Spatial Wage Inequality within the Firm*

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Abstract

We analyze the role of location in explaining US wage inequality, for workers employed in the same firm but at establishments in different cities. We apply a wage variance decomposition to a massive and detailed dataset from Glassdoor. Wage variation across cities for comparable workers declines by 81% for same-firm employees. Utilizing a fixed effect model of wage determination, we find that the decline is equally attributable to firms locating their establishments in similar cities as to firm-level wage anchoring. This novel city selection channel suggests caution to place-based policies predicated on bringing high-wage firms to low-wage cities.

Keywords: Firm-level wage anchoring, local labor markets, variance decomposition, wage fixed effects model

JEL Codes: J31, R11

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1 Introduction

Multi-establishment firms play a disproportionate role in the US economy. Despite comprising only 5% of all firms, they employ 55% of the workforce (Cao et al., 2017).[1] These firms have been the primary drivers of the increase in wage inequality since the 1980s (Kleinman, 2022),[2] and, as relatively large firms, are typically more productive and pay higher wages (Oi and Idson, 1999; Schmidt and Zimmermann, 1991).[3] Governments have long internalized these facts, with place-based policies often predicated on bringing establishments of high-wage firms to low-wage cities (Greenstone et al., 2010; Kline, 2010; Busso et al., 2013). Yet, it is also well-known that location is a key determinant of earnings (Gould, 2007; Moretti, 2010; Diamond, 2016; Chetty and Hendren, 2018). To what extent firms anchor their wages at the firm level (e.g. a firm-wide wage setting policy), as opposed to the city level (e.g. indexing against local cost of living), is therefore essential in assessing the efficacy of place-based policies. Only the former is conducive to such policies; the latter would suggest that high-wage firms would pay lower wages in low-wage cities.

In this paper, we provide insight into this question. We approach this by analyzing the variation of nominal wages between establishments of the same firm but in different cities. Our first main finding is that the between city variation is dramatically compressed within the firm. This is an interesting result because it is well-known that wages, worker ability, and cost of living all vary considerably across space. Yet, if we look at individuals employed in the same firm, but at establishments in different cities, the role of location is much diminished. This is suggestive of wages being anchored at the firm level, and therefore conducive to place-based policies. Recent work by Hjort et al. (2020) and Hazell et al. (2022) corroborate this finding, and provide evidence for such firm-level anchoring.

We build on the literature by recognizing that firms may still be engaging in city-level wage anchoring, but this would be effectively hidden if a firm tends to open its establishments in similar cities (e.g. if establishments of high wage firms are mostly located in high wage cities). This city selection channel, which is empirically plausible given firms are known to sort into locations (Gaubert, 2018; Lindenlaub et al., 2022; Bilal, 2023), would also be consistent with the aforementioned wage compression. But, importantly, may have the opposite implication to firm-level anchoring for the efficacy of place-based policies, because firms may still be anchoring wages at the city level. We find that both of these channels in fact contribute about equally. We close the paper by investigating these two channels further, notably using originally collected data on firms' headquarters.

To answer this research question, earnings data identifying both the firm and city of employment is required. Standard data sources have typically lacked both of these identifiers simultaneously, though recently, exceptions are emerging (e.g. Card et al. (2022a)).[4] We use an employer-employee matched dataset from the online salary platform Glassdoor, Inc., which includes both of these variables. Our preferred sample spans 2015-2019, covering 3,471,345 employees, 24,679 firms, and 858 cities in the U.S. Benchmarking against the Current Population Survey (CPS), we find that the Glassdoor respondents are likely representative of workers employed in multi-establishment firms — our segment of interest — though positively selected overall.

[1] In Germany they employ 34% of workers while constituting 9% of firms (Gumpert et al., 2022).

[2] Without conditioning on multi-establishment firms, Song et al. (2019) find that one third of rising earnings inequality has occurred within firms. Rossi-Hansberg et al. (2021) find that multi-establishment firms are key to understanding recent trends in the concentration of local product market.

[3] They are also linked to the rising mark-ups and declining labor share in the US (De Loecker et al., 2020).

[4] For example, Barth et al. (2016); Card et al. (2013) document wage variation across space (between establishment) but do not have data on the firm. Song et al. (2019) document within firm variation but do not have data on the city. Bartelme and Ziv (2023), Castro-Vincenzi (2022) and Ziv and Bartelme (2023) analyze the spatial distribution of establishments within a firm, but do not have worker earnings.

Note that our data is more universal than Hazell et al. (2022), who only have data on posted, not realized, wages. Hjort et al. (2020) restricts attention to multinational corporations.

For our first main finding, when comparing all workers vs those employed at the same firm, the share of wage variance between cities declines by 81%. We restrict this analysis to comparable workers: those of the same occupation and tenure (years of relevant experience). This dramatic decline is quite surprising: firms tend to pay their workers the same wage regardless of location. Indeed, we may have expected the reverse to be true: by controlling for the firm, as well as occupation and tenure, we are increasingly leaving only location to explain the remaining variation in wages. Yet, we find that location explains less. This finding is however potentially encouraging for place-based policies, suggesting high wage firms will pay high wages in low-wage cities. However, one first needs to assess the city selection channel.

To investigate this, we utilize a variant on the workhorse fixed effects model of wage determination (Abowd et al., 1999; Card et al., 2018). We decompose the decline in wage variation between cities into the two channels of interest. The first is the variation arising from systematic differences in wages across cities, holding the firm and worker characteristics fixed — the city fixed effect. The second is the variation arising from differences in the composition of firms across cities, resulting in systematic differences in wages across cities — the firm fixed effect. The first reflects the city selection channel, while the second reflects firm-level wage anchoring. Card et al. (2022b) use a similar model to decompose wage variation between commuting zones; we show how to extend their method for a subset of workers, such as those in the same firm or in similar occupations and tenure levels.

With this model, we arrive at our second main finding. The decline in the wage variance between cities when we go within the firm is driven in almost equal parts by the two channels. Firms opening their establishments in similar cities explains 44 percentage points out of the 81% decline in the variance, while firm-level wage anchoring explains 35 percentage points. Policy-wise, because of the prominence of the city selection channel, this suggests one should be careful in extrapolating the wage rate to prospective locations that the firm may be considering opening an establishment in, especially insofar as they differ from the current locations the firm operates in.

We end our analysis by decomposing these two channels to understand more concretely what is driving their contributions. Which ways are the cities similar that a firm opens its establishments in? How are wages anchored at the firm level, given its establishments in different cities face differing local labor markets conditions? We investigate this by projecting the city and firm fixed effects of our model, respectively, onto observables informative of these (see Kline et al. (2020) for a general discussion of this method). Regarding the characteristics of cities, we find that they are mostly similar in terms of cost of living (proxied by the Zillow house price index), with population and unionisation — two other key local labor market features influencing wages — contributing negligible amounts.

Regarding firm-level anchoring, we assess two possibilities. The first is an anchoring of the wage to the local labor market of the city containing the firm's headquarters; a mechanism that has began to receive attention in the literature (Hjort et al., 2020; Kleinman, 2022). We construct an original dataset by scraping Google's databases to obtain the headquarter addresses of all 24,679 firms in our Glassdoor sample. The second is an anchoring of the wage to an average of the local labor markets across all cities that the firm operates in. We operationalize this method by using the estimated city fixed effects from our wage determination model. First, the value of the city fixed effect for the headquarter's city, and second, the average (weighted by number of employees) of their values across all the cities the firm has an establishment in. We find that each of these channels contribute about equally to explaining wage variation between cities. Combined, their variance contribution is about half of that of the labor market of the worker's city of employment.

The rest of the paper is structured as follows. In section 2, we detail our empirical methodology. In section 3, we describe our data. In section 4, we present our results. In section 5, we conclude.

2 Empirical Method

In subsection 2.1, we show how to calculate the change in the share of wage variance between cities for all comparable workers vs those employed at the same firm. In subsection 2.2, we show how to decompose the variance share change into the city selection and firm-level wage anchoring channels. In subsection 2.3, we present a further decomposition of these components to provide concrete insight into what is driving them.

We use the following notation throughout. With each worker is associated a vector $\{Y, F, C, S\}$. Each element represents a random variable: the wage (log annual earnings), firm identifier, city identifier and worker skill identifier, respectively. We will also use the notation $\Delta^A Z \equiv Z - E[Z|A]$, for any $Z, A \in \{Y, F, C, S\}$.

2.1 How Much Does City Matter within the Firm?

To quantify how much individual worker wages vary by city of employment, we extract the share of wage variance that is between city. To assess how much this changes within the firm, we calculate the change in the share of between city variance when we use all workers vs when we condition on firm of employment. Throughout we use only the variance that is within skill in order to restrict analysis to comparable workers. Empirically, we will operationalize skill using the occupation (two-digit SOC code) interacted with the tenure (years of relevant work experience) group of the worker. Two natural proxies for worker-specific effects on wage, such as human capital.[5]

To extract the within skill component of the wage variance, we use the law of total variance[6]:

$$Var[Y] = \underbrace{Var(\overbrace{Y - E[Y|S]}^{=\Delta^S Y})}_{\text{within skill}} + \underbrace{Var(E[Y|S])}_{\text{between skill}} \tag{1}$$

where Y is the wage and S is skill. We refer to $\Delta^S Y = Y - [Y|S]$ as the within skill wage — the deviation of a worker's wage from the average wage of workers with the same skill. $\Delta^S Y$ is identified from the residual of a regression of wages on skill fixed effects. To quantify how much wages vary by city, C, for workers of the same skill, we extract the between city component of the within skill wage variation by reiterating the law of total variance:

$$Var\left[\Delta^S Y\right] = \underbrace{Var\left(\Delta^S Y - E\left[\Delta^S Y \middle| C\right]\right)}_{\text{within city}} + \underbrace{Var\left(E\left[\Delta^S Y \middle| C\right]\right)}_{\text{between city}} \tag{2}$$

The second term is the between city variation of within skill wages, equal to the variance of the city-average within skill wage, $E\left[\Delta^S Y \middle| C\right]$. Intuitively, this object is equal to how much, on average, wages for workers

[5] As we see in figure A.2, professional tenure, as one would expect, has a very robust positive relationship with wages, even within firm and occupation. We see a flattening at about 20 years onwards.

[6] Often the law of total variance is written in a slightly different form using the identity $Var(Y - [Y|A]) = E(Var[Y|A])$ for some random variable A.

in city C deviate from wages of comparable (equal skill, S) workers in other cities. Taking the ratio of this to the total variance of within skill wages:

$$\text{VarSh}^S \equiv \frac{Var\left[E\left\{\Delta^S Y \middle| C\right\}\right]}{Var\left[\Delta^S Y\right]} \tag{3}$$

This share quantifies how much wages vary across cities for workers of the same skill. This is identified from the R-squared of a regression of within skill wages on city fixed effects.[7] We apply a bias correction to the estimates of all variance share in this section based on Kline et al. (2020).[8]

Next, for workers employed in the same firm. We begin by extracting the within firm-skill component of the wage variation by:

$$Var\left[Y\right] = \underbrace{Var(\overbrace{Y - E\left[Y|F,S\right]}^{\Delta^{FS}Y})}_{\text{within firm-skill}} + \underbrace{Var\left(E\left[Y|F,S\right]\right)}_{\text{between firm-skill}} \tag{4}$$

where F denotes the firm of employment, and $\Delta^{FS}Y = Y - [Y|F,S]$ we refer to as the within firm-skill wage — the deviation of a worker's wage to the average wage of workers within the same firm and of the same skill. We then extract the between city component of this by:

$$Var\left[\Delta^{FS}Y\right] = \underbrace{Var\left(\Delta^{FS}Y - E\left[\Delta^{FS}Y \middle| C\right]\right)}_{\text{within city}} + \underbrace{Var\left(E\left[\Delta^{FS}Y \middle| C\right]\right)}_{\text{between city}} \tag{5}$$

The between city variation is the second term. $E\left[\Delta^{FS}Y \middle| C\right]$ describes how much wages for workers in city C on average deviate from wages of comparable (equal skill, S) workers in the same firm F in other cities. Taking the ratio of this to the total variance of within firm-skill wages:

$$\text{VarSh}^{FS} \equiv \frac{Var\left[E\left\{\Delta^{FS} Y \middle| C\right\}\right]}{Var\left[\Delta^{FS} Y\right]} \tag{6}$$

This share quantifies the amount that wages vary across cities for workers of the same skill in the same firm. This can be identified from the R-squared of a regression of within firm-skill wages on city fixed effects.

The percentage change in the variance shares from equation (3) to (6), given in equation (7), provides us with a measure for the relative importance of city for wages across all workers of the same skill vs workers of the same skill employed by the same firm:

$$\Delta\%\text{VarSh} \equiv \frac{\text{VarSh}^{FS} - \text{VarSh}^S}{\text{VarSh}^S} \tag{7}$$

2.2 City Selection vs Firm-Level Wage Anchoring

To distinguish between the two channels of interest — city selection vs firm-level wage anchoring — we utilize the workhorse fixed effect model of wage determination (Abowd et al., 1999; Card et al., 2018), modified slightly for our setting:

[7] The city fixed effect in this regression identifies $E\left[\Delta^S Y \middle| C\right]$. The R-squared equals the variance of the fixed effect divided by the variance of the dependent variable, $\Delta^S Y$. Hence, the share in equation (3).

[8] Variance estimates may be biased if our sample has a small number of workers in the corresponding fixed effect group, akin to a limited mobility bias (Card et al., 2018). We correct for this by using equation (4) from Kline et al. (2020) to get a bias-corrected estimate for $Var\left(E\left[Y|S\right]\right)$, and use this in our equation (1) to get a bias-corrected estimate of $Var\left[\Delta^S Y\right]$ for equation (3). We apply analogous steps for $Var\left[\Delta^{FS} Y\right]$ in equation (6). Following Card et al. (2022b), we do not need to correct the numerators in either share because these are variances of city averages, and each city contains many workers.

$$Y = \gamma_C + \alpha_F + \mu_S + \varepsilon \tag{8}$$

where γ_C, α_F and μ_S are city, firm and skill fixed effects. This statistical decomposition measures the extent to which workers of a specific city, firm, or skill, respectively, receive systematically different wages, while holding the others fixed. The value of each term may reflect causal mechanisms, such as those due to variation in the cost of living or agglomeration economies for the city effects, technology or rent-sharing for the firm effects, and human capital for the skill effects. Unobserved confounders (e.g. ability) give caution to a causal interpretation, so we only interpret our results as being consistent with causality.[9]

We use the model in equation (8) to decompose the wage variation across cities. Starting with the within skill wage variance share that is between cities, equation (3). We use equation (8) to calculate the within skill wage:

$$\Delta^S Y = \Delta^S \gamma_C + \Delta^S \alpha_F + \underbrace{\Delta^S \mu_S}_{=0} + \Delta^S \varepsilon \tag{9}$$

where $\Delta^S \mu_S = 0$ because skill is, by definition, constant for workers of the same skill. Next we calculate the city-average of the within skill wage:

$$E\left[\Delta^S Y \middle| C\right] = E\left[\Delta^S \gamma_C \middle| C\right] + E\left[\Delta^S \alpha_F \middle| C\right] + \underbrace{E\left[\Delta^S \varepsilon \middle| C\right]}_{=0} \tag{10}$$

where $E\left[\Delta^S \varepsilon \middle| C\right] = 0$ because the residual of equation (8) is, by construction, orthogonal to both skill S and city C. Inserting this into the numerator of the variance share in equation (3), we decompose the variance as follows (see Card et al. (2018) pg S26-S27 for details)[10]:

$$\underbrace{\frac{Var\left(E\left[\Delta^S Y \middle| C\right]\right)}{Var\left(\Delta^S Y\right)}}_{=\text{VarSh}^S} = \frac{Cov\left(E\left[\Delta^S Y \middle| C\right], E\left[\Delta^S \gamma_C \middle| C\right]\right)}{Var\left(\Delta^S Y\right)} + \frac{Cov\left(E\left[\Delta^S Y \middle| C\right], E\left[\Delta^S \alpha_F \middle| C\right]\right)}{Var\left(\Delta^S Y\right)} \tag{11}$$

This equation decomposes the extent to which workers of the same skill are located across cities with systematic differences in wages, VarSh^S, into the contribution from the city effect γ_C and firm effect α_F. The city effect term quantifies any systematic differences in wages across cities, holding fixed the firm of employment and skill of the worker, such as due to the cost of living (Glaeser and Mare, 2001; Glaeser and Gottlieb, 2009; Behrens et al., 2014; Card et al., 2022b). The firm effect term quantifies the wage variation associated with variation in the composition of firms across cities, resulting in systematic differences in wages across cities, which may arise from sorting of firms by location (Mion and Naticchioni, 2009; Combes et al., 2012; Dauth et al., 2022; Bilal, 2023).

For the within firm-skill wage variance share that is between cities, equation (6), we proceed similarly but for the within firm-skill wages, $\Delta^{FS} Y$. This results in the following variance decomposition:

[9] See Card et al. (2018) for more information on causality in these models. Our cross-sectional approach follows others in the urban wage premia literature (Moretti, 2013; Autor, 2019).

[10] We do not bias-correct the estimates of the (co)variances in the numerators given the arguments are city aggregates. See footnote 8.

$$\underbrace{\frac{Var\left(E\left[\Delta^{FS}Y\middle|C\right]\right)}{Var\left(\Delta^{FS}Y\right)}}_{=\text{VarSh}^{FS}} = \frac{Cov\left(E\left[\Delta^{FS}Y\middle|C\right], E\left[\Delta^{FS}\gamma_C\middle|C\right]\right)}{Var\left(\Delta^{FS}Y\right)} + \frac{Cov\left(E\left[\Delta^{FS}Y\middle|C\right], E\left[\Delta^{FS}\alpha_F\middle|C\right]\right)}{Var\left(\Delta^{FS}Y\right)} + \frac{Cov\left(E\left[\Delta^{FS}Y\middle|C\right], E\left[\Delta^{FS}\varepsilon\middle|C\right]\right)}{Var\left(\Delta^{FS}Y\right)} \tag{12}$$

Unlike in the case of the within skill wages in equation (10), the residual term in the case of within firm-skill wages is not zero, $E\left[\Delta^{FS}\varepsilon\middle|C\right] \neq 0$. Mathematically, this is because the residual is not orthogonal to firm-skill interactions, as the model in equation (8) does not contain such an interaction. This term captures any wage variation between cities unexplained by our model of wage determination.

Finally, we combine the variance share decompositions from equations (11) and (12) to decompose the change in the between city variance share when going within the firm, equation (7):

$$\Delta\%\text{VarSh} = \frac{1}{\text{VarSh}^S}\left[\frac{Cov\left(E\left[\Delta^{FS}Y\middle|C\right], E\left[\Delta^{FS}\gamma_C\middle|C\right]\right)}{Var\left(\Delta^{FS}Y\right)} - \frac{Cov\left(E\left[\Delta^{S}Y\middle|C\right], E\left[\Delta^{S}\gamma_C\middle|C\right]\right)}{Var\left(\Delta^{S}Y\right)} + \cdots\right] \tag{13}$$

where, to conserve on space, we've only displayed the term in the decomposition corresponding to city effect, γ_C. The firm effect and residual term are identical, except for γ_C replaced with α_F and ε, respectively.

Equation (13) provides the decomposition of the variance change, $\Delta\%$VarSh, into the two channels of interest to us. The city effect term captures the city selection channel: the contribution from firms locating their establishments in cities that are associated with similar wages (e.g., reflecting the local cost of living). Mathematically, the extent to which there is less variation in the city effects γ_C across the cities of comparable workers employed by the same firm, $E\left[\Delta^{FS}\gamma_C\middle|C\right]$, than there is across cities of comparable workers across all firms, $E\left[\Delta^{S}\gamma_C\middle|C\right]$. The firm effect term (not displayed) captures the firm-level wage anchoring channel: the contribution from firms offering similar wages regardless of the location of its establishment (e.g., reflecting a firm-wide wage setting policy, Hjort et al. (2020); Hazell et al. (2022)). Mathematically, the extent to which there is less variation in the firm effects across cities for comparable workers employed by the same firm, $E\left[\Delta^{FS}\alpha_F\middle|C\right] = 0$ (which is zero because the firm effects are constant within a firm), than there is for comparable workers across all firms, $E\left[\Delta^{S}\alpha_F\middle|C\right]$.

2.3 Features of the Two Channels

To gain concrete insight into the two channels of interest, we project the city and firm fixed effects from section 2.2 onto relevant observable features, in order to assess the contribution of each of these to the wage variation. We detail the procedure here for the city effect, but it is entirely analogous for the firm effect. We project the city fixed effect as follows:

$$\gamma_C = \beta^{(0)} + \sum_{k=1}^{K} \beta^{(k)} x_C^{(k)} + \epsilon_C \tag{14}$$

where $k \in \{1, ..., K\}$ is an index for the observable features of interest, and $x_C^{(k)}$ is the value of feature k in city C (for example, the cost of living in city C). The city effect component of VarSh^S, equation (11), is decomposed by inserting equation (14) to give

$$\frac{Cov\left(E\left[\Delta^S Y|C\right],E\left[\Delta^S \gamma_C|C\right]\right)}{Var\left(\Delta^S Y\right)}=\sum_{k=1}^{K}\beta^{(k)}\frac{Cov\left(E\left[\Delta^S Y|C\right],E\left[\Delta^S x_C^{(k)}\middle|C\right]\right)}{Var\left(\Delta^S Y\right)}+\frac{Cov\left(E\left[\Delta^S Y|C\right],E\left[\Delta^S \epsilon_C|C\right]\right)}{Var\left(\Delta^S Y\right)} \tag{15}$$

The result is a variance contribution from each of the k features (and the unexplained component in the residual). We can apply an analogous decomposition for within firm-skill variance share between cities, equation (12), and thus quantify the contribution of each feature k to the change in the variance share between cities using equation (13).

For the city effects, we use three features, each capturing key factors of wage determination across cities (Combes and Gobillon, 2015; Card et al., 2018). The first feature is the Zillow house price index, which is a reasonable proxy for the cost of living at the city level. This is because labor supply in a city likely depends on the real wage and therefore the cost of living. The second feature is the city's population. In the presence of agglomeration economies, both worker productivity and local amenities, and therefore local labor demand and supply, respectively, might be a function of the economic size of the location. The third feature is union membership, which is a proxy of how much market power workers have in the labor market.

For the firm effects we use two features, each capturing distinct alternatives for how a firm anchors its wages instead of using the local labor market condition of the city of employment (Hjort et al., 2020; Hazell et al., 2022). The first is whether they anchor wages against an average of the local labor market conditions across all the cities their establishments operate in; the second is against the local labor market condition of the city of their headquarters. This first is constructed as an average (weighted by number of employees) of the city effects across the cities that the firm operates in, $E[\gamma_C|F]$. The second is equal to the city effect of the city where their headquarters is located. We use the city effects, those estimated from equation (8), as these appropriately capture the labor market conditions of any given city.

3 Data

We present our data sources and sample selection in section 3.1, benchmark our sample to the CPS in section 3.2 and provide summary statistics in section 3.3.

3.1 Sources and Sample

Earnings Data. We use the population of respondents to the 2015-2019 waves of Glassdoor's salary survey. This contains 7,092,651 entries with 6,657,104 unique individuals — that is, for the most part our data is not a panel. There are 34 variables, including demographic characteristics (e.g. highest education, gender, birth year), job-related (job title, occupation, years of relevant experience, base salary and additional compensation such as stock options, bonuses and tips), and company-related variables (firm identifiers, annual revenue, firm employment, sector, and location of employment). While there are several missing responses for personal demographic variables, most job-related and company-related variables were required to be filled out by respondents. We matched the occupation to 2-digit SOC codes. We matched the locations of employment almost entirely to official US Census designations, primarily Incorporated Places. There are a total of 858 locations, which we refer to as cities, for convenience.

There are two very useful and unique features of this data for our purposes. First, we can distinguish among same-firm employees who are employed in establishments in different cities. Second, we observe both occupation and years of relevant experience–both of which are rarely observed in survey or administrative data–which is used to condition on comparable workers in our analysis. We categorize the years of relevant experience into nine tenure groups 0, 1, 2, 3, 4-5, 6-10, 11-15, 16-20, 20+.

Additional Data. We use data with characteristics related to the location of employment: city house prices from Zillow, population data from the US Census, and union membership from the CPS.[11] We produced an original data set on the location (city) of the headquarters of each firm. We scraped from Google the full address and latitude/longitude of each of the 24,679 firms in our the Glassdoor sample. In the cases where there was not an exact match with the cities in the Glassdoor dataset, we set it equal to the closest city. New York City is the most common headquarter city (2553 firms); 2142 firms have their headquarters outside the U.S.

Main Sample: We remove respondents from the Glassdoor survey who had missing data on location of employment, firm of employment, or occupation (1,807,177 observations dropped). Further, we limit the sample to working-age (18-64) adults who have up to 40 years of experience in their profession, and who work in multi-location firms such that there are at least 20 respondents per firm. We include workers whose base annual earnings is at least $10,000 to ensure our workers have some labor market attachment (we do not observe hours worked).[12] Base earnings is truncated above $215,000 USD (approximately the 99th percentile in our data set) and total earnings above $400,000 USD; this includes all but the top earners, whose overall earnings mainly comprise of bonuses and stock options. We trim the data further to employ the variance bias correction in Kline et al. (2020), by dropping observations where the firm-occupation-tenure cell equals one. Our final sample consists of 3,471,345 person-year entries, 24,679 firms and 858 metropolitan areas.

3.2 Comparison with the CPS

Respondents of Glassdoor's salary survey are not a random sample. Individuals self-select in, presumably to learn about labor market opportunities in their profession. The information on Glassdoor (salary ranges, amenities, promotion opportunities, etc) is hidden until individuals complete the survey, thus incentivizing their participation. Additionally, employees of multi-location firms may use the platform to understand differences in opportunities across establishments within a firm. Given this setup, one concern might be that workers in our sample are more sophisticated on average and not nationally representative. To assess this, we compare salaries and education levels from different subsets of our data with those from the CPS for the same time frame, 2015-2019.

We graph the distribution of annual earnings for workers using both data sets in figure A.1a for a broad set of workers and find that Glassdoor workers earn about 28% more than their CPS counterparts. We then limit base earnings from both surveys to our sample range, $10,000 to $215,000, and restrict the CPS sample to full-time workers (who likely have greater labor market attachment) in figure A.1b; the difference in annual earnings shrank to 20.5%.

Salaries in our main Glassdoor sample are likely higher since we impose firm size and other cell size

[11] Zillow: https://www.zillow.com/research/data/. Population: https://www.census.gov/data/tables/time-series/demo/popest/2020s-total-cities-and-towns.html. Union membership: www.unionstats.com.

[12] We replaced base earnings with total earnings for respondents whose base annual earnings was less than $10,000 USD.

restrictions to create our sample of interest. Since our research question is primarily concerned with understanding the role of location for same-firm workers, employees of small businesses and single-location firms are naturally excluded and may represent a significant share of low-wage earners. In fact, Table A.1 reveals that earnings of individuals employed in single-location firms in the Glassdoor sample are much closer to average earnings among CPS respondents, and substantially lower than earnings of workers in multi-location firms. This is consistent with evidence in the literature of larger firms paying higher wages (Song et al., 2019).

3.3 Summary Statistics

Summary statistics for the main variables used in this analysis are displayed in table 1. On average, workers are 31 years old, most of which have at least a four-year college degree and about five years of relevant work experience in their profession. On average, workers' base annual earnings are $58,758 and they earn approximately $6500 extra beyond their base salary. There is considerable heterogeneity, with those in the bottom decile earning less than $22,000 while those in the top decile earning over $125,000. Non-base earnings are mild in the bottom half of the earnings distribution but increase rapidly as we approach the top percentiles. For workers in the top percentiles, non-base earnings consist of 25-45% of total annual earnings.

At the city level, average wages are $41,988, ranging from $23,740 to $101,025. These statistics show that spatial wage inequality is substantial, explaining why the role of location has attracted considerable attention from policymakers and academics alike. Employees in high-wage cities (P90 and above) earn 1.7-3 times more than their counterparts in low-wage cities (P10 and below). The standard deviation of city-average (ln) wages is 0.18, almost twice as high as that reported in Germany (Dauth et al., 2022).

Our sample of 3,471,345 workers are employed in 24,679 unique firms, with firms opening establishments in an average of 19 cities. The firm operating in the most cities is Walmart (840 cities). Note that the distribution of the number of cities of operation is highly skewed to the right; the median number of establishments (8) is half the mean number of establishments (19) — similarly with firm size, median of 30 vs mean of 141. The fact that the bulk of the data is on the left side of the distribution implies that our results are not driven by a few firms located in hundreds of cities.

4 Results

We quantify how much location matters for all workers, compared to those employed by the same firm, in subsection 4.1. In subsection 4.2, we present the decomposition into the two channels: city selection vs firm-level wage anchoring. In subsection 4.3 we analyze the features of these two channels.

4.1 Location matters less within the Firm

The results from the exercise of section 2.1 are given in table 2. The analysis for comparable workers, our specification of interest, is in column (2). We see that the share of earnings variance across cities is 0.113 (column 2, row 1) — corresponding to equation (3). When we restrict the variance calculation to comparable workers employed in the same firm, we see the share falls to 0.022 (column 2, row 2) — corresponding to equation (6). This is a substantial decline in the share explained by cities, amounting to 81% (column 1, row 3) — corresponding to equation (7). The same result emerges if we do not restrict to comparable workers. These results are presented in column (1) of table 2, where there is a decline of 77%. That is, for all workers or for only comparable workers, location matters much less for wages once we examine workers employed by the same firm.

We provide a related calculation as a benchmark: instead of going within the firm, we go within a particular skill level instead. That is, we compute the difference in the share of wage variance between cities for all workers vs workers of the same skill. This is displayed in column (3) row 1 of table 2. The share declines by only 1.7%. Another benchmark is in column (3) row 2: restricting to workers of the same firm, the difference in the share of wage variance between cities for all workers vs that of workers of the same skill. The share declines here by 19%. These declines are much smaller than in the previous exercise, suggesting that location distinctly matters much less for workers employed by the same firm.

4.2 City Selection vs Firm-Level Wage Anchoring

Following the method in section 2.2, we decompose the variance decline into the contribution from the city selection channel (the city effect), and that arising from the firm-level wage anchoring channel (the firm effect). Table 3 presents the decomposition of the wage variance between cities for all comparable workers in column (1), for all comparable workers in the same firm in column (2), and the decline of the variance between the two in column (3). This decline is also displayed visually in figure 1. For reference, in row 1 of table 3, and visualized in figure 1a, we repeat the figures from table 2 column (2) showing the non-decomposed variance. The remaining rows show the contribution of each term labelled in the row header. Note that these all sum up to the corresponding value in row 1.

For comparable workers, the share of wage variation between cities attributable to the city effects is 0.073 (column 1, row 2) and to the firm effects is 0.040 (column 1, row 7). These correspond to equation (11). This reveals that most of the variation is coming from the city effect — systematic differences across cities, holding the firm and skill fixed — rather than the firm effect — systematic differences in wages due to a varying composition of firms across cities. For comparable workers employed in the same firm, the city effects contribute 0.024 and the firm effects, by construction, contribute precisely zero (column 2, rows 2 and 7). These correspond to equation (12).

In column (3), and visualized in figure 1b, we use equation (7) to calculate how much the city and firm effects contribute to the 81% decline in wage variation between cities, when we go within the firm. The city effect contributes 44 percentage points, and the firm effect contributes 35 percentage points. That is, both effects contribute roughly equally. In understanding why wages vary much less across locations within the firm, firms opening establishments in similar cities (the city effect) is just as important as wages being anchored at the firm-level (the firm effect).

4.3 Features of the Two Channels

We apply the method of section 2.3 to decompose the two channels into their relevant features.

City selection. The decline attributed to the city effect (table 3 column 3, row 2) reveals that firms open their establishments in relatively similar cities. In which ways are these cities similar? Using equation (15), we decompose the city effect's variance contribution into three standard factors of local wage determination. The results are presented in rows 3 to 6 of table 3, and visually in figure 1c. Focusing on the contribution to the decline in the between city wage variance, column (3), we see that the Zillow house price index accounts for over half of the decline (27 of the 44 percentage points), while population and union membership contribute negligible amounts (3.3 and 4.1 percentage points, respectively).

That is, firms are opening establishments in cities that have, to a large extent, a similar cost of living (proxied for by Zillow). Cities characterized by similar agglomeration economies (proxied for by population) or labor market power (proxied for by union membership) are not as relevant.

Firm-level wage anchoring. The decline attributed to the firm effect (table 3 column 3, row 7) reveals that a firm tends to offer similar wages across its cities of operations, regardless of the local labor market conditions. How is a firm anchoring their wages, if not entirely against the worker's city of employment? Using equation (15), we decompose the firm effect's variance contribution into a component capturing the average of the local labor markets across all cities that the firm operates in, and a component capturing the local labor market of the city of its headquarters. The results are presented in rows 8 to 10 of table 3, and visually in figure 1c.[13] Focusing on the contribution to the decline in the between city wage variance, column (3), we see that both these components contribute about equally, 10 and 11 percentage points (out of 35), respectively. Combined, these factors contribute about the same as the cost of living (27 pp) of a worker's city, and are about half as important as all local labor market factors of the worker's city of employment (44 pp).

That is, firms are anchoring their workers' wages equally to the average labor market across all its cities of operation, as it is to the labor market of the headquarter's city, which combined are about half as important as the labor market of the worker's city of employment.

5 Conclusion

We investigate how wages vary between establishments of the same firm but in different cities. We find that this variation declines dramatically for workers in the same firm. This is an interesting result because it is well-known that wages vary considerably across space. Yet, for employed in the same firm, we find the role of location is highly diminished.

An important question for policy is why is this so? Can this be attributed to firm-level wage setting policy, or is it because the labor market conditions of the cities a firm operates in are sufficiently similar? Both would lead to a compression in wages across space, and thus be consistent with our findings. Yet only the former is conducive for a place-based policy predicated on bringing high-wage firms to low-wage cities.

Using a fixed effect model of wage determination, we find that both channels contribute about equally. This suggests that policy-makers need to be cautious about assuming high-wage firms will bring high-wage jobs to prospective low-wage cities.

[13] We exclude firms with headquarters outside the U.S. for this specification as we cannot estimate the city fixed effects, γ_C, in equation (8) for them.

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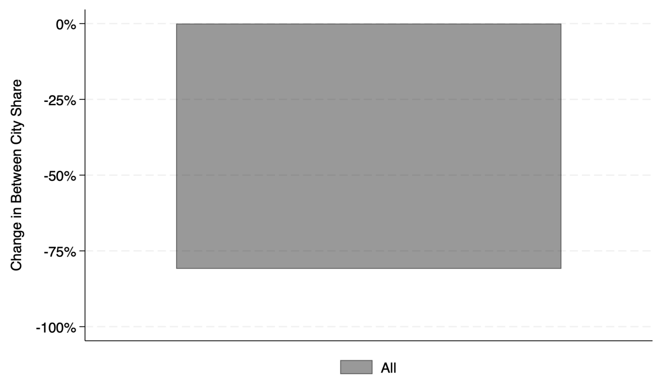
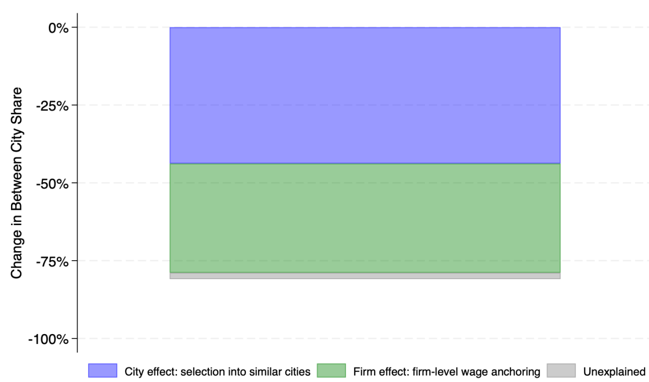
Figure 1: Going within the Firm: Decomposition of the reduction in Wage Variation between Cities

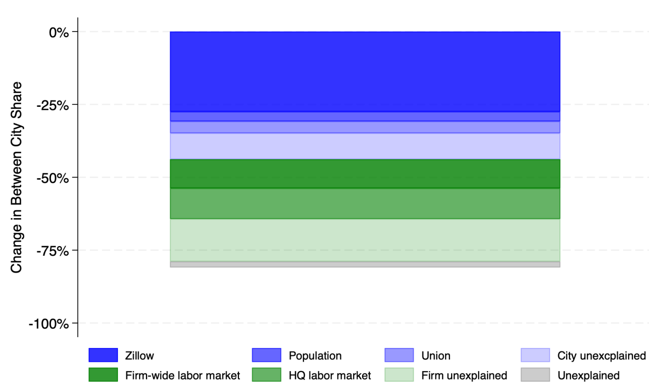
(a) Overall Reduction in Wage Variation



(b) Decomposition by City and Firm Effects



(c) Decomposition by Features of City and Firm Effects



Notes. The decomposition of the variance share, equation (7), using the model in sections 2.2 and 2.3 is displayed. Sub-figure 1a shows the full between city variance share for reference. Sub-figure 1b shows the decomposition using city and firm effects. Sub-figure 1c shows the further decomposition of this using the features.

Table 1: Descriptive Statistics

	N	Mean	Sd	Min	P10	P25	P50	P75	P90	P99	Max
Individual-level											
Age	1,003,014	31.1	9.2	18	22	24	28	36	45	59	64
Years of Schooling	878,843	15.9	1.59	12	12	16	16	16	18	18	21
At least Bachelors Degree	878,843	0.88	0.325	0	0	1	1	1	1	1	1
Relevant Years of Experience	3,471,345	4.97	5.99	0	0	1	3	7	13	28	40
Annual Base Earnings	3,471,345	58,758	38,265	10,000	21,276	29,447	48,048	77,077	114,839	181,443	214,984
Log (Annual Base Earnings)	3,471,345	10.8	0.624	9.21	9.97	10.3	10.8	11.3	11.7	12.1	12.3
Total Annual Earnings	3,471,345	65,175	48,614	10,000	21,518	30,506	51,037	83,717	128,128	244,121	399,961
Ln (Total Annual Earnings)	3,471,345	10.9	0.666	9.21	9.98	10.3	10.8	11.3	11.8	12.4	12.9
City-level											
City-Average Base Earnings	858	41,988	8,554	23,740	32,971	36,373	40,623	45,836	53,790	68,524	101,025
City-Average Log Base Earnings	858	10.5	0.18	9.96	10.3	10.3	10.5	10.6	10.7	11	11.4
Firm-level											
Number of firm-city units	24,679	19.3	37.8	2	2	4	8	19	41	185	840
Firm Size*	24,679	141	653	2	10	15	30	79	244	1,872	31,257
Firm-occupation-tenure level											
Firm-Occ-Ten Size	421,967	8.23	29.8	2	2	2	3	6	14	84	3,083

Notes. Glassdoor data (2015-2019). Sample is restricted such that all workers are employed in multi-location firms, each of which includes at least 20 observations per firm and at least 2 observations per firm-occupation-tenure group in the data set. Workers are between the ages of 18 and 64, have a maximum number of years of relevant experience at 40 and their base (total) annual earnings is restricted to those earning between $10,000 and $215,000 ($400,000) per year. *When restricting the original data set, we only included workers who were employed in firms such that there are at least 20 workers per firm in the data set. However, when dropping all observations such that firm-occ-ten size is less than 2, we lost several thousand observations. Consequently, our final sample includes some firms (8504 firms) that have fewer than 20 observations; 105,138 workers (3%) are employed in these firms.

Table 2: Wage Variation between Cities

	y Total (1)	y Skill (2)	Change (3)
Share of within y wage variance between cities	0.115	0.113	-1.7%
Share of within firm-y wage variance between cities	0.027	0.022	-19%
Change	-77%	-81%	

Notes. The non-shaded cells show the variance share specified in the row header, with y indicated in the column header. The shaded cells show the percentage change in the variance share in the respective row or column. The number of observations in each specification is 3,471,345.

Table 3: Decomposition of the Wage Variation between Cities

	Skill (1)	Firm-Skill (2)	Change (3)
All	0.113	0.022	-81%
City	0.073	0.024	-44%
Zillow	0.045	0.014	-27%
Population	0.006	0.002	-3%
Union membership	0.006	0.002	-4%
City unexplained	0.016	0.006	-9%
Firm	0.040	0.000	-35%
Firm-wide labor market*	0.011	0.000	-10%
HQ labor market*	0.012	0.000	-11%
Firm unexplained*	0.016	0.000	-15%
Unexplained	0.000	-0.002	-2.0%

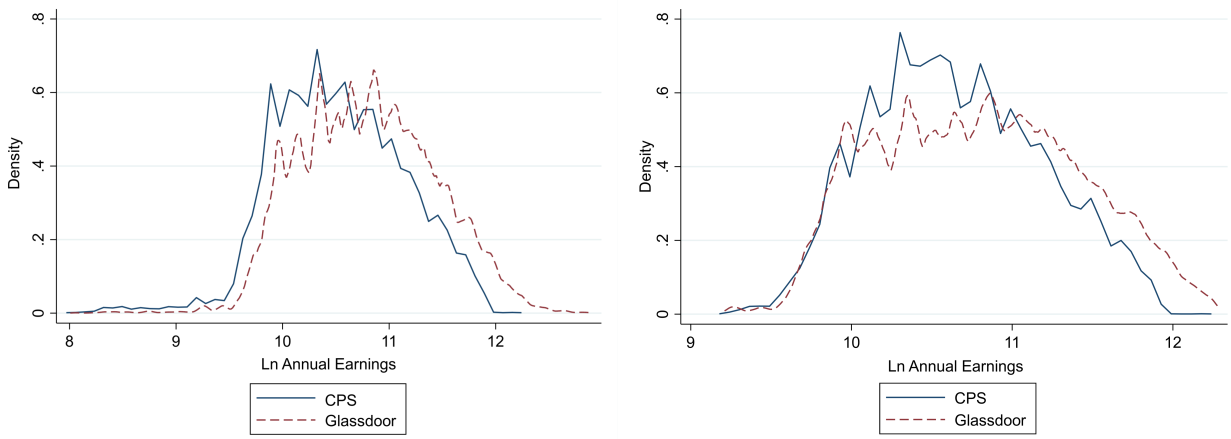
Notes. Column (1) shows the variance contribution to the within skill wage between cities, column (2) to the within firm-skill wage between cities. The first row shows the entire variance, with column (3) displaying the change between the first two columns in percentage points. Note that the first row is equal to table 2, column (2). The remaining rows show the contribution of each term labelled in the row header, where column (3) displays the contribution to the percentage change of the first row (the difference in column 2 from 1 relative to entire variance of the within skill wage, column 1 row 1). Note that the remaining (non-header) rows add up to the values in the first row (subject to rounding). The number of observations in each specification is 3,471,345, except in the rows market by *, where we only use 3,189,955 observations. This is because 281,390 individuals are employed in firms whose HQ office is located outside the US.

Appendices

A Additional Figures and Tables

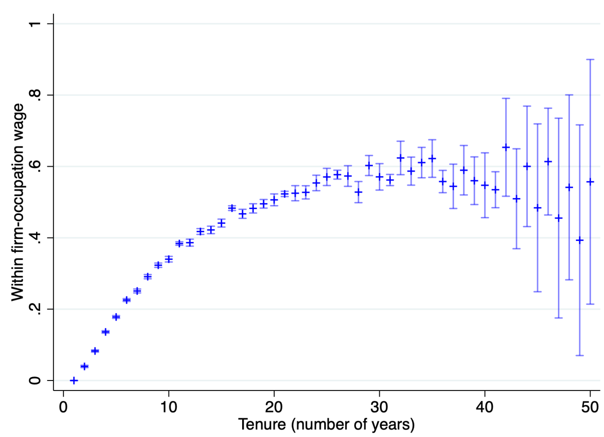
Figure A.1: Density of Annual Earnings: Glassdoor vs CPS

(a) \$3,000<Annual Earnings<\$400,000 (b) CPS (Full-time); \$10,000<Annual Earnings <\$215,000



Notes. Figure A.1a displays the distribution of ln earnings for all CPS and Glassdoor respondents (from 2015 to 2019) who reported (ln) annual earnings between \$3,000 (8) and \$400,000 (12.9). The sample size of Glassdoor was 7,012,109 while that of the CPS was 776,311. Figure A.1b restricts the CPS sample to full-time workers whose (ln) annual earnings ranged from \$10,000 (9.21) to \$215,000 (12.3) per year. The Glassdoor sample has the same earnings restrictions while also being subjected to other restrictions in the main sample (see text for more details). The Glassdoor and CPS sample sizes are 3,471,345 and 591,167 respectively.

Figure A.2: Average Wage by Tenure



Notes. Within firm-occupation annual earnings is regressed on tenure fixed effects. The fixed effect estimates are displayed, interpreted as the average wage by duration of tenure, relative to other workers in the same firm and occupation.

Table A.1: Glassdoor vs CPS: Covariates

	Glassdoor Broad Sample (1)	Glassdoor Main Sample (2)	Glassdoor Single-Location (3)	CPS Full-time Workers (4)
Annual Earnings	59,725	58,758	50,256	48,726
Ln Annual Earnings	10.8	10.79	10.68	10.65
Hourly Wage	29.86	29.38	25.13	24.36
Ln Hourly Wage	3.2	3.19	3.08	3.05
Years of Schooling	15.9	15.9	15.9	13.8
Bachelors Degree or Higher	0.88	0.88	0.88	0.37

Note: Glassdoor and CPS data (2015-2019). In column (1), the broad sample of Glassdoor data is restricted to those who reported (ln) annual earnings between \$3,000 (8) and \$400,000 (12.9). The sample size is 7,012,109 for earnings variables and 1,651,791 for education variables. Column (2) includes the main sample of Glassdoor where workers are employed in multi-location firms and their base (total) annual earnings are restricted between \$10,000 and \$215,000 (\$400,000) per year; the sample sizes for earnings and education variables are respectively, 3,471,345 and 878,843. Summary statistics for workers in single-location firms (according to our data set) are included in column (3); the sample sizes for earnings and education variables are respectively 739,152 and 159,614. Summary statistics for full-time workers in the CPS are presented in column (4), where the sample size for all variables is 591,167.

Table A.2: Descriptive Statistics for Glassdoor (Broad Sample)

	N	Mean	SD	Min	P10	P25	P50	P75	P90	P99	Max
Age	1,916,532	32	9.68	18	22	25	29	37	47	60	64
Years of Schooling	1,651,791	15.9	1.58	12	12	16	16	16	18	18	21
Bachelors or More	1,651,791	0.879	0.326	0	0	1	1	1	1	1	1
Relevant Years of Experience	7,012,109	5.54	6.54	0	0	1	3	8	15	30	40
Annual Earnings	7,012,109	59,725	40,467	3,003	21,645	30,525	48,452	76,313	114,342	198,769	400,000
Ln (Annual Earnings)	7,012,109	10.8	0.626	8.01	9.98	10.3	10.8	11.2	11.6	12.2	12.9
Total Earnings	7,012,109	65,484	49,738	3,003	22,336	31,746	50,968	81,942	126,897	260,613	400,000
Ln (Total Earnings)	7,012,109	10.9	0.662	8.01	10	10.4	10.8	11.3	11.8	12.5	12.9

Note: Glassdoor data (2015-2019). The sample is restricted to workers whose age is either missing or between 18 and 64, those with less than 40 years of relevant work experience and those with annual earnings between $3,000 and $400,000 per year. There are no firm-related restrictions or other cell size restrictions.

Table A.3: Total Wage Variance Explained by Covariates

	R^2	
	(1)	(2)
Adnan, Norris	0.68	
Card et al. (2022b)		0.86

Notes. Comparison of the R^2 from the wage determination model in the current study and in Card et al. (2022b). The R^2 of row 1 is of equation (8) (city fixed effect, firm fixed effect, and occupation-tenure fixed effects). The R^2 of row 2 is from Card et al. (2022b) table 3, column 2 using all their covariates (age, calendar time, commuting zone-industry fixed effect, and individual fixed effects).