Employer Dominance and Worker Earnings in Finance

by

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Abstract

Large firms in the U.S. financial system achieve substantial economic gains. Their dominance sets them apart while also raising concerns about the suppression of worker earnings. Utilizing administrative data, this study reveals that the largest financial firms pay workers an average of 30.2% more than their smallest counterparts, significantly exceeding the 7.9% disparity in nonfinance sectors. This positive size-earnings relationship is consistently more pronounced in finance, even during the 2008 crisis or compared to the hightech sector. Evidence suggests that large financial firms' excessive gains, coupled with their workers' sought-after skills, explain this distinct relationship.

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The U.S. financial system is dominated by large firms. Ongoing concerns have been expressed over the substantial market share enjoyed by these firms, specifically that they are empowered to extract surplus from consumers.[1] Yet, how workers fare in terms of earnings at these large financial firms remains underexplored. As major employers in the labor market, large firms may limit workers' outside options and have market power to suppress labor compensations, thereby retaining more surplus (Yeh, Macaluso, and Hershbein 2022; Jarosch, Nimczik, and Sorkin 2024).[2] On the other hand, financial workers may possess scarce but in-demand skills that boost productivity at large firms and strengthen their bargaining power, potentially enabling them to command a larger share of the surplus and higher compensations. To better understand the implications of firm market power in the labor market, this study examines the relationship between firm size and worker earnings in the finance sector, as well as the unique attributes of financial firms and workers that explain the relationship.

By utilizing micro-level data from the U.S. Census spanning from 1990 to 2013, I compare within-industry relationships between firm size and worker earnings across finance and nonfinance sectors. Although this approach does not necessarily establish a causal relationship, it offers a clearer interpretation of cross-sector comparisons and highlights distinct dynamics within the finance sector by isolating factors like regulatory changes and technology adoption that commonly drive firm size distribution and worker earnings.

For the baseline analysis, I define firm size as its employment normalized by the employment of its industry (firm relative size), classified by two-digit Standard Industrial Classification (SIC).[3] The availability of universal business employment data from the Longitudinal Business Dynamics (LBD) database allows for accurate measurement of firm and industry sizes in the U.S. domestic market. Normalizing firm size by its industry size adjusts for cross-industry differences in potential labor market sizes and directly reflects

[1]For example, the *Financial Times* reported that the four biggest U.S. lenders captured almost 50% of all banking profits in the third quarter of 2023 as they were able to pay less interest to savers than smaller lenders (Gandel 2023)

[2]Similar concerns raised by policy makers can be found in Council of Economic Advisers (2016) and Council of Economic Advisers (2021).

[3]Baseline results remain consistent when defining markets more precisely using three-digit SIC codes or by commuting zone-by-industry (i.e., local labor market).

workers' outside job opportunities in a given market. Firms with larger relative sizes offer more jobs than smaller ones, thereby increasing (decreasing) the likelihood of their workers encountering current employers (other employers) when searching for alternative job opportunities (Jarosch, Nimczik, and Sorkin 2024).

The main finding of this paper is that while larger firms within a given industry tend to pay workers higher earnings, this positive relationship is more pronounced in the finance sector. Specifically, after controlling for firm age and demographic and educational compositions of the workforce, one standard deviation higher in firm relative size within a given finance industry is associated with a 3.8% higher average quarterly earnings, compared to only a 0.5% higher within a given nonfinance industry-year-quarter. The marginal difference between finance and nonfinance is statistically significant at the 1% level and equals to \$555 per worker-quarter based on sector means of earnings. The difference remains robust with granular industry definitions and is also observed in other firm-level measures of worker earnings, including median earnings and payroll per worker.

Interestingly, my findings reveal that in the finance sector, the positive relationship between firm relative size and average worker earnings consistently remains significantly stronger than that of other industries across three subperiods: pre-2008 crisis (1990–2006), during the crisis (2007–2009) and postcrisis (2010–2013). This consistent pattern can be partially explained by the resilience of larger financial firms' operations, potentially attributable to government interventions and productivity gains from shedding less productive workers during the 2008 crisis. Additionally, finance professionals have likely gained bargaining power over the years as their skills, particularly in math and social interactions, have been increasingly demanded and rewarded by high-paying sectors like high-tech since the early 2000s (Shu 2016; Deming 2017; Ellul et al. 2021).

Comparing the entire finance sector with the rest of the economy may obscure important differences in firm and worker characteristics that are vital to understanding the pronounced link between firm relative size and worker earnings within the finance sector. To illuminate these differences, I examine the heterogeneity across three finance subsectors—broker, dealer, exchange, and services (BDE), banking and credit Institutions (CB), and insurance (IS)—and compare them to the high-tech sector. Unlike the rest of the economy, which encompasses a wide variety of industries with diverse characteristics, the high-tech sector is similarly dominated by large players, relies on highly skilled workers, and is known for competitive pay. This comparison helps isolate these common characteristics and further highlights the unique attributes of the finance sector.

Compared to the high-tech sector, the positive relationship between firm relative size and average earnings is significantly stronger in both the BDE and CB sectors. This variance is partly attributed to larger firms' higher revenue per worker in the CB sector. In the BDE sector, workers tend to possess additional time-invariant qualities (e.g., talent or alma maters) that are portable across firms. Furthermore, unlike high-tech jobs, which primarily require quantitative and technical skills with less emphasis on social skills (Deming 2017), jobs in both BDE and CB sectors demand not only higher levels but also a more balanced mix of math and social skills. These factors strengthen workers' bargaining power and contribute to the distinct rent-sharing patterns in these subsectors.

Building on the existing literature on market power and suggestive evidence from the previous heterogeneity analyses, I next conduct two sets of tests on mechanisms that may explain the pronounced relationship between firm relative size and worker earnings in the finance sector. First, firm relative size in the finance sector may be linked to greater economic gains in the finance sector than in nonfinance sectors, potentially allowing for more rent-sharing with workers. In support of this channel, I show that within a given industry-year-quarter, firms with relatively larger sizes are associated with higher profitability (proxied by ROA) as well as higher markups (proxied by Lerner Index) than smaller firms, and these positive relationships are more pronounced in the finance sector. The differences between the finance and nonfinance sectors are statistically and economically significant. Additionally, I observe a significantly positive relationship between firm relative size and revenue per worker in the finance sector, while a null relationship in nonfinance industries. These findings suggest that, by exerting their monopoly power and/or being more productive, larger financial firms are linked to greater economic gains, which may be shared with employees.

The second explanation for the heightened relationship between firm relative size and worker earnings in the finance sector could be the skills of financial workers, which may not only boost productivity at larger firms but also strengthen their bargaining power. To test this explanation, I conduct two analyses. First, using employer-employee matched data from the Longitudinal Employer-Household Dynamics Program (LEHD), I estimate time-invariant worker quality that is portable across firms (e.g., alma maters, talent or social skills acquired before the first job) following Abowd, Kramarz, and Margolis (1999) and Card, Heining, and Kline (2013). I find that the average time-invariant worker quality is significantly higher in the finance sector than in other sectors, suggesting that finance workers possess skills that command a wage premium across firms.

In the second test, I explore industry heterogeneity in job tasks using data from the American Community Surveys (ACS). Financial workers may be more productive and command higher earnings if their skills better complement tasks highly demanded by larger firms, such as monitoring and operating technologies (Mueller, Ouimet, and Simintzi 2017; Autor et al. 2020). Moreover, they may possess higher bargaining power if their skills are highly sought-after and costly for firms to replace. By matching ACS with occupation task scores from Autor and Dorn (2013) and Deming (2017), I find that tasks in the finance sector require a higher level of nonroutine skills in direction, coordination, negotiation, social perceptiveness, and quantitative reasoning, which have been increasingly demanded and rewarded in the labor market. Similar variations are observed for job tasks in the three finance subsectors compared to high-tech sector jobs. These findings reinforce the notion that the stronger correlation between firm relative size and worker earnings in finance can be partially explained by workers' superior productivity and strong bargaining power, rooted in their inherent qualities and highly valued skill sets.

Within a given industry, larger firms often rely more on high-skill workers to manage teams, operate advanced technologies, and handle large-scale projects (Mueller, Ouimet, and Simintzi 2017; Célérier and Vallée 2019; Autor et al. 2020). This increased demand may strengthen the bargaining power of high-skill workers at larger firms, leading to economic gains disproportionately favoring them. As a result, larger pay gaps may emerge within larger firms. Consistent with this, my findings indicate that the average earnings of high-skill workers are more sensitive to firm relative size than those of lower-skill workers. This disparity is particularly pronounced in the finance sector, where larger firms tend to be more capital-intensive and rely more heavily on high-skill workers than smaller peers, and there is a greater synergy between large-scale tasks and talent.

In the final part of the study, I discuss several alternative explanations for why firm relative size is associated with higher earnings in the finance sector than in other sectors. First, it is probable that nonfinancial firms are more likely to compete in local product markets than financial firms. Consequently, nonfinancial firms' economic gains—and thus worker earnings—are more (less) sensitive to their market shares in local markets (the national market). However, this explanation seems implausible because when firm relative size is measured relative to the size of the local market, I consistently find a stronger positive relationship between firm relative size and average worker earnings in the finance sector compared to the nonfinance sector. This robust finding also rules out the possibility that normalizing firm size by industry size might overestimate potential labor market size and underestimate the labor market power of financial firms due to financial workers being less geographically mobile than nonfinancial workers.

Second, it may be well valid that measuring a firm's relative size within the domestic market might overlook the impact of import competition. Financial firms' economic gains—and consequently, worker earnings—may be more positively correlated with their relative size in the domestic market because financial firms are less negatively affected by import competition than nonfinancial firms. However, this explanation seems unlikely because, compared to firms in nontradable sectors that face low import competition, I consistently observe a significantly stronger positive relationship between firm relative size and earnings in finance industries.

Third, one could hypothesize that firm relative size is less correlated with labor monopsony power in finance because the sector is perceived as less concentrated (i.e., more competitive) than other industries. However, this seems unlikely, as the data indicates that finance industries have been more concentrated (i.e., less competitive) than nonfinance industries over the sample period.[4] Additionally, my analysis shows that, unlike those in nonfinance sectors, workers in more concentrated (i.e., less competitive) finance industries earn higher earnings than those in less concentrated industries. This suggests that industry concentration in the finance sector does not grant the same level of power in the labor market as in other industries.

Finally, it might be posited that finance workers are in a stronger bargaining position because they are less subject to noncompete agreements or more heavily unionized. However, a national-level survey of private-sector employers conducted by Colvin and Shierholz (2019) shows that the share of workplaces where any employees are subject to noncompete agreements is 58% in the finance sector, higher than the national rate of 49%. Unionization as an explanatory factor also seems unlikely in the context of the finance sector, which has exhibited a significantly lower rate of unionization compared to nonfinance sectors based on the statistics reported by the Bureau of Labor Statistics for the sample period.

This paper contributes to three strands of literature. First, it addresses the recently renewed interest in the implications of firm market power. For example, De Loecker, Eeckhout, and Unger (2020) show that firms have increased power in the product market, as evidenced by rising price-cost margins over recent decades. My study is more closely related to recent studies focusing on labor outcomes. Works by Benmelech, Bergman, and Kim (2022), Azar, Marinescu, and Steinbaum (2022), and Qiu and Sojourner (2023) explore the aggregate effects of industry concentration, revealing a negative effect on worker compensation. These studies suggest that reduced competition in concentrated markets allows employers to suppress worker earnings. Diverging from this set of literature, my paper builds on the theoretical framework established by Robinson (1933) and Jarosch, Nimczik, and Sorkin (2024), which emphasize the role of employer size in affecting workers' outside options and, in turn, their earnings. I empirically examine the

[4] Concentration is measured as the sum of the squared firm employment shares in a given industry, that is, Herfindahl-Hirschman Index (HHI).

within-industry relationships between employer size and worker earnings. In a related study, Yeh, Macaluso, and Hershbein (2022) documents a positive association between firms' employment share and labor market power in the manufacturing sector. My paper instead focuses on the finance sector, where the unique skill profiles of workers influence their bargaining power and firms' behaviors in rent-sharing.

This study also complements works that document and explain finance wage premium (Philippon and Reshef 2012; Axelson and Bond 2015; Boustanifar, Grant, and Reshef 2017; Célérier and Vallée 2019; Ellul, Pagano, and Scognamiglio 2021; Böhm, Metzger, and Strömberg 2022). Consistent with the previous literature, I find finance earnings are, on average, higher than nonfinance earnings using micro-data from the U.S. Census. My paper enhances the understanding of finance wage premium, likely driven by larger employers who hire most workers, through the lens of firm rent-sharing behavior. I show that workers at larger financial firms earn significantly higher earnings than those at small counterparts, and the within-industry gap is more pronounced in the finance sector than in the rest of the economy. This disparity is not only solely due to the superior financial performance of larger financial firms but also because of the distinct skill sets of finance workers and their stronger bargaining power.

Lastly, this study is related to the discussion on cross- and within-firm wage inequality. Song et al. (2018) shows that two-thirds of the rise of inequality from 1978 to 2013 can be explained by the earnings dispersion between firms. Consistently, I show that earnings vary significantly among firms, even within industries, which correlates with their relative size within their respective industries. Furthermore, I establish that this variation is more pronounced within finance industries compared to the nonfinance sector because of the unique attributes of financial firms and workers. Focusing on within-pay inequality, Mueller, Ouimet, and Simintzi (2017) shows that, on average, larger firms in the United Kingdom are associated with higher levels of pay inequality. Consistent with their finding, my results show firms in the United States that are relatively larger exhibit higher within-firm pay gaps. In addition, I show that the link between firm size and the within-firm pay gap is more prevalent in the finance sector, where larger firms tend to be more capital-intensive and rely more heavily on high-skill workers than smaller peers. Moreover, there is a greater synergy between large-scale tasks and talent (Célérier and Vallée 2019).

1 Data

This study relies on data from various sources, including the Longitudinal Employment-Household Dynamics (LEHD) database, the Longitudinal Business Database (LBD), Compustat, and the American Community Survey (ACS). In this section, I describe these data sources and how baseline samples and key variables are constructed. Additionally, I provide summary statistics and other descriptive evidence that motivates my analysis.

1.1 Data sources

I use the employer-employee matched data administrated by the LEHD program to track workers' quarterly earnings at their employers. The LEHD program is constructed from administrative unemployment insurance (UI) records of states participating in the program and contains every worker who is ever employed in any participating state (Abowd et al. 2009; Vilhuber 2018). I have access to LEHD for 24 participating U.S. states from 1990Q1 to 2013Q4. Table 1 lists the accessible states and periods.

Within the LEHD program, I use data from the Employment History Files (EHF) to track workers' quarterly earnings, locations, and industries across employers and use the National Individual Characteristics File (ICF) to identify worker demographic characteristics, such as sex, birth year, and education.[5,6] Workers' earnings include all forms of immediately taxable compensation, including gross earnings and salaries, bonuses, exercised stock options, tips, and other gratuities. For this reason, the findings in this study do not apply to other nonmonetary compensations, such as unexercised stock options

[5]See Abowd et al. (2009) and Vilhuber (2018) for more detailed descriptions of the LEHD program.

[6]Information on demographic characteristics is imputed by the LEHD program using a hierarchical approach when missing. See more details about the imputation process in section 5.1.1.2 of Vilhuber (2018).

and nonwage benefits.

I supplement data from LEHD with firm-level information on employment, payroll, and industry from the LBD.[7] Specifically, the LBD tracks all domestic establishments in the United States annually.[8] It provides establishment-level information on total employment, total payroll, and industry, as well as a unique firm identifier that longitudinally links establishments that are part of the same firm. I aggregate data across establishments to get firm- and industry-level employment.

For one set of mechanism tests, I collect firm-level financial data from Compustat and link it to publicly listed firms in the LBD through the Compustat-SSEL Bridge (CSB). For another set, I collect individual-level survey data from the ACS, which provides demographics and work characteristics, such as occupation, industry, work hours, and annual income.

1.2 Baseline sample construction

The baseline sample is at firm-year-quarter-level and spans from 1990 to 2013. To obtain firm-level earning patterns and workforce compositions, I start by linking selected employment records from the LEHD to firm identifiers in the LBD through the Business Register Bridge (BRB).[9] Specifically, I restrict the sample to full-time workers in the LEHD by only including workers aged between 16 and 65 years old and by excluding employee-quarter that earned less than 80% of the 1990 federal minimum earning following Philippon and Reshef (2012), where earnings are converted to 2018 constant dollars.[10] Since worker transitions between jobs not occurring at the exact start of a new quarter would lead to a downward bias in earnings around a job change, I drop observations that do not have the same employee-employer pair in both the preceding and the subsequent

[7] See Jarmin and Miranda (2002) for more details about the LBD program.

[8] An establishment is any separate physical location operated by a firm with at least one paid employee.

[9] Workers in the LEHD can be linked to firms, rather than establishments, in the LBD through the BRB. Matching the LBD and the LEHD is an imperfect process because the LBD infrastructure is based on physical establishments, while the LEHD infrastructure uses tax reporting units (SEINs) for a given firm, which are defined at the state level. SEINs may or may not match the physical establishments identified in the LBD. Therefore, this study conducts analyses at the firm level instead of the establishment level.

[10] Eighty percent of the 1990 federal minimum earning in 2018 constant dollars is equal to \$2,801.66/quarter (=$0.8\times$\$3.8/hour $\times 40$ hours/week $\times$ 12 weeks/quarter $\times 1.92$).

quarter.

I then aggregate selected employee data to obtain firm-year-quarter-level earning patterns and workforce composition measures. Since self-employment may have different wage-setting behavior, I exclude firms with zero or only one paid employee to minimize such cases.

1.3 Defining key variables

For a firm with only one establishment, its industry (or market) is determined by the industry of that establishment. A firm with multiple establishments is classified in an industry where it allocates more than 50% of its workforce.[11] Industries are classified using the 1987 Standard Industry Classification (SIC) codes in the sample, available for all LBD establishments throughout the sample period. While I repeat some tests using three-digit SIC codes, I use two-digit SIC codes as the baseline for two reasons: First, it increases the probability that large corporations operating in multiple granular industries are grouped as competing firms in the same industry. For example, a large insurance company may have a similar proportion of activities within SIC 631 (life insurance), SIC 632 (medical service and health insurance), SIC 633 (fire, marine, and causality insurance), and SIC 639 (insurance carriers). As these firms compete in all three markets, their primary industries would be too narrowly defined by three-digit SIC codes or more granular market classifications. Second, classifying firm industries at the two-digit SIC level reduces potential measurement errors in worker earnings. These errors arise from the lack of one-to-one mapping between workers and firms in their industries. Specifically, as workers from LEHD are matched with the firm instead of each establishment in the LBD, worker earnings are aggregated to the firm level, regardless of their industries. Classifying a firm with more granular industry codes increases the probability of misclassifying workers and measurement errors in firm-level earnings.

A firm is in finance if it is in one of the industries described in Philippon and Reshef

[11] In the Statistics of U.S. Businesses (SUSB) program, a firm is classified in an industry where it paid the largest share of its payroll. See more details at here. I do not use payroll to classify industries as it is mechanically correlated with worker earnings, which is the outcome variable of interest.

(2012): depository institutions (excluding central reserve depository institutions), non-depository institutions, security and commodity brokers, insurance carriers, insurance agents, brokers and service, and holdings and other investment offices. A firm is classified as a nonfinancial firm if it is in one of the private nonfinancial industries. To examine heterogeneity within the finance sector, I group financial firms into three groups: broker, dealer, exchange, and services (BDE), banking and credit Institutions (CB), and insurance (IS). These finance subsectors are compared to high-tech industries, including computers, biotech, telecom, and electronics.[12] Within the baseline sample, financial firms account for approximately 3.9% of the observation, similar to the statistics reported in the Statistics of U.S. Businesses (SUSB): 4.1% in 2000 and 4% in 2013. Within the finance industry, BDE, CB, and IS take 11%, 39%, and 50% of the observations, respectively.

Recent policy concerns about firm power in the labor market are based on a Cournot Oligopoly type model derived in Jarosch, Nimczik, and Sorkin (2024). Larger firms offer more jobs than smaller firms, increasing the likelihood of their workers encountering their current employer when searching for alternative job opportunities. When the costs of not hiring their own worker but hiring another identical worker are low, a larger firm will not compete with itself. Consequently, the worker has limited external options, allowing the employer to suppress wages.[13] Based on this argument, a firm f's relative size within a given industry j is defined as:

$$\text{RelativeSize}_{f,j,y} = \frac{emp_{f,j,y}}{emp_{j,y}}, \times 100\%, \tag{1}$$

where $emp_{f,j,y}$ is the employment of firm f in industry j in year y. $emp_{j,y}$ is the total

[12] I identify high-tech industries following Babina (2019) and Babina et al. (2021).

[13] This is rather intuitive. Assume two firms, A and B, are in a given industry. Firm A has 10 workers, and firm B has 90 workers. In total, there are 100 positions available in the industry. For workers working at firm B, which takes 90% of the employment share, they only have 10 potential outside options offered by firm A. In this case, firm B possesses a higher market power than firm A. Similarly, Council of Economic Advisers (2021) wrote: "the case of a pure monopsony, a concept first developed by Robinson (1933), there is a single employer that uses its market power to set wages below what the competitive rate would be; that is, the firm has the power to set such wages. Robinson's theoretical model of a single employer has been extended to incorporate the concept that an employer's monopsony power can come from representing a larger share of the labor market, limiting employees' options to push toward competitive wages."

employment in industry j in year y. As industry sizes are measured using employment data for almost all private and publicly listed firms in the United States, they are more accurate than the ones constructed using survey data or publicly listed firms' employment data.

The firm-level measure of worker earnings in the baseline analysis is calculated by averaging the quarterly earnings of matched workers at a given firm. For robustness tests, I also measure firm-level earnings using the median of the firm earning distribution in a given year-quarter.

As mentioned earlier, earning and workforce composition measures constructed using the LEHD are at firm-year-quarter level. However, measures constructed using the LBD, including $RelativeSize$ and firm age, are at an annual frequency. Given the LBD is a snapshot of statistics of March 12th in each year, these measures in year y are linked to quarterly measures constructed using LEHD in the first three quarters of year y and the last quarter of year $y - 1$.

1.4 Summary statistics

Table 2 reports summary statistics of firm-level variables from the baseline sample. Column 1 reports mean values and standard deviations in parentheses calculated across all firm quarters within the sample. Columns 2 and 3 report summary statistics calculated for financial and nonfinancial firms, respectively. The last column reports the differences between columns 2 and 3 and the statistical significance level from two-sample t-tests.

Column 2 shows that the quarterly average earning in finance is \$16280 (in 2018 constant dollars) within the sample, which is 27.6% higher than the nonfinance one reported in column 3. Compared to the existing literature, I document a lower excess earning in finance mainly because I can only access employment records of workers in 24 states in the LEHD program. New York and Connecticut, where excess earnings paid by financial firms are even higher (Philippon and Reshef 2012), are not included in the sample.[14,15] Moreover, the average earning of high-skill workers is 42.9% higher in finance than nonfinance. Consistent with the high-skewness of finance earnings documented in Philippon and Reshef (2012) and Ellul, Pagano, and Scognamiglio (2021), financial firms, on average, have a higher inequality—measured by 90th-to-10th earning ratios and standard deviation of earnings—compared to nonfinancial firms.

Moreover, Table 2 shows that the average firm relative size in two-digit SIC industries, measured using Equation (1) is 0.006 percentage points (column 2), which is higher than the average for nonfinancial firms by 0.002 percentage points. The difference is statistically significant at the 1% level, indicating the finance industries are composed of larger firms.

Table 2 also reports summary statistics of other firm characteristics. Consistent with the existing literature, financial firms, on average, hire a 16.16-percentage-point higher share of college workers and a 3.82-percentage-point higher share of white workers than nonfinancial firms. Interestingly, the share of male workers in financial firms is 31.8%, which is 23.6-percentage-points lower than the share in nonfinancial firms. The fact that financial firms hire relatively fewer male employees on average is consistent with employment statistics reported by the Bureau of Labor Statistics (BLS).[16]

2 Firm Relative Size and Worker Earnings

How do financial workers fare in terms of earnings when their employers dominate the market? To answer this question, I exploit within-industry relationships between firms' relative size and worker earnings and compare them between the finance and nonfinance sectors. The empirical strategy aims to isolate other industry trends, such as regulation or

[14] There are two other potential reasons: (1) As the frequency of my baseline sample is quarterly. The excess earnings paid by financial firms, which is mainly driven by bonuses (Bell and Van Reenen 2013), may be smoothed out by taking averages across quarters. (2) I also drop firms that are too diversified to be classified into one industry. Diversified firms tend to be larger and pay higher earnings (Oi and Idson 1999).

[15] To eliminate concerns related to omitting these states, I conduct robustness tests in Section 2.2 using total payroll divided by total employment as an alternative measure of firm earnings, where payroll and employment are available in the LBD program for all domestic businesses.

[16] See employment statistics by sex and industry published by the BLS at `https://www.bls.gov/cps/wlf-databook-2013.pdf`.

technology adoption, that drive within-industry firm size distribution and worker earnings and offers a cleaner interpretation of intersector comparison.

2.1 Baseline analysis

To examine the relationship between firm relative size and worker earnings, I estimate the following regression:

$$\begin{aligned}\text{logEarnings}_{f,j,t} = \gamma_1 \text{RelativeSize}_{f,j,t-4} + \gamma_2 \text{FIN}_f + \gamma_3 \text{FIN}_f \times \text{RelativeSize}_{f,j,t-4} \\ + \text{X}'_{f,j,t-4}\beta + \alpha_{j,t} + \epsilon_{f,j,t}, \quad (2)\end{aligned}$$

where f represents firm, j represents industry and t represents year-quarter. The outcome variable of interest, $logEarnings$, is the logarithm of average quarterly earnings of workers in firm f (in 2018 constant dollars). $RelativeSize$ is the employment share of firm f in its industry j defined by Equation (1). In the regression, $RelativeSize$ is lagged by four quarters to minimize the probability of reverse causality. FIN equals one for financial firms, and zero otherwise. X is a vector of controls in 4-quarter lags comprising the logarithm of firm age, the share of male workers, the share of college workers, and the share of white workers. $\alpha_{j,t}$ represents the industry-by-year-by-quarter fixed effects, which absorb unobserved industry trends, such as (de)regulation and industry concentration, that may affect firm size distribution and worker earnings. Standard errors are clustered at the firm level. Conditioning on industry-by-year fixed effects, γ_1 identifies the within-industry relationship between firm size and worker earnings. I am interested in γ_3, which informs the marginal difference between finance and nonfinancial firms in the estimated firm relative size and earning relationships.

Column 1 of Table 3 shows that financial firms in my sample pay an average of 14.9% higher than the nonfinance private sector when controlling for year-by-quarter fixed effects that absorb the macro trends. Column 2 adds the key covariate, $RelativeSize$, measured in two-digit SIC codes and its interaction with FIN as well as firm-level controls included in vector X. Column 3 additionally controls for industry-by-year-quarter fixed effects. The estimates reported in columns 2 and 3 suggest a significant and positive relationship between firm relative size and firm earnings. The effect is significantly stronger in finance industries. Based on the preferred specification reported in column 3, on average, one-standard-deviation higher in firm relative size within a given two-digit SIC-year is associated with 0.5% (= $0.097 \times 0.0511 \times 100\%$) higher in average quarterly earnings, which is about \$64 per worker-quarter based on the average quarterly earnings of nonfinance sector reported in column 3 of Table 2. In the finance sector, one-standard-deviation higher in firm relative size within a given two-digit-year is associated with 3.8% (= $0.097 \times (0.0511 + 0.341) \times 100\%$) higher in average quarterly earnings, which can be translated to \$619 per worker-quarter. The difference between the finance and nonfinance sectors is about \$555 per worker-quarter and is statistically significant at the 1% level.

Columns 4 and 5 repeat the specifications in columns 2 and 3 but define firm industry and size using three-digit SIC codes. When defining industries at a granular level, I consistently find a significantly stronger positive relationship between firm relative size and worker earnings. The robust results eliminate the concern that firms may compete at a more granular level, and the relationship between firm size and earnings within two-digit SIC codes may reflect earning differences across subsectors.[17] It is worth noting that the marginal difference between finance and nonfinance industries is smaller in column 5 than the one reported in column 3. This is likely caused by the reasons described in Section 1.3, and we should interpret results reported in columns 4 and 5 with caution.

To visualize the differential relationships between firm relative size and average earnings and simplify the interpretation, I next estimate the following equation for finance and nonfinancial firms separately and plot estimated γ_1, γ_2, and γ_3 in Figure 1.

$$\text{logEarnings}_{f,j,t} = \gamma_1 \mathrm{D}^{2nd}_{f,j,t-4} + \gamma_2 \mathrm{D}^{3rd}_{f,j,t-4} + \gamma_3 \mathrm{D}^{4th}_{f,j,t-4} + \mathrm{X}'_{f,j,t-4}\beta + \alpha_{j,t} + \epsilon_{f,j,t}, \quad (3)$$

where $D^{2nd}_{f,j,t-4}$, $D^{3rd}_{f,j,t-4}$, or $D^{4th}_{f,j,t-4}$ are equal to one if the firm f's relative size in year-

[17] For example, suppose there are two firms in a simplified world: A is in SIC 621, and B is in SIC 622. A has a 100% market share of 621 and B has a 100% market share of 622. When defining markets at two-digit SIC codes, A and B have 30% and 70 % of the market share, respectively. In this simple example, the estimated effects of firm relative size on worker earnings within SIC 62 actually reflect the earning differences between 621 and 622.

quarter $t-4$ is respectively in the second, third, or fourth quartile of the sample distribution. Firm relative size is measured using Equation (1) based on two-digit SIC codes. Other variables are defined identically to those described in Equation (2).

Figure 1 reveals that the relationship between firm relative size and worker earnings appears to be convex in both sectors, but the slope is significantly steeper in finance. Specifically, within a given industry-year, workforce composition-adjusted earnings (earning premium) paid by the financial firms in the fourth quartile of firm relative size (the largest ones) are about 30.2% higher than those paid by the peers in the first quartile (the smallest ones), whereas the largest nonfinancial firms pay only about 7.9% higher than the smallest ones. These results suggest that financial workers benefit significantly more than nonfinancial workers when their employers dominate the market.

2.2 Alternative measures of worker earnings

In the baseline analysis presented in Section 2.1, worker earnings are aggregated to the firm level by taking averages. This raises the question of whether the observed difference in the relationship between firm relative size and worker earnings is solely driven by ultra-high income earners, who often cluster in larger financial firms. If this is the case, we should expect a negligible difference between the finance and nonfinance sectors when measuring firm-level worker earnings by the median of the within-firm earning distribution instead of the average. To investigate, I repeat the analysis reported in columns 1 and 3 of Table 3, but for median earnings. Table 4, columns 1 and 2, report the results. While the finance earning premium is lower than the one reported in column 1 of Table 3 when measuring earnings using the median, the relationship between firm relative size and worker earnings remains significantly stronger in the finance sector compared to the nonfinance sector.

As discussed in Section 1.1, I have access to 24 states in the LEHD, which may introduce selection biases and make conclusions less generalized. To address this concern, I calculate firm-level worker earnings using total payroll (in 2018 constant dollars) over total employment (payroll per worker). Total payroll and employment data are from the

LBD program and are available for all establishments in the United States. Therefore, payroll per worker does not suffer the issue of omitting states. I repeat the analysis reported in columns 1 and 3 of Table 3 for payroll per worker and report results in columns 3 and 4 of Table 4. Compared to the finance earning premium reported in column 1 of Table 3, column 3 of Table 4 reports a higher finance wage premium, potentially because of the inclusion of high-premium states like New York and Connecticut (Philippon and Reshef 2012). Column 4 of Table 4 reports that payroll per worker is also more sensitive to variations in firm relative size in finance than in nonfinance. In fact, the estimated coefficients are comparable to the ones reported in the baseline (Table 3, column 3), which mitigates the concern of selection biases and generalizability.[18]

2.3 Cross-period heterogeneity

As the relationship between a firm relative size and worker earnings depends on firms' economic gains as well as workers' bargaining power, we may expect different dynamics in the finance sector across periods. Particularly during the crisis period, if larger financial firms cannot sustain their excessive gains and diminished job opportunities weaken workers' bargaining power during the crisis period, the relationship could be weaker. To test the cross-period heterogeneity, I rerun Equation (2) to replicate the specification in column 3 of Table 3 using three subperiod samples: precrisis (1990–2006), crisis (2007–2009), and postcrisis (2010–2013).

Figure 2 plots the coefficients of $RelativeSize_{2d}$ in panel A and the coefficients of $FIN \times RelativeSize_{2d}$ in panel B. Interestingly, the relationships between firm relative size and worker earnings stay stable across three periods in both finance and nonfinance sectors. Although the difference between the finance and nonfinance sectors experiences a slight decrease during the crisis period—about 2.39 percentage points compared to the precrisis period—this decline is statistically insignificant. Furthermore, the difference increases by about 6 percentage points postcrisis compared to the precrisis level, albeit

[18] Worker earnings measured using earning records from the LEHD is the preferred measure in the study. This is because worker characteristics, which are used to construct key control variables that may drive worker earnings and firm relative size, are only observed in the LEHD program.

this change is also statistically insignificant.

Three potential reasons may explain the stability of the relationship between firm relative size and worker earnings in finance: First, the 2008 government bailout improved financial stability by injecting $700 billion into the system. This intervention primarily benefited larger financial institutions, enabling them to maintain their performance during the crisis. Second, financial firms might have become more efficient in generating economic gains after shutting down unprofitable divisions and shedding less productive workers. Third, despite decreased job demand during the crisis, the number of new entrants to the financial sector has been declining because of the poor image of the finance sector and increasing talent competition coming from other industries, notably the high-tech sector (Shu 2016; Ellul, Pagano, and Scognamiglio 2021). At the same time, financial firms tend to hire talents within finance industries.[19] These factors increased labor market tightness in finance industries and allowed finance workers who remained in the finance sector to maintain their bargaining power.

2.4 Within-finance heterogeneity

Comparing the entire finance sector with the rest of the economy may obscure important cross-industry heterogeneity that is essential for understanding why financial worker earnings are particularly sensitive to firm relative size. To investigate this heterogeneity, I run a similar specification reported in column 3 of Table 3, further segmenting the finance sector into broker, dealer, exchange, and services (BDE), banking and credit institutions (CB), and insurance (IS). Similarly, I decompose the nonfinance sector into manufacturing, service, and other industries. These sectors are then compared to the high-tech sector. Like the finance sector, the high-tech sector is dominated by large players, reliant on highly skilled workers, known for competitive pay, and has been a major draw for individuals who might have otherwise entered finance (Ogawa 2019; Ellul, Pagano, and

[19] According to PwC's 2019 report on "Financial Services Talent Trends," in the aftermath of the 2008 financial crisis, the finance industry faced challenges in hiring and retaining workers because of a damaged reputation. Concurrently, most financial firms preferred a "same talent" recruiting strategy, focusing on internal promotions or poaching employees from competitors rather than recruiting from other industries. These factors significantly limited labor supply and enhanced the bargaining power of financial workers following the crisis.

Scognamiglio 2021).[20] Comparing the finance subsectors with the high-tech sector helps isolate these common characteristics and further highlights the unique attributes of the finance sector. Specifically, I estimate the following regression:

$$\begin{aligned}\text{logEarnings}_{f,j,t} &= \sum_k \gamma_{1,k}\text{Sub}_k \times \text{RelativeSize}_{f,j,t-4} \\ &+ \gamma_2\text{RelativeSize}_{f,j,t-4} + \sum_k \gamma_{3,k}\text{Sub}_k + \text{X}'_{f,j,t-4}\beta + +\alpha_{j,t} + \epsilon_{f,j,t}, \quad (4)\end{aligned}$$

where f represents a firm, j represents two-digit SIC industry, and t is a year-quarter. *RelativeSize* represents firms' size relative to its two-digit SIC industry size measured using Equation (1). Sub_k represents industry sectors, including BDE, CB, IS, manufacturing, services, or others not in finance, tech, or farming. The high-tech sector, the omitted group in the specification, includes computers, biotechnology, electronics, and telecommunications industries following Babina (2019) and Babina et al. (2021). Other variables are defined identically to those described in Equation (2).

Based on the estimation from Equation (4), one-standard-deviation higher in a two-digit SIC of the high-tech sector is associated with 1.61% higher quarterly earnings ($= 0.097 \times 0.166 \times 100\%$, where 0.166 is the coefficient of $RelativeSize_{2d}$). Figure 3 plots the coefficients of the interaction terms (i.e., $\gamma_{1,k}$)—marginal difference of each sector compared to the high-tech sector—estimated from Equation (4). Compared to the high-tech sector, worker earnings in finance consistently exhibit greater sensitivity to variations in firm relative size. In contrast, sectors like services or other nonfinance sectorshave a lower sensitivity, and while manufacturing shows a higher sensitivity than the high-tech sector, the difference is relatively negligible.

Within the finance sector, worker earnings in CB have the highest sensitivity, followed closely by workers in BDE. Specifically, one-standard-deviation higher in firm relative

[20] Table B1 reports the summary statistics of the high-tech sector's key variables and how they differ from the finance sector. The average quarterly earnings reported for the high-tech sector are only $50 short of those in the finance sector. Consistent with the existing literature, both finance and high-tech sectors heavily rely on high-skill human capital. On average, firms in the high-tech (finance) sector have about 39% (42%) of workers with college or above degrees. High-tech firms are younger than firms in the finance sector.

size in a two-digit SIC industry in CB is associated with 6.5% ($= 0.097 \times (0.5 + 0.166) \times 100\%$) higher quarterly earnings. The difference between CB and the high-tech sector is statistically significant at the 1% level. One-standard-deviation higher in firm relative size in a two-digit SIC industry in BDE is associated with 4% ($= 0.097 \times (0.247 + 0.166) \times 100\%$) higher quarterly earnings. The difference between BDE and the high-tech sector is statistically significant at the 10% level. While the relationship between firm relative size and earnings is stronger in IS than in the high-tech sector, the difference is statistically insignificant.

One plausible explanation for these findings is that larger firms within the finance sector may confer an advantage, enabling them to secure higher economic returns compared to those in the high-tech sector. Additionally, financial workers, especially those in BDE and CB, may possess skills and attributes that are highly valued by the labor market. This, in turn, strengthens workers' bargaining power. I will examine these channels formally in the next section.

3 Mechanisms

In this section, I explore the underlying mechanisms that may account for the pronounced correlation between firm relative size and worker earnings within the finance sectors. Drawing on the existing literature, I identify two competing effects of firm relative size on worker earnings. On the one hand, larger firms, compared to their smaller counterparts, may charge higher markups by exerting monopoly power and/or generate profits more efficiently by hiring more productive workers and reaching economies of scale (Coase 1937; Hall and Weiss 1967; Abowd, Kramarz, and Margolis 1999; Crouzet and Eberly 2018; Autor et al. 2020). Consequently, larger firms have greater rents to distribute among their workers.[21]

On the other hand, larger firms may exert monopsony power in the labor market, potentially suppressing the share of rents distributed among workers. Specifically, based

[21] Card et al. (2018) comprehensively summarize studies that show firms distribute rents among their workers.

on the model derived in Jarosch, Nimczik, and Sorkin (2024), larger firms offer more job opportunities compared to smaller peers, and thus, a worker at a larger firm is more likely to encounter their current employer when searching for alternative jobs. When the costs of not hiring the worker but replacing her with another identical worker are low, the firm will not compete with itself, leaving workers with limited external options and diminishing workers' bargaining power. Therefore, firm size-associated economic gains and the balance between employer and employee bargaining power jointly shape the relationship between firm relative size and worker earnings in each industry.

I propose that the heightened sensitivity of finance worker earnings to variations in firm size can be attributed to two non-mutually-exclusive factors. First, firm size in the finance sector may be associated with higher economic gains compared to nonfinance sectors, allowing larger financial firms to create a larger "pie" that can be shared with employees. Second, finance workers may have greater bargaining power than those in nonfinance sectors, likely because their in-demand skills allow them to search for job opportunities in a wider labor market and are costly for employers to replace with alternatives. Consequently, financial firms have to share a larger slice of the "pie" to retain their talents.

3.1 Firm relative size and financial performance

3.1.1 Finance versus nonfinance.

To examine the first mechanism, I test the relationship between firm relative size and financial performance, focusing on how it varies in finance. The hypothesis is that larger firms in finance can generate higher economic gains than those in nonfinance sectors, potentially allowing for more rent-sharing with workers. This would imply a stronger positive relationship between firm size and profitability within the finance sector.

To this end, I link financial statement data from Compustat to the baseline sample described in Section 1.2. The matched sample only contains publicly listed companies because of the availability of Compustat data.[22] Within the matched sample,

[22]The baseline sample is matched with Compustat using the Compustat-SSEL Bridge (CSB) following

I replicate the same specification reported in column 3 of Table 3 using Equation (2) but for profitability. Table 5, column 1, reports the results. The positive coefficient of $RelativeSize_{2d}$ suggests that larger firms are associated with a significantly higher ROA, on average, compared to smaller firms within a given industry year. The positive coefficient of $FIN \times RelativeSize_{2d}$ shows that the positive relationship between firm relative size and ROA is stronger in finance than nonfinance. This suggests that, compared to other sectors, firm relative size is associated with higher economic gains in the finance sector, which can be distributed among workers.

To understand the source of excess profitability associated with firm relative size in finance, I analyze ROA by deconstructing it into the Lerner Index and asset utilization ratio following Grullon, Larkin, and Michaely (2019). The Lerner Index, which measures the extent to which product prices exceed marginal costs (i.e., markup), is calculated as operating income after depreciation over total revenue, per Aghion et al. (2005).[23] The asset utilization ratio, indicating the efficiency of using assets for revenue generation, is derived from the ratio of total revenue to total assets.

In the analysis presented in Table 5, columns 2 and 3 repeat the specification from column 1 but focus on the Lerner Index and asset utilization ratio as the dependent variables, respectively. Column 2 reveals that, on average, firms with larger relative sizes are associated with significantly higher markups, as indicated by the Lerner Index. This positive relationship is significantly stronger in the finance sector. Conversely, column 3 illustrates that larger firms, on average, utilize assets less efficiently than their smaller industry peers. While the negative correlation between firm relative size and asset utilization ratio is less pronounced in the finance sector, the difference is not statistically significant. These findings indicate that larger firms in the finance sector can extract higher rents primarily through charging a higher markup rather than through more effi-

Tello-Trillo and Streiff (2020). Table B2 in the Appendix Breports the sample's summary statistics of key variables. I have replicated the baseline specification reported in Table 3, column 3, using the Compustat matched sample, and have found consistent results, which are available upon request. However, as the sample is limited to a subset of publicly listed firms, the results presented in this section only apply to publicly listed firms.

[23]Depreciation is excluded from operating income to reflect the cost of physical capital, which may vary significantly across industries (Hall and Jorgenson 1967).

cient utilization of assets.

One might argue that the fundamental differences in operations and asset utilization across industries underlie the observed variations in the relationship between firm size and asset-based performance measures, such as ROA and asset utilization ratio. In essence, these measures lack cross-industry comparability. For instance, unlike firms that primarily depend on physical capital, financial firms emphasize human capital, which is not reflected as assets on the balance sheet. Consequently, a modest increase in assets, paired with an increase in firm size, can yield higher returns in the finance sector. To improve cross-industry comparability, I employ revenue per worker to measure firm financial performance.

In column 4 of Table 5, I repeat the same specification as in column 1 but replace the dependent variable with the logarithm of revenue per worker. The results show that larger firms in finance are associated with significantly higher revenue per worker, but this relationship appears muted in nonfinance industries. Such difference can be attributed to two possible reasons. First, as indicated by results on the Lerner Index (see Table 5, column 2), the significant market power of these firms allows them to charge higher prices for their services. Second, workers at larger financial firms are likely to be more skilled and productive than those in nonfinance industries due to the positive assortative matching between firm quality and worker skills (Abowd, Kramarz, and Margolis 1999; Card, Heining, and Kline 2013). Consequently, financial workers command higher pay at larger firms. Section 3.2 will explore the skill characteristics of financial workers.

In summary, the findings in this section suggest that, compared to other sectors, firm size in the finance sector is associated with more economic gains that can potentially be distributed among workers. If financial firms share a greater or equal portion of these gains with workers compared to finance firms, we should observe a more pronounced positive relationship between firm size and worker earnings, as described in Section 2.

3.1.2 Cross-period heterogeneity.

Section 2.3 shows that the relationship between finance worker earnings and firm relative size is consistently stronger than in nonfinance industries across three periods: precrisis, during the 2008 crisis, and postcrisis. One possible explanation for the resilience of the relationship is that firm relative size in finance has been consistently associated with higher rents than in nonfinance. This is plausible as the 2008 government bailout program bolstered financial stability and primarily aided larger financial institutions (Lucas 2019). In addition, financial firms might have increased their productivity postcrisis by closing their unprofitable desks and laying off unproductive workers during the crisis. To test this hypothesis, I repeat the analysis reported in Table 5 within three subperiod samples. Given the challenges in comparing ROA and asset utilization ratios across industries described in the previous section, in this section, I focus on the Lerner index (markup) and revenue per worker.

Figure 4 plots coefficient estimates of $FIN \times RelativeSize_{2d}$ for the Lerner Index in panel A and revenue per worker in panel B. Panel A shows that, over the three periods, firm relative size is linked to higher markups in finance than in nonfinance, though the marginal difference is not statistically significant during the crisis period. The most substantial marginal difference emerges postcrisis, indicating that larger financial firms that survived the crisis possess enhanced market power to charge higher markups. Panel B shows that the relationship between firm relative size and revenue per worker also stays consistently stronger in finance. However, this marginal difference only attains statistical significance at a 10% level after 2007. These results suggest that firm relative size is associated with higher rents in finance than in nonfinance, especially postcrisis, which allows larger financial firms to pay excessively higher earnings to their workers.

3.1.3 Within-finance heterogeneity

Section 2.4 documents that financial firms, particularly those in banking and credit institutions (CB) and broker, dealer, exchange, and services (BDE), exhibit a stronger relationship between firm relative size and worker earnings than the high-tech sector

(Figure 3). One potential explanation is that firms in BDE and CB generate excessive rents that can be distributed among their workers. If so, we should expect larger BDE and CB firms to show higher markups or revenue per worker than high-tech firms. To test this, I estimate Equation (4) for the Lerner Index and revenue per worker.

Figure 5 plots the coefficient estimates of the interaction terms (i.e., $\gamma_{1,k}$) for three finance subsectors. Panel A shows that, compared to the high-tech sector, while firm relative size in three finance subsectors is associated with higher markups, the marginal differences are statistically insignificant. This may not be surprising, considering that large tech firms have been able to generate excessive rents.

Panel B reveals that of the three finance subsectors, only CB exhibits a more pronounced positive relationship between firm relative size and revenue per worker relative to the high-tech sector. This heightened sensitivity in CB reflects either their workers' superior efficiency in generating revenue or the greater market power of larger CB firms in charging higher markups. However, the latter is less evident, as panel A shows that the relationships between firm size and markups are statistically indifferent between CB and the high-tech industries.

The unique characteristics of financial projects, as described in Acharya, Pagano, and Volpin (2016), can potentially explain the enhanced efficiency in generating revenue at larger CB firms. Unlike R&D projects in the tech sector, which require extended periods to start generating revenue, projects in CB (e.g., loans) begin producing revenue immediately (e.g., interest). However, these financial projects can carry long-term risks, such as default. The competition for talent increases worker turnover, complicating firms' ability to assess whether an employee can deliver high returns in the short term without incurring corresponding long-term risks. In general, larger firms face less competition for talent and lower turnover rates, as workers at these firms often have fewer external opportunities compared to those at smaller firms. This reduced competition for larger firms creates additional value in CB as it allows firms to discern and leverage the true capabilities of their bankers, that is, their ability to generate high returns with minimal long-term risks. As a result, these firms can allocate projects and generate revenue more efficiently.

3.2 Skills and bargaining power of financial workers

Section 3.1.1 establishes that, in the finance sector, firm relative size is associated with higher revenue per worker compared to nonfinance sectors. This difference can potentially be attributed to financial workers' skills, which may complement tasks highly demanded at larger firms and boost workers' productivity. Additionally, these skills may enhance financial workers' bargaining power in rent sharing if they are portable across firms, highly valued by the labor market, and costly for firms to replace. Consequently, the observed heightened sensitivity of worker earnings to employer size in the finance sector may be further explained by the skills of financial workers, which not only contribute to the firm's ability to generate a larger "pie" but also enable workers to demand and secure a larger share of that "pie."

To explore this channel, I conduct two sets of tests comparing the quality of finance and nonfinance workers and the required skills. First, I examine whether finance workers are characterized by certain qualities not captured by workers' observable characteristics (e.g., education level or age) but are highly rewarded by the labor market.[24] To estimate such qualities, using employer-employee matched data from LEHD-LBD, I estimate worker fixed effect at the individual level following Abowd, Kramarz, and Margolis (1999) and Card, Heining, and Kline (2013):

$$logEarnings^{worker}_{i,f,y} = \phi_i + \delta_f + \alpha_y + X^{'}_{i,f,y}\beta + \epsilon_{i,f,y}, \tag{5}$$

where $logEarnings^{worker}_{i,f,y}$ represents the logarithm of individual i's averaged quarterly earning at firm f in year y.[25] ϕ_i represent worker fixed effects and reflect time-invariant

[24] Table 2 shows that financial firms, on average, hire a significantly higher share of workers with college or above degrees, which can also contribute to enhanced worker productivity and bargaining power in finance. However, education attainment is not the focus of this test as the baseline analyses on firm relative size and worker earnings are conditioned on heterogeneity in shares of college-educated workers. Also, education levels can have different meanings across different industries, occupations, or worker generations (Philippon and Reshef 2012), and thus less comparable across industries.

[25] Because of limitations in computing power, I reduce the sampling frequency from quarterly to annual when estimating Equation (5) at the individual level, which includes high-dimensional fixed effects.

worker characteristics (e.g., alma maters, talent, or social skills obtained before the first job) that are portable across firms. δ_f represent firm fixed effects and capture time-invariant firm characteristics that may affect firm wage-setting policies. α_y are time fixed effects that absorb unobserved macro trends. $X_{i,y}$ is a vector of time-varying controls, including year dummies interacted with education dummies and function of worker age interacted with education dummies.

In this test, I am interested in estimated worker fixed effects (ϕ_i) and how they differ between finance and nonfinance sectors. By conducting the two-sample t-test, I find that, on average, finance worker fixed effects (mean of $\phi_i = 0.02$) are higher than nonfinance worker fixed effects (mean of $\phi_i = -0.0008$).[26] The difference is statistically significant at the 1% level. This finding suggests that finance workers possess a higher level of unobserved qualities that are portable across firms and valued by the labor market, which strengthens their bargaining position in rent sharing (Cahuc, Postel-Vinay, and Robin 2006). Moreover, because of the positive assortative matching between firm size and worker qualities, as documented in Abowd, Kramarz, and Margolis (1999), it is plausible that financial workers at larger firms have even higher levels of these unobserved qualities compared to their counterparts at smaller firms. These qualities enable larger financial firms to generate revenue more productively as suggested by Table 5, column 4, allowing these workers to command higher wages.

To further absorb cross-industry variations in labor market dynamics and flesh out the uniqueness of finance workers, I compare average worker fixed effects in each finance subsector against that in the high-tech sector, which heavily relies on talent in handling complex and quantitative problems (Shu 2016; Ellul, Pagano, and Scognamiglio 2021). Figure 6 plots the marginal differences in average worker fixed effects between three finance subsectors and the high-tech sector.

Among the three finance sectors, only the average fixed effects of workers in the BDE sector exceed those in the high-tech sector, and this difference is statistically significant at the 1% level. This finding suggests that, compared to workers in the high-tech sector,

[26]By construction, the sample mean of estimated worker fixed effects is zero.

who tend to be talented in math but less social (Deming 2017), workers in the BDE sector have additional time-invariant qualities (e.g., alma maters, talent, or social skills acquired before their first job) that are highly valued by the labor market. These qualities seem not to directly translate into enhanced productivity at larger BDE firms, as suggested by Figure 5, panel B. However, potentially because of their scarcity and transferability, these qualities are costly for firms to replace and empower BDE workers to secure a larger share of rents, partially explaining the heightened relationship between worker earnings and firm relative size in the BDE sector, as presented in Figure 3.

In the second set of tests, I explore industry heterogeneity in job tasks. Workers in finance may have higher bargaining power if the tasks performed within this sector require skills that are highly valued and costly for firms to find substitutes. I conduct this test using individual-level data from the 2001-2013 American Community Surveys (ACS).[27] Each survey reports individual demographics and work characteristics in a given year, such as occupation, industry, work hours, and annual income, that are key to this test.[28,29]

To quantify job tasks, I assign each nonfarming and nonmilitary occupation in the ACS three scores from Autor and Dorn (2013) that capture abstract, routine, and manual task intensities, and two scores from Deming (2017) that measure math and social skill task intensities. Abstract tasks include direction, control, and planning of activities and quantitative reasoning requirements generally concentrated in high-skill occupations. The routine score measures adaptability to work requiring set limits, tolerances or standards, and finger dexterity. Manual tasks demand coordination of eye, hand, and foot. Math task intensity captures an occupation's mathematical reasoning and problem-solving requirements, while social skill intensity captures the requirements of coordination, nego-

[27] ACS is used here because this test requires information on occupations, which is not available in the LEHD-LBD. Each year's ACS is a 1-to-100 national random sample of the population, publicly available from 2001 to 2022 at IPUMS USA website, `https://usa.ipums.org/usa/`.

[28] The ACS sample used in the analysis consists of individuals who are between 18 and 64 years old who were employed in the prior survey. I apply the same sample criteria as in Autor and Dorn (2013) and drop military and farming occupations, residents of institutional group quarters (e.g., prisons), and unpaid family workers. The ACS sample ends in 2013 to align with samples constructed using LEHD-LBD for other analyses.

[29] Unlike the LEHD-LBD sample, employers are not identifiable in the ACS. Therefore, it is not possible to analyze variations in job tasks across different firm sizes.

tiation, persuasion, and social perceptiveness. These task scores are standardized with a mean of 0 and a standard deviation of 1 within the sample.

I first examine correlations between occupational task scores and worker earnings to identify highly valued skills. Occupations that rely on skills that are more productive and highly valued should be associated with higher earnings. To this end, I regress individual hourly wages on these two sets of task scores separately in a horse race setting. Table B3 in the appendix shows that among three task scores from Autor and Dorn (2013), abstract intensity is associated with the highest hourly wages within the ACS sample.[30] Specifically, column 1 shows that occupations with one standard deviation higher in abstract (routine or manual) task intensity are associated with 30% (1.7% or 5%) higher hourly wages. The return on abstract skill diminishes but remains statistically and economically significant after controlling for sex-by-race, education-by-year, state-by-year fixed effects, and a function of worker age interacted with education dummies (column 2). Column 3 shows that occupations demanding one standard deviation higher in math and social skills from Deming (2017) are associated with 17% and 17.8% higher hourly wages, respectively. These findings align with existing literature, affirming that abstract, math, and social skills are more valuable than routine and manual skills in the labor market (Autor and Dorn 2013; Autor 2015; Deming 2017).

Finance workers might possess higher bargaining power if tasks in the finance sector intensively demand abstract, math, and social skills. Next, I investigate how job tasks differ in the finance sector by regressing each task score on a finance dummy at individual-level, conditioning on sex-by-race fixed effects and a vector of time-varying controls, including state-by-year fixed effects, education-by-year fixed effects and function of worker age interacted with education dummies. The coefficient of the finance dummy measures the marginal differences in tasks performed by workers from similar demographic backgrounds in finance versus nonfinance sectors. Figure 7 plots the estimated coefficients. The results show that, on average, finance jobs are less routine and manual intensive while more demanding in tasks requiring abstract, math, and social skills. The

[30] As ACS are surveys, regressions are weighted by the Census sampling weight multiplied by hours worked per year following Autor and Dorn (2013) to obtain nationally representative statistics.

marginal differences are statistically significant at the 1% level. Given abstract, math and social skills are highly valued in the labor market—because of either higher demand or scarcity, as shown in Table B3 in the appendix—employers would incur higher costs to find substitutes. Consequently, finance workers have stronger bargaining power than nonfinance workers.[31] To retain workers with such sought-after skills, financial firms have to share a larger share of economic gains with them.[32]

Considering that high-tech firms are major competitors of financial firms in the labor market, it might be conceived that tasks performed in these two sectors would have substantial similarities; thereby, finance and high-tech workers should possess comparable levels of bargaining power. To examine the difference in tasks conducted in these two sectors, I repeat the test in Figure 7 but compare five task scores of three finance subsectors with the ones of high-tech industries. Figure 8 presents the estimated marginal differences by finance subsectors for each task intensity score. Interestingly, relative to the high-tech sector, where science, technology, engineering and mathematics (STEM) jobs concentrate and primarily rely on math skills, the three finance subsectors depend more heavily not only on math skills but also on abstract and social skills.

Among the finance subsectors, broker, dealer, and exchange services (BDE) require the highest level of abstract and social skills for coordinating, directing, and planning. Jobs in banking and credit institutions (CB) have the highest quantitative requirements while also demanding higher abstract and social skills. Because of strong relative demand and high returns for occupations requiring both cognitive and social skills in recent decades (Acemoglu and Autor 2011; Deming 2017), finance workers, particularly those in BDE and CB sectors, enjoy relatively higher bargaining power than high-tech workers. These findings help to explain the more pronounced positive relationship between firm relative

[31] It's worth noting that financial workers possess significantly lower manual skills compared to nonfinancial workers. This finding also indicates that financial workers have stronger bargaining power than those performing manual intensive tasks, who are at a disadvantage in bargaining, as described by Marshall (1890) and Oi and Idson (1999).

[32] It is also plausible that financial workers may be compensated additionally for their superior productivity at larger firms, particularly if their advanced abstract, math and social skills complement tasks that are more prevalent at those firms, such as management and technology operations (Mueller, Ouimet, and Simintzi 2017; Autor et al. 2020). However, because of the lack of firm size information in the ACS sample, I defer the investigation of task profiles by firm size and the complementarity between firm size and skill sets to future studies.

size and worker earnings in the finance subsectors, as illustrated in Figure 3.

4 Firm Relative Size and Within-Firm Inequality

Section 3.1 demonstrates that larger firms in the finance sector are associated with excessive economic gains, suggesting that these firms have more rents to distribute among their workers. This observation raises an important question: Are these gains distributed equitably within firms? One might expect a more uniform distribution to minimize the perceptions of unfairness and promote worker effort (Akerlof and Yellen 1990). In this scenario, the relationship between firm relative size and worker earnings would appear more balanced across different pay ranks. Conversely, it is plausible that high-skill workers create more value and have a stronger bargaining position in larger firms, which often demand enhanced managerial skills and capabilities of working with larger-scale jobs and advanced technologies (Mueller, Ouimet, and Simintzi 2017; Célérier and Vallée 2019; Autor et al. 2020). This would imply a higher degree of earning inequality within such firms. In this section, I examine the relationship between firm relative size and within-firm pay inequality, with a particular focus on the finance sector.

To investigate, I first rerun the specification reported in column 3 of Table 3 but for the average earnings of high-skill workers. These workers are identified in three ways: those earning above the 90th and 99th percentiles of the within-firm earning distribution and those exceeding the top tercile of the sample's earning distribution in the previous year.[33] Table 6, columns 1–3, show that, on average, high-skill worker earnings increase even more with firm relative size within a given industry-year-quarter. The positive relationship between firm size and high-skill workers' earnings is more pronounced in the finance sector. For instance, column 1 indicates that one standard deviation higher in firm relative size in nonfinance industries is associated with 1.1% (=$0.097 \times 0.112 \times 100$) higher

[33] The within-firm pay distribution reflects job ranks within a firm, with the highest-paid rank likely including executives and managers (Tate and Yang 2015). Defining skills based on within-sample distribution assumes that the labor market prices worker skills effectively. Workers in the right tail of the sample distribution are typically highly educated, more experienced, and equipped with managerial or nonroutine skills (Autor and Dorn 2013). Skills are not defined based on workers' education levels, which can have different meanings across different occupations or worker generations (Philippon and Reshef 2012).

earnings for high-skill workers, approximately \$367 based on the mean reported in column 3 of Table 2. In the finance sector, the same increase in firm relative size correlates with 7.3% higher earnings for high-skill workers ($= 0.097 \times (0.112 + 0.638) \times 100$), translating to about \$3483 per worker-quarter based on the sample mean reported in column 2 of Table 2. These sensitivity estimates exceed the baseline estimates for average workers (Table 3, column 3), indicating that larger firms disproportionately allocate more rents to high-skill workers in finance and nonfinance sectors.

Further, I explore whether such within-firm inequality is more pronounced in the finance sector. To do so, I rerun the specification from column 3 of Table 3 for within-firm inequality, measured by comparing the average earnings of workers above the 90th (99th) percentile to those below the 10th (1st) percentile at a given firm in the previous year. I also measure within-firm inequality using the standard deviation of worker earnings, following Barth et al. (2016) and Ma, Ouimet, and Simintzi (2016). Columns 4–6 of Table 6 reveal that larger firms are associated with higher within-firm inequality than smaller industry peers, aligning with findings from Mueller, Ouimet, and Simintzi (2017) and Song et al. (2018). Notably, the positive relationship between firm size and inequality is significantly stronger in the finance sector.

While investigating the exact reasons larger firms in finance are associated with a larger within-firm pay gap than in nonfinance is beyond the scope of this paper, I offer some discussions here. First, larger financial firms compared with nonfinancial firms may invest more in technology because of low financing costs, and, consequently, they rely heavily on high-skill and nonroutine workers (Autor et al. 2020). This conjecture is supported by suggestive evidence in columns 1 and 2 of Table B4 in the appendix, where within a sample of publicly listed firms, firm relative size correlates with higher values of the net property, plants, and equipment (PPE) as well as capital expenditures (CapEx), more so in finance than in nonfinance. Additionally, columns 3 and 4 reveal that larger financial firms are more capital-intensive—defined by PPE or CapEx normalized by firm employment—than their smaller peers, with this gap larger than that in the nonfinance sector.

Second, it might be speculated that corporate governance in larger financial firms is less effective, allowing managers to extract a disproportionate amount of rents without corresponding performance (Bebchuk and Fried 2004). However, this is unlikely since firm size correlates with superior financial performance in larger financial firms, as discussed in Section 3.1. Instead, the superior financial performance suggests that larger financial firms may disproportionately share more rents with productive workers to reduce monitoring costs that escalate with firm size (Alchian and Demsetz 1972; Oi and Idson 1999). Lastly, the job scale may expand with firm size. Talents in finance are often matched with projects larger than those in nonfinance sectors (Célérier and Vallée 2019). This high synergy between talent and job scale may lead to a more unequal distribution of rents between high-skill and low-skill workers in the finance sector.

In summary, the findings in this section reinforce the notion that the relationship between firm relative size and worker earnings is influenced by employee skills and bargaining power. The higher demand for high-skill workers in larger financial firms places these employees in a stronger bargaining position compared to their peers. This, in turn, contributes to a greater pay gap within larger financial firms.

5 Alternative Explanations

In this section, I explore alternative explanations for the heightened relationship between firm relative size and worker earnings in the finance sector documented in Section 2. First, one potential argument is that defining firm size relative to the national market instead of the local market may underestimate nonfinancial firms' market power in extracting rents, particularly those in industries like restaurants and healthcare services, which primarily compete locally. Such firms could extract high rents without a high market share in national markets. However, this hypothesis can be ruled out by the findings presented in Section 2.4: compared to the high-tech sector, in which firms tend to compete at the national level, worker earnings are still more sensitive to firm relative size in finance industries on average.

Second, one could hypothesize that measuring firm size relative to the national market may underestimate financial firms' monopsony power in the labor market because job search is largely local (Enrico 2011; Molloy, Smith, and Wozniak 2014). This explanation would be plausible if financial workers were less mobile than nonfinancial workers. While there is no direct evidence supporting that financial workers are less mobile, to rule out this explanation, I define firms' relative size based on their employment shares in a given commuting zone-industry and replicate the baseline analysis on worker earnings using a firm-commuting-zone-quarter-level sample.[34,35] Table 7 shows that, on average, firms that are relatively larger in a given two-digit SIC-commuting zone are associated with higher average earnings, average earnings of high-skill workers, as well as within-firm inequality. The positive relationships are more pronounced in the finance sector, and the gaps between finance and nonfinance are statistically significant at the 1% level. These findings effectively counter the first two alternative explanations.

Third, one could posit that tradable nonfinance industries, such as manufacturing and wholesale trade, may be exposed to relatively higher import competition than are financial industries. Measuring firm relative size using firms' domestic contributions to the market may understate the degree of competition faced by firms in nonfinancial industries, and this may explain why firm relative size has a weaker relationship with firm performance in nonfinance than in finance. To rule out this explanation, I compare finance industries with nontradable industries, which are less exposed to import competition. Specifically, I repeat the baseline analysis but omit firms in nontradable sectors as the reference group. When comparing the finance sector with nontradable industries, I continually find more positive relationships between firm relative size and average worker earnings, earnings of high-skill workers, and within-firm inequality are stronger in the finance sector (Table 8). These findings help rule out the notion that financial firms are less exposed to important competition, and thus, their economic gains, as well as worker earnings, are more sensitive

[34] Commuting zones are clusters of U.S. counties characterized by strong within-cluster and weak between-cluster commuting ties. See details about commuting zones at David Dorn's website.

[35] To construct the sample, I select workers from LEHD following the same rules discussed in Section 1.2 and aggregate worker-firm-commuting zone-level data to get earning patterns and workforce compositions at a firm-commuting zone-quarter level. Table B5 reports the summary statistics of key variables in the sample.

to variations in firm relative size.

Fourth, it might be speculated that firm relative size is less correlated with labor monopsony power in finance because more firms compete in the sector than in other sectors. However, this explanation seems unlikely. As Figure B1 in the appendix demonstrates, finance industries are, on average, less competitive (measured by industry concentration) than nonfinance industries over the sample period.[36] Interestingly, Table B6 shows that, on average, industry concentration is negatively correlated with worker earnings in nonfinance sectors. This is consistent with previous literature (e.g., Benmelech, Bergman, and Kim 2022; Rinz 2022) and suggests that the lack of competition suppresses worker pay in nonfinance sectors. However, in columns 3 and 4 of Table B6, the positive coefficients of the interaction terms indicate that, on average, workers in less competitive finance industries earn higher earnings. In other words, industry concentration in the finance sector does not confer firms the same level of labor market power as it does in other industries.

Finally, it might be posited that finance workers are in a stronger bargaining position because they are less subject to noncompete agreements or more heavily unionized (Cahuc, Postel-Vinay, and Robin 2006; Council of Economic Advisers 2016; Starr, Prescott, and Bishara 2021). However, noncompete agreements are widely adopted in the finance sector. Based on a national-level survey of private-sector employers conducted by Colvin and Shierholz (2019) shows that the share of workplaces where any employees are subject to noncompete agreements is 58% in the finance sector, which is higher than the national percentage of 49%. Additionally, Starr, Prescott, and Bishara (2021) documents that noncompete agreements are more likely to be found in high-skill, high-paying jobs, which are concentrated in the finance sector. Unionization as an explanatory factor also seems unlikely because finance industries have a lower unionization rate than nonfinance industries during the sample period. For example, based on the statistics reported by the Bureau of Labor Statistics (BLS) in 2013, the unionization rate in the finance sector is

[36] Industry concentration is measured as the sum of the squared firm employment shares in a given industry, that is, Herfindahl-Hirschman Index (HHI).

only 2% and ranked the lowest among nonfarming private sectors.[37]

6 Conclusion

To what extent do employees benefit when their employers dominate the market? The answer depends on the industry. This study conducts a comprehensive analysis of the within-industry relationship between firm size relative to its industry and worker earnings, with a particular focus on the finance sector, where large firms dominate. Using micro-level data administrated by the U.S. Census Bureau, I show that larger firms (measured by employment share in a given market) are associated with higher average earnings than smaller peers within the market, with this relationship being more pronounced in the finance sector. The difference between finance and nonfinance remains consistent across different time periods and various measures of worker earnings and market definitions. When compared to the high-tech sector, the within-industry relationship between firm size and worker earnings remains stronger in the finance sector but only statistically significant in specific subsectors, such as broker, dealer, exchange, and services, as well as banking and credit institutions. As the high-tech sector also heavily relies on high-skill human capital, such difference further highlights the uniqueness of these finance industries.

This study also provides evidence on mechanisms underlying the heightened relationship between firm relative size and worker earnings in finance industries. It documents that larger financial firms achieve greater economic gains than their smaller counterparts and potentially have more rents to distribute among workers. Such a positive relationship between firm size and economic gains is more pronounced than that in the rest of the economy. Additionally, financial firms demand not only higher levels but also a more balanced mix of math and social skills, which have been highly demanded in recent decades and empower financial workers to bargain for a larger proportion of rents.

[37]For comparison, in the nonfarming private sector, industries with high unionization rates include utilities (25.6%), transportation and warehousing (19.6%), and construction (14.1%). Industries with low unionization rates include financial activities (2%), professional and business services (2.4%), and leisure and hospitality (2.7%). See more details reported by the BLS at `https://www.bls.gov/opub/ted/2014/ted_20140128.htm`.

Moreover, this study uncovers within-firm heterogeneity in the relationship between firm relative size and earnings by skill level, showing that firm relative size is associated with higher within-firm inequality. Such inequality is more pronounced at larger financial firms, potentially because of the increased demand for monitoring, working with new technologies, and handling larger-scale tasks.

The findings suggest a unique dynamic between firm size and worker earnings within the finance sector, which deviates from the conventional view that employer dominance suppresses worker earnings. It's important, however, to acknowledge a limitation of this analysis: the sample includes only actively operating firms and their employed workers. As a result, the identified link between the size of a firm and its workers' earnings primarily reflects the dynamics of firms and employees who have successfully weathered competition and other economic challenges, such as the 2008 financial crisis.

Code Availability: The replication code and pseudo datasets are available in the Harvard Dataverse at `https://doi.org/10.7910/DVN/TI03NS`.

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Figure 1. Firm relative size and worker earnings: Finance versus nonfinance

This figure plots how average quarterly earnings (in 2018 constant dollars) differ in response to a difference in firm relative size from the first quartile of the sample distribution in finance and finance sectors separately. Firm relative size is measured within two-digit SIC codes using Equation (1). The dots represent the coefficients of $D^{2nd}_{f,j,t-4}$, $D^{3rd}_{f,j,t-4}$, and $D^{4th}_{f,j,t-4}$ estimated from Equation (3) within finance (dark-gray) and nonfinance (light gray). The vertical bands represent 95% confidence intervals based on standard errors clustered at the firm level. The underlying sample is at the firm-year-quarter level spanning from 1990Q1 to 2013Q4. Appendix A defines the variables. This analysis was performed at a Federal Statistical Research Data Center under FSRDC Project Number 1589. (CBDRB-FY24-P1589-R11070).

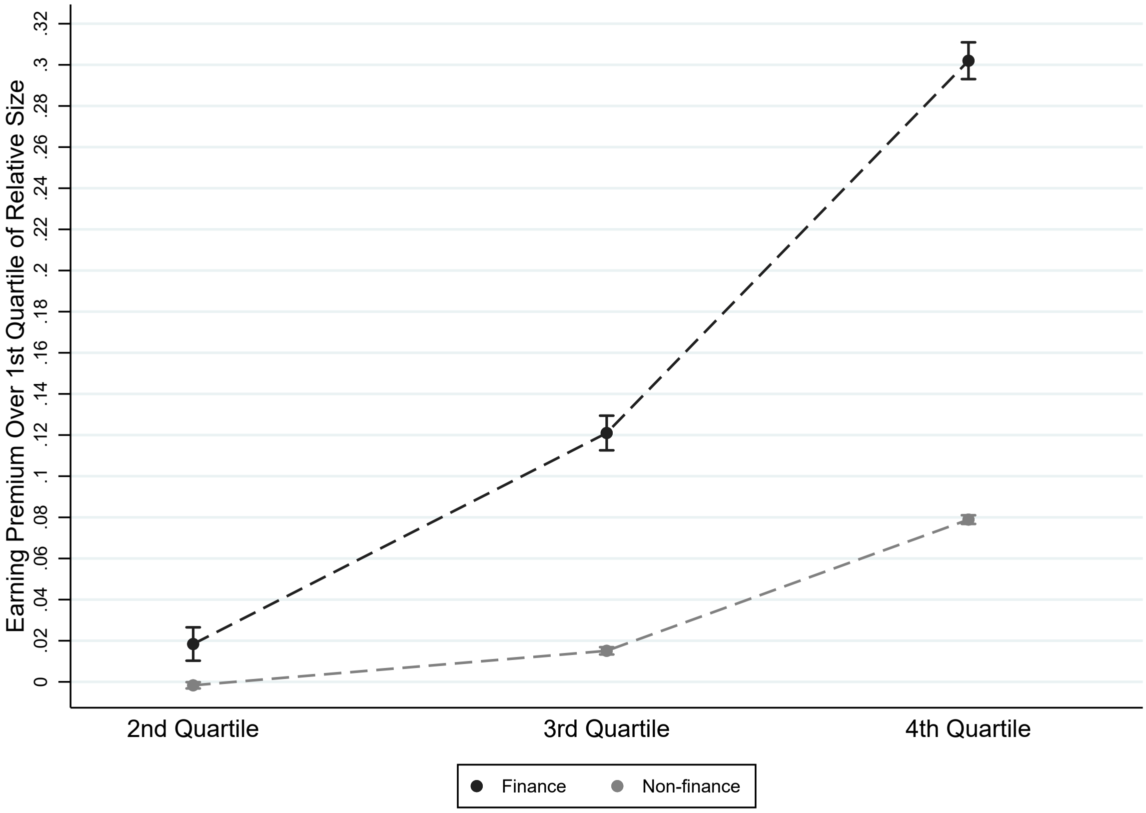
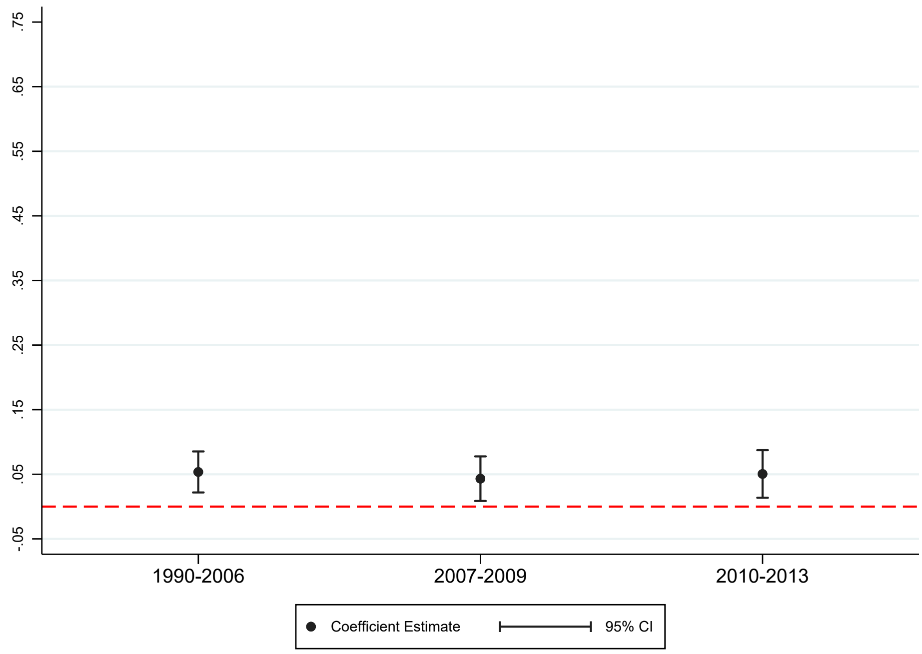


Figure 2. Firm relative size and worker earnings: Cross-period heterogeneity

This figure plots the relationship between firm relative size and worker earnings (panel A) and the marginal differences between finance and nonfinance in the relationship (panel B) within three subsample periods: precrisis (1990–2006), crisis (2007–2009), and postcrisis (2010–2013). Firm relative size is measured within two-digit SIC codes using Equation (1). Equation (2) is estimated for the logarithm of average quarterly earnings within each subperiod sample conditioning on two-digit SIC-year-quarter fixed effects, logarithm of firm age, and measures of workforce compositions in 4-quarter lags. Panels A and B report coefficient estimates of $RelativeSize$ and $FIN \times RelativeSize$, respectively. The vertical bands represent 95% confidence intervals based on standard errors clustered at the firm level. The underlying sample is at the firm-year-quarter level spanning from 1990Q1 to 2013Q4. Appendix A defines the variables. This analysis was performed at a Federal Statistical Research Data Center under FSRDC Project Number 1589. (CBDRB-FY24-P1589-R11070).

(A) Coefficients of $RelativeSize_{2d}$



(B) Coefficients of $FIN \times RelativeSize_{2d}$

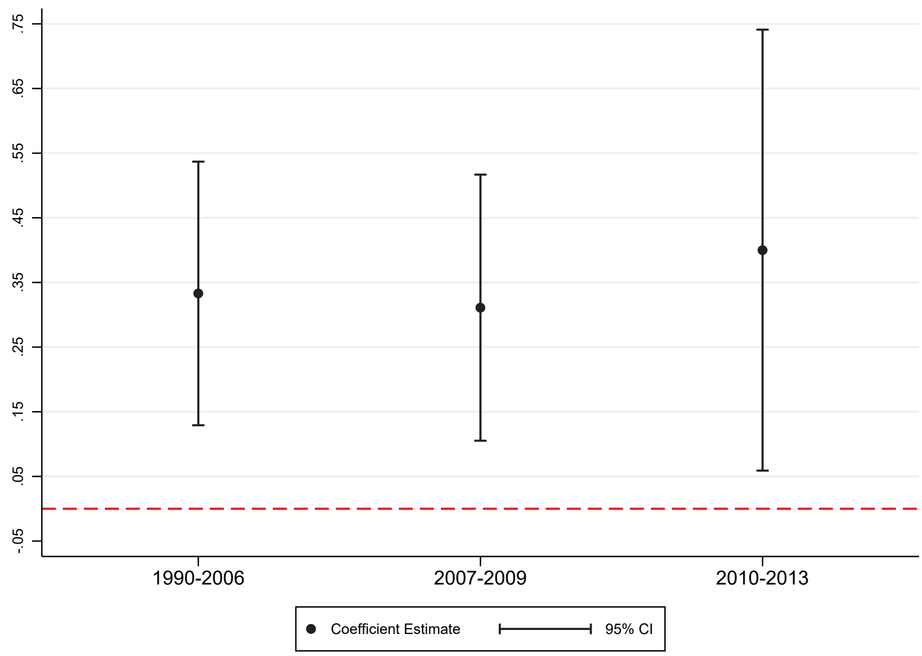


Figure 3. Firm relative size and worker earnings: Subsector heterogeneity

This figure plots the marginal differences in the relationship between firm relative size and average quarterly earnings (in 2018 constant dollars). It compares various finance subsectors, manufacturing, service, and other nonfinance industries to the high-tech sector. Finance subsectors include broker, dealer, exchange and services (BDE), banking and credit institutions (CB), and insurance (IS). High-tech includes computers, biotechnology, electronics, and telecommunications industries. "Other" includes mining, construction, transportation, retail trade, and wholesale trade industries. Firm relative size is measured within two-digit SIC codes using Equation (1). The marginal differences plotted in the figure are estimated for the logarithm of average quarterly earnings using Equation (4) (i.e., $\gamma_{1,k}$), conditioning on two-digit SIC-year-quarter fixed effects, logarithm of firm age and measures of workforce compositions in 4-quarter lags. The vertical bands represent 95% confidence intervals based on standard errors clustered at the firm level. The underlying sample is at the firm-year-quarter level spanning from 1990Q1 to 2013Q4. Appendix A defines the variables. This analysis was performed at a Federal Statistical Research Data Center under FSRDC Project Number 1589. (CBDRB-FY24-P1589-R11070).

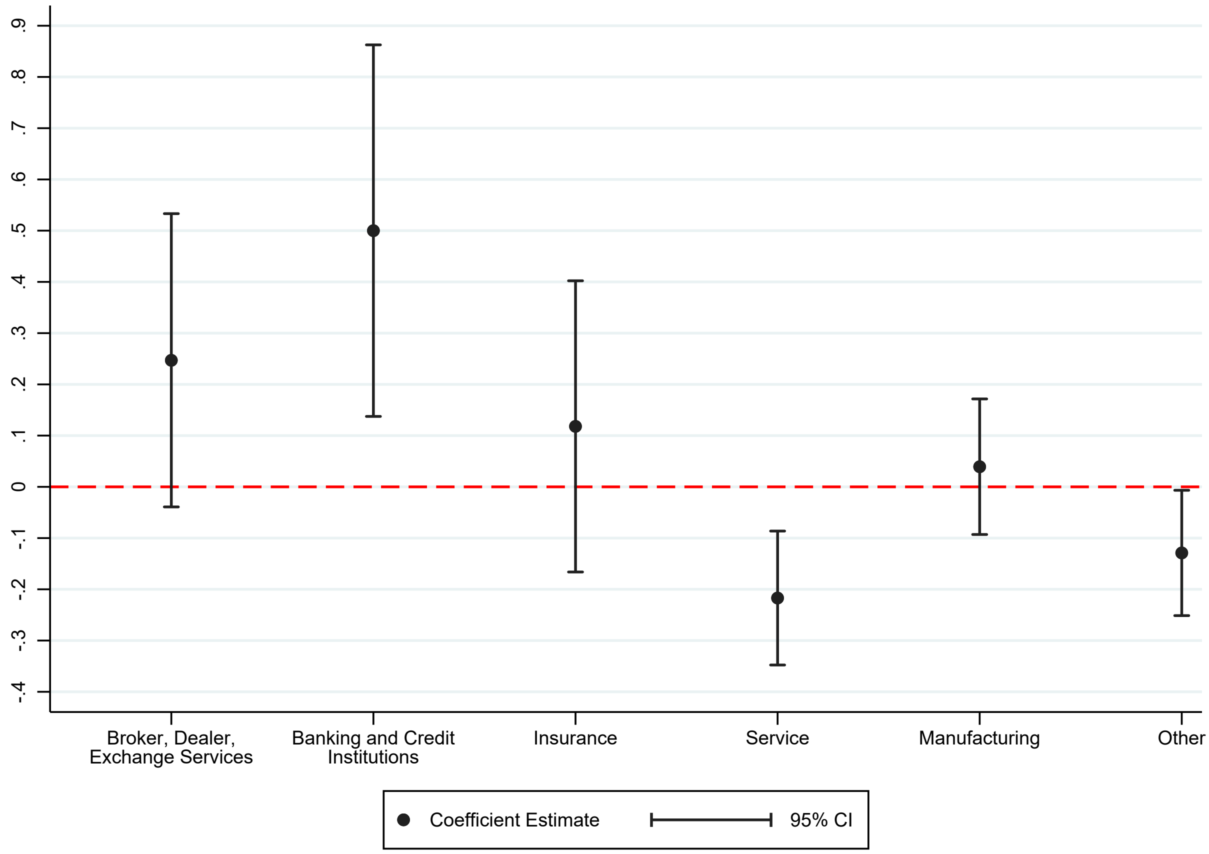
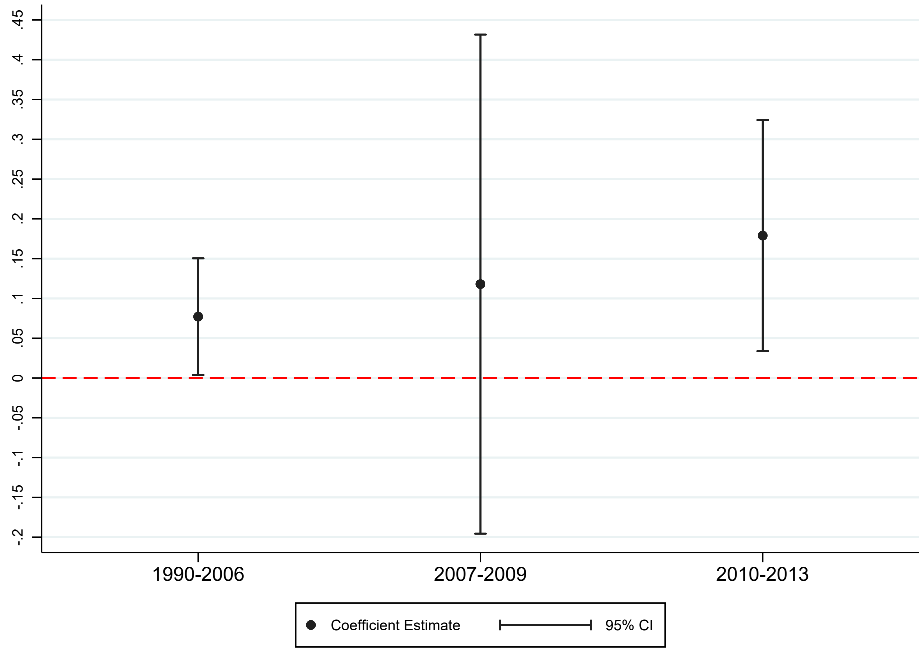


Figure 4. Firm relative size and financial outcomes: Cross-period heterogeneity

This figure plots the marginal differences between finance and nonfinance in the relationship between firm relative size and financial performance for three subperiods: precrisis (1990–2006), crisis (2007–2009), and postcrisis (2010–2013). The marginal differences plotted in the figure are estimated using Equation (2) (i.e., γ_3), conditioning on two-digit SIC-year-quarter fixed effects, logarithm of firm age and measures of workforce compositions in 4-quarter lags. The dependent variables in panels A and B are the Lerner Index and revenue per worker, respectively. Firm relative size is measured within two-digit SIC codes using Equation (1). The vertical bands represent 95% confidence intervals based on standard errors clustered at the firm level. The underlying sample is at the firm-year-quarter level spanning from 1990Q1 to 2013Q4. Appendix A defines the variables. This analysis was performed at a Federal Statistical Research Data Center under FSRDC Project Number 1589. (CBDRB-FY24-P1589-R11070).

(A) Lerner Index



(B) Revenue per worker

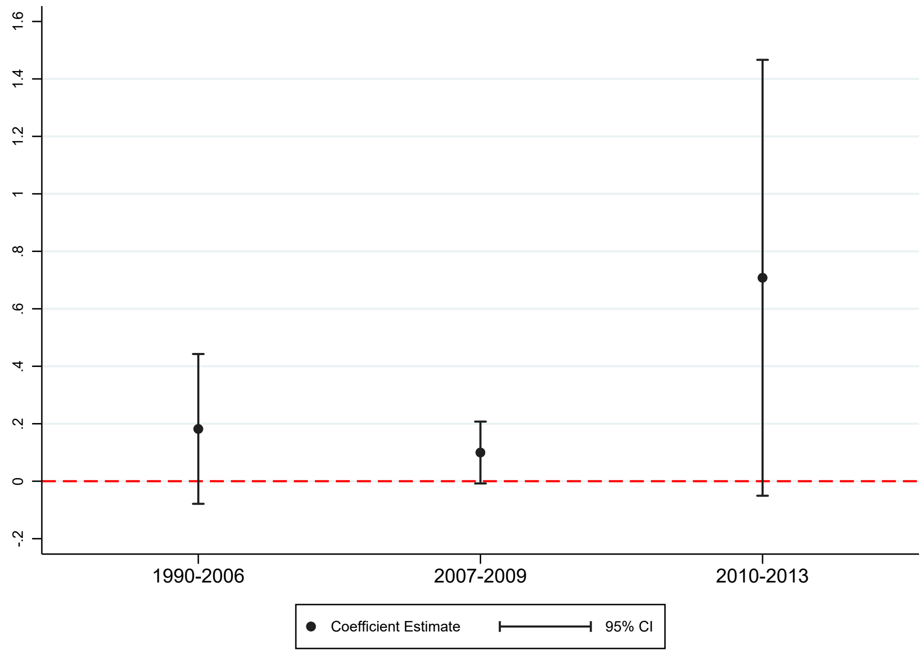
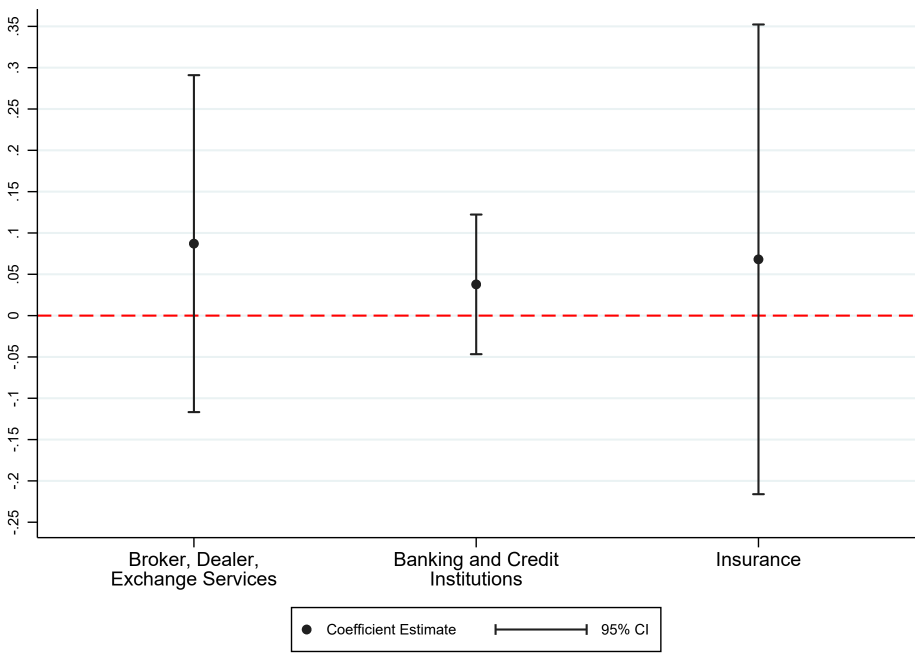


Figure 5. Firm relative size and financial outcomes: Subsector heterogeneity

This figure plots the marginal differences in the relationship between firm relative size and financial performance. It compares finance subsectors to the high-tech sector. Finance subsectors include broker, dealer, exchange and services (BDE), banking and credit institutions (CB), and insurance (IS). High-tech includes computers, biotechnology, electronics, and telecommunications industries. The marginal differences plotted in the figure are estimated using Equation (4) (i.e., $\gamma_{1,k}$, where k=BDE, CB or IS are plotted), conditioning on two-digit SIC-year-quarter fixed effects, logarithm of firm age and measures of workforce compositions in 4-quarter lags. The dependent variables in Panels A and B are the Lerner Index and revenue per worker, respectively. Firm relative size is measured within two-digit SIC codes using Equation (1). The vertical bands represent 95% confidence intervals based on standard errors clustered at the firm level. The underlying sample is at the firm-year-quarter level spanning from 1990Q1 to 2013Q4. Appendix A defines the variables. This analysis was performed at a Federal Statistical Research Data Center under FSRDC Project Number 1589. (CBDRB-FY24-P1589-R11070).

(A) Lerner Index



(B) Revenue per worker

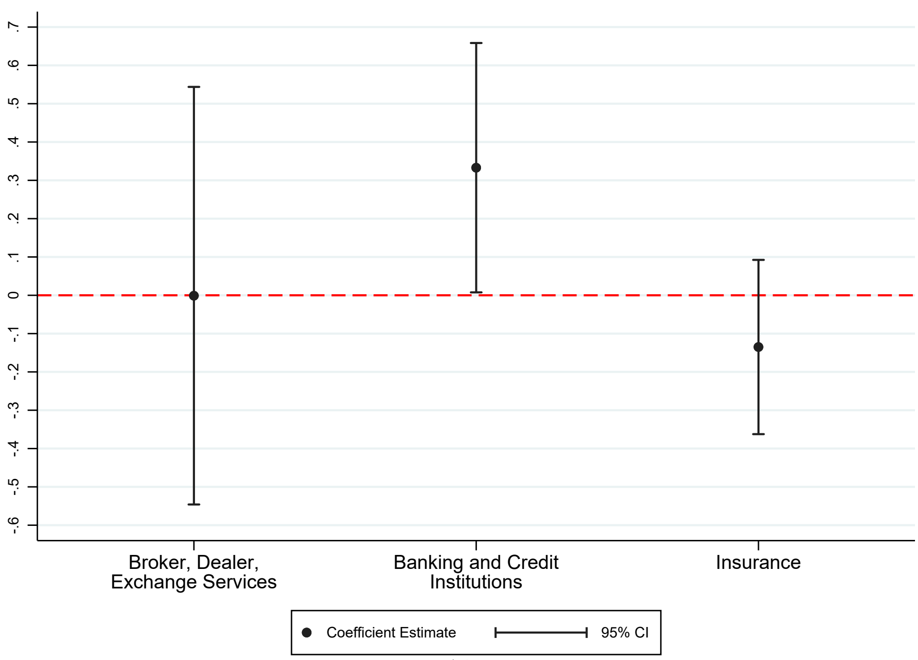


Figure 6. Worker fixed effects: Finance subsectors versus high-tech

This figure plots level differences between finance subsectors and the high-tech sector in average worker fixed effects. Finance subsectors include broker, dealer, exchange and services (BDE), banking and credit institutions (CB), and insurance (IS). High-tech includes computers, biotechnology, electronics, and telecommunications industries. Worker fixed effects are estimated following Abowd, Kramarz, and Margolis (1999) and Card, Heining, and Kline (2013) by Equation (5) using worker-year-level data spanning from 1990 to 2013. The plots show average worker fixed effects differences between each finance subsector and the high-tech sector. Vertical bands represent 95% confidence intervals from t-tests. Appendix A defines the variables. This analysis was performed at a Federal Statistical Research Data Center under FSRDC Project Number 1589. (CBDRB-FY24-P1589-R11070).

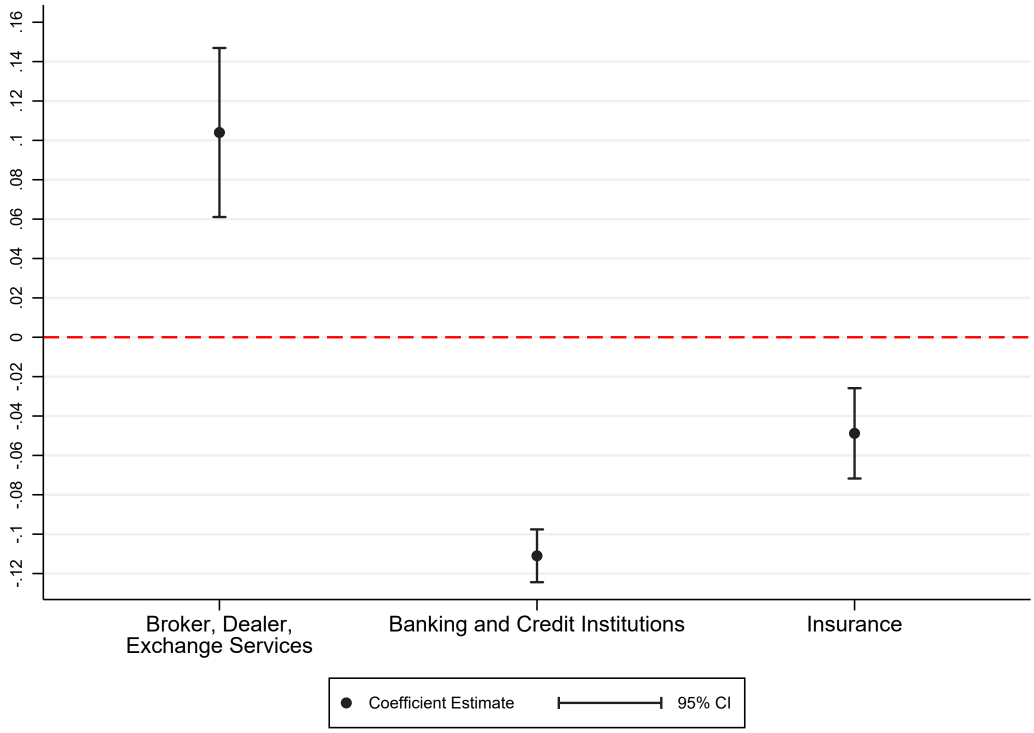


Figure 7. Occupational task intensities: Finance versus nonfinance

This figure plots marginal differences between finance and nonfinance sectors in occupational task intensities. Abstract, routine, and manual task intensities are collected from Autor and Dorn (2013). Math and social skill intensities are collected from Deming (2017). Within a sample of 2001–2013 American Community Surveys, the marginal difference in each task intensity between finance and nonfinance is estimated at individual-level conditioning on state-by-year fixed effects, education-by-year fixed effects, and function of worker age interacted with education dummies. The estimations are weighted by the Census sampling weight multiplied by working hours to obtain nationally representative statistics. Vertical bands represent 95% confidence intervals based on standard errors clustered at the state level. Appendix A defines the variables.

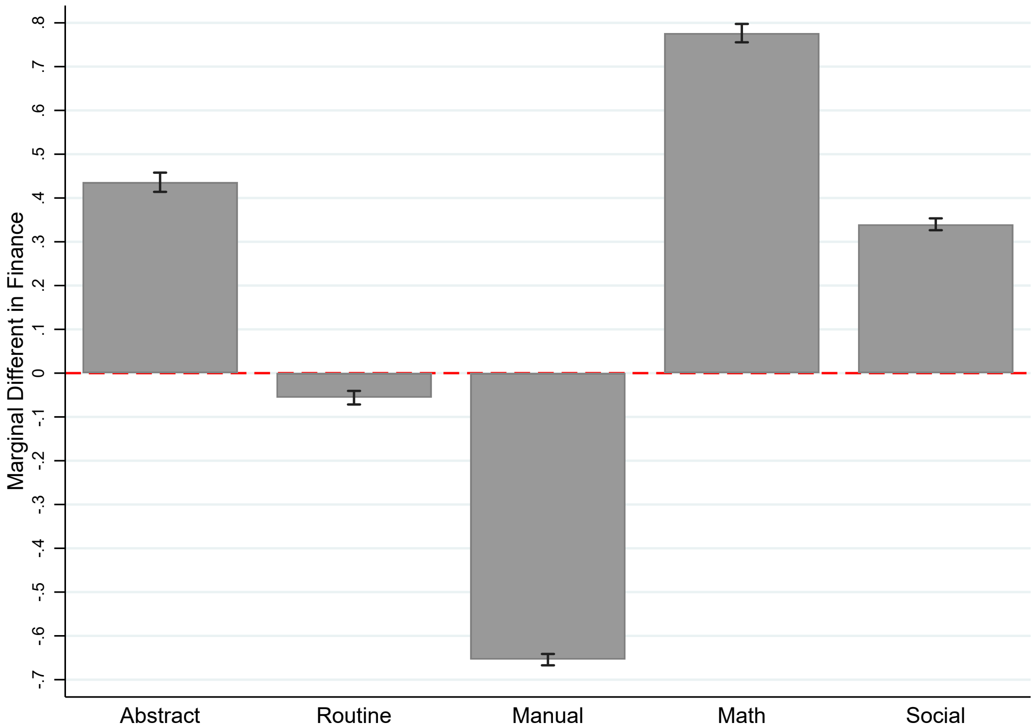


Figure 8. Occupational task intensities: Finance subsectors versus high-tech

This figure plots marginal differences between finance subsectors and the high-tech sector in occupational task intensities. Finance subsectors include broker, dealer, exchange and services (BDE), banking and credit institutions (CB), and insurance (IS). High-tech includes computers, biotechnology, electronics, and telecommunications industries. Abstract, routine, and manual task intensities are collected from Autor and Dorn (2013). Math and social skill intensities are collected from Deming (2017). Within a sample of 2001–2013 American Community Surveys, the marginal difference in each task intensity between finance and nonfinance is estimated at individual-level conditioning on state-by-year fixed effects, education-by-year fixed effects, and function of worker age interacted with education dummies. The estimations are weighted by the Census sampling weight multiplied by working hours to obtain nationally representative statistics. Vertical bands represent 95% confidence intervals based on standard errors clustered at the state level. Appendix A defines the variables.

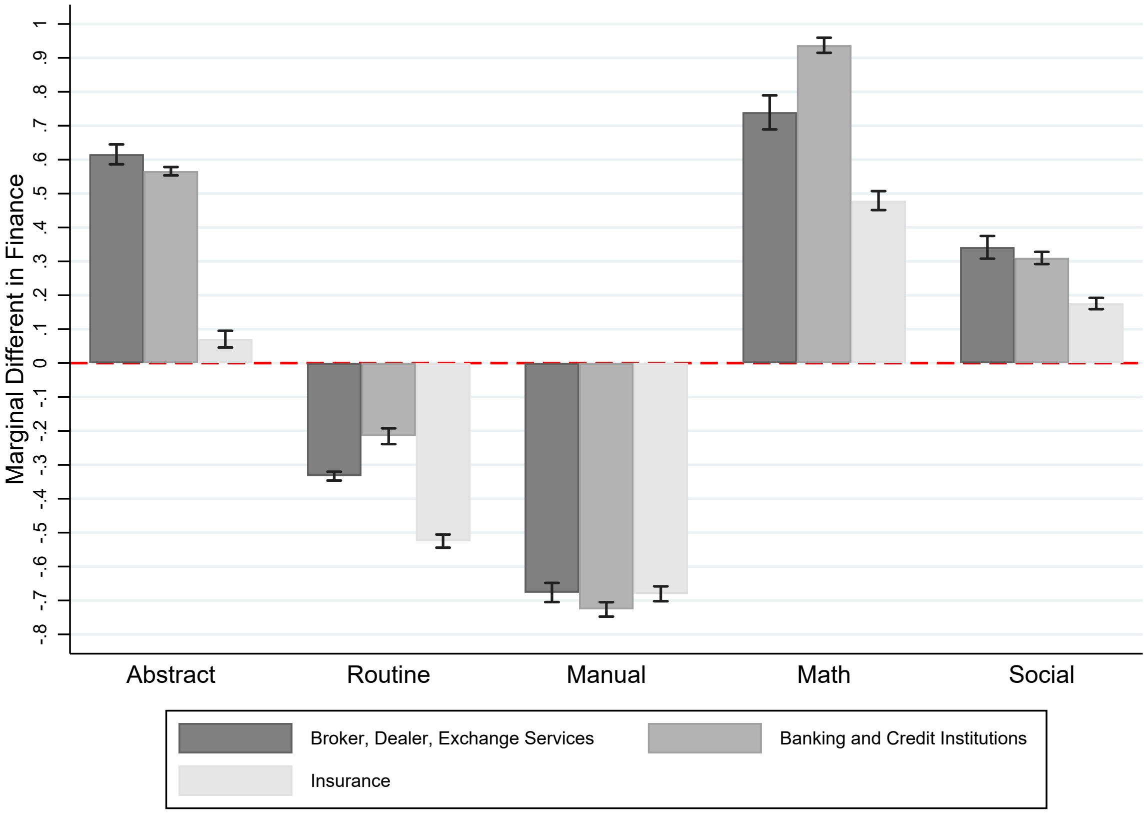


Table 1
LEHD sample coverage

This table presents the accessible states and year-quarters in the Employment History File (EHF) maintained by the U.S. Census LEHD program. See Vilhuber (2018) for details of the LEHD program.

State	Starting period	Ending period
Arkansas	2002Q3	2013Q4
Arizona	1992Q1	2013Q4
California	1991Q3	2013Q4
Colorado	1990Q1	2013Q4
District of Columbia	2002Q2	2013Q4
Delaware	1998Q3	2013Q4
Florida	1992Q4	2013Q4
Iowa	1998Q4	2013Q4
Illinois	1990Q1	2013Q4
Indiana	1990Q1	2013Q4
Kansas	1990Q1	2013Q4
Maryland	1985Q2	2013Q4
Maine	1996Q1	2013Q4
Missouri	1990Q1	2013Q4
Montana	1993Q1	2013Q4
New Mexico	1995Q3	2013Q4
Nevada	1998Q1	2013Q4
Oklahoma	2000Q1	2013Q4
Oregon	1991Q1	2013Q4
Pennsylvania	1991Q1	2013Q4
South Carolina	1998Q1	2013Q4
Tennessee	1998Q1	2013Q4
Washington	1990Q1	2013Q4
West Virginia	1997Q1	2013Q4

Table 2
Summary statistics: Finance versus nonfinance

This table reports summary statistics of key variables in the baseline firm-level sample of U.S. public and private firms and spans from 1990Q1 through 2013Q4. *All* refers to all observations in the sample. *Finance* refers to observations in financial industries. *Nonfinance* refers to observations in nonfinancial industries. In columns 1 to 3, sample means (standard deviations) are computed across all-firm-quarter observations in each category. Appendix A defines the variables. The number of observations is rounded following the Census Bureau's disclosure rules. Column 4 provides differences between means in columns 2 and 3 and the statistical significance level of the difference: *$p < .1$; **$p < .05$; ***$p < .01$. This analysis was performed at a Federal Statistical Research Data Center under FSRDC Project Number 1589. (CBDRB-FY24-P1589-R11070).

	(1)	(2)	(3)	(4)
	All	Finance	Nonfinance	Difference
Average quarterly earning ($)	12,880	16,280	12,760	3,520***
	(34,500)	(15,060)	(34,950)	
Average quarterly earning of high-skill ($)	33,860	47,730	33,400	14,330***
	(206,800)	(85,840)	(209,600)	
90th/10th percentile earning ratio	8.801	10.38	8.749	1.631***
	(46.51)	(14.84)	(47.19)	
Standard deviation	10,880	15,790	10,720	5,070***
	(87,630)	(37,530)	(88,790)	
Firm relative size (2-digit SIC, %)	0.004	0.006	0.004	0.002***
	(0.097)	(0.062)	(0.098)	
Share of college-educated workers (%)	26.63	42.27	26.11	16.16***
	(15.98)	(15.27)	(15.75)	
Share of male (%)	54.63	31.78	55.38	-23.6***
	(25.85)	(16.78)	(25.75)	
Share of white workers (%)	79.17	82.87	79.05	3.82***
	(18.85)	(16.40)	(18.91)	
Firm age	14.59	16.2	14.53	1.67***
	(9.437)	(10.05)	(9.41)	
Number of observations	39,280,000	1,519,000	37,760,000	

Table 3
Firm relative size and average quarterly earnings

This table presents the differential relationship between firm relative size and average quarterly earnings in the finance sector compared to the nonfinance sector, estimated using Equation (2). The sample comprises U.S. public and private firms and spans from 1990Q1 through 2013Q4. The dependent variable is the log-transformed average quarterly earnings at the firm. Earnings are in 2018 constant dollars. FIN equals one for financial firms and zero otherwise. $RelativeSize_{2d}$ ($Relative_{3d}$) represents firm employment size relative to the size of a given two-digit (three-digit) SIC in the previous year measured using Equation (1). Other controls (lagged by four quarters) include the logarithm of firm age as well as the shares of male workers, college workers, and white workers. Standard errors are clustered at the firm level and reported in parentheses. Appendix A defines the variables. The number of observations is rounded following the Census Bureau's disclosure rules. *p <.1; **p <.05; ***p <.01. This analysis was performed at a Federal Statistical Research Data Center under FSRDC Project Number 1589. (CBDRB-FY24-P1589-R11070).

	(1)	(2)	(3)	(4)	(5)
	$logEarnings$	$logEarnings$	$logEarnings$	$logEarnings$	$logEarnings$
FIN	0.149***	0.0736***	0.0696***	0.0746***	0.0693***
	(0.00172)	(0.00163)	(0.00574)	(0.00155)	(0.00580)
$RelativeSize_{2d}$		0.0353**	0.0511***		
		(0.0143)	(0.0169)		
$FIN \times RelativeSize_{2d}$		0.424***	0.341***		
		(0.121)	(0.107)		
$RelativeSize_{3d}$				0.0187***	0.0270***
				(0.00212)	(0.00229)
$FIN \times RelativeSize_{3d}$				0.0481***	0.0243**
				(0.0119)	(0.00994)
Observations	39,280,000	39,280,000	39,280,000	39,280,000	39,280,000
R^2	.02	.148	.301	.148	.358
$Year \times Quarter$ FE	Yes	Yes		Yes	
$SIC \times Year \times Quarter$ FE			Yes		Yes
Other controls		Yes	Yes	Yes	Yes

Table 4
Robustness: Firm relative size and different measures of worker earnings

This table presents the finance earning premiums in columns 1 and 3, conditioning on year-quarter fixed effects. Columns 2 and 4 present the differential relationship between firm relative size and worker earnings in the finance sector compared to nonfinance sectors, estimated using Equation (2). The sample consists of U.S. public and private firms and spans from 1990Q1 through 2013Q4. In columns 1 and 2, firm earnings are measured using the median of its worker earnings in a given year-quarter. In columns 3 and 4, firm earnings are measured using payroll per worker from the LBD. FIN equals one for financial firms and zero otherwise. $RelativeSize_{2d}$ represents firm employment size relative to the size of a given two-digit SIC in the previous year measured using Equation (1). Other controls (lagged by four quarters) include the logarithm of firm age as well as the shares of male workers, college workers, and white workers. Standard errors are clustered at the firm level and reported in parentheses. Appendix A defines the variables. The number of observations is rounded following the Census Bureau's disclosure rules. *$p<.1$; **$p<.05$; ***$p<.01$. This analysis was performed at a Federal Statistical Research Data Center under FSRDC Project Number 1589. (CBDRB-FY24-P1589-R11070).

	(1)	(2)	(3)	(4)
	$logEarnings_{med}$	$logEarnings_{med}$	$logPayroll/Emp$	$logPayroll/Emp$
FIN	0.125***	0.0512***	0.211***	0.103***
	(0.00149)	(0.00535)	(0.00198)	(0.00711)
$RelativeSize_{2d}$		0.0469***		0.0401***
		(0.0151)		(0.0129)
$FIN \times RelativeSize_{2d}$		0.212***		0.335***
		(0.0663)		(0.107)
Observations	39,280,000	39,280,000	39,280,000	39,280,000
R^2	.013	.302	.008	.291
$Year \times Quarter$ FE	Yes		Yes	
$SIC \times Year \times Quarter$ FE		Yes		Yes
Other controls		Yes		Yes

Table 5
Firm relative size and financial outcomes

This table presents the relationship between firm relative size and financial outcomes in the finance and nonfinance sectors estimated using Equation (2). The sample comprises U.S. public firms and spans from 1990Q1 through 2013Q4. The dependent variables in columns 1–4 are ROA, the Lerner Index, the asset utilization ratio, and the logarithm of revenue per worker. FIN equals one for financial firms and zero otherwise. $RelativeSize_{2d}$ represents firm employment size relative to the size of a given two-digit SIC in the previous year measured using Equation (1). Other controls (lagged by four quarters) include the logarithm of firm age as well as the shares of male workers, college workers, and white workers. Standard errors are clustered at the firm level and reported in parentheses. Appendix A defines the variables. The number of observations is rounded following the Census Bureau's disclosure rules. *p <.1; **p <.05; ***p <.01. This analysis was performed at a Federal Statistical Research Data Center under FSRDC Project Number 1589. (CBDRB-FY24-P1589-R11070).

	(1)	(2)	(3)	(4)
	ROA	$LernerIndex$	$AssetUtilization$	$Revenue/Emp$
FIN	0.0064	0.165***	-0.423***	0.215**
	(0.0299)	(0.0591)	(0.151)	(0.104)
$RelativeSize_{2d}$	0.0050**	0.0044**	-0.0381***	0.0005
	(0.0019)	(0.0020)	(0.0084)	(0.0068)
$FIN \times RelativeSize_{2d}$	0.0121*	0.0914**	0.0293	0.201*
	(0.00742)	(0.0455)	(0.0626)	(0.112)
Observations	126,000	126,000	126,000	126,000
R^2	.171	.098	.478	.514
$SIC \times Year \times Quarter$ FE	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes

Table 6
Firm relative size and within-firm inequality

This table presents the relationship between firm relative size and within-firm inequality in the finance and nonfinance sectors estimated using Equation (2). The sample consists of U.S. public and private firms and spans from 1990Q1 through 2013Q4. Columns 1–3 present the relationship between firm relative size and average quarterly earnings of high-skill workers. High-skill workers in column 1 (2) are those whose earnings are above the 90th (99th) percentile of the firm earning distribution in that year-quarter. High-skill workers in column 3 are those whose earnings are above the top tercile of sample distribution in that year-quarter. Within-firm inequality in column 4 (5) is measured by the log difference of the average quarterly earnings above the 90th (99th) percentile and below the 10th (1st) percentile of the earning distribution in a given firm-year-quarter. In column 6, within-firm inequality is measured using the logarithm of the standard deviation of worker earnings. FIN equals one for financial firms and zero otherwise. $RelativeSize_{2d}$ represents firm employment size relative to the size of a given two-digit SIC in the previous year measured using Equation (1). Other controls (lagged by four quarters) include the logarithm of firm age as well as the shares of male workers, college workers, and white workers. Standard errors are clustered at the firm level and reported in parentheses. Appendix A defines the variables. The number of observations is rounded following the Census Bureau's disclosure rules. *p <.1; **p <.05; ***p <.01. This analysis was performed at a Federal Statistical Research Data Center under FSRDC Project Number 1589. (CBDRB-FY24-P1589-R11070).

	(1)	(2)	(3)	(4)	(5)	(6)
	$logEarnings_{p90}$	$logEarnings_{p99}$	$logEarnings_{top}$	$EarningRatio_{p90/p10}$	$EarningRatio_{p99/p1}$	$logStdEarnings$
FIN	0.0799***	0.0774***	0.0435***	0.0412***	0.0364***	0.106***
	(0.00823)	(0.0105)	(0.00518)	(0.00786)	(0.0117)	(0.00897)
$RelativeSize_{2d}$	0.112***	0.296***	0.0712***	0.0746***	0.385***	0.126***
	(0.0346)	(0.0872)	(0.0206)	(0.0228)	(0.112)	(0.0362)
$FIN \times RelativeSize_{2d}$	0.638***	1.149***	0.318***	0.281**	1.187***	0.640***
	(0.214)	(0.397)	(0.110)	(0.118)	(0.429)	(0.206)
Observations	39,280,000	39,280,000	39,280,000	39,280,000	39,280,000	39,280,000
R^2	.194	.152	.167	.194	.1	.19
$SIC \times Year \times Quarter$ FE	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 7
Firm relative size in local market and earnings

This table presents the relationship between firm earning patterns and firm relative size in local markets in finance industries compared to nonfinance industries. The sample is at the firm-commuting zone-year-quarter level and spans from 1990Q1 to 2013Q4. The dependent variables in columns 1–3 are the logarithm of average quarterly earnings, the logarithm of average quarterly earnings of high-skill workers, and within-firm inequality measured at the firm-commuting zone level. Earnings are in 2018 constant dollars. FIN equals one for financial firms and zero otherwise. $RelativeSize_{2d}^{CZONE}$ represents firm employment size relative to the size of a given two-digit SIC-commuting zone in the previous year measured using Equation (1). Other controls (lagged by four quarters) include the logarithm of firm age as well as the shares of male workers, college workers, and white workers measured at the firm-commuting zone-year-quarter level. Standard errors are double clustered at firm and commuting zones and reported in parentheses. Appendix A defines the variables. The number of observations is rounded following the Census Bureau's disclosure rules. *p <.1; **p <.05; ***p <.01. This analysis was performed at a Federal Statistical Research Data Center under FSRDC Project Number 1589. (CBDRB-FY24-P1589-R11070).

	(1)	(2)	(3)
	$logEarnings^{CZONE}$	$logEarnings_{p90}^{CZONE}$	$EarningRatio_{p90/p10}^{CZONE}$
FIN	0.0717***	0.0699***	0.0018
	(0.0058)	(0.0076)	(0.0077)
$RelativeSize_{2d}^{CZONE}$	0.0163***	0.0430***	0.0562***
	(0.0002)	(0.0004)	(0.0005)
$FIN \times RelativeSize_{2d}^{CZONE}$	0.0106***	0.0235***	0.0270***
	(0.0014)	(0.0031)	(0.0037)
Observations	108,500,000	108,500,000	108,500,000
R^2	.344	.269	.11
$SIC \times CZONE \times Year \times Quarter$ FE	Yes	Yes	Yes
Other controls FE	Yes	Yes	Yes

Table 8
Firm relative size and earnings: Tradable versus nontradable sectors

This table presents the relationship between firm earning patterns and firm relative size in finance industries compared to nontradable industries. The sample consists of U.S. public and private firms and spans from 1990Q1 through 2013Q4. The dependent variables in columns 1–3 are the log-transformed average quarterly earnings, the log-transformed average quarterly earnings of high-skill workers, and within-firm inequality measured at the firm level. $RelativeSize_{2d}$ represents firm employment size relative to the size of a given two-digit SIC in the previous year measured using Equation (1). FIN equals one for financial firms and zero otherwise. $Trade_{excludeFIN}$ equals one for non-finance-tradable sectors, such as professional service, manufacturing, and zero otherwise. The reference group is the nontradable sector, such as retail, low-skill services, and transportation. Other controls (lagged by four quarters) include the logarithm of firm age as well as the shares of male workers, college workers, and white workers. FIN and $Trade_{excludeFIN}$ are included in the estimation, but not reported for brevity. Standard errors are clustered at the firm level and reported in parentheses. Appendix A defines the variables. The number of observations is rounded following the Census Bureau's disclosure rules. *p <.1; **p <.05; ***p <.01. This analysis was performed at a Federal Statistical Research Data Center under FSRDC Project Number 1589. (CBDRB-FY24-P1589-R11070).

	(1)	(2)	(3)
	$logEarnings$	$logEarnings_{p90}$	$logEarnings_{p90/p10}$
$RelativeSize_{2d}$	0.00187	0.0633**	0.0994*
	(0.0035)	(0.0322)	(0.0509)
$FIN \times RelativeSize_{2d}$	0.390***	0.687***	0.258**
	(0.106)	(0.214)	(0.126)
$Trade_{excludeFIN} \times RelativeSize_{2d}$	0.119***	0.117***	-0.0602
	(0.0184)	(0.0416)	(0.0517)
Observations	39,280,000	39,280,000	39,280,000
R^2	.301	.194	.114
$Year \times Quarter$ FE	Yes	Yes	Yes
$SIC \times Year \times Quarter$ FE	Yes	Yes	Yes

Appendix A. Variable Definitions

Average quarterly earning is the average quarterly earning of workers in each firm-year-quarter. Earnings are adjusted to 2018 constant dollars. *Source*: LEHD

Average quarterly earning of high-skill is the average quarterly earning of high-skill workers in each firm-year-quarter. High-skill workers are defined as workers whose earnings are above the 90th percentile of the earning distribution in a given firm-year-quarter. Earnings are adjusted to 2018 constant dollars. *Source*: LEHD

90th/10th percentile earning ratio is calculated as the average quarterly earnings above the 90th percentile divided by the average quarterly earnings below the 10th percentile of the earning distribution in a given firm-year-quarter. Earnings are adjusted to 2018 constant dollars. *Source*: LEHD

Standard deviation is the standard deviation of worker earnings within a given firm-year-quarter. *Source*: LEHD

Firm relative size (two-digit SIC) ($RelativeSize_{2d}$) is a firm's employment share in its main industry in a given year-quarter where industries are defined using two-digit SIC codes. *Source*: LBD

Share of college is the employment share of workers (in percentage) who have at least 4-year college education in each firm-year-quarter. *Source*: LEHD

Share of male is the employment share of male workers (in percentage) in each firm-year-quarter. *Source*: LEHD

Share of white is the employment share of white workers (in percentage) who have at least 4-year college education in each firm-year-quarter. *Source*: LEHD

Firm age is defined following Haltiwanger et al. (2014) as the oldest establishment that the firm owns in the first year the firm is observed in the LBD. *Source*: LBD

logEarnings is the logarithm of the average quarterly earnings (*Average quarterly earning*) in each firm and year-quarter. Earnings are adjusted to 2018 constant dollars. *Source*: LEHD

FIN equals one if a firm is classified as a financial firm and zero otherwise. A firm is classified as a financial firm if more than 50% of its employees work in one of the private financial industries: depository institutions (except central reserve depository institutions), nondepository institutions, security and commodity brokers, insurance carriers, insurance agents, brokers and service, and holdings and other investment offices (i.e., two-digit SIC codes: 60, 61, 62, 63, 64, and 67, excluding the following three-digit SIC codes: 601 and 611). *Source*: LBD

Firm relative size (three-digit SIC) ($RelativeSize_{3d}$) is a firm's employment share in its main industry in a given year-quarter where industries are defined using three-digit SIC codes. *Source*: LBD

$logEarnings_{med}$ is the logarithm of the median quarterly earnings in each firm-year-quarter. Earnings are adjusted to 2018 constant dollars. *Source*: LEHD

$logPayroll/Emp$ is the logarithm of total payroll divided by total employment in each firm-year. Total payrolls are adjusted to 2018 constant dollars. *Source*: LBD

High-tech equals one for firms in SIC codes corresponding to computers, biotechnology, electronics, and telecommunications (i.e., three-digit SIC codes: 283, 360–362, 364, 366–369, 382, 384, 481–489, 504, 506, 512, 537, 573, 745, and 747 and two-digit SIC: 80), and zero otherwise. *Source*: LBD

Manufacturing equals one for firms in manufacturing, excluding any high-tech industries (i.e., two-digit SIC codes 20–39, excluding the following three-digit SIC codes: 283, 360–362, 364, 366–369, 382, and 394), and zero otherwise. *Source*: LBD

Service equals one for firms in service industries, excluding any high-tech industries (i.e., two-digit SIC codes 70–80, excluding the following three-digit SIC codes: 735 and 737), and zero otherwise. *Source*: LBD

Other equals one for firms in mining, construction, transportation, retail trade, or wholesale trade, and zero otherwise. *Source*: LBD

ROA is the ratio of earnings before tax, interest, depreciation, and amortization (EBITDA) to total assets in a given firm-year. *Source*: Compustat

Lerner Index is the ratio of operating income after depreciation to total sales in a given firm-year. *Source*: Compustat

Revenue/Emp is the ratio of total revenue to total employment in a given firm-year. *Source*: Compustat

Asset utilization is the ratio of total revenue to total assets in a given firm-year . *Source*: Compustat

Abstract measures the intensity of an occupation's requirements for direction, control, and planning, where occupations are classified using $occ1990dd$ from Dorn (2009). The score is standardized with a mean of 0 and standard deviation of 1. *Sources*: ACS and Autor and Dorn (2013)

Routine measures an occupation's requirements on adaptability to work requiring set limits, tolerances or standards, and finger dexterity, where occupations are classified using $occ1990dd$ from Dorn (2009). The score is standardized with a mean of 0 and standard deviation of 1. *Sources*: ACS and Autor and Dorn (2013)

Manual measures an occupation's requirements on coordination of eye, hand, and foot, where occupations are classified using $occ1990dd$ from Dorn (2009). The score is standardized with a mean of 0 and standard deviation of 1. *Sources*: ACS and Autor and Dorn (2013)

Math measures an occupation's requirements on mathematical reasoning and problem-solving requirements, where occupations are classified using $occ1990dd$ from Dorn (2009). The score is standardized with a mean of 0 and standard deviation of 1. *Sources*: ACS and Deming (2017)

Social measures an occupation's requirements on coordination, negotiation, persuasion, and social perceptiveness, where occupations are classified using $occ1990dd$ from Dorn (2009). The score is standardized with a mean of 0 and standard deviation of 1. *Sources*: ACS and Deming (2017)

$logEarnings_{p90}$ ($logEarnings_{p99}$) is the logarithm of the average quarterly earnings of high-skill workers. High-skill workers are those whose earnings are above the 90th (99th) percentile of the earning distribution in a given firm-year-quarter. Earnings are adjusted to 2018 constant dollars. *Source*: LEHD

$logEarning_{top}$ is the logarithm of the average quarterly earnings of high-skill workers. High-skill workers are those whose earnings are above the top tercile of sample distribution in that year-quarter. Earnings are adjusted to 2018 constant dollars. *Source*: LEHD

$EarningRatio_{p90/p10}$ ($EarningRatio_{p90/p10}$) is the log difference of the average quarterly earnings above the 90th (99th) percentile and below the 10th (1st) percentile of the earning distribution in a given firm-year-quarter. *Source*: LEHD

logStdEarnings is the logarithm of the standard deviation of worker earnings within a given firm-year-quarter. *Source*: LEHD

$logEarnings^{worker}$ is the logarithm of individual quarterly earnings of a given worker-year. Earnings are adjusted to 2018 constant dollars. *Source*: LEHD

$logEarnings^{CZONE}$ is the logarithm of the average quarterly earnings in each firm-commuting zone-year-quarter. Earnings are adjusted to 2018 constant dollars. *Source*: LEHD

$logEarnings^{CZONE}_{p90}$ is the logarithm of the average quarterly earnings of workers who earn above the 90th percentile in a given firm-commuting zone-year-quarter. Earnings are adjusted to 2018 constant dollars. *Source*: LEHD

$EarningsRatio^{CZONE}_{p90/p10}$ is the log difference of the average quarterly earnings above the 90th percentile and below the 10th percentile of the earning distribution in a given firm-commuting zone-year-quarter. *Source*: LEHD

$RelativeSize^{CZONE}_{2d}$ is a firm's employment share in its main industry in a given year-quarter where industries are defined using two-digit SIC codes. *Source*: LBD

$Trade_{exclFIN}$ equals one for firms in nonfarming tradable sectors, excluding finance industries (i.e., SIC codes 10–14, 20–49, 73, 81, and 87), and zero otherwise. *Source*: LBD

$logWages_{ACS}$ is the logarithm of hourly wages. Wages are adjusted to 2018 constant dollars. *Source*: ACS

$logPPE$ $(logPPE/Emp)$ is the logarithm of property, plant, and equipment (normalized by employment). *Source*: Compustat

$logCapEx$ $(logCapex/Emp)$ is the logarithm of capital expenditure (normalized by employment). *Source*: Compustat

HHI_{2d} (HHI_{3d}) is a measure of concentration for a two-digit (three-digit) SIC industry in a given year-quarter. It is the summation of the square of firm employment shares in the industry. *Source*: LBD

Appendix B. Additional Graphs and Tables

Figure B1. Industry concentration: Finance versus nonfinance

This figure plots Herfindahl-Hirschman Indices (HHI) averaged across periods during 1990–2013 by finance and nonfinance sectors. The underlying sample is at the firm-year-quarter level spanning from 1990Q1 to 2013Q4. HHI is constructed using firm employment data from the LBD as the sum of the squared firm employment shares in industry j in year y:

$$\text{HHI}_{j,y} = \sum_{f} \left(\frac{emp_{f,j,y}}{emp_{j,y}}\right)^2,$$

where $emp_{f,j,y}$ is the employment of firm f in industry j in year t. $emp_{j,y}$ is the total employment in industry j in year t. This analysis was performed at a Federal Statistical Research Data Center under FSRDC Project Number 1589. (CBDRB-FY24-P1589-R11070).

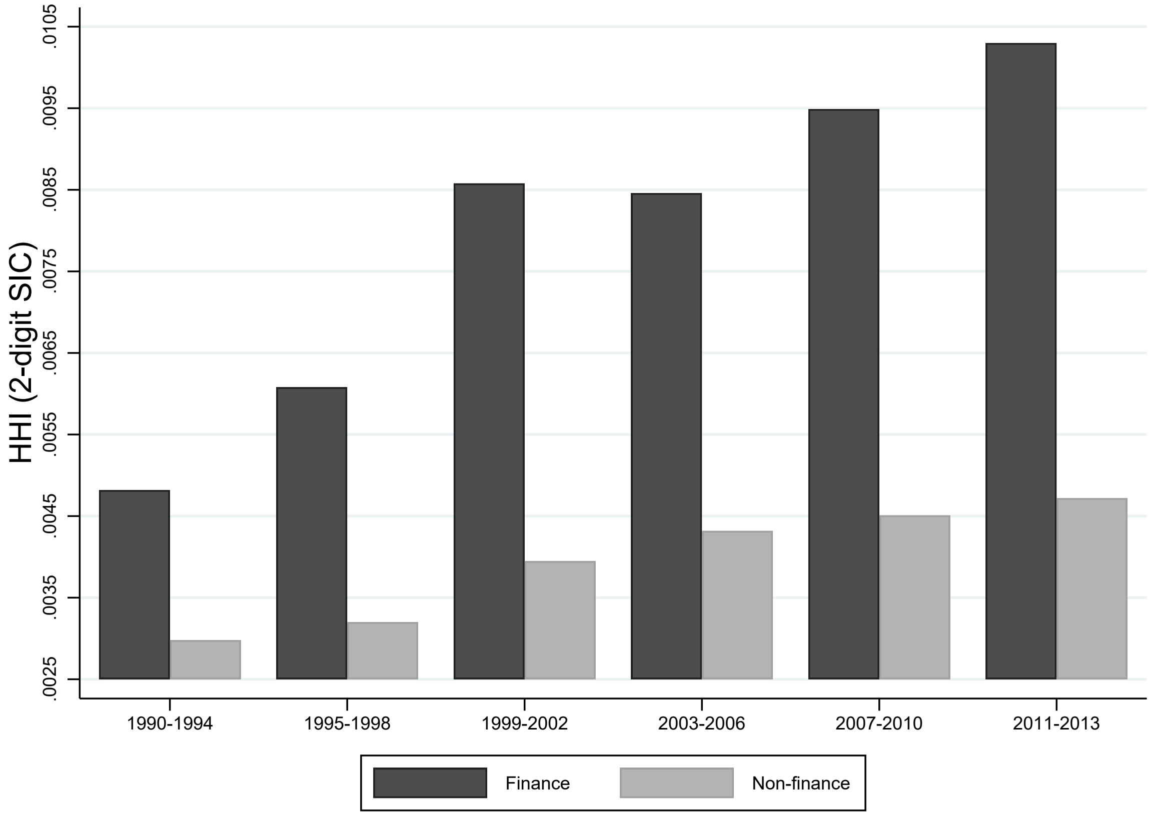


Table B1
Summary statistics: Finance versus high-tech

This table reports summary statistics of key variables in the baseline firm-level sample by the finance and high-tech sectors. *Finance* refers to observations in financial industries. *High-tech* refers to observations in high-tech industries. Sample means (standard deviations) in columns 1 and 2 are computed across firm-quarter observations in each category. Column 3 provides differences between means in columns 1 and 2 and statistical significance levels from two-sample t-tests. Appendix A defines the variables. The number of observations is rounded following the Census Bureau's disclosure rules. *$p < .1$; **$p < .05$; ***$p < .01$. This analysis was performed at a Federal Statistical Research Data Center under FSRDC Project Number 1589. (CBDRB-FY24-P1589-R11070).

	(1)	(2)	(3)
	Finance	High-tech	Difference
Average quarterly earning ($)	16280	16230	50***
	(15060)	(10230)	
Firm relative size (2-digit SIC, %)	0.006	0.004	0.002***
	(0.062)	(0.064)	
Share of college-educated workers (%)	42.27	38.65	3.62***
	(15.27)	(19.52)	
Share of male (%)	31.78	58.39	-26.61***
	(16.78)	(20.44)	
Share of white workers (%)	82.87	77.29	5.58***
	(16.40)	(19.69)	
Firm age	16.2	13.15	3.05***
	(10.05)	(8.937)	
Number of observations	1,519,000	3,724,000	

Table B2
Summary statistics: Publicly listed firms

This table reports summary statistics of key variables in a subsample of U.S. publicly listed firms. The sample spans from 1990Q1 through 2013Q4. *All* refers to all observations in the sample. *Finance* refers to observations in financial industries. *Nonfinance* refers to observations in nonfinancial industries. Sample means (standard deviations) reported in columns 1–3 are computed across firm-quarter observations in each category. Column 4 provides differences between means in columns 2 and 3 and the statistical significance level of two-sample t-tests. Appendix A defines the variables. The number of observations is rounded following the Census Bureau's disclosure rules. *$p<.1$; **$p<.05$; ***$p<.01$. This analysis was performed at a Federal Statistical Research Data Center under FSRDC Project Number 1589. (CBDRB-FY24-P1589-R11070).

	(1)	(2)	(3)	(4)
	All	Finance	Nonfinance	Difference
Firm relative size (2-digit SIC, %)	0.29	0.093	0.326	-0.233***
	(1.083)	(0.269)	(1.169)	
ROA	0.096	0.033	0.108	-0.075***
	(0.148)	(0.057)	(0.157)	
Lerner Index	0.056	0.235	0.023	0.212***
	(0.662)	(1.326)	(0.433)	
Revenue per worker (thousand $)	264.1	319.6	253.9	65.7***
	(340.2)	(382.6)	(330.8)	
Asset utilization ratio	1.195	0.165	1.386	-1.221***
	(0.966)	(0.356)	(0.922)	
Firm age	21.65	24.1	21.19	2.91***
	(8.305)	(8.076)	(8.268)	
Number of observations	126,000	19,500	106,000	

Table B3
Task scores and worker earnings

This table presents estimated correlations between task intensity and hourly wages within a sample of 2001–2013 American Community Surveys. The dependent variable is the logarithm of hourly wages. The independent variables in columns 1 and 2 are abstract, routine, and manual task intensities collected from Autor and Dorn (2013). The independent variables in columns 3 and 4 are math and social skill intensities, collected from Deming (2017). Columns 1 and 3 control for year fixed effects. Columns 2 and 4 control for sex-by-race, education-by-year, state-by-year fixed effects, and a function of worker age interacted with education dummies. Standard errors are clustered at the state level and reported in parentheses. Appendix A defines the variables. *p <.1; **p <.05; ***p <.01.

	(1)	(2)	(3)	(4)
	$logWages_{ACS}$	$logWages_{ACS}$	$logWages_{ACS}$	$logWages_{ACS}$
Abstract	0.3036***	0.1598***		
	(0.0054)	(0.0024)		
Routine	0.0166***	0.0370***		
	(0.0038)	(0.0025)		
Manual	0.0498***	0.0217***		
	(0.0026)	(0.0018)		
Math			0.1677***	0.1119***
			(0.0030)	(0.0018)
Social			0.1776***	0.0845***
			(0.0081)	(0.0048)
Observations	11,247,633	11,247,633	11,234,377	11,234,377
R^2	.181	.383	.207	.391
Year FE	Yes		Yes	
Worker controls		Yes		Yes

Table B4
Firm relative size and capital investment

This table presents the relationship between firm relative size and capital investment in the finance and nonfinance sectors estimated using Equation (2). The sample comprises U.S. public firms and spans from 1990Q1 through 2013Q4. The dependent variables in columns 1–4 are the logarithm of property, plant, and equipment value (PPE), capital expenditure ($CapEx$), PPE normalized by firm employment, and $CapEx$ normalized by firm employment. FIN equals one for financial firms and zero otherwise. $RelativeSize_{2d}$ represents firm employment size relative to the size of a given two-digit SIC in the previous year measured using Equation (1). Other controls (lagged by four quarters) include the logarithm of firm age as well as the shares of male workers, college workers, and white workers. Standard errors are clustered at the firm level and reported in parentheses. Appendix A defines the variables. The number of observations is rounded following the Census Bureau's disclosure rules. *p <.1; **p <.05; ***p <.01. This analysis was performed at a Federal Statistical Research Data Center under FSRDC Project Number 1589. (CBDRB-FY24-P1589-R11070).

	(1)	(2)	(3)	(4)
	$logPPE$	$logCapEx$	$logPPE/Emp$	$logCapEx/Emp$
FIN	-0.228	-0.474*	-0.0886	-0.451**
	(0.313)	(0.265)	(0.216)	(0.229)
$RelativeSize_{2d}$	0.491***	0.46***	-0.0021	-0.007
	(0.127)	(0.116)	(0.015)	(0.010)
$FIN \times RelativeSize_{2d}$	2.240***	1.626***	0.171*	0.129
	(0.459)	(0.364)	(0.103)	(0.099)
Observations	126,000	126,000	126,000	126,000
R^2	.434	.384	.5	.41
$SIC \times Year \times Quarter$ FE	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes

Table B5
Summary statistics: Local market level

This table reports summary statistics of key variables used in local market-level analysis. The sample is at the firm-commuting zone-year-quarter level and spans from 1990Q1 through 2013Q4. *All* refers to all observations in the sample. *Finance* refers to observations in financial industries. *Nonfinance* refers to observations in nonfinancial industries. Sample means (standard deviations) reported in columns 1–3 are computed across firm-commuting zone-quarter observations in each category. Appendix A defines the variables. The number of observations is rounded following the Census Bureau's disclosure rules. Column 4 provides differences between means in columns 2 and 3 and the statistical significance level of two-sample t-tests: *p <.1; **p <.05; ***p <.01. This analysis was performed at a Federal Statistical Research Data Center under FSRDC Project Number 1589. (CBDRB-FY24-P1589-R11070).

	(1)	(2)	(3)	(4)
	All	Finance	Nonfinance	Difference
Average quarterly earning ($)	12,730	15,870	12,640	3,230***
	(36,480)	(14,540)	(36,890)	
Average quarterly earning of high-skill ($)	33,220	44,940	32,900	12,040***
	(217,700)	(81,190)	(220,200)	
90th/10th percentile earning ratio	8.823	10.31	8.783	1.527***
	(48.17)	(15.83)	(48.76)	
Firm relative size (2-digit SIC, %)	0.53	0.755	0.521	0.234***
	(3.519)	(3.615)	(3.515)	
Firm age	12.28	13	12.25	0.75***
	(9.020)	(9.361)	(9.003)	
Number of observations	108,500,000	4,491,000	10,400,000	

Table B6
Industry concentration and average quarterly earnings

This table presents correlations between industry concentration and average quarterly earnings. The sample consists of U.S. public and private firms and spans from 1990Q1 through 2013Q4. The dependent variable is the log-transformed average quarterly earnings at the firm. Earnings are in 2018 constant dollars. HHI_{2d} (HHI_{3d}) represents the industry concentration level of a given two-digit (three-digit) SIC in the previous year. FIN equals one for financial firms and zero otherwise. Other controls (lagged by four quarters) include the logarithm of firm age as well as the shares of male workers, college workers, and white workers. Standard errors are clustered at the firm level and reported in parentheses. Appendix A defines the variables. The number of observations is rounded following the Census Bureau's disclosure rules. *p <.1; **p <.05; ***p <.01. This analysis was performed at a Federal Statistical Research Data Center under FSRDC Project Number 1589. (CBDRB-FY24-P1589-R11070).

	(1)	(2)	(3)	(4)
	$logEarnings$	$logEarnings$	$logEarnings$	$logEarnings$
HHI_{2d}	-2.251***		-2.490***	
	(0.0250)		(0.0259)	
HHI_{3d}		-0.500***		-0.606***
		(0.0145)		(0.0148)
FIN			0.0420***	0.0511***
			(0.00210)	(0.00176)
$FIN \times HHI_{2d}$			5.794***	
			(0.198)	
$FIN \times HHI_{3d}$				2.461***
				(0.0837)
Observations	39,280,000	39,280,000	39,280,000	39,280,000
R^2	.15	.147	.152	.149
$Year \times Quarter$ FE	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes