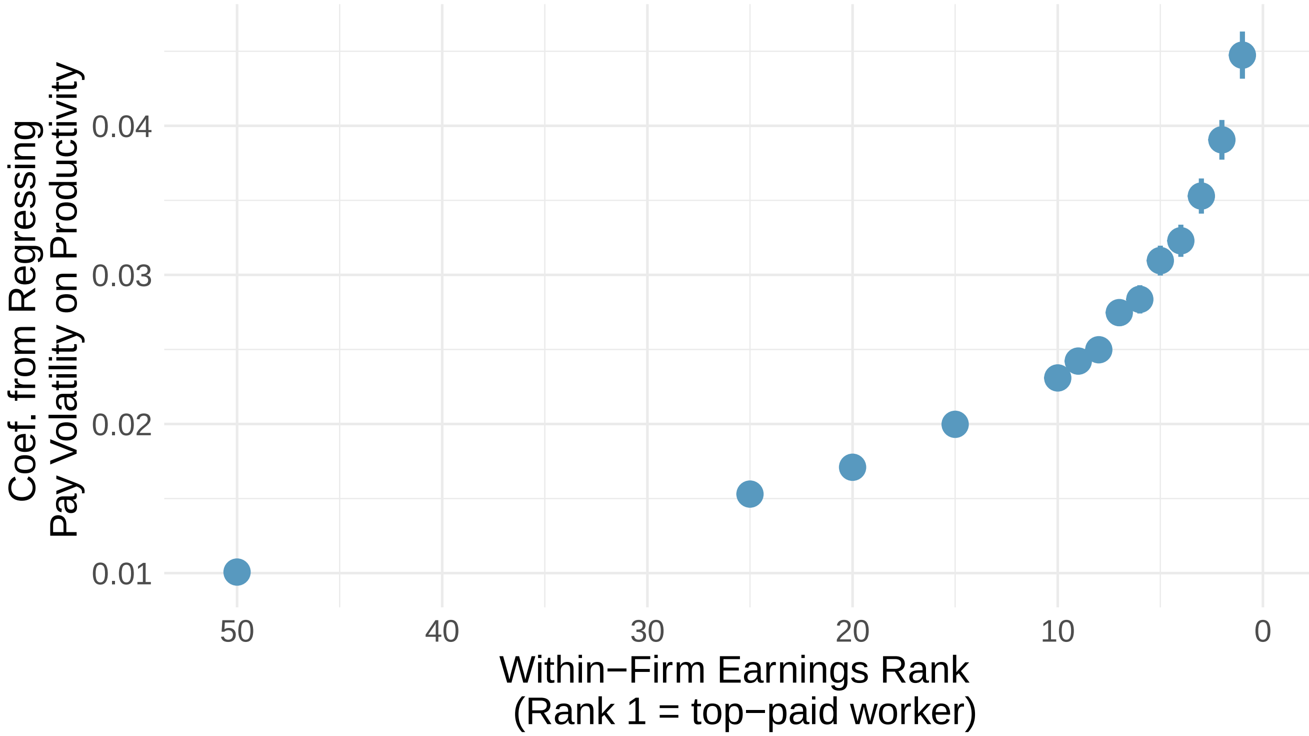
Figure 3: Pay is particularly strongly correlated with productivity for top earners in public firms

(a) Unweighted (b) Weighted to match employment distribution



Notes: In both panels, 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 on the interactions and controls from Figure 1 and an indicator for being publicly traded, by rank. In panel a, 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 Execucomp on productivity and year and 6-digit industry fixed effects. Observation-level is the firm-year. In panel a, regressions are unweighted (i.e., firm-year-weighted). In panel b, regressions are weighted to match the employment distributions of public firms to private firms in our Census sample to improve comparability; private firms are given weight 1, and 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 (based on ventiles of employment). Census N = 443,000. (410,000 firm-years are private; 33,000 are public.) Execucomp N = 4,681.

Figure 4: Pay volatility is more correlated with productivity for top earners

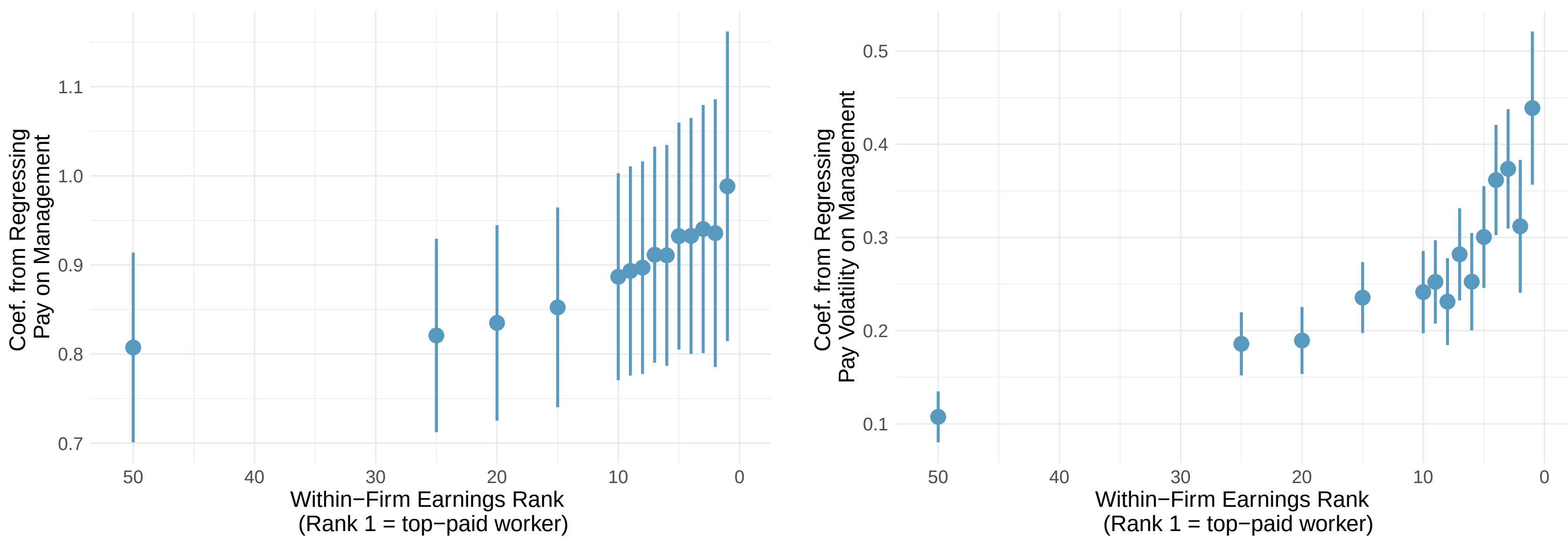


Notes: Each value represents the coefficient (and 95% confidence interval) on productivity from a regression of the within-year pay volatility, of a given within-firm earnings rank, on productivity and controls from Figure 1. Pay volatility is the standard deviation of log quarterly earnings, within 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 5: Pay and pay volatility are more correlated with structured management for top earners

(a) Pay Levels

(b) 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.

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Table A.1: Selection into sandwich sample by productivity and rank

Dependent Variable:	Sandwich Worker Next Year		
	(1)	(2)	(3)
Log Productivity Next Year	0.01762***		0.009929***
	(0.000075)		(0.000119)
Rank		-0.000656***	
		(0.000002)	
Rank $\times$ Log Productivity Next Year			0.000152***
			(0.000002)
Rank Fixed Effects			x

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: 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). N = 41,860,000.

Table A.2: IV analysis: 2SLS with 1st stages

Stage:	1st Stage	2nd Stage	1st Stage	1st Stage	2nd Stage
Dependent Variable:	Productivity	Log Annual Earnings	Productivity	Rank × Productivity	Log Annual Earnings
	(1)	(2)	(3)	(4)	(5)
Log Productivity		0.1467*			0.2198**
		(0.0829)			(0.1023)
Rank × Log Productivity					-0.001447**
					(0.000632)
IV CAD	1.506		1.506	-529.1*	
	(1.080)		(1.080)	(294.7)	
IV Euro	-0.04002		-0.04002	-135.1	
	(0.4951)		(0.4951)	(351.8)	
IV JPY	-0.2250		-0.2250	265.4	
	(0.4965)		(0.4965)	(377.7)	
IV AUD	0.5603		0.5603	-225.0	
	(0.6970)		(0.6970)	(284.2)	
IV SEK	0.6418		0.6418	131.5	
	(0.3853)		(0.3853)	(168.5)	
IV CHF	-0.4541		-0.4541	-621.7*	
	(0.5310)		(0.5310)	(360.4)	
IV GBP	-1.215		-1.215	-495.3**	
	(1.235)		(1.235)	(216.5)	
IV Oil	0.7483*		0.7483*	-8.451	
	(0.3931)		(0.3931)	(250.1)	
IV EPU	775.2**		775.2**	-223900**	
	(382.3)		(382.3)	(104700)	
Rank × IV CAD				11.98**	
				(5.750)	
Rank × IV Euro				2.636	
				(6.743)	
Rank × IV JPY				-5.481	
				(7.509)	
Rank × IV AUD				5.015	
				(5.232)	
Rank × IV SEK				-1.962	
				(3.301)	
Rank × IV CHF				11.86*	
				(7.093)	
Rank × IV GBP				8.594**	
				(3.584)	
Rank × IV Oil				0.9157	
				(4.854)	
Rank × IV EPU				5209**	
				(2405)	
Joint F-stat	2.723	3.133	2.723	6.719	2.905

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the full 2SLS first and second stages underlying the analysis in Table 3. We reshape our main 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 (2024), 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. N = 37,770,000.

Table A.3: Earnings on current vs. lagged productivity and rank

Dependent Variable:	Log Annual Earnings			
	(1)	(2)	(3)	(4)
Log Productivity	0.1872***	0.1955***		
	(0.000193)	(0.000148)		
Rank × Log Productivity	-0.000619***	-0.000619***		
	(0.000003)	(0.000002)		
Lag Log Productivity			0.1994***	0.2028***
			(0.000204)	(0.000156)
Rank × Lag Log Productivity			-0.000675***	-0.000675***
			(0.000003)	(0.000002)
Log Total LEHD Employment		x		x

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

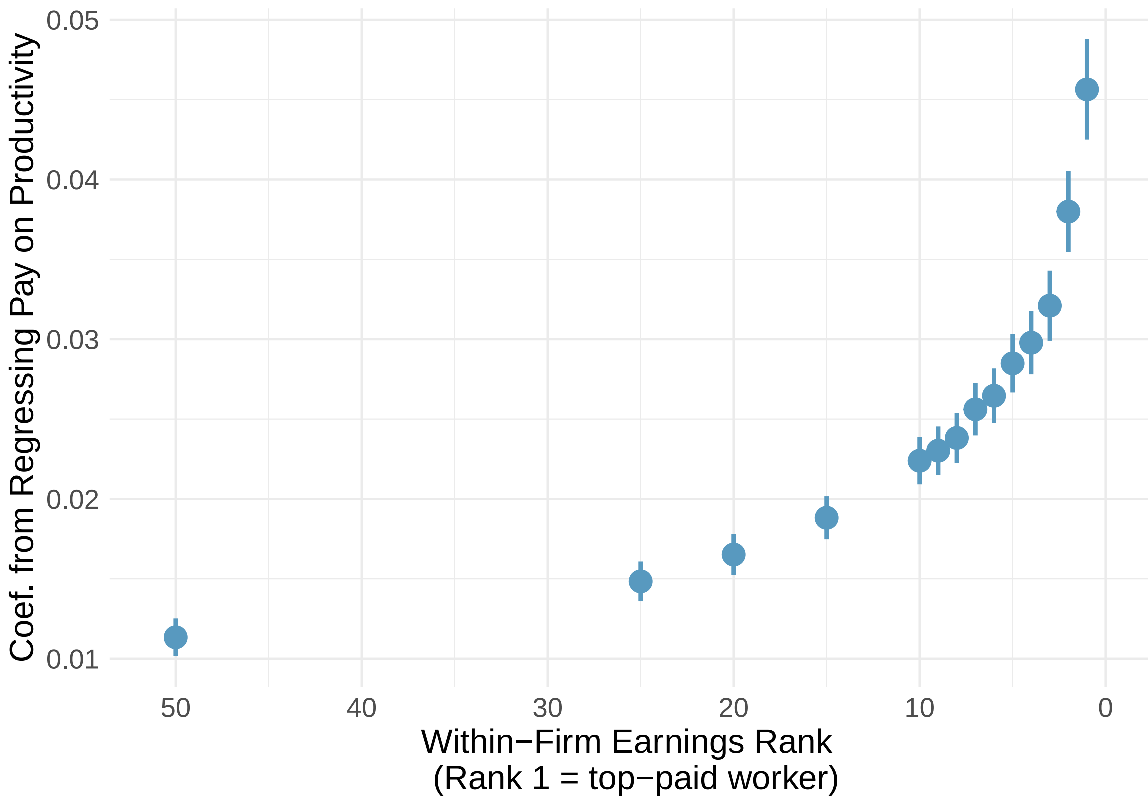
Notes: This table demonstrates that the earnings-productivity relationship by rank is robust to considering lagged productivity. The table presents several regression estimates for our main sample, where we reshape the sample to be at the firm-year-rank level; we restrict to the top 100 paid employees 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 (in columns (2) and (4)). Columns (3) and (4) additionally include as a control an indicator for whether the firm has information on previous year productivity; if the firm does not have previous year productivity information, we replace the lagged productivity with the sample mean. N = 44,300,000.

Table A.4: Comparing our main sample of public firms to Execucomp

	Main Sample, Public Firms		Compustat		Execucomp		Execucomp, Emp<4,000	
	Mean (1)	Std Dev (2)	Mean (3)	Std Dev (4)	Mean (5)	Std Dev (6)	Mean (7)	Std Dev (8)
Total Employment	7,763	29,630	10,292	44,242	16,169	40,516	1,542	1,106
Log Productivity (revenue/employment)	5.598	1.082	5.628	1.302	5.929	1.035	6.263	1.021
Log Pay of 1st-Ranked Worker (2015)	14.82	1.321			15.07	1.038	14.65	0.933
Log Pay of 2nd-Ranked Worker (2015)	14.30	1.189			14.38	0.977	13.99	0.857
Log Pay of 3rd-Ranked Worker (2015)	14.06	1.126			14.15	0.924	13.77	0.811
Log Pay of 4th-Ranked Worker (2015)	13.88	1.088			13.98	0.880	13.60	0.743
Log Pay of 5th-Ranked Worker (2015)	13.74	1.061			13.82	0.901	13.47	0.789
N (firm-year pairs) ('000s)	33	33	60.184	60.184	4.743	4.743	2.370	2.370
Number of underlying worker-year pairs ('000s)	128,900	128,900						
Number of unique firms ('000s)	5.4	5.4	10.71	10.71	0.552	0.552	0.280	0.280

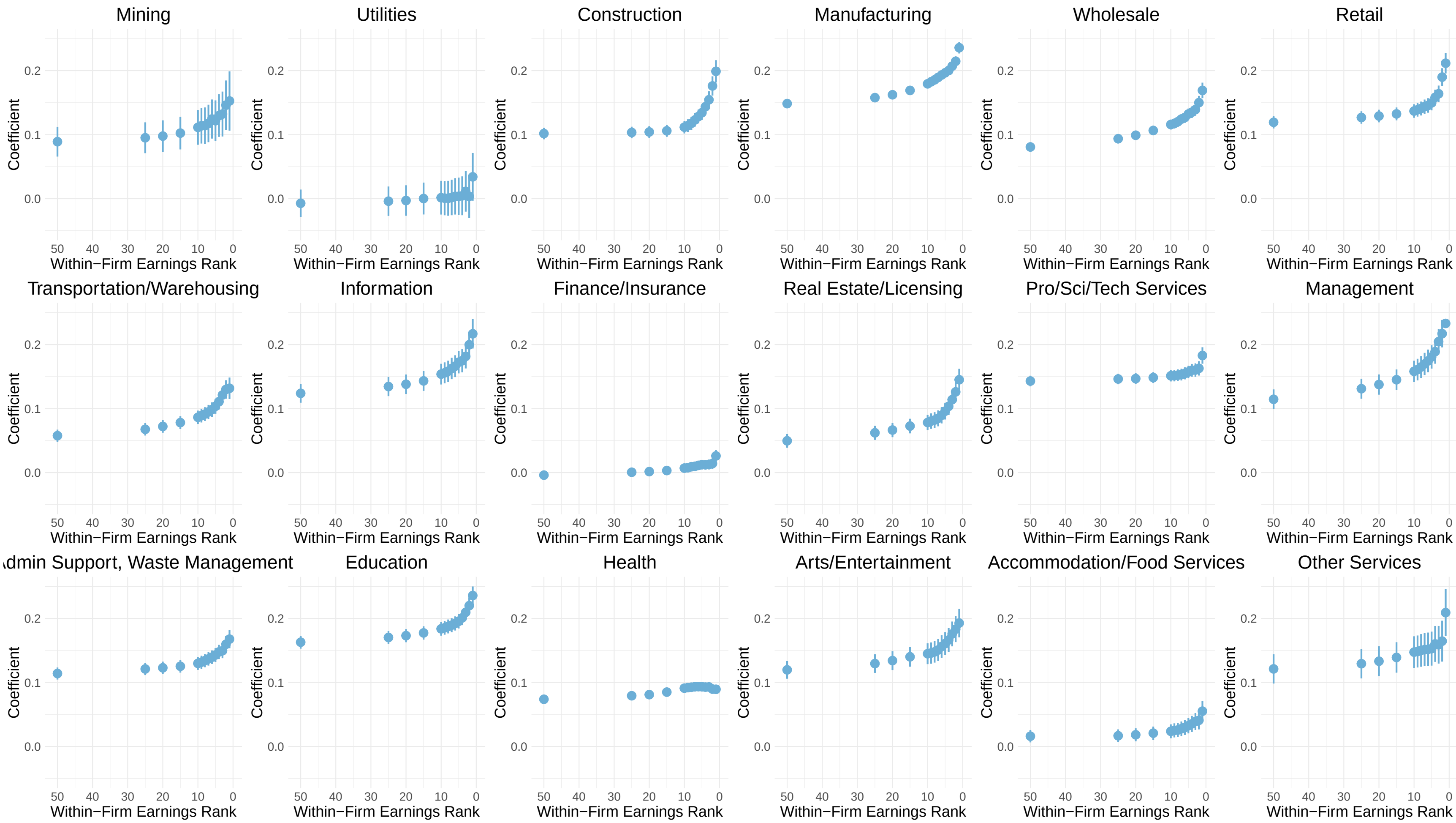
Notes: Statistics are calculated based on several years of data (2003-2015 for the main sample of publicly-traded firms in columns (1) and (2); 2007-2015 for the Compustat-based samples in columns (3)-(8)). Columns (5)-(8) restrict top Compustat firms covered in Execucomp; columns (7) and (8) further restrict to firms below the median employment in Execucomp in our sample (4,000 employees) in order to demonstrate how selection into Execucomp (on size) affects the comparison between our Census-based pay values and Execucomp's. Observation counts in footer refer to the multi-year sample; Compustat contains more firms than our main sample of public firms, since we do not restrict to firms with at least 100 full-year workers in Compustat. Average earnings of the top-ranked workers are calculated in 2015. Revenue is measured in thousands of 2010 USD. Observation counts are in thousands.

Figure A.1: Pay is more correlated with productivity for top earners, with firm fixed effects



Notes: Each value represents the coefficient (and 95% confidence interval) on productivity from a regression of log annual earnings, with controls from Figure 1 *and* firm 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. N = 443,000.

Figure A.2: Pay is more correlated with productivity for top earners for most industries



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 A.3: Pay is more correlated with productivity for top earners for 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 $\geq$ Age $<$ 25) = 98,000. N(Age $\geq$ 25) = 301,000.

Figure A.4: Pay volatility is higher 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.