National Wage Setting*

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July 2025

Abstract

How do firms set wages across space? We document four facts using matched employer-employee data. First, firms rather than locations explain most of the variation in wages within a job, with an excess mass of firms paying near-identical wages across space. Second, nominal wages within the firm vary relatively little with local prices, compared to how wages vary between firms. Third, wage growth is more correlated with firm-level rather than regional factors. Fourth, local wage shocks cause wage growth in the rest of the firm, but only for jobs that initially pay similar wages across space. We argue these patterns indicate *national wage setting*, in which firms compress nominal wages across space relative to what benchmark models predict.

JEL Codes: J24, J45, J33, H56

*We thank Lila Englander, Michael Galperin, Andrew Hicks, Nidhaan Jain, Prerna Kundu, Isaac Liu, Mélyne Nzabonimpa and Daniela Villacreces for excellent research assistance; Anna Stansbury for sharing code; Sean Wang for pointing us to the H1B Visa Application data; and Otis Reid for helpful discussions that shaped the development of the project. We thank our discussant Matthew Gentzkow, as well as Daron Acemoglu, David Autor, Adrien Bilal, Allison Cole, Ellora Derenoncourt, Jonathan Dingel, Alex Frankel, Erik Hurst, Anders Humlum, Thomas Lemieux, Isabela Manelici, Simon Jager, Lisa Kahn, Alan Manning, Matt Notowidigdo, Benjamin Schoefer, Isaac Sorkin, John Van Reenen and Jose Vasquez for helpful discussions that shaped this draft. This research uses data from the Census Bureau's Longitudinal Employer Household Dynamics Program, which was partially supported by the following National Science Foundation Grants SES-9978093, SES-0339191 and ITR-0427889; National Institute on Aging Grant AG018854; and grants from the Alfred P. Sloan Foundation. Any views expressed are those of the authors and not those of the U.S. Census Bureau. The Census Bureau has reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 2347. (CBDRB-FY24-P2347-R11115). In the interest of disclosure, Bledi Taska was previously chief economist of Burning Glass Technologies, who provided one of the main datasets for this paper. First version: September 2021.

1 Introduction

In the U.S., big firms have grown in large part by expanding into new regions (Hsieh and Rossi-Hansberg, 2021). As a result, local labor markets have become dominated by a small number of large firms that operate in many regions. Therefore, while the concentration of employment across firms in local labor markets has fallen in recent decades, the concentration of employment nationally has risen (Autor, Dorn, Katz, Patterson, and Van Reenen, 2020; Rossi-Hansberg, Sarte, and Trachter, 2021). How do these large national firms set wages? The answer matters for many phenomena, such as wage inequality and the response of the economy to local shocks. For instance, reducing aggregate wage and earnings inequality by aiding low wage regions is a key objective of policymakers (e.g. Brookings Institution, 2018). However, little is known about how national firms affect wage inequality.

This paper investigates how firms set wages across space. To fix ideas, we start with a benchmark framework that integrates standard models of imperfect labor market competition and spatial equilibrium. In the benchmark model, firms set wages in each of their locations as a markdown of local nominal marginal revenue products. We then introduce *national wage setting*, defined as firms compressing wages across space relative to what the benchmark model predicts. Our contribution is to show that empirically, a large minority of firms are national wage setters.

We establish this result with a dataset that measures wages and contains firm, occupation, and location information. Our dataset is a merge between the Longitudinal Employer-Household Dynamics (LEHD), a linked employer-employee database sourced from state unemployment insurance programs in 27 states, and the American Community Survey (ACS), a large representative survey of U.S. households. The LEHD linked with the ACS (LEHD-ACS) measures quarterly earnings for workers in the same occupation but different locations of the same firm. Moreover, the LEHD-ACS contains a nationally representative sample of firms, avoiding selection concerns. There are, however, some disadvantages to the LEHD-ACS. Specifically, there is only limited information on hours worked, meaning a noisier measure of wages, and occupation information is coarse and potentially measured with error.

We therefore supplement our primary dataset with additional information, namely online job vacancies from Burning Glass Technologies. The dataset includes roughly 70% of U.S. vacancies, either online or offline, between 2010 and 2019 (Carnevale et al., 2014). We restrict our attention to the approximately 3% of Burning Glass, or 2% of total US vacancies, that provide posted point wages for detailed occupations with firm and location information. Burning Glass provides information on specific job titles, allowing us to distinguish between fine occupation categories, and measures hourly wages with less noise than the LEHD-ACS. However, there are different concerns about sample selection and differences between posted and realized wages. Lastly, we also fielded a survey with human resource managers and executives to understand how and why firms set wages across space.

We document four facts that together reveal the prevalence of national wage setting. First, we find compression in wage levels within firms across space. The clear majority of variation in wages across locations is explained by the firm rather than the location. Moreover, there is an excess mass of firms that pay similar or identical wages for the same job in different regions. Second, wages within the firm and across locations are relatively insensitive to local prices, compared to a between firm benchmark. This insensitivity holds even when firms operate in regions with a wide range of prices and across a variety of occupations and industries. Third, wage growth is more strongly correlated with firm-level factors than with regional factors. Fourth, to rule out explanations for similar wage growth across space other than national wage setting, we provide causal evidence that local shocks to wage growth pass through to the rest of the firm. After shocks to wage growth in a single location, firms that initially pay similar wages across space—whom we hypothesize to be national wage setters—increase wages for similar jobs in their other unaffected establishments. By studying the pass through of local wage shocks, we avoid confounding factors such as firm-wide productivity shocks, which could lead wage growth to comove within the firm even in the absence of national wage setting. We conservatively estimate that at least 51% of jobs have wages set nationally.

We then study some characteristics of national wage setters in the LEHD-ACS. We show that national wage setters pay higher wages than other firms, not only in regions with low prices, but even in regions with high prices. Perhaps as a result, we also find that national wage setters retain workers at a higher rate. We then ask why firms set wages nationally. Our survey with HR managers provides suggestive evidence that firms set national wages to simplify management or when workers are geographically mobile or concerned about pay fairness in nominal terms. Taken together, the evidence from the survey and the LEHD-ACS allow the possibility that national wage setting confers benefits to the firm that offset the cost of compressing wages across space.

We conclude by carrying out a suggestive, model-based exercise to put bounds on the profits at stake from national wage setting. Under a set of assumptions, we show that in the absence of national wage setting, wages for national wage setters would vary across establishments by a median of 10%, and profits would be 2.5% higher. If firms set wages nationally to raise productivity, our estimate bounds the increase in profits that is needed to make national wage setting optimal.

Related literature. The main contribution of our paper is to empirically show that a large share of firms set the same nominal wage for the same job in different regions, despite varying local labor market conditions. This finding relates to several literatures. First, several papers show that multi-establishment firms do not respond to local conditions in the context of price setting. For example, DellaVigna and Gentzkow (2019) show that most firms in the retail sector set the same price for the same product in different regions of the United States; Cavallo, Neiman, and Rigobon (2014) show that global retailers set the same price for the same product in different countries of the same currency union.[1] We complement these papers by studying wage setting instead of price setting and by studying the entire economy beyond the specific setting of the retail sector.

A second literature studies the firm-level determinants of worker pay. Evidence suggests that different firms often pay similar workers different wages (Card, Heining, and Kline, 2013; Song, Price, Guvenen, Bloom, and Von Wachter, 2019). There are a range of explanations for this phenomenon, including amenities (Sorkin, 2018; Lamadon, Mogstad, and Setzler, 2022), rent sharing of firm productivity (Card, Cardoso, Heining, and Kline, 2018), and variation in firms' wage setting power due to their market share (Berger, Herkenhoff, and Mongey, 2022; Jarosch, Nimczik, and Sorkin, 2019).[2] National wage setting policies are another reason why different firms may pay workers performing the same job in the same location different wages. As such, our paper contributes to growing evidence that firms' wage policies are hard to reconcile with fine-grained optimization (Dube, Manning, and Naidu, 2020).

Several recent papers share our specific focus on how pay varies within firms and across space. Hjort, Li, and Sarsons (2020) study wage setting in multinationals using granular firm by occupation data. Their results complement ours by showing that firms anchor the real wage paid overseas to wages paid at headquarters. By contrast, this paper compares *nominal* wages across space, which is not feasible using

[1] Nakamura (2008), Hitsch, Hortaçsu, and Lin (2019) and Cavallo (2018), among others, document such "uniform price setting" in the retail sector. Clemens and Gottlieb (2017) show that Medicare's uniform pricing impacts the pricing strategies of private insurers.

[2] Related to this literature, Cullen, Li, and Perez-Truglia (2022) look at the impacts of salary benchmarking, and find that this practice leads to more similar pay across firms, as well as higher average pay for workers.

international data on wages paid in different currencies. Our setting allows us to shed more light on the nature of firm wage setting and highlight reasons why a particular subset of firms sets wages nationally.[3]

Finally, a third literature studies the spatial determinants of pay and other local labor market conditions.[4] For instance, Card, Rothstein, and Yi (2021) study the impact of location on earnings, finding that worker skills vary widely across space and account for much of the difference in wages across space. This work builds on papers such as Moretti (2013) and Diamond (2016), who show that worker sorting by skill across space has increased dramatically since 1980, and dissect the consequences of this sorting. While this literature tends to study differences in wages across space in general, we focus on differences in wages across space but within firms. Our results suggest that firm level behavior is an important determinant of the overall variation in wages across space.

2 A Simple Framework for Wage Setting Across Space

We begin with a simple framework to clarify how firms set wages across space. We recover a standard result: firms do not vary wages across space only if the product of markdowns and the marginal revenue product of labor is the same across establishments. We then define a concept of national wage setting as wage compression relative to that benchmark.

Since our model ingredients are standard, we outline them in the main text and leave the formal details to Appendix Section C1.1. There are R regions, and a unit measure of workers. Each region contains a discrete number of firms, who hire workers in all regions, meaning that in region r, firm f operates an establishment.

Establishments have productivity A_{rf}, and pay a nominal wage W_{rf} to all their workers. Given employment L_{rf}, the establishment operates a decreasing returns to scale production function $F(L_{rf})$

[3]Five more papers on firm wage setting across space are Cappelli and Chauvin (1991), who study the consequences of national wage setting for shirking, within a large, unionized U.S. manufacturer; Propper and Van Reenen (2010), who study the consequences of national wage setting among nurses in English hospitals on healthcare quality; Alfaro-Urena, Manelici, and Vasquez (2021), who report survey evidence that multinational corporations partly pay high wages overseas to ensure cross-country pay fairness; Boeri, Ichino, Moretti, and Posch (2021), who study the effect of national wage setting among unions in Italy, compared with flexible wage setting among unions in Germany; and Derenoncourt, Noelke, Weil, and Taska (2021), who study the consequences for local labor markets of four large firms' national minimum wage policies. In addition, a qualitative literature finds small-scale evidence of national wage setting (e.g. Adler, 2023). Some prior industry surveys document evidence of national wage setting (e.g. Empsight International LLC, 2018). Our survey adds information on the reasons for national wage setting.

[4]See Moretti (2011) for a survey of this vast literature, or recent contributions by Caliendo, Parro, Rossi-Hansberg, and Sarte (2018), Hornbeck and Moretti (2022), Brinatti, Cavallo, Cravino, and Drenik (2021), or Schoefer and Ziv (forthcoming).

and produces non-tradeable and region specific output $A_{rf}F\left(L_{rf}\right)$, sold in a competitive market at a price P_r which varies by region. Establishment profits are

$$\Pi_{rf} = P_r A_{rf} F\left(L_{rf}\right) - W_{rf} L_{rf}. \tag{1}$$

Workers choose a region in which to work, and consume goods produced in this region. As in the standard Rosen-Roback model of spatial equilibrium, workers choose the region in which they work and consume in order to maximize their utility, taking into account regional differences in wages and consumer prices, and preferences to locate in a given region. As in the standard Card et al. (2018) model of firm wage setting, workers supply labor within markets to different establishments to maximize their utility, taking into account differences in establishment wages and preferences to work for a given establishment. Following Card et al. (2018), we assume that workers have idiosyncratic, nested logit preferences for working at each establishment and region. These standard assumptions lead to a labor supply curve to the establishment

$$L_{rf} = \kappa_r W_{rf}^{\rho_r}. \tag{2}$$

Here, ρ_r is the labor supply elasticity to the establishment, which may vary by region. κ_r is an endogenous object that shifts labor supply and depends on regional variables such as regional wages and consumer prices (we define κ_r in Appendix section C1.1).

Wage Setting in the Benchmark Model. The model leads to a familiar equation for wage setting. Let W_{rf}^{*} be the nominal wage optimally set by an establishment of firm f operating in region r, from maximizing profits (1) subject to establishment labor supply (2). This wage satisfies

$$W_{rf}^{*} = \frac{\rho_r}{1+\rho_r} P_r A_{rf} F'\left(L_{rf}\right). \tag{3}$$

Therefore, establishments set nominal wages as a markdown $\rho_r/(1+\rho_r)$ of nominal marginal revenue product $P_r A_{rf} F'\left(L_{rf}\right)$, where the markdown depends on the labor supply elasticity to the establishment. Nominal marginal revenue product can vary due to workers' productivity A_{rf}, producer prices P_r, and the optimal scale of the firm, L_{rf}. Separate from producer prices, higher local consumer prices will also raise wages by causing workers to migrate out of the region, reducing labor supply to the region via the

κ_r term in the labor supply equation (2), lowering L_{rf}, and thus raising the marginal revenue product.[5] In this simple framework, the markdown $\rho_r/(1+\rho_r)$ varies exogenously across regions, though richer models endogenize markdowns as a function of establishments' market share (Berger et al., 2022).

Equation (3) shows that firms pay similar nominal wages in two establishments if the establishments share similar values of both the marginal revenue product and the markdown. For instance, firms operating nationally might have the same productivity and labor market power in all of their locations. Alternatively, firms might sell purely tradeable goods.[6] However, existing evidence suggests a great deal of dispersion in both productivity and local competition, meaning the benchmark model predicts meaningful wage dispersion within the firm for many sectors.[7]

National Wage Setting. In the following sections, we will argue that for a substantial minority of firms, the empirical evidence is inconsistent with the benchmark model. Instead, we suggest that certain firms set wages nationally—that is, they compress wages across their establishments relative to what the benchmark model predicts. Formally, let $W_f \equiv \sum_{r\in R} W_{rf}/R$ be the mean wage of the firm across its establishments. Then in all of its regions r, a national wage setter f sets establishment level wages according to

$$|W_{rf} - W_f| < |W^*_{rf} - W_f|.$$

That is, actual wages W_{rf} in each region are close to the mean wage of the firm, relative to what the benchmark wage W^*_{rf} would imply. In one extreme example of national wage setting, firms set identical wages across regions with $W_{rf} = W_f$, even though the benchmark wage W^*_{rf} may vary across regions. Other less extreme forms of national wage setting are also possible. National wage setters could allow wages to vary a little across regions, but by less than the labor market conditions summarized by W^*_{rf} would dictate. National wage setting only affects a subset of firms. The remaining firms, who we refer to as "local wage setters", behave as in the benchmark model.

[5]In Appendix Section C1, we show that in partial equilibrium, higher consumer prices raise the wages paid by an establishment, in the empirically reasonable case in which establishment labor demand is less than fully elastic.

[6]In Appendix Section C1.5 we extend the model to show that if labor market power does not vary across space, then purely tradeable firms (who aggregate output across establishments and sell to a national product market) pay the same wage in all locations.

[7]Kehrig and Vincent (2019) find large dispersion of productivity within manufacturing firms across their establishments; Schoefer and Ziv (forthcoming) find that local productivity varies substantially across places; Macaluso, Hershbein, and Yeh (2019) estimate significant variation in labor markdowns within narrowly defined industries; and there is substantial dispersion of local consumer prices across space (e.g. Diamond and Moretti, 2021).

Our definition of national wage setting does not take a view on why firms might choose to set wages nationally. National wage setting could confer some benefits to the firm by raising productivity, which offsets the cost of failing to vary wages across space. As such, some firms might prefer to set wages nationally.

One reason why firms might choose to set wages nationally relates to national price setting (DellaVigna and Gentzkow, 2019). In the benchmark model, we abstract from price setting power. However in practice firms might have power to set prices, and choose a price that does not vary across space. If prices do not vary across space, then the value of varying wages across space is lower. Equally, if wages do not vary across space, then the value of varying prices across space is lower. Therefore, the choice over whether to vary wages or prices across space will interact. Firms might choose "national policies" for both wages and prices, with national wage setting being one aspect of the national policy. Therefore, we believe that with price setting power, one still ought to define national wage setting as wage compression—but relative to a benchmark in which *both* prices and wages vary frictionlessly. A model of the joint decision to set wages or prices nationally is beyond the scope of the current paper.

3 Data Description

Our main dataset is a merge between the Longitudinal Employer-Household Dynamics (LEHD) dataset and the American Community Survey (ACS). The LEHD is a linked employer-employee database sourced from state-level unemployment insurance programs. The ACS is a large representative survey of households. The LEHD-ACS provides us with earnings and some information on hours, as well as occupation, firm, and location information. We supplement our primary dataset with a dataset of vacancies from Burning Glass, which contains posted wages, occupation, firm, and location information sourced from online job boards. We also make use of a survey of HR managers and executives, and a dataset of wages from mandatory filings for foreign workers' visas.

Longitudinal Employer-Household Dynamics and American Community Survey. We merge the LEHD, a linked employer-employee dataset, and the ACS, a large survey of households. This merge contains realized earnings with firm, occupation, location, and hours information, for a representative sample of workers from 2000-2019.

The LEHD is a census of workers covered by state unemployment insurance programs in 27 states.[8] State unemployment insurance covers roughly 95% of workers, and the states in our subsample of the LEHD covers 48% of total US employment. The LEHD measures workers' quarterly earnings, which are the product of total earnings per hour and hours worked. Earnings include gross wages and salaries, bonuses, stock options, tips, other gratuities, and the value of meals and lodging. The LEHD contains a firm identifier, 6-digit NAICS industry information, and the estimated commuting zone where the worker is employed.[9] Therefore, our notion of a region in the LEHD is a commuting zone. We define an establishment as a commuting zone-by-firm observation. Throughout the analysis, our baseline definition of a firm is the firm's EIN number.[10]

The ACS is a cross-sectional annual survey beginning in 2001 of US households, covering a representative 1% sample of the population. We supplement the ACS data with the 2000 Decennial Census. The ACS and the Decennial Census contain information about workers' self-reported hourly wages and usual hours worked, as well as their detailed occupation, as reported to a surveyor. Both the LEHD and the ACS also contain demographic information (age, race, gender, and education).

Merging the LEHD and ACS at the worker level produces a dataset of workers' quarterly earnings, usual weekly hours, occupation, location, and firm information. This combination of information is unique among currently available nationally representative administrative datasets within the United States.[11] We merge observations from the ACS to the LEHD in the quarter in which the household is surveyed. In all baseline specifications, we maximize our sample by assuming that the worker's occupation does not change within an employment spell. Specifically, while we link ACS respondents only to the LEHD in the quarter in which they are surveyed, we impute occupation for all quarters in which the worker stays in the same state and employer. We do not impose that the occupation remain constant

[8]The states are Arizona, Colorado, DC, Delaware, Hawaii, Idaho, Illinois, Kansas, Louisiana, Maryland, Maine, North Dakota, Nebraska, New Jersey, New Mexico, Nevada, Ohio, Oklahoma, Pennsylvania, South Carolina, Tennessee, Texas, Utah, Virginia, Washington, Wisconsin, and Wyoming.

[9]The establishment location within the LEHD is not directly observed in most states. Rather, it is imputed based on the location of the worker and the location of the firm's establishments. Given the noise in this procedure, we aggregate all establishments of the firm within a commuting zone.

[10]We will also consider a more aggregated definition of a firm (firmid), which is constructed by the Census to account for firms with common ownership, as well as more disaggregated firm definitions based on the state EIN number, which is the unit at which the LEHD data is collected.

[11]For instance, Social Security or tax data measure annual earnings without hours or occupation. ADP contains wage information with hours, but does not currently make occupation information available (Grigsby, Hurst, and Yildirmaz, 2021). Glassdoor, Paychex, Homebase, and Payscale (which was used in a previous draft of the paper) are selected samples of workers' wages that are not nationally representative. The Occupational Employment Statistics measures wages only within coarse bins. The National Compensation Survey only surveys single locations of a firm.

once the worker transitions to another employer or state. In referring to the LEHD-ACS, we use "job" to refer to a firm by occupation (e.g. a pest control worker at a specific company). We call this merged sample the LEHD-ACS.

Our primary outcome in the LEHD-ACS is quarterly earnings, although we show additional results using implied hourly earnings, which is quarterly earnings from the LEHD divided by a worker's usual weekly hours from the ACS, multiplied by 13; and self-reported hourly wages in the ACS. The first measure is available for the full LEHD-ACS sample, that is, for all workers in the LEHD who are surveyed by the ACS at some point during their job spell. The second and third measures are available only for the quarter in which a worker from the LEHD is interviewed for the ACS.

We make several additional restrictions to form our main sample for analysis. First, we restrict to commuting zones for which we observe local prices (from the Bureau of Economic Analysis) and local house prices (from Zillow). Second, to limit the influence of outliers, we drop workers whose quarterly earnings are above the 99th percentile in a given commuting zone by year. Third, we exclude workers in public administration (NAICS code beginning with 9). Fourth, we restrict the sample to workers in firms with at least 2 establishments in our 27 state sample of the LEHD. Fifth, we restrict the dataset to workers who hold only 1 job in the month in which they are sampled in the ACS. This increases our confidence that the reported occupation corresponds to the matched job within the LEHD. Lastly, we exclude all workers in the ACS who do not report the usual hours that they work in a week or who report usually working 0 hours in a week; drop the first and last quarters of each worker's employment spell with each firm; and study workers who earn more than the full time federal minimum wage in any given quarter.

Table 1 shows several summary statistics for the main LEHD-ACS sample. Panel A shows the number of commuting zones, firms, occupations, or workers for the different subsamples we use throughout our analysis. Panel B presents worker-level demographic information.

As a reference, the first column shows statistics from a 10% subsample of the LEHD. This sample makes all the restrictions discussed above other than limiting to workers who are surveyed in the ACS. The second column shows statistics from the full LEHD-ACS merge. The third column shows statistics in the LEHD-ACS subsample for firms that employ workers in the same occupation and in different locations (i.e. the subsample in which we can make within-job, cross-region comparisons). The fourth and fifth columns show the same two subsamples from the LEHD-ACS but using only the quarters in

Table 1: Summary Statistics in the LEHD-ACS

	Panel A: Sample Information				
Sample:	10% of LEHD	Full LEHD-ACS	LEHD-ACS Subsample	Full LEHD-ACS ACS Quarters	LEHD-ACS Subsample ACS Quarters
	(1)	(2)	(3)	(4)	(5)
Number of CZ in Firm x Year in sample	3.41	2.19	1.50	2.95	2.80
Number of Firms	278,000	208,000	109,000	87,500	14,000
Number of CZ in Firm x Year in full LEHD	5.03	6.37	12.70	9.65	35.75
Number of workers	6,921,000	4,961,000	910,000	3,790,000	278,000
Total LEHD Employment in Firm x Year	150	200	750	450	3,500

	Panel B: Demographics				
Sample:	10% of LEHD	Full LEHD-ACS	LEHD-ACS Subsample	Full LEHD-ACS ACS Quarters	LEHD-ACS Subsample ACS Quarters
	(1)	(2)	(3)	(4)	(5)
Age	43.64	45.92	44.5	45.94	44.23
Share w/ College Degree	0.35	0.36	0.39	0.37	0.41
Quarterly Earnings per Worker	17,000	17,000	16,500	16,500	16,500
Female Share	0.42	0.43	0.45	0.43	0.48

Notes: this table reports summary statistics for the LEHD and the ACS. In the first column we report summary statistics for a 10% subsample of the LEHD, for 27 states over 2000-2019. In the second column we study the subsample that merges with the ACS. In the third column we consider the merged subsample that contains firms employing workers in the same occupation and different regions. In the fourth and fifth columns, we repeat the third and fourth columns, but restrict to observations in a quarter that merges with the ACS. In Panel A, Row 1, we report the number of commuting zones (CZ) per firm and year in the sample. In Row 2 we report the number of firms. In row 3, for each firm and year we report the number of CZs in which the firm operates, in the full LEHD. In row 4 we report the number of workers. In Row 5 we report LEHD employment per firm and year. In Panel B we report demographics: the average age, share with college degree, earnings per worker, and female share. Statistics are rounded to pass disclosure review.

which the person is directly observed in the ACS (i.e. excluding the quarters in which we have imputed stable occupation and hours).

The summary statistics suggest several points. First, firms in the LEHD-ACS matched sample in column (2) are bigger than in the overall LEHD sample in column (1), in terms of the number of establishments (Panel A, Row 3) and in terms of total employment (Panel A, Row 5). Second, the LEHD-ACS merged sample remains large in absolute terms—for instance, there are almost as many firms and workers in the merged sample, as in the 10% sample of the entire LEHD (Panel A, Row 4). Third, the LEHD-ACS sample is similar to the full LEHD in terms of workers' demographics and earnings. None of age, college education, earnings per worker, or female share differ greatly across the samples. The industry composition for the samples in Columns 1, 2, and 3 in Table 1 are broadly similar. However the LEHD-ACS slightly over-represents trade, transport, education, and healthcare, and under-represent information and finance (Appendix Figure A4). Overall, the LEHD-ACS is close to being representative, being the product of administrative earnings records and a representative survey. The main LEHD-ACS sample differs from the full LEHD only by restricting to large multi-establishment firms and geographically dispersed occupations—necessary restrictions in order to focus on the population potentially affected by national wage setting.

The main limitations of the LEHD-ACS are that occupation and hours worked are measured with noise. Surveys like the ACS often code occupations with measurement error (e.g. Kambourov and Manovskii, 2013). Quarterly earnings (measured in the LEHD) contains variation in both hourly wages and hours worked. Weekly hours from survey data (measured in the ACS) typically includes measurement error (e.g. Bound and Krueger, 1991) and is only available for the LEHD in the quarters that match to the ACS. As a result we will supplement the LEHD-ACS with a secondary dataset of online vacancies from Burning Glass. Burning Glass is useful because it contains detailed occupation, wage, and hours information, with less measurement error than the LEHD-ACS. However, there are other disadvantages with Burning Glass that we will discuss, concerning sample selection and the difference between posted and realized wages.

Burning Glass Data. Our secondary data source contains vacancies from 2010 to 2019, with firm, occupation, and location information. The dataset was developed by Burning Glass Technologies. Burning Glass collects data from roughly 40,000 company websites and online job boards, with no more than 5% of vacancies from any one source. They then apply a deduplication algorithm and convert the vacancies into a form amenable to data analysis. In total, Burning Glass covers around 70% of the vacancies in the United States (Carnevale et al., 2014). However, only 3% of vacancies in Burning Glass, or approximately 2% of total US vacancies, include point wages and the other variables necessary for our analysis. As such there is selection into posting a wage. We exclude jobs posting wage ranges from our analysis, but show the robustness to including those observations and taking the midpoint of the range.[12]

For those vacancies that include a wage, we have detailed information on the wage, including the pay frequency of the contract (e.g., whether pay is annual or hourly) and the type of salary (e.g. whether compensation includes a bonus). In addition to the posted wage, vacancies specify several additional features of the job and characteristics of the desired worker that we use throughout our analysis. On the

[12] Batra, Michaud, and Mongey (2023) points out that wage ranges may be imputed by job boards such as LinkedIn, especially after 2018, making them inappropriate for our analysis. Consistent with their logic, the number of vacancies posting a wage range after 2018 jumps, while the number of vacancies posting a point wage evolves smoothly (Appendix Figure A1).

worker side, the vacancy includes information on required years of education or years of experience. On the job side, we see the firm name, industry, county, and occupation, which Burning Glass codes into a six-digit (SOC) occupation code.[13,14] We cleaned firm names using a deduplication procedure outlined in Appendix Section A1.1, and we define an establishment as a county-by-firm observation, aggregating observations within counties. Using this definition, 75% of employers only have vacancies within a single establishment in a given year, but among those firms with multiple locations, the average number of establishments is 8.6. In our Burning Glass analysis, we will use the term "occupation" to refer to the combination of the occupation, salary type, and pay frequency (e.g. pest control workers with hourly base pay) and the term "job" to refer to an occupation within a firm (e.g. a pest control worker with hourly base pay, within a specific company).[15]

Table 2 summarizes how the main sample that we use for the analysis changes with our restrictions. In addition to the restrictions discussed above, we exclude the public sector, military occupations, and all jobs with commission pay. It is important to note that these restrictions lead to a very large reduction in sample size, which raises concerns about sample selection. Our main sample includes only those vacancies with non-missing wage, occupation, industry, and location information, in the private sector, not in a military occupation, and without commission pay. This sample, in Row 4 of the table, is 2.8% of total Burning Glass vacancies. In Row 5, we collapse to have one observation per year in each establishment, occupation and pay group (e.g. hourly base pay) and take the average salary across vacancies.[16] Relative to the U.S. economy, the resulting sample over-represents occupations in computing, transportation, and management and under-represent food preparation and construction occupations. Additionally, the sample over-represents the transportation and education industry and under-represents wholesale and retail trade (Appendix Figure A2). Throughout, we show robustness with data re-weighted to match the

[13]Six-digit occupation codes are highly granular, including occupations such as pest control worker, college professor in physics, and home health aide. In addition to detailed occupations, we also explore alternate specifications defining jobs using the standardized detailed job titles. Lastly, we assign to each firm the industry in which it posts the most vacancies.

[14]If the vacancy posts multiple locations, Burning Glass selects the first, which will under-state national wage setting. For instance, suppose that job can be done in either Boston or New York, with the same wage. By assigning this vacancy only to Boston, we will not identify national wage setting for these vacancies if it is present.

[15]It is challenging to make wage comparisons across different pay frequencies and salary types. We find that, within an occupation, firms rarely post vacancies with different salary types and pay frequencies, with only 1.8% of occupation/firm pairs posting multiple salary types across locations within a year and 0.8% posting multiple pay types. This small dispersion suggests that firms do not strategically vary pay structure across locations so that looking within jobs defined by the combination of occupation, salary type and pay frequency is unlikely to bias our estimates of wage compression within the firm.

[16]This averaging potentially biases downward some of our measures of wage compression. To see this, consider a firm that sets identical wages across 2 locations but posts in location 1 in Q1 and location 2 in Q4 and changes its wages in all locations in Q3. In truth, the firm sets identical wages across locations, but by averaging we do not detect this pattern.

Table 2: Summary Statistics on Sample Formation

	Vacancies (1)	Firms (2)	Establishments (3)	Counties (4)
Full 2010-2019 data	239,029,970	2,742,555	9,117,549	3,224
Drops missing wages, includes ranges	40,625,295	1,267,503	3,529,712	3,221
Drops ranges	15,205,219	490,125	1,414,096	3,208
Drops missing: firm, county, sector, occup., military, comm. or public sector	6,902,766	366,688	1,215,979	3,186
Collapses to year-establishment-occ-pay group	3,697,295	366,688	1,215,979	3,186
Restrict to 2 establishments in year	1,876,644	59,241	714,506	3,184

Notes: The first row reports counts for the full data from Burning Glass, for 2010-2019. The second row restricts to observations with non-missing wage information, but includes wage ranges. The third row drops wage ranges. The fourth row drops observations with missing firm, region, industry sector or occupation information, and excludes military occupations, the public sector and commission pay. This row is the main sample for our analysis. The fifth row collapses the data to the year by occupation by pay group by establishment level. A pay group is the pay frequency and type of the salary (e.g. hourly base pay). The sixth row restricts to firm by occupation by pay groups by year cells where there are postings in at least 2 establishments. It is on this sample that we will define national firms.

occupation distribution in the OES.

Burning Glass is useful because it contains detailed occupation and wage information with hours. These variables are measured with noise in the LEHD-ACS, our primary dataset. However, there are two limitations. First, Burning Glass provides posted wages, which might differ from realized wages paid to workers. Second, the main Burning Glass sample only contains jobs that post point wages, raising selection concerns related to firms' decisions about whether to post wages. We provide some tests to assuage these concerns, but they cannot be ruled out entirely.

Regarding the difference between posted and realized wages, Burning Glass wages closely track realized wages from official sources, at a granular region-by-occupation level.[17] In particular, a region-by-occupation cell with a 1% higher wage in Burning Glass, also has approximately a 1% higher wage in official sources—see Appendix Figure A3, and Appendix Tables A1 and A2. If posted wages systematically differed from realized wages across certain locations or occupations, then one would expect a coefficient significantly different from 1. For instance, if posted wages tend to be similar in high and low wage regions, while realized wages differ greatly due to ex post bargaining, regressions would produce a coefficient far greater than 1.[18] Regarding selection into posting a wage, point wages are more likely

[17]We use a split-sample instrumental variables approach to deal with measurement error, because wages in both Burning Glass and the OES are measured with noise. Within each occupation-by-region cell, we create two random samples and instrument for one wage measure in Burning Glass with the other. This procedure corrects for attenuation bias in presence of i.i.d. measurement error (Angrist and Krueger, 1995).

[18]Batra et al. (2023) study Burning Glass wages by regressing the ratio of Burning Glass and occupation wages from the

to be posted at smaller firms, in occupations that have lower wages, and for vacancies with lower education and experience requirements. In all cases the magnitudes are relatively modest—for instance, firms are 2.3 percentage points less likely to post a wage for occupations with wages 1 standard deviation above the mean (Appendix Table A3).[19] These statistics suggest that the strategic posting of wages across locations is unlikely to meaningfully affect our estimates of national wage setting. We also show that within firms, selection into posting wages is uncorrelated with local prices, local high prices, or being in a "superstar city" like New York or San Francisco (Appendix Table A3).

4 Evidence for National Wage Setting

This section presents four facts that together indicate national wage setting. First, firms pay a similar level of wages across space, with an excess mass of firms paying identical or near-identical wages across different locations. Second, within firms, nominal wages are relatively insensitive to local prices—compared to a benchmark of how wages vary between firms and across space. Third, wage growth is strongly correlated within the firm and across space. Fourth, for jobs that pay similar wages across space, local shocks affecting wage growth in a single establishment pass through to wages in the other locations of the firm.

Fact 1: Wage Levels are Similar Across Space within the Firm

We begin by documenting a similar wage levels within firms across locations. To do so, we ask what explains variation in wages for a given job. If wages are similar within firms and across space, much of the variation should be explained by the firm as opposed to the geographic location of a job.

We implement this idea following Nakamura (2008) and DellaVigna and Gentzkow (2019). We

Occupational Employment Statistics (OES), on an occupation's rank in the wage distribution from the OES; they find a weaker relationship between the two data sources. Our analysis is better suited to validating our wage measure for four reasons. First, the regression of Batra et al. (2023) risks a mechanical bias, because a function of the same variable (OES wages) is both an outcome and a regressor. Second, we drop wage ranges. Third, we correct for attenuation bias using a split sample IV procedure, which is important given noisy measures of wages. Fourth, Batra et al. (2023) compare postings with annual pay and hourly pay by multiplying hourly pay by 2080, which might not measure pay correctly.

[19] Also, there is no clear relationship between whether firms post wages and the cost of living as the magnitudes of any relationship are small. Within a firm, a county with a 1 standard deviation higher consumer price level has a probability of posting that is lower by 0.06. Moreover there is no strong connection between firms being more likely to post wages in areas with a high cost of living (Appendix Table A3).

regress the log wage for occupation o in firm f on a region fixed effect, γ_r, and a firm fixed effect, γ_f:

$$\log(w_{ofrt}) = \gamma_f + \gamma_r + \varepsilon_{ofrt}. \tag{4}$$

We then run the same regression while dropping either firm or region fixed effects. The reduction in the adjusted R-squared from dropping firm fixed effects measures the marginal contribution of firm level factors to explaining wages; likewise, dropping region fixed effects measures their marginal contribution. We calculate the difference in the adjusted R-squared from dropping either region or firm fixed effects, separately for each occupation, and plot the distributions in Figure 1. Panel A shows the results using the LEHD-ACS, with worker-level quarterly earnings as the outcome variable. Panel B shows results with supplementary data from Burning Glass, with job-level wages as the outcome variable.[20]

Both datasets suggest similar wages within the firm across its locations. The shape of the histograms and the magnitude of wage compression in the two datasets are similar. Dropping firm fixed effects greatly reduces explanatory power for the vast majority of occupations, whereas dropping region fixed effects is less consequential. Therefore, the variation explained by the firm is significantly higher than the variation explained by location. The fall in adjusted R-squared for the average occupation, when dropping region fixed effects, is 0.03 in both Burning Glass and the LEHD-ACS, while the average fall in adjusted R-squared from dropping firm fixed effects is 0.32 and 0.33, respectively. However, the magnitudes are not strictly comparable across the two datasets as the wage measures are different.

One possible explanation for the patterns in the LEHD-ACS is compression of work hours, rather than wages. We explore this by re-estimating regression (4), pooled across all occupations, with reported hourly wages as the outcome variable; this variable is available only in the quarters in which workers appear in both the LEHD and ACS. The adjusted R-squared falls by 0.0629 when we drop firm fixed effects; whereas the adjusted R-squared falls by only 0.0052 when we drop region fixed effects.[21]

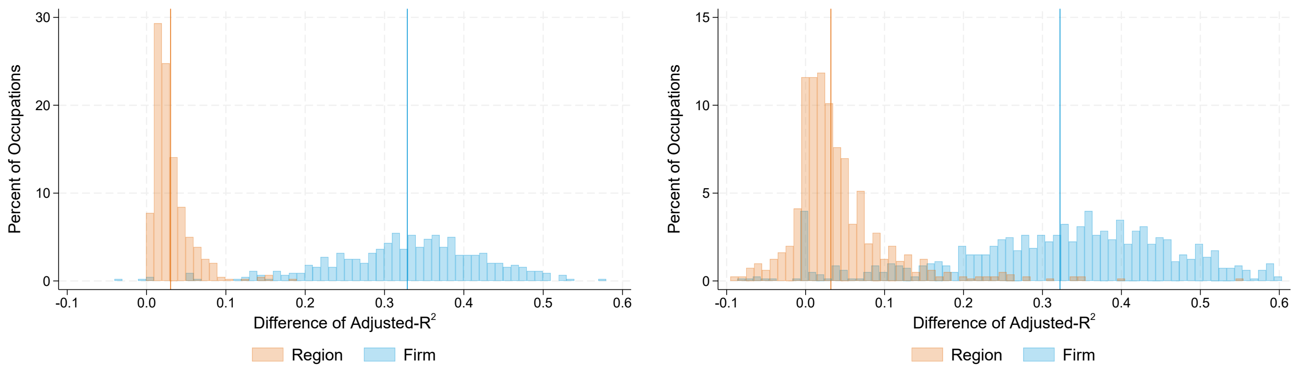
The similarity of wages across locations within the firm could take various forms. For instance, all jobs and locations could be paying somewhat similar wages. Alternatively, some jobs and locations

[20]For the LEHD-ACS regression, we also control for demographics (year, race, education, age and gender) and run the regression at the worker level instead of the firm-by-occupation level. For the Burning Glass regression, we also add fixed effects for pay frequency and salary type.

[21]One alternative to the baseline two way fixed effect model, with firm and region effects, is firm-by-region fixed effects. In the LEHD-ACS, the adjusted R squared from regressing log earnings on firm effects is 0.1708, whereas regressing on firm-by-region effects has an adjusted R squared of 0.1774. Therefore, there is a small increase in explanatory power, suggesting the baseline model is well specified.

Figure 1: Variation in Wages is Explained by the Firm

(a) LEHD-ACS (b) Burning Glass



Notes: Each panel plots the share of wage variation explained by either the region or the firm, for each occupation; and then plots the distribution across occupations. In Panel B, the data range has been truncated to a minimum value of -0.1 and a maximum of 0.6, which excludes 3.12% and 3.48% of the sample for the region and firm histograms, respectively. The vertical lines are the share of variation explained by either region or firm for the mean occupation. In Panel A, we restrict to the fourth quarter of each year for computational tractability.

might be paying particularly similar wages. We discriminate between these possibilities by comparing the wage paid by a given job across its various locations.

To start, we compare the distribution of wages across locations, either within firms or between firms. If there is wage compression within the firm and across space, then the within-firm distribution should be more compressed than the between-firm distribution. Specifically, in the LEHD-ACS, we compare earnings within a firm, job, and year across its different locations. For instance, a within-firm job pair might compare earnings of an administrative assistant at Deloitte in 2019 in their Boston and San Francisco offices. For each of these pairs, we construct a corresponding between-firm pair for the same occupation in the same locations, but with the second location containing a randomly selected different firm in the same 4-digit industry. In our example, the corresponding between-firm job pair might compare earnings of an administrative assistant at Deloitte in 2019 in Boston, to an administrative assistant at McKinsey in 2019 in San Francisco. For both the within- and between-firm pairs, we also match the workers according to detailed demographic information, namely race (a binary for white or non-white), 5-year age bins, 4 bins of education, and gender. By comparing within-firm differences in wages to between-firm differences, one can gauge the degree of wage similarity within firms, relative to a natural benchmark.

These results are shown in Figure 2, Panel A. We see that wages are similar within the firm, with the distribution of within-firm pairs being shifted left relative to the distribution of between-firm pairs.

Notably, there is a sizable gap between the first blue and orange bar, which represent wage gaps between 0-3% for between- and within-firm pairs respectively.[22] This suggests a mass of jobs that pay identical or near-identical wages across their locations within the firm. Overall, the histograms illustrate a large degree of wage compression within firms.

This exercise is likely to understate the share of firms setting identical or near-identical wages across space for two reasons. First, if hours worked in a quarter vary across space, then the distribution of earnings across space will be more dispersed than the distribution of wages across space. To confirm this point, we construct a version of the figure for salaried workers only, who we identify as those workers with stable earnings quarter-to-quarter.[23] Salaried workers have less variation in hours across space and, as a result, wages are even more similar (Appendix Figure A5).

Second, we measure jobs with error in the ACS. Suppose that Deloitte pays the same wage for administrative assistants everywhere. We look for this pattern in the data by looking at the differences in wages for different workers in the same occupation across locations. However, if the more aggregated occupation measure in the LEHD-ACS contains related jobs, such as office managers and receptionists, we will then understate the extent of national wage setting among administrative assistants in the firm.

We shed light on the extent of this concern by comparing the within-firm across location wage gaps to the within-firm *within-location* wage gaps (i.e. comparing the quarterly wage in 2019 for two administrative assistants in the Boston office). The within-firm within-location wage gaps capture the amount of variation in wages across workers within job cells within a location. This distribution provides a benchmark for the amount of variation across workers that we should expect to see absent any location-specific adjustments. Indeed, with the most extreme version of national wage setting, where firms set exactly the same wage for the same job for all workers across all locations, the between-location distribution of wages gaps would look similar to this within-location distribution of wage gaps.

Figure 2 Panel B compares the between-location and within-location wage gaps within firms. We see that the distributions are broadly similar, with the between-location distribution shifted only slightly to the right. This pattern again indicates significant wage compression within the firm across space – there is almost as much within-firm variation in wages across workers within a location as there is across

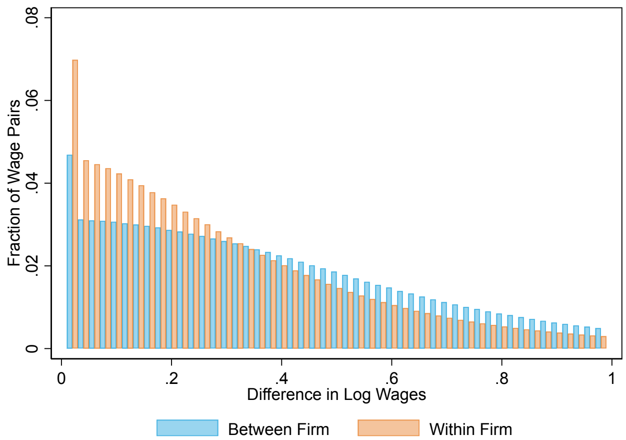
[22]The remaining bins are approximately 0.2 percentage points wide.

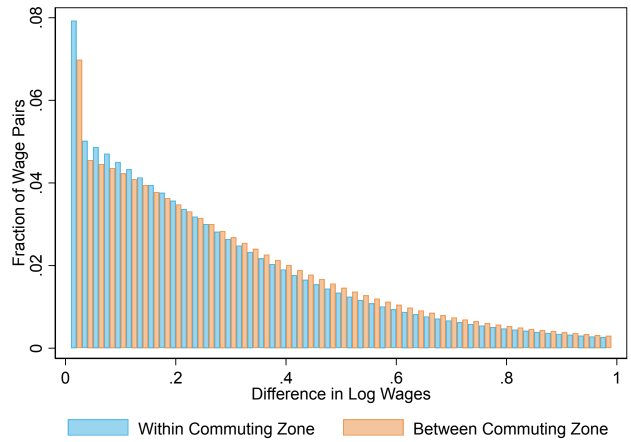
[23]Specifically, we infer that a worker is likely salaried if the mean absolute value of the change in their quarterly earnings across quarters within their job spell is less than 5%.

Figure 2: Distribution of Wage Comparisons Between and Within Firms in the LEHD-ACS

(a) Across Locations: Between Firms vs Within Firms

(b) Within Firm: Within vs Between Locations





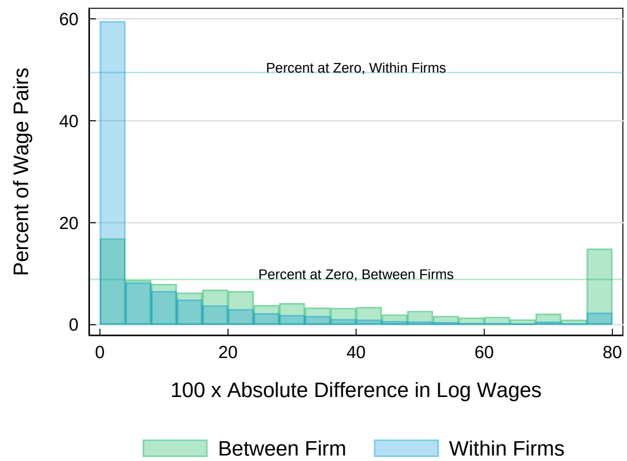
Notes: Panel A plots the distribution of differences in log quarterly earnings between pairs of workers located in two different counties using the LEHD-ACS. The orange histogram shows "within-firm" pairs (same firm, same demographics, same occupation, different commuting zone); the blue histogram shows matched "between-firm" pairs (a worker in a different firm in the same 4-digit NAICS industry, same demographics, same occupation, same pair of commuting zones as the "within-firm" pair). The demographics we match workers on are: gender, race (white/non-white), 5-year age bin, and four education bins. Panel B repeats the exercise within firms, comparing earnings gaps for pairs of workers in the same county ("within location", blue) with gaps for pairs in different counties ("across locations", green). Differences are expressed in log points and binned into intervals of 0.002 (0.2 percentage points), with exception of the first bin which represents log wage differences between 0 and 3%. We do not plot differences above 1 but the y-axis is calculated over the full distribution of wage differences.

workers in different locations. Moreover, the large dispersion in wages for the same job within-locations highlights the pervasiveness of unobserved heterogeneity within the LEHD-ACS.

We refine our estimates with additional results from Burning Glass. Burning Glass has job-level wages that are not affected by worker-specific variation or the noise inherent in self-reported occupations, meaning one can test more thoroughly for identical wages at the job level. To carry out the test, in Figure 3, we repeat Figure 2, Panel A, but for posted wages on vacancies.[24] The distribution of wage differences for the within-firm pairs (blue) and the corresponding between-firm pairs (green). 49% of within-firm pairs have exactly the same posted wage, while only 8.9% of between-firm pairs have the same posted wage. That number rises to 52% if we consider all within-firm wage pairs rather than just those with a between-firm match. Moreover, 62% of within-firm pairs are within 5% of each other, while only 19% of between-firm pairs are within that same band.

[24] We carry out the exercise at the firm-by-occupation level, and study wages instead of earnings. Since demographics are not available, we match the between- and within-firm pairs on the quintile of the firm vacancy size distribution. Within firm, occupation and location information—required for the analogue of Figure 2, Panel B—is unavailable in Burning Glass.

Figure 3: Distribution of Wage Comparisons Between and Within Firms in Burning Glass



Notes: The figure shows the distribution of wage differences for within- and between-firm pairs using the Burning Glass data. Differences in the log of the wage are top-coded at 80. The within-firm sample includes all pairs of job postings in the same job, firm, and year but in different counties. We restrict to the set of pairs where we find a between-firm match as described in the main text. This results in 30,332,268 pairs within firms and the same number between firms. All figures exclude job postings using salary ranges.

Fact 2: Within firms, nominal wages are relatively insensitive to local prices

We have shown that wages are similar across space within the firm, which is potentially consistent with national wage setting. However, wages might be similar simply because firms locate in regions with similar labor market conditions, and not because firms compress wages across space. Our next fact shows that within the firm, wages are similar across locations with different conditions—compared to a benchmark of how wages vary between firms and across locations.

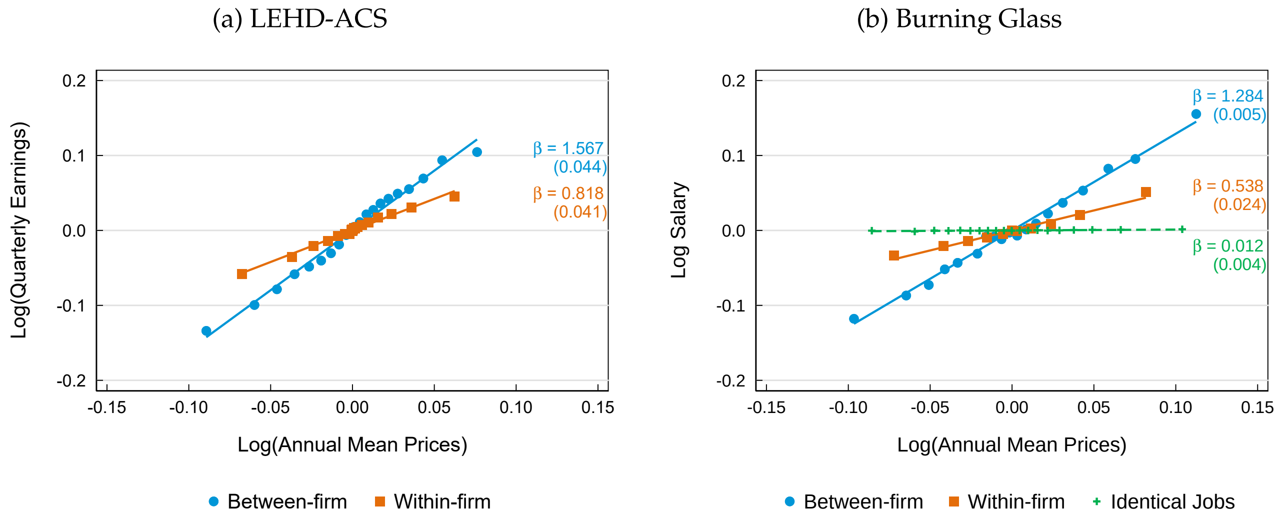
We explore how wages vary with local prices by estimating the within-firm relationship between wages and local prices as

$$\log w_{ofrt} = \beta \text{price level}_{rt} + \theta_{oft} + \varepsilon_{ofrt} \tag{5}$$

where $\log w_{ofrt}$ is the wage in occupation o in firm f in region r in year t. Price level$_{rt}$ represents a local price index for the region (i.e. a commuting zone in the LEHD-ACS).[25] Including occupation-by-firm fixed effects (θ_{oft}) means we estimate the correlation between nominal wages and prices within the firm, and also hold fixed trends in wages over time. To account for measurement error in local price indices,

[25]This measure of local consumer prices, from the Bureau of Economic Analysis, closely correlates with several other measures of local prices using other techniques and data sources (Diamond and Moretti, 2021, Appendix Table A5).

Figure 4: Sensitivity of Nominal Wages to Local Prices



Notes: This binned scatterplot shows the relationship between the local price index and the log wage using data from the LEHD-ACS (Panel A) and Burning Glass (Panel B). We instrument for local prices with county-level home prices, by regressing prices on house prices and the other variables of the regression, and then using the fitted value of prices in the scatter, while partialling out all control variables. The blue line and circles correspond to Equation (6) and the orange line and squares correspond to Equation (5). In Panel A, we restrict to the fourth quarter of each year for computational tractability. In Panel B, the dashed green line and crosses correspond to Equation (5) but we run this regression restricting to national occupations. National occupations are those occupations by firms for which 80% of job pairs have identical wages. All regressions include job and year fixed effects and the green and orange regressions include firm fixed effects as well. Because of the fixed effects, both the y-axis and x-axis are demeaned. Standard errors, in brackets, are clustered by firm.

we instrument the local price index with region-level home price indices from Zillow.

For comparison, we also estimate the correlation of nominal wages and local prices *between* firms and across locations. To do so, we follow DellaVigna and Gentzkow (2019) and estimate

$$\log w_{ofrt} = \gamma\overline{\text{price level}}_{ft} + \theta_o + \theta_t + \varepsilon_{ofrt} \tag{6}$$

where $\overline{\text{price level}}_{ft}$ is the average value of local prices for all regions in which the firm operates. Using the average price level in the firm, instead of the price level in location r, purges the within-firm variation and isolates the between-firm relationship. The between firm variation is a useful point of comparison, being unaffected by wage setting within firms across establishments.

Panel A of Figure 4 plots binned scatter plots using the main LEHD-ACS dataset, with orange squares corresponding to the within-firm and occupation regression (equation 5) and blue circles corresponding to the between-firm regression (equation 6). We estimate equations (5) and (6) with quarterly earnings as an outcome variable, and include demographic and industry controls to account for sorting of workers across space. Specifically, we control for gender, race, and age dummies, all interacted with year; and we include 6-digit industry-by-year fixed effects for the between-firm regression in equation (6). The within-firm slope is relatively low, with a value of 0.8. By comparison, the between-firm slope is significantly higher, with a value of 1.57. Hours variation across space does not account for these results: the results are similar using weekly wages from the ACS or quarterly earnings from the LEHD divided by usual weekly hours from the ACS; moreover, hours vary little across space within the firm (Appendix Table A5).[26]

At first glance, both the within-firm and the between-firm estimates of the slope seem somewhat high in the LEHD-ACS. For instance, the between-firm slope of 1.57 suggests that comparing between firms, workers receive significantly higher real wages in regions with high prices. We hypothesise this pattern is because high price regions tend to attract workers with unobservably higher productivity (our regression controls for observable correlates of worker productivity). This pattern is consistent with a large urban economics literature that finds observably and unobservably higher skill workers sort into high price areas (Moretti, 2013; Diamond, 2016; Card et al., 2021). To test our hypothesis, in Appendix Section A2.1 we describe and implement a version of the benchmark regression that controls for unobservable worker skill. The regression studies workers that switch commuting zones, either between or within firms. In this regression, we find that the between-firm slope of 0.48 and a within-firm slope of 0.17, i.e. both slopes fall by a factor of 3 relative to the baseline (see Appendix Figure A22). Helpfully, the ratio of the between- and within-firm slopes remains similar. Our estimates of the relationship between local earnings and prices are also consistent with other work in the urban economics literature. For instance, Diamond and Moretti (2021) regress income on prices across regions, using bank data on income and scanner data on prices, and find a relationship around 1. The average of our between- and within-firm coefficients, which roughly corresponds to the Diamond-Moretti regression, is similar.

Panel B of Figure 4 shows similar results using the supplementary dataset from Burning Glass. The slope of the orange line is positive, implying that within the firm, nominal wages are higher in counties

[26] The results are robust to using local prices without instrumenting with housing prices, using other measures of prices, using average earnings, and restricting the between-firm sample to be the same set of firms as the within-firm sample. In all cases the between-firm coefficient is roughly twice as large as the within-firm coefficient (Appendix Table A4). The results are similar with two other firm definitions from the Census Bureau and shows that the average occupation wage varies similarly across space, within versus between firms, suggesting occupation composition cannot explain the results (Appendix Table A5).

with higher prices. However, the coefficient is 0.54—within the firm, a job in a county with 1% higher prices tends to pay a nominal wage that is only 0.54% higher. By contrast, the estimate of γ is much higher: a 1% higher price level is associated with 1.3% higher nominal wages.[27]

As elsewhere, the magnitude of the regression coefficients are different in Burning Glass and the LEHD-ACS. However the ratio of the coefficients is similar in the two datasets, being roughly 0.5. We will show at the end of this section that under certain assumptions, the ratio of the within- and between-firm slopes is informative about the extent of national wage setting, meaning the estimates across the two datasets are roughly consistent on this point.

The within-firm slope is flatter because firms pay similar wages across locations. However, firms paying similar wages might only operate in areas with similar labor market conditions. To test for this possibility, we again exploit that in Burning Glass, one can easily detect which jobs pay identical wages across locations—which is more difficult in the LEHD-ACS, with its noisier wage and occupation measures. The dashed green line in Panel A of Figure 4 shows Equation (5) estimated on the subsample of occupations and firms where at least 80% of the postings for that occupation pay the same wage. The slope is close to zero by construction, but the range of prices that the firms face is similar to the range of prices faced by other firms. Therefore, firms with identical wages operate in areas that have very different local prices.[28]

The relative insensitivity of wages to prices within the firm, compared to the between-firm benchmark, is widespread in both datasets. In the LEHD-ACS, we study heterogeneity in the sensitivity of wages to local conditions by worker tenure, age, the average occupation wage, firm size, and industry type—again finding that wage compression is pervasive. The within-firm coefficients are consistently half the magnitude of the between-firm coefficients (Appendix Table A7). In addition, we see substantial wage compression in non-tradable industries, suggesting that the results are not driven by a national product market. For Burning Glass, we estimate equations (5) and (6) for various subsets of the

[27] We also find similar results using Zillow home price indices directly or using measures of average local nominal incomes, and with the non-instrumented version of the regressions (Appendix Table A6). In all cases the between-firm coefficient is roughly twice as large as the within-firm coefficient. Additionally, the results are robust to including salary ranges in Burning Glass (Panel A of Appendix Figure A7). Panel B shows that the results are nearly identical when re-weighting 6-digit occupations to match the distribution from the Occupational Employment Statistics, while Panels C and D show robustness to limiting our sample to firms with at least five and ten establishments, respectively. Finally, Panel E illustrates that the results are robust to using local prices without instrumenting with housing prices. Appendix Section A2.3 discusses how relabeling of job titles in Burning Glass might affect our result.

[28] The within-firm slope rises for jobs with fewer pairs of identical wages, in Burning Glass (Appendix Figure A8).

data—tradable and non-tradable industries and occupations, and high and low wage occupations—and demonstrates that the pattern is present for many types of jobs (Appendix Figure A9). Also, the degree of wage compression is similar in each year of the sample (Appendix Figure A10).

We have shown wage compression when using posted wages and realized earnings as outcomes. We conduct a final test of wage compression using a dataset of wages from Labor Condition Applications (LCA). The dataset is sourced from visa applications submitted to the Department of Labor, and contains information on realized salaries net of hours, as well as occupations, and work locations. We describe the data in more detail in Appendix A1.2. We again find that the between-firm slope is twice as large as the within-firm slope, indicating significant wage compression of comparable magnitude to the other datasets (Appendix Figure A11). Morever, using a unique feature of the visa applications data, we can look at the change in the wage for a *given* worker across locations within the firm. Specifically, firms can list the wages that they would pay a given worker at up to 10 different worksites. This is admittedly a very selected sample, but even when the prevailing wages are very different, firms report that they would pay that worker the same nominal wage across locations (Appendix Figure A12).

Fact 3: Wage Growth is Similar within the Firm Across Space

So far, we have seen that firms set similar wages across space, even in regions with different prices. These facts are consistent with national wage setting—that is, firms choosing to set identical or similar wages across space. Absent national wage setting, our simple model suggests wages should be different in regions with different prices, especially for nontradable industries in which one expects significant dispersion in marginal revenue products across space.

We now ask whether wage *growth* within the firm is correlated across space. By studying wage growth, we difference out any persistent or fixed factors that might lead firms to pay similar wages across space absent national wage setting, even in places with different prices. For instance, firms might pay similar wages across locations with different prices if local amenities are better in areas with high prices. However, local amenities typically evolve slowly and are unlikely to affect annual wage growth.

To study how wage growth varies within the firm across space, we relate wage growth for a given occupation and establishment to wage growth in (i) other establishments in the same region and (ii) establishments in other regions but belonging to the same firm. If wage growth is primarily determined by firm level factors, then wage growth should co-move strongly with wage growth in the rest of the firm. Instead, if wage growth is mostly due to regional factors, wage growth of other firms in the region will have greater explanatory power.

We implement this test with a regression

$$\Delta w_{ofrt} = \beta_1 \overline{\Delta w}_{rt,-f} + \beta_2 \overline{\Delta w}_{ft,-r} + \text{controls}_{ofrt} + \varepsilon_{ofrt} \tag{7}$$

where Δw_{ofrt} is annual wage growth for workers within the occupation, region, firm, and year; $\overline{\Delta w}_{jt}$ is the average growth in wages in region r in year t, calculated over workers in all firms other than f operating in the same region; and $\overline{\Delta w}_{ft,-r}$ is the average growth in wages in firm f for workers in all other regions in year t.

Table 3 presents the main results. Panel A studies the primary LEHD-ACS dataset. In column (1), we regress wage growth in the job on average wage growth in the rest of the firm and in the rest of the region. A 1% increase in regional wage growth associates with a 0.14% increase in the wage growth of the job; whereas a 1% increase in firm wage growth associates with a 0.87% increase in the wage growth of the job—roughly 8 times larger. The coefficients are unchanged as we add in occupation by year, industry by year, and occupation by industry by year fixed effects. In column (4), we drop the firm wage growth regressor. In column (5), we calculate wage growth at the region by occupation level, and the firm by occupation level. Again, the firm level factor associates much more strongly with wage growth at the job level.[29] Panel B studies the supplementary Burning Glass dataset, with similar results. Again, in column (1), the co-movement between firm wage growth and job level wage growth is much higher than between regional wage growth and job level wage growth. Results remain similar as we include the same additional specifications as Panel A.[30] Again, we caution that the magnitudes are not strictly comparable, given that the wage concept is different across the two datasets.

[29]We are unable to measure growth in quarterly wages in the LEHD-ACS, because our measure of hours worked, from the ACS, does not vary over time.

[30]Our Burning Glass results study only jobs with a 1-year gap between postings. We show similar results for jobs with a 2-year gap between postings in Appendix Table A8.

Table 3: Firm versus Regional Factors and Wage Growth

	Panel A: LEHD-ACS				
Dependent Variable:	Growth In Individual Quarterly Earnings				
	(1)	(2)	(3)	(4)	(5)
Avg. Growth In Earnings In Community Zone	0.135	0.122	0.120	0.185	
	(0.029)	(0.027)	(0.027)	(0.042)	
Avg. Growth In Earnings In Other Establishments Within Firm	0.873	0.852	0.844		
	(0.019)	(0.015)	(0.014)		
Avg. Growth In Earnings In Community Zone–Occupation					0.018
					(0.008)
Avg. Growth In Earnings In Other Establishments Within Firm–Occupation					0.387
					(0.014)
Observations	15,060,000	15,060,000	15,060,000	15,060,000	15,060,000
	Panel B: Burning Glass				
Dependent Variable:	Growth In Posted Wages				
	(1)	(2)	(3)	(4)	(5)
Avg. Growth In Posted Wages In County	0.065	0.049	0.051	0.059	
	(0.017)	(0.015)	(0.015)	(0.014)	
Avg. Growth In Posted Wages In Other Establishments Within Firm	0.462	0.429	0.368		
	(0.083)	(0.074)	(0.052)		
Avg. Growth In Posted Wages In County–Occupation					0.051
					(0.014)
Avg. Growth In Posted Wages In Other Establishments Within Firm–Occupation					0.576
					(0.050)
Observations	405,047	398,799	389,330	552,231	144,566
Fixed-Effects:					
Occupation×Year		✓			
2-Digit-Industry×Year		✓			
Occupation×2-Digit-Industry×Year			✓	✓	✓

Note: This table relates annual wage growth for workers, at the occupation, region, firm, and year level, to: average wage growth in the region, calculated over workers in all other firms in the region; and average wage growth in the firm, calculated over workers in all other regions. In Panel A, the data is from the LEHD-ACS. All columns control for demographics (dummies for age, gender, and race). The unit of observation is the individual, and the wage growth is defined as the Q4-Q4 change in quarterly earnings, which we winsorize at the top and bottom 1%. Standard errors are two-way clustered at the firm and commuting zone. The sample is held constant across columns, and observations are rounded to pass disclosure review. Panel B studies outcomes in Burning Glass and restricts the dataset to data with a 1-year gap between vacancy postings. Firm clustered standard errors are in parentheses.

Fact 4: National Wage Setters Pass Through Local Shocks

Our evidence so far suggests national wage setting, but is not conclusive. Jobs that have similar wages in levels and growth rates might be those jobs for which labor productivity varies little across space. According to our simple framework, these jobs will pay similar wages even without national wage setting. An example could be a firm producing purely tradeable output, sold at a nationwide price. Even if tradeable prices and productivity vary over time, they may not vary across space within the firm, meaning the level and growth rate of wages would be similar absent national wage setting.[31]

We now provide a sharper test of national wage setting using the pass-through of local wage shocks. In the previous Fact 3, we documented that wage growth is correlated across locations of the firm. Now, we will document a causal counterpart to Fact 3, by showing that shocks to wage growth in one location of the firm cause higher wage growth elsewhere, consistent with national wage setting.

To start, consider the predictions of national wage setting for the co-movement of wages within a job across locations. Jobs that pay similar wages across locations—who we hypothesize to be national wage setters—should continue to pay similar wages in the future. As such, wage growth should be highly correlated across different locations of these jobs. By contrast, jobs that initially pay different wages across locations are not national wage setters and need not have correlated wage growth.

We test these predictions of national wage setting in the LEHD-ACS. We are interested in heterogeneity in the degree of national wage setting at the job level. As such, we calculate a version of the histogram in Figure 1, Panel A, separately for every firm by occupation (i.e. job). We then take the mean of the within firm distribution and the matched between firm distribution. The difference between these two means, job by job, is our measure of whether a job has nationally set wages. This measure is one way to summarize the gaps between the distributions in Figure 1 for each job. If the within- and between-firm distributions are the same, then the job does not have nationally set wages. If the gaps between the two distributions are large, then there is more wage compression. Since our proxy for national wage setting is continuous, we discretize the measure by selecting the top quartile of the measure. We compare their behavior to firms in the bottom 50% of the distribution, who are unlikely to have national wages.[32]

We then consider the regression

$$\Delta \log w_{iofrt} = \beta_1 \Delta \log w_{i'ofr't} + \gamma_{k(f)ort} + \varepsilon_{ofrt} \tag{8}$$

where the outcome, $\Delta \log w_{iofrt}$, is the annual growth in the average quarterly earnings between year $t-1$ and t for individual i in firm f and occupation o in commuting zone r. We relate $\Delta \log w_{i'ofrt}$ to

[31] In Appendix Section C1.5 we extend the baseline model to show that if labor market power does not vary across space, then purely tradeable firms pay the same wage in all locations.

[32] This exercise is not intended to gauge the total fraction of jobs that have national wages, which we will carry out later in a separate exercise. We classify only the top 25% of the distribution as national wage setters in order to be conservative and identify firms that are highly likely to be national wage setters. As it turns out, firms with less wage compression tend to be relatively small. Therefore, in order to have a similar number of "control" and "treatment" observations, we use the bottom 50% of the distribution as "control" observations. We also only define national wage setting for occupations within a firm for which we have at least 10 within-firm and between-firm pairs.

the growth in the wage at that firm for another worker i' in the same occupation in another county, r'. We also control for occupation by year by region by 2-digit NAICS fixed effects ($\gamma_{k(f)ort}$), where $k(f)$ denotes the industry of the firm. For this regression, we use a pairwise dataset similar to that in Figure 2 but where we measure the annual change in average quarterly wages for each worker rather than the quarterly level of wages.[33]

National wage setting predicts that β_1 will be larger among the firms and occupations that compress wages across space. However, there is an identification concern—shocks to labor productivity that are correlated across establishments could also explain these patterns, even absent national wage setting. We therefore instrument for wage growth, $\Delta \log w_{oir't}$ in Equation (8), with a purely local shock to wages in county r'. For this instrument to be valid in equation (8), the shock should raise establishment wages in exposed county r'. However, conditional on the fixed effect $\gamma_{k(f)ort}$, the shock cannot affect wages in a paired establishment r with compressed wages through channels other than national wage setting. For instance, the instrument is invalid if it raises productivity in establishment r by more than other establishments in the same region and occupation, and also differentially affects jobs that particularly compress wages.

The shock we use comes from national booms and busts in demand for natural resources employment, driven in large part by a boom and bust in global oil prices between 2010 and 2019. After a boom, certain areas that concentrate in natural resources have reason to pay higher wages, including in sectors that do not produce natural resources. Other areas, without natural resource employment, will be relatively unaffected. This shock is appealing as natural resource employment is highly localized. Therefore, natural resource booms likely directly affect certain establishments, with minimal direct effects on the rest of the firm (see Appendix Figure A13 for a map of the shock). For instance, consider a retail firm employing workers in Houston and New York. After a natural resources boom, wages will rise in Houston, meaning the retail firm has reason to pay higher wages in Houston but not necessarily in New York.

Importantly, we account for the market-level effects of the natural resources shock with the occupation by county by year by industry fixed effects ($\gamma_{k(f)ort}$) in equation (8). For instance, natural resource shocks will affect all establishments in a given region, even if the shock does not directly affect that re-

[33] In order for a worker to be included in this sample, they must have at least 3 quarters of complete earnings in both years t and $t-1$. Because this limits the sample meaningfully, we match worker i and i' on the following variables: 8 5-year age bins, 4-digit industry, 4 education bins, and occupation.

gion, through forces such as migration across regions or market level supply shocks. However, the fixed effect $\gamma_{k(f)ort}$ absorbs this market level variation.

We take two additional steps to try to ensure the exclusion restriction holds. First, we exclude firms that directly operate in the natural resource sector, since all establishments in those firms are likely to be affected by resource booms regardless of where they are located. We also require that non-exposed jobs locate in a county in which less than 1% of the employment share is in mining. Second, to avoid geographic spillovers, we only study non-exposed establishments r located more than 100 miles from the exposed establishment r'.

We construct a shift-share instrument that measures a county's exposure to natural resource shocks as

$$\frac{\text{Natural resources employment}_{r,2009}}{\text{Total employment}_{r,2009}} \times \log(\text{Natural resources employment}_{-r,t}).$$

This instrument measures a county's predicted exposure to aggregate changes in natural resource demand using county j's employment share in natural resources measured in 2009, the year before our sample period, and the growth in all other counties' employment in natural resource industries. We take the difference of the instrument over time, in line with equation (8).

This regression raises the challenge of selecting "clean controls", emphasized by Cengiz, Dube, Lindner, and Zipperer (2019), Borusyak, Jaravel, and Spiess (2022), and the literature estimating two way fixed effects regressions. By adding the fixed effects $\gamma_{k(f)ort}$, this regression assigns to the "treatment group" establishments who are exposed to the natural resource shock in their paired establishments, whereas the regression assigns to the "control group" establishments in county r that are not exposed to natural resources shocks in their paired establishment r'. However, an establishment in the control group of this regression might still be exposed to natural resource shocks, via a third establishment r'' in the same firm, located in an exposed area. If so, then the control establishments have been treated, which would bias our estimates. Therefore, we refine our regression to select a "clean" control group.[34] Specifically, we define unexposed observations as those for which the maximum absolute value of the natural resources shock is below the 75th percentile, taking the maximum across all establishments and years within the firm. Unexposed observations form the control group. As such, all variables in Equation

[34]The method proposed in Borusyak et al. (2022) paper does not directly apply here, because our setting has a continuous treatment with respect to time.

Table 4: Pass Through of Natural Resources Shock to Wages in other Establishments

	First Stage		Reduced Form		IV	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \text{Shock}_{r,t}$	0.024	0.012	0.019	0.002		
	(0.005)	(0.003)	(0.003)	(0.002)		
$\Delta \log w_{iofr't}$					0.786	0.194
					(0.147)	(0.166)
Observations	720,000	2,538,000	720,000	2,538,000	720,000	2,538,000
First-Stage F-stat					24.77	13.95
P-value for diff. in coefs.					< 0.01	
Included Sample	NWS	No NWS	NWS	No NWS	NWS	No NWS

Notes: This table uses the LEHD-ACS pairwise sample to examine the impact of a natural resource-induced shock on establishment wages across a firm. Natural resource industries are NAICS sectors 11 and 12, and we measure employment in each county using the Quarterly Census of Employment and Wages. The regression sample excludes firms in national resources, establishment pairs that are located within 100 miles of one another, and workers in firms that we classify as ”non-exposed (see text for definition). All variables are demeaned using unexposed observations. The outcome in columns 1-2 is the change log of earnings of workers in exposed establishments. The outcome in columns 3-4 is the change log of the earnings of workers in the unexposed establishments. In columns 5-6 we instrument for earnings growth in the exposed establishments with the natural resources instrument. The sample is restricted to columns 1, 3, and 5 restrict to firm-occupations that are identified as national wage-setters while columns 2, 4, and 6 restrict to non-national wage-setters. The Kleibergen-Paap F-statistic is reported in columns 5 and 6. The number of observations has been rounded to meet disclosure requirements.

(8) are demeaned using unexposed observations. More details on this method as well as an example are provided in Appendix A2.4.[35]

Table 4 presents the results of the regression, which are consistent with national wage setting. Columns 1 and 2 of Table 4 show the first stage result from regressing the natural resources shock in the second establishment on the average earnings of workers in that establishment. A 1% increase in exposure leads to a 2.4% increase in earnings if wages are set nationally (column 1) and by 1.2% if wages are not set nationally. While both types of establishments have a strong first stage, columns 3 and 4 show that there is a reduced form effect of a natural resources shock on earnings only among national wage-setters. These columns show the impact of a natural resources shock on the earnings of individuals in the second, unexposed establishment. Among occupations with nationally set wages, earnings increase in the unexposed establishment by 1.9% while there is zero impact among firms that set wages flexibly. We see the same pass-through of wages in the IV estimates (columns 5-6): an increase in the wages in an establishment

[35]One concern is mechanical bias stemming from the fact that we classify firms as national wage setters based on their wage compression. To purge the mechanical bias, we classify whether a firm is a national wage setter using only wage gaps for locations within the firm that are not exposed to natural resource shocks.

in an exposed county passes through to wages in unexposed establishments, if and only if the firm sets wages nationally for that job. The magnitude of the coefficient on wage growth in column 5 implies that when establishments with national wages raise wages by 1% in one location, they raise wages (earnings) by an average of 0.79% in the second. The difference between the coefficients in columns 5 and 6 are statistically significant at the 1% level.

We probe the robustness of the main result. We show that the results are robust to considering only non-tradable occupations or industries—in either case, the response of wages for national wage setters is significantly greater than the response for other firms (Appendix Table A9). This result is important because our simple conceptual framework of Section applies to non-tradeable firms, for whom labor productivity varies across space. For these firms, and under our identification assumption, local shocks pass through to the rest of the firm only if there is national wage setting. The pass through for tradeables is less relevant for assessing whether there is national wage setting (see Appendix Section C1.5 for details).[36]

We also show robustness to studying large firms, to reweighting so that the firm size distribution in the pairwise sample matches the firm size distribution in the main LEHD-ACS sample, and to running a pooled regression that includes firm fixed effects, effectively using variation in the extent of national wage setting across occupations within the firm (Appendix Table A9). Finally, we find similar results with data from Burning Glass (Appendix Table A10). Moreover, with Burning Glass, we are able to exploit a sharper measure of national wage setting, namely jobs that set identical wages—again finding greater pass through of local shocks for this measure of national wage setting.

In Table 4, the first stage regression is somewhat higher for jobs with national wages. One might expect the local wage of national wage setters to be less sensitive to local shocks. The reason for the larger first stage for national wage setters appears to be that national wage setting is more common in certain occupations and parts of the firm size distribution. These occupations and firms happen to be more responsive to natural resources shocks. If we restrict only to large firms, the first stage is the same for firms that do or do not set wages nationally according to our measure. Likewise, if we estimate the regression separately for the 5 largest occupation groups, we also find that the first stage is the same

[36]We caution that for non-tradeables, there is some pass through of the shock even for firms with relatively dispersed wages. One reason could be that in the non-tradeable sector, there could be some national wage setting even among firms with more dispersed wages.

for firms that do or do not set wages nationally. This heterogeneity does not affect the validity of our IV estimates, as the IV estimate is rescaled and does not depend on the magnitude of the first stage estimate, although it could affect the representativeness of these estimates.

Our pass through results suggest that firms that pay similar wages across space are setting wages nationally for those occupations—for these jobs, shocks to a single establishment raise wages everywhere, whereas jobs setting different wages do not pass the shock through. However, we note two caveats. First, our empirical results are narrow in scope because we focus on a particular shock affecting only a subset of firms that have at least some establishments in natural resource exposed regions. Second, there are several other potentially important reasons why firms might pass purely local wage shocks through the rest of the firm—for instance, internal capital markets or production complementarities across establishments. However, even if these mechanisms affect the *average* pass through of local shocks, they will only confound estimates of national wage setting if they *differentially* affect firms that compress wages.

Discussion of Magnitudes

We close this section by measuring the degree of national wage setting implied by our estimates. We use the LEHD-ACS estimates from Figure 2, which shows the distribution of wages within and between firms. National wage setting shifts the within-firm wage pairs to the left relative to the corresponding between-firm wage pairs. We use this shift to measure national wage setting.

Formally, let $W(x)$ be the cumulative distribution function (CDF) of the absolute difference of wage pairs within the firm and across locations, i.e. the CDF corresponding to the orange probability density function (PDF) in Figure 2, Panel A. By definition, $W(x)$ is a weighted average of the distributions for jobs with national wages $N(x)$, and jobs with local wages $\mathcal{L}(x)$, weighted by the share of jobs with national wages $\mathcal{N}$. Therefore, $W(x)$ satisfies

$$W(x) = \mathcal{N} N(x) + (1 - \mathcal{N}) \mathcal{L}(x). \tag{9}$$

To identify $\mathcal{N}$, we make two assumptions. First, we assume that the distribution of wages across regions for local wage setters, $\mathcal{L}(x)$, equals the between-firm distribution of wages $B(x)$. Our assumption implies that, absent national wage setting, within-firm and cross-location wage variation would resemble between-firm and cross-location variation.

Second, we bound $N(x)$ using the CDF of within-firm, within-location wage differences, denoted by $\mathcal{F}(x)$ and corresponding to the blue PDF in Figure 2, Panel B. In the extreme, national wage setters set exactly the same wage across all locations of a given job. However, even in this extreme case, we would still measure some differences in wages within the firm and across location. The reason is that, as we have discussed, unobserved heterogeneity leads wages to vary in the LEHD-ACS. Therefore, we assume that the distribution of wages within a firm and across locations cannot be more compressed than the distribution of wages within a firm and within locations. By construction, the latter distribution has no wage dispersion from locations, making it a natural benchmark for the minimal degree of wage dispersion across locations. Our assumption implies $N(x) \leq \mathcal{F}(x)$.

We derive a bound on $\mathcal{N}$ by combining these two assumptions with Equation (9). Our bound is

$$\underline{\mathcal{N}} \geq \max_{x:B(x)<1} \left[\frac{W(x) - B(x)}{\mathcal{F}(x) - B(x)} \right]. \tag{10}$$

The bound within the square brackets holds for any value of x; in order to calculate the highest lower bound possible, we take the maximum value across x such that the bound is well defined (i.e. $B(x)$ is less than 1). This bound is tight if all national wage setters have the minimal wage dispersion across space (i.e. $N(x) = \mathcal{F}(x)$). The bound is loose if national wage setters have some wage dispersion across space (i.e. $N(x) < \mathcal{F}(x)$). Intuitively, if there is more wage dispersion among national wage setters, then there must also be more national wage setters in order to generate the compressed within-firm wage distribution that we observe in the data.

Implementing this calculation, we find that at least 84% of jobs in our sample set wages nationally. Our estimate is relatively high because, from Figure 2, Panel B, there is significant wage dispersion even within firms and within locations. Nevertheless, in Figure 2, Panel A, there is still an excess mass for jobs paying similar wages across space. In order to generate both patterns, there must be many jobs with national wages.[37] Our LEHD-ACS sample restricts to multi-establishment firms, which are roughly 60% of US employment (Carballo et al., 2024). Therefore, the share of overall employment in jobs with nationally set wages is at least 51% (i.e. 60%×84%).

Our calculation relies on the assumption that the distribution of wages between locations and firms,

[37]We can also ignore unobserved heterogeneity in the data, and derive a bound without using the distribution of wages within firms and locations. Instead, we can assume that the minimal amount of wage dispersion for national wage setters is zero (i.e. $\mathcal{N}(x) = 1$ for all $x \geq 0$ instead of $\mathcal{N}(x) = \mathcal{F}(x)$). This bound is 37% instead of 84%.

$B(x)$, is a valid counterfactual for the distribution of wages between locations and within locally wage setting firms, $\mathcal{L}(x)$. This assumption may lead us to overstate the share of national wage setters if $B(x)$ overstates the wage dispersion of local wage setters. This would make our bound for the share of national wage setters too high. $B(x)$ is greater than $\mathcal{L}(x)$ if there is wage dispersion between firms in the same location and same narrow industry, among workers with the same demographics. In that case, $B(x)$ represents wage dispersion not only due to location, but also due to level differences across firms. Wage dispersion of this kind is probable, even with our detailed industry and worker level controls. Therefore, in Appendix Section C1.4, we use a second exercise to bound the fraction of national wage setters. This exercise relies on a different statistic: the within and between firm relationship between wages and prices that we documented in Fact 2. As we explain in the Appendix, the exercise relies on a different assumption: that high-productivity firms do not sort into high-price regions, rather than assuming that firms within a region pay similar wages for similar workers. Reassuringly, using the alternative approach we arrive at a similar although slightly smaller estimate, finding that at least 60% of firms in the sample (containing 36% of US employment) set wages nationally.

5 Characteristics of National Wage Setters

We now explore how the pay of national wage-setters differs from local wage-setters, and discuss why some firms choose to set wages nationally. In the LEHD-ACS, we show that jobs with national wages tend to pay a premium over firms that set wages locally. Perhaps as a result, we also find that national wage-setters have higher worker retention. We find suggestive evidence that these firms pay a premium because they are more productive. Our survey with HR managers suggests that firms set national wages when they help simplify management, or when workers are geographically mobile or concerned about pay fairness in nominal terms. Taken together, these results allow the possibility that national wage setting confers some benefits to the firm that offset the cost of failing to vary wages with labor market conditions. However, we stress that these results are suggestive.

5.1 The Pay of Nationally Wage Set Jobs

A natural question is how the wages of national wage-setters compare to other firms. We investigate wage premia in the LEHD-ACS with the following regression

$$\log(w_{iofrt}) = \beta_1 \,\text{NWS}_{of} + \beta_2 \log(E_{ft}) + \gamma_{rot} + \gamma_j + \alpha X_i + \varepsilon_{iofrt} \tag{11}$$

where $log(w_{iofrt})$ is earnings (or wages) of individual i, γ_{rot} are CZ by year by occupation fixed effects, γ_j are industry fixed effects, X_i are demographic controls for age, race, gender, and education, and NWS_{of} is an indicator for whether the firm sets wages nationally in occupation o.[38] Recall that an occupation is classified as having a nationally set wage if it is in the top 25% of the distribution of wage similarity, and non-national occupations are in the bottom 50%. The middle of the distribution is excluded. Because large firms pay higher wage on average, we also control for the number of workers in a firm's establishment (E_{ft}). The fixed effects control for differences in average wages across markets and across workers with different demographics. We are interested in β_1, which captures whether jobs with national wages pay more than comparable jobs in that market without national wages.

In Table 5, we find that national wage setters pay a premium, even in high price regions. Column 1 shows that firm-occupations with national pay earn a premium: earnings among workers in these jobs are 3.9 percentage points higher than similar workers in firms that do not set national wages. In column 2, we interact the national wage setting indicator with terciles of the regional price level. Unsurprisingly, we find that the premium is highest in low-price regions: workers' earnings in national jobs are 5.3 percentage points higher than those in non-national jobs in the lowest price regions, and the differences are statistically significant at the 5 percent level. Interestingly, though, we find that national firms pay a premium everywhere —the earnings of workers in national jobs are 2.9 percentage points higher in the highest price regions. Columns 3 and 4 repeat the first two columns with wages instead of earnings, using reported hourly wages from the ACS, and find a wage premium.

If national wage setters pay higher wages, then they should be more attractive to workers and retain

[38]We focus on occupations within firms as national wage setting appears to be a characteristic of occupations within firms—that is, a firm either sets pay nationally for an occupation or it does not. However, if a firm sets national wages for an occupation, it does so in all of its locations. This is shown in Appendix Figure A15, with Burning Glass data. Panel A shows that the majority of firms that set national wages only do so for a subset of their occupations. In Panel B, we see that there is a mass of occupations within firms that have no national wage setting and a mass that have national wage setting in all establishments. There are relatively few occupations that have national wages in only a subset of locations.

Table 5: Wage Premium and Worker Tenure in the LEHD

Dependent Variable:	Log Earnings		Log Wage		Tenure	
	(1)	(2)	(3)	(4)	(5)	(6)
NWS	0.038		0.034		0.569	
	(0.008)		(0.009)		(0.159)	
NWS × Bottom Terc.		0.053		0.046		0.843
		(0.009)		(0.013)		(0.238)
NWS × Middle Terc.		0.036		0.042		0.423
		(0.008)		(0.011)		(0.205)
NWS × Top Terc.		0.029		0.023		0.457
		(0.008)		(0.010)		(0.205)
P-value for equality of coefs.		<0.05		<0.05		>0.1
Observations	7,252,000	7,252,000	121,000	121,000	342,000	342,000

Notes: This table presents estimates of the pay of national wage-set firm-occupations relative to locally wage-set firm-occupations (columns 1-4) and job tenure (columns 5-6). We identify national wage setting by taking the average difference in wages for within-firm between-location pairs and between-firm, between-location pairs in the LEHD pairwise data for each firm and occupation. NWS is an indicator that takes the value one if a firm by occupation is in the top 25% in terms of the gap size and 0 if it is in the bottom 50%. The middle part of the distribution is excluded. Standard errors are clustered at the firm $\times$ occupation level. In columns (1)-(4), we include as controls the log of firm size on its own (columns 1 and 3) and interacted with the price of the area (columns 2 and 4), year, commuting zone, occupation fixed effects, industry fixed effects, gender, 5-year age bins, race, and 4 education bins. In columns (5)-(6), we include as controls the log of firm size on its own (column 5) and interacted with the price of the area (column 6), year, commuting zone, industry, occupation, gender, age bins, race, and education fixed effects. The number of observations has been rounded to meet disclosure requirements.

them at a higher rate. We test this hypothesis by repeating the analysis of columns (1)-(4) of Table 5 but replacing workers' quarterly earnings with their completed tenure at the firm. Columns (5)-(6) of the table report the results. Workers in jobs with national wages spend more years at their firm (column 1), and this correlation is larger in low-cost regions where the pay premium is largest (column 2), although the differences across locations are not statistically significant. Our results are in line with research showing that establishments are viewed more favorably by workers when they pay more than the local benchmark wage (Dube, Naidu, and Reich, 2022).[39]

We find similar results in the supplementary dataset from Burning Glass. In particular, in Burning Glass national wage setters—who we associate with jobs paying identical wages across locations—pay a wage premium. These jobs pay a premium even in high price areas, but especially in low price areas

[39]With completed tenure as an outcome, the dataset is smaller, being at the worker-by-job spell level, instead of the worker-by-year level. As a result, we use less granular fixed effects—separately including year, commuting zone, and occupation fixed effects, instead of their interaction.

(Appendix Figure A14).[40]

One possible reason for the pay premium is that national wage setters are more productive. We explore this on the subsample of firms within Burning Glass that we are able to match based on firm name to Compustat. Within this sample, which is admittedly small, we find suggestive evidence that firms with more identical wages have higher output per worker and more R&D spending per worker (see Appendix Table A12, which also finds no clear relationship of national wage setting to total firm employment). Consistent with this evidence, the simple framework of Section 2 predicts that national wage setters pay a wage premium if they are more productive than local wage setters, as we establish formally in Appendix Section C1.7.[41]

5.2 Survey Evidence: Motivations for National Wage Setting

We now turn to an additional data source to understand why there is national wage setting, from a survey of human resources (HR) managers. While suggestive, the patterns indicate that firms set national wages to help simplify management, and when workers are geographically mobile or concerned about pay fairness in nominal terms.

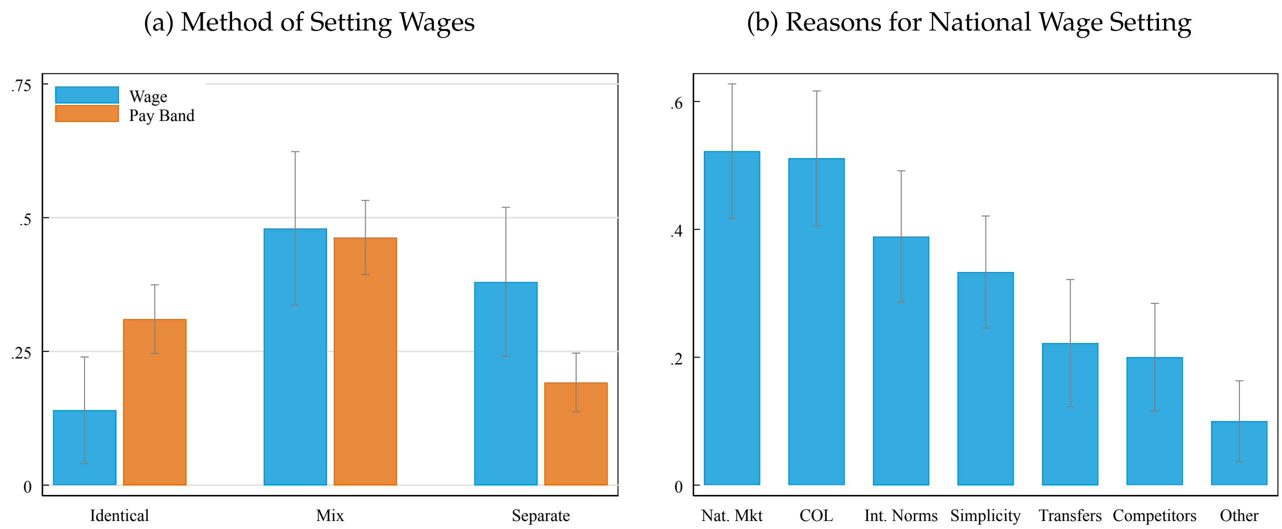
We administered a survey to human resources professionals across the U.S. The survey was run in partnership with a large HR association to which tens of thousands of HR professionals belong. We asked respondents questions about how their firm sets pay across geographic locations, as well as a series of questions designed to understand the factors that inform their pay-setting strategy.

We sent the survey to roughly 3,000 HR professionals who belong to the association and had a 13% response rate. The sample of respondents primarily work at large firms with more than 500 employees (Appendix Figure B1) and work in a range of industries. The HR association is one of the two largest in the United States, suggesting a broad sample of firms. However, we note that the survey sample is skewed towards manufacturing, professional and scientific industries, and finance (Appendix Figure B2). For our analysis, we drop all respondents who work at firms operating in only one city as we are

[40] We summarize these patterns with regressions, showing jobs in firms where at least 80% of the jobs have identical wages pay 12% more than other comparable jobs within their markets (Appendix Table A11). We also show that firms where at least 50% of job pairs are identical pay a small premium for all their jobs, even those that are not in occupations with identical wages (Appendix Table A11).

[41] There, we establish an additional reason why national wage setters could pay a premium. There is a premium if high productivity areas tend to also have high regional labor supply—perhaps due to paying high nominal wages and providing cheap local consumption. If so, national wage setters reallocate towards high wage areas, and in doing so, must raise their nationally set wage relative to other firms.

Figure 5: Survey Evidence of National Wage Setting



Notes: Panel A shows the fraction of respondents who report setting wage (blue) or pay bands (orange) identically, both identically and separately, and separately for the majority of its workers. 20% of respondents (N=60) report setting point wages for the majority of their occupations. 80% (N=244) set pay bands. "Identical" means that a respondent stated that pay bands (wages) are set identically across establishments so that workers with the same job title face the same pay band. "Mix" means that a respondent stated that pay bands (wages) are sometimes determined separately, but not always. "Separate" means that a respondent stated that pay bands (wages) are determined separately for each establishment/plant/store. The exact question asked is shown in the survey appendix. In Panel B, the sample is restricted to the set of respondents working at firms that set identical pay for some or all of their jobs. The y-axis is the fraction of respondents who choose a given factor as a top three reason for setting identical wages. *Nat. Mkt* means that the firm hires on a national market. *Norms* is the selection "We want workers performing the same job to be paid the same wage." *COL* is the selection "All of our employees work in areas with similar costs of living". *Simplicity* is the selection "It is administratively costly to tailor wages to each location." *Transfers* is the selection "Workers in these jobs sometimes transfer across locations and we do not want to adjust their pay if they do". *Competitors* means that the firm sets pay nationally because it is following its competitors. The full responses can be seen in the online survey appendix. We presented options to the full sample in a randomized order.

interested in the behavior of firms that operate in multiple regions.[42] The majority of respondents are HR managers or executives who are directly involved in setting pay (Appendix Figure B3). More details on the sample and survey design are provided in Appendix Section B1 and the online survey appendix.

As a preliminary finding, we establish that in our survey, national wage setting appears to be common. Figure 5, Panel A shows responses to the question "Which of the following describes how your firm sets wages (pay bands) across locations for the majority of your workers?"[43] Respondents could choose one of three options: wages (pay bands) are determined separately for each establishment, are set identically so that workers with the same job title face the same wage (pay bands), or sometimes

[42]Our survey does not select only national firms, since 18% of respondents do not operate in multiple cities.
[43]Earlier in the survey, we ask respondents whether their firm primarily uses pay bands or a point wage.

separately but not always. In blue, we show the results for firms that use point wages, and in orange we show the results for those firms using pay bands. Just under 15% of firms with point wages set identical wages across establishments and over 30% of those using pay bands do so as well. Consistent with our results in Burning Glass, nearly 50% who use point wages or pay bands state that they set wages identically for some jobs but not all. Of course, firms could be making adjustments within pay bands based on geographic factors. Therefore we ask firms that use pay bands whether they adjust pay within a band for any of the following reasons: to reward worker performance, based on a worker's experience, based on a worker's prior pay, based on workers receiving outside offers, and the local cost of living. Cost of living is chosen the least among firms that set identical bands across space (see Appendix Figure A17). Therefore, while firms may adjust wages across space within pay bands, it does not appear to happen within the majority of firms.

We then ask why firms set wages nationally. We asked respondents whose firms do not vary the nominal wages of at least some jobs to rank seven reasons for not doing so.[44] Figure 5, Panel B shows the fraction of HR managers that report each reason as one of the top three. The most commonly cited reason for setting national wages is hiring on a national labor market—that is, firms set national wages when they hire across the country for all of their establishments, meaning that the workers who take these jobs are more likely to be geographically mobile. Notably, hiring nationally mobile workers seems to cause firms to equalize nominal and not real wages across space. Indeed, a human resources executive told us that paying a national wage was important for "*attracting and retaining talent*" in low wage locations of the firm, since the company was "*competing in a national labor market*" for relatively mobile and high wage occupations.[45]

Many firms also set national wages to simplify management. Around 35% of respondents report that they set national wages in part because it is administratively costly to tailor the wage to each location. This policy only benefits the firm, on net, when the costs of compressing wages are relatively small. Consistent with this logic, almost half of all respondents say that they set national wages because their workers are in areas with similar costs of living.[46] Finally, nearly 40% of survey respondents cited inter-

[44]When piloting our survey, we included a free-form question asking managers who report working at firms setting the same nominal wages across locations *why* their company adopted this practice. We grouped these answers into seven reasons.

[45]Consistent with this view, survey respondents who do *not* set wages nationally in some or all jobs report hiring on a local market as an important reason (see Appendix Figure A18).

[46]It is possible that firms operate in areas with a similar cost of living *because* they adopt rigid pay structures. For example, if a firm cannot or chooses not to vary nominal pay across establishments, it may decide not to open up establishments in high

nal fairness norms as a reason for national wage setting. These internal norms again seem to matter for *nominal* and not real wages across establishments.

We conclude by noting that some factors that could lead to national wage setting are notable by their absence from the pilot and the free-form answers. First, firms did not mention labor market institutions, such as unions or minimum wages, as a reason for national wage setting. Second, none of our survey respondents mentioned national price setting as reason for national wage setting. DellaVigna and Gentzkow (2019) show that large retailers set prices nationally, that is, setting a constant price across regions with different product market conditions. With a constant price across regions, the revenue product of labor varies little, which could lead firms to vary wages little across space. Since none of our survey respondents mentioned national price setting as a reason for national wage setting, the two phenomenon may be somewhat independent. This finding notwithstanding, firms might jointly adopt national price- and wage-setting as part of a more general set of national policies.[47] We believe the potential interactions between national price- and wage-setting are an important topic for future research.

6 The Effect of National Wage Setting on Profits and Wage Dispersion

How much is at stake for the firms that choose to set wages nationally? In this section, we make simple assumptions about how firms would have set wages in the absence of national wage setting and then, using the model in Section 2, provide a back-of-the-envelope estimate of the profits at stake from national wage setting. It is possible that setting wages nationally increases worker productivity and maximizes profits, since firms setting national wages pay a premium and are slightly more productive. If so, our benchmark reflects the increase in firm profits due to national wage setting required to offset the costs. Given the simplicity of the model, and because the LEHD-ACS offers at best a coarse measure of whether a firm sets wages nationally, the results of this section are also suggestive.

We use a proxy for whether a firm sets wages nationally in the same way as Section 4, again using the primary LEHD-ACS dataset. That is, we identify as national wage setters those occupations and firms in the top quartile of wage compression across space, and local wage setters as the occupations

cost of living areas. However, we found limited evidence in our survey that national wage setting affects where firms locate (see Appendix Figure A19).

[47]Notably, DellaVigna and Gentzkow (2019) find that firms set prices nationally in part to simplify management; some firms set wages nationally for similar reasons according to our survey.

Table 6: Effect of National Wage Setting on Median Establishment Profits

	Panel A: Percent Difference in Wages
	10.4
	Panel B: Percent Difference in Profits
$\rho = 2$, constant returns	0.8
$\rho = 4$, constant returns	2.5
$\rho = 6$, constant returns	5.3
$\rho = 4$, decreasing returns	1.7

Notes: The sample includes the set of job cells that we have identified as national wage setters, meaning that they are in the top 25% of the distribution of firm-by-occupation wage compression. In the calibration with decreasing returns to labor, the exponent on labor is 0.66.

and firms with below median wage compression across space. We attempt to provide a lower bound for what wage dispersion would have been for these firms had they not chosen to set wages nationally. Specifically, for each location pair in which a national wage setter has workers, we calculate the median absolute percent difference in the wage across those two locations within firms that are not setting wages nationally, matching firms by location, occupation, and industry.[48] According to the simple framework and equation (3), this is the correct counterfactual if (i) productivity differences across space are the same for these two firms (i.e. for firms f and k and locations r and r' we have $A_{fr}/A_{fr'} = A_{kr}/A_{kr'}$), and (ii) all firms within a market face the same labor supply elasticity.

Panel A of Table 6 shows the results. The median absolute difference between the actual wage and the wage suggested by the within-firm benchmark is 10.4 %. Therefore, firms engage in national wage setting even across markets that have meaningful dispersion in wages.

We combine these empirical benchmarks with the structure of the simple model in Section 2 to provide an estimate for the share of the consequences of national wage setting for profits. Specifically, we combine the definition of establishment profits given by equation (1) and the labor supply curve to the establishment given by equation (2). Some algebra implies that to a second order, the loss of profits from national wage setting are

$$\pi_{rf} - \pi^*_{rf} = -\frac{\alpha\rho\,(1+\rho)}{2}\left(w^*_{rf} - w_{rf}\right)^2 \tag{12}$$

[48]For example, if local wage setters in healthcare that operate in both Boston and Austin have an average wage difference of 7% for receptionists in these two locations, we assume that national wage setters in the healthcare industry hiring receptionists, which operate across those two locations, would similarly have wages 7% apart in the absence of national wage setting.

where w_{rf} and π_{rf} are the actual log wages and log profits of national wage setters, w^*_{rf} and π^*_{rf} are the wages and profits in the counterfactual of local wage setting, ρ is the labor supply elasticity to the establishment, and α is the exponent on labor in the production function. We derive this expression in Appendix Section C1.6. We also show that the benchmark described above provides an estimate for w^*_{rf}. As such, we can calculate the profit loss from national wage setting for given values of ρ and α, without other hard-to-measure objects such as local productivity or the productivity difference between local and national wage setters.[49]

The profits at stake from national wage setting seem to be moderately large, though a range of values are possible depending on the calibration of the model. Panel B of Table 6 presents this result. The numbers reported in this table are the median percent increase in profits that a national job would receive from setting wages locally, holding constant other factors. The baseline estimate in Row 2 assumes constant returns to scale in production ($\alpha = 1$) and a labor supply elasticity of 4, which is in the range of estimates found in the recent literature (see for example Dube et al., 2020, Lamadon et al., 2022). The median job is 2.5 % less profitable than it would be with flexible wage setting. Rows 1 and 3 maintain constant returns to scale but consider a labor elasticity of 2 and 6, respectively. Row 5 assumes decreasing returns to scale with an exponent on labor of 0.66. The estimates across these specifications range from 0.8 to 5.3%.

The results in Table 6 also show how national wage setting interacts with textbook notions of monopsony power in the labor market. As the labor supply elasticity rises, comparing rows 1-3 of Panel B, the profits lost by setting wages nationally rise. Intuitively, with more elastic labor supply and less monopsony power, setting a suboptimal wage is more costly because firms are further from their optimal choice of labor. More generally, the presence of national wage setting suggests monopsony power in the labor market—under perfect competition, national wage setting would be prohibitively costly to firms. As such, our finding relates to Dube et al. (2020). That paper argues employer mis-optimization, in the form of round number bunching in wage setting, suggests significant monopsony in the labor market.

Given the simplicity of the exercise, our findings are only illustrative. Nevertheless, they are a useful guide about the magnitude of the profits at stake from national wage setting.

[49] For this back of the envelope, we additionally assume that the labor supply elasticity is the same in all markets for all firms (i.e. $\rho_j = \rho$ for all j). This assumption is innocuous, since differences in local productivity and markdowns are not separately identified by our model. As is well known, the profit loss with freely varying capital corresponds to the profit loss with constant returns to scale; whereas the profit loss with fixed capital corresponds to the case of decreasing returns to scale.

7 Conclusion

This paper demonstrates the prevalence of national wage setting. We first demonstrated, descriptively, that firms tend to pay similar wages across their locations. In the most extreme form of this behavior, an excess mass of firms pay near-identical or identical wages for the same job in different locations. As such, wages and prices co-move weakly within the firm, relative to a between-firm benchmark. Using the co-movement of wages over time within the firm, we demonstrated that this compression is the result of national wage setting, meaning that firms choose to pay similar nominal wages in all of the regions in which they operate.

We found that firms adopt national wage setting for several reasons, including that it simplifies management, accords with firms' sense of fairness, and attracts mobile workers who make nominal, rather than real, wage comparisons across locations. Lastly, we found that at the establishment level, the profits at stake from national wage setting seem substantial.

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A1 Data Appendix

A1.1 Cleaning Firm Names

We cleaned firm names within the Burning Glass vacancy data using a combination of standard cleaning procedures and a machine learning algorithm. Examples of stages in this process can be found in the table below.

We began with a list of (unclean) unique employer names from observations satisfying all restrictions unrelated to employer (such as requirements for non-missing variables), truncated to 128 characters; in the vacancy data, there are 1,129,983 such names. Next, we manually correct the names of some large employers, making use of code from Schubert et al. (2021) and the NBER Patent Data Project. We additionally stripped common words ("The", "Corp.", "Company", etc.), all non-alphanumeric punctuation, spacing, and capitalization.

Next, we implemented the dedupe fuzzy matching algorithm to create clusters of similar employer names. Dedupe makes use of a combination of squared edit distance comparisons subject to a confidence score threshold (which we chose to be 0.5, or 50% based on sample performance), as well as a small sample of names with manual labeling provided as training. For computational reasons, we employ blocking to limit the number of comparisons for each name to roughly 90% of each group of names sharing the first two letters. Within each cluster of names generated by dedupe, we set all names to that of the most common employer to form a list of 933,718 unique cleaned employer names.

Finally, we merge this crosswalk back onto the main Burning Glass data and set the names to the new, cleaned versions to complete the process.

Table: Examples of Precleaning and Dedupe Clusters

emp	**cluster_id**	**confidence_score**	**employer_original**
abcnursery	61334	0.796	ABC Nursery
abcnursery	61334	0.796	ABC Nursery Inc
abcnurserydaycare	61334	0.828	ABC NURSERY DAYCARE
abcnurserydaycareschool	61334	0.811	ABC NURSERY DAYCARE SCHOOL

Notes: For this example, the employer_original variable represents the original employer name, the emp variable represents the pre-cleaned name fed to dedupe, and the cluster_id and confidence_score represent dedupe's assignment of a cluster and confidence threshold for that cluster. In the step following this, each cluster would have a cleaned firm name assigned, which represents the most common name for that cluster.

A1.2 Labor Condition Application (LCA) Data

We additionally make use of a dataset that includes wages from Labor Condition Applications (LCAs) submitted to the Department of Labor (DOL). An LCA is a requirement for a firm's application for an H1-B, H1-B1, or E-3 visa. The goal of this document is to ensure that employers will pay the foreign worker at least the prevailing wage for the occupation in the area of employment. As such, employers are required to submit information about the worker; i.e. their occupation (6-digit SOC code), work location of the employee (state and county), and wage for the worker (either as range or as a point) as well as information about the prevailing wage for that specific job, which is defined by the DOL to be the average wage paid to similarly employed workers in a specific occupation in the area of intended employment. The wage reported on the LCA application is close to or identical to the actual wage the worker receives, as it is costly for employers to change the wage after the application. We use data from 2010 to 2019. The program is large, with an average of 460,000 job applications per year, including both approved and unapproved applications. These jobs are highly concentrated in a subset of high-skill occupations.[50] However, the jobs are geographically dispersed, with nearly 70% of primary worksites outside the 10 biggest cities in the U.S., and dominated by large firms.

This database offers two main advantages over the LEHD-ACS and Burning Glass. First, while Burning Glass is posted wages and the LEHD-ACS provides a perhaps-noisy measure of wages, the LCA data provides data on a worker's wages without noise, and unaffected by differences between the posted and realized wage. Second, unlike the LEHD-ACS, which contains self-reported occupations, the LCA has employer-reported occupations that are comparable across space.

A2 Additional Empirical Results

A2.1 Nominal Wages and Local Prices—Job Switchers

This subsection studies the sensitivity of nominal wages to local prices within and between firms. Different from the main text, we use workers switching jobs in order to control for unobserved heterogeneity.

For this exercise, we must construct a different sample of workers from the main text. We study the full LEHD, and not only the subsample that merges to the ACS. We restrict to quarters where workers have 1 job only. We restrict to workers who we only ever see in two commuting zones over the sample period, and who only move commuting zones once. We consider the year of earnings before the move and then the year of earnings after the move. As in the main text, we drop the first quarter and last quarter of earnings to deal with incomplete quarters. We then construct two samples. The first is a sample of workers who switch commuting zones within the firm. The second is a sample of workers who switch commuting zones and also switch firms. For our sample of between firm switchers, we consider only between-firm moves that are to firms in the same 6-digit industry. Given the data construction, in both samples, all workers have 2 observations (i.e. 1 from before they move, and 1 afterwards.)

We then estimate the following regression, separately for the within-firm and the between-firm sample:

$$\log y_{ict} = \beta \text{Price}_{ct} + \gamma_t + \gamma_{\text{gap}} + \gamma_i + \varepsilon_{ict},$$

where y_{ict} is earnings of worker i in commuting zone c and year t, $\text{Price}_c t$ is the local price level, γ_t is a time fixed effect, γ_{gap} is a fixed effect for the length of time between jobs, and γ_i is a worker fixed effect.

The results are shown in Appendix Figure A22.

A2.2 National Wage Setting at Franchised Firms

Since the Burning Glass data does not include information on whether a firm is franchised, we manually coded the largest firms as either being franchised, not franchised, or following an agent model, wherein employees are independent contractors. We collected this data by searching on the company's website, trade organizations, or news stories mentioning franchises. We found that of the largest 400 firms, 98 firms that are franchises and 235 firms that are not franchises. We excluded the set of firms that we determined followed an agent model, as well as a handful where we could not easily identify the structure. We then looked at the prevalence of national wage setting for the firms we were able to identify as either

[50] Over 70% of the sample is in computers (SOC 15), 10% in business operations (SOC 13), and 8% in engineering (SOC 17).

franchised or not franchised. Appendix Table A13 reports the results. In Panel A, we find evidence that firms following a franchising model have less uniform wages. This is true overall (column 1) and when looking within industries, occupations, and regions (columns 2 through 4).

Similarly, Panel B shows that the slope of wages with respect to prices within the firm is slightly steeper for franchises than for non-franchised firms, again supporting the finding that franchises have less uniform wage setting than similar non-franchised firms.

A2.3 Robustness: Comovement of Wages and Prices with Job Title Relabelling

If firms wish to vary workers' wages across locations while keeping wages for the same job identical, they could use different job titles across locations (e.g. Starbucks might hire "junior baristas" in Houston but "senior baristas" in NYC as a way of circumventing national wage setting policies). We define jobs using occupations, rather than job titles, in the baseline Burning Glass analysis to account in part for this margin of adjustment; we always study occupations in the LEHD-ACS. However, we also present two pieces of evidence that demonstrate that this margin is not quantitatively meaningful in Burning Glass data. First, Appendix Figure A20 explores the robustness of the patterns in Figure 4 to using either job titles, which fully disaggregates the data, or using average establishment wages, which fully aggregates the data within an establishment. The patterns are strikingly similar to the baseline. Second, in Appendix Figure A21, we explicitly test for this by estimating Equation (5) replacing the posted wage with the average wage in the 6-digit SOC for the OES and replacing the 6-digit SOC fixed effects with increasingly aggregated SOC fixed effects (5-digit, 3-digit, 2-digit, or no SOC codes). If firms were strategically shifting to higher-wage 6-digit occupations in high-price areas (e.g. calling baristas managers in New York City), we would see a strong positive slope. Instead, we find very small slopes.

A2.4 Constructing a "Clean" Control Group in the IV Regression

A growing literature has pointed to issues that arise from using a difference-in-differences event study design, if all observations are treated at some point. Comparing units to other units that have already been treated can result in biased estimates. Borusyak et al. (2022) label these "forbidden comparisons" and Cengiz et al. (2019) propose a method to select untreated "clean controls".

Our regression equation (8) risks forbidden comparisons, but does not correspond to a standard event study—we are looking at a continuous treatment in which some counties are always treated but the degree of the shock varies over time, different from the typical event study design in which a unit is treated at one point in time. In addition, many counties have some exposure to the natural resources sector, but the degree of exposure is small. Figure A13 shows that there is a relatively small number of counties that are heavily exposed to natural resource shocks.

In our regression, the "treatment" group is firms that have one establishment in a county exposed to a natural resource shock and one establishment in a county with no exposure. For example, take an accounting firm with an establishment in Houston (exposed) and an establishment in Chicago (unexposed). To estimate the impact of a resource shock in Houston on wages in Chicago, we require a control firm that is hiring for the same job, operates in the same sector, and that also has an establishment in Chicago, but is not directly exposed to a natural resource shock through any of their establishments. Continuing with our example, we would like to compare the Houston/Chicago accounting firm to another accounting firm operating in Boston (unexposed) and Chicago (also unexposed). The latter firm is a "clean" control.

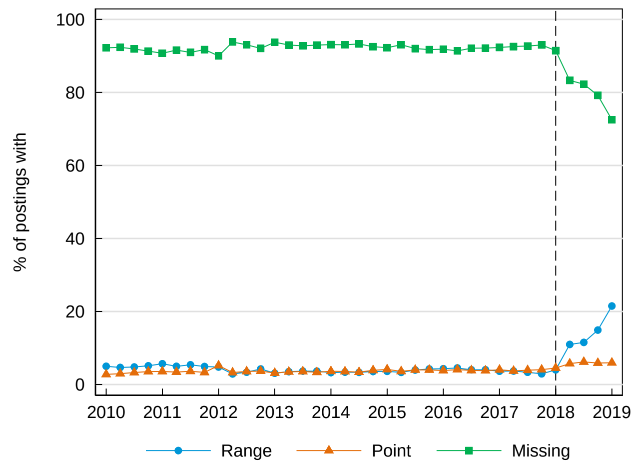
To facilitate a comparison between treatments and clean controls, we first calculate the absolute value of the natural resources shock that each firm faces across all years. We then define a set of untreated units (where a unit is an occupation-county-year) as those whose maximum natural resource shock value is in the bottom 25th percentile of the shock. We use these untreated units to calculate the year$\times$county$\times$job fixed effects that are included in our regressions. Specifically, we demean each variable in our regressions using the average of that variable for untreated units within the same year$\times$county$\times$job cell. In our regressions estimated on subsamples for which the lagged wage is either equal or different, the demeaning is carried out only within the subsample included in the regression.

Without this adjustment our regression would make "forbidden comparisons". Suppose instead that we had estimated regression (8) by IV without selecting a clean control group. If we simply used the full dataset to estimate the fixed effects, we would erroneously be using some exposed firms are controls. To see this, return to the example above and consider the case where the exposed firm has a third establishment in Boston. The full dataset would include an observation for the Chicago/Boston pair of the exposed firm (i.e. the firm that operates in Houston, Chicago, and Boston), which the regression would erroneously assign to the control group. Our procedure prevents us from assigning exposed firms to the control group.

Appendix Tables and Figures

Figures

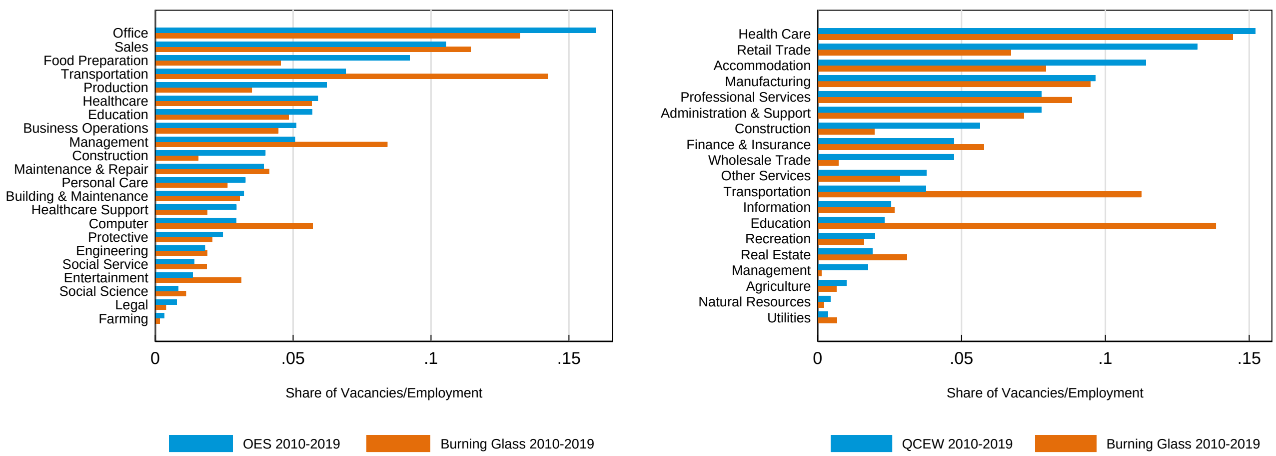
Figure A1: Percentage of Vacancies with Missing Wage Information in Burning Glass



Notes: This timeline depicts the percentage distribution of salaries posted on Burning Glass. The green line, with square markers, indicates the proportion of vacancies with missing wage information. Meanwhile, the blue line with circle markers and the orange line with triangle markers represent the percentage of vacancies with a posting range and point salaries, respectively. Notably, the vertical dashed line in 2018 highlights a shift in the trend of wage postings in Burning Glass.

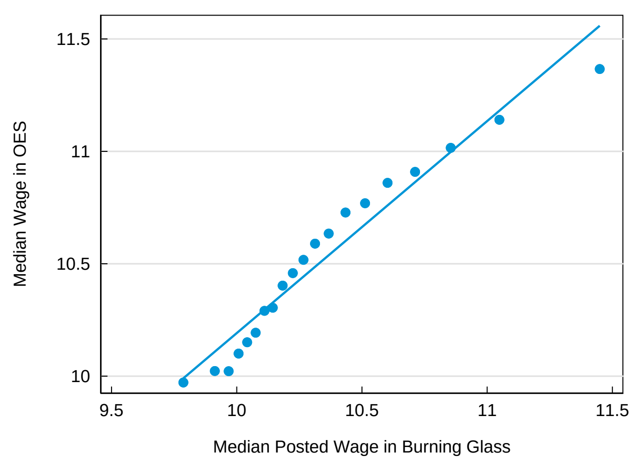
Figure A2: Occupation and Industry Shares in Burning Glass and Public Administrative Data

(a) Occupation (b) Industry



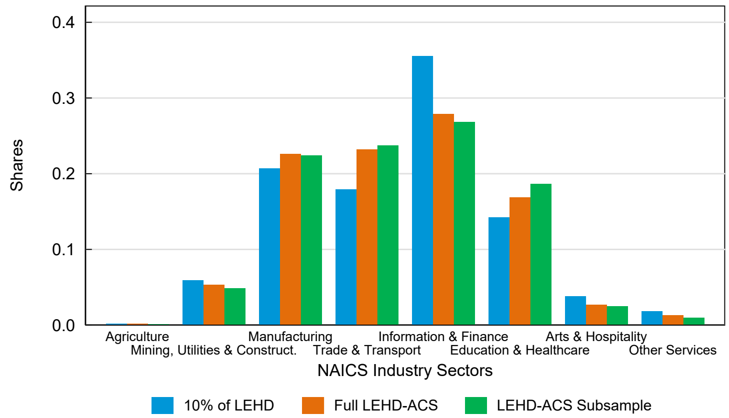
Notes: Shares are calculated using the total number of vacancies or employment summed across 2010-2019. In the left panel, employment is from the 2010-2019 Occupational Employment Statistics, by broad occupation. In the right panel, employment is by broad industry from the Quarterly Census of Wages and Employment from 2010-2019. The sample includes the set of vacancies, including a posted point wage (See Table 2, row 5).

Figure A3: Distribution of Median Wages in Burning Glass and Occupational Employment Statistics



Notes: The OES wage on the y-axis is the log of the occupation by MSA median hourly wages from the Occupational Employment Statistics. The x-axis is the log median wages from Burning Glass for all jobs posting hourly base pay. In both cases, we study the wage averaged over 2010-2019. In both datasets, occupations are at the 6-digit level. MSA by Occupation cells are weighted by average occupation employment over 2010-2019. This is a binscatter plot, and each dot represents 5% of the data. The slope of the line of best fit is reported in Table A1, Column 2.

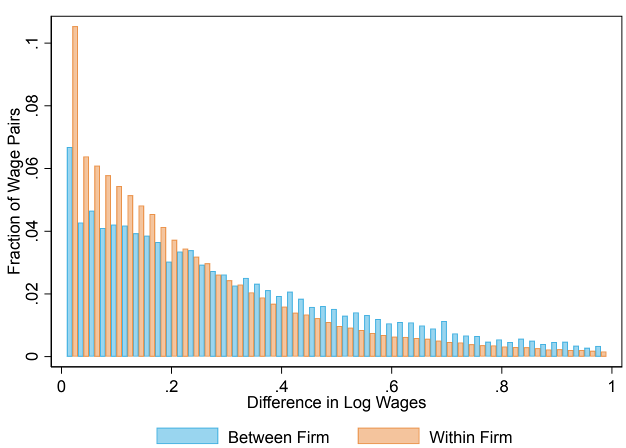
Figure A4: LEHD-ACS Industry Distribution



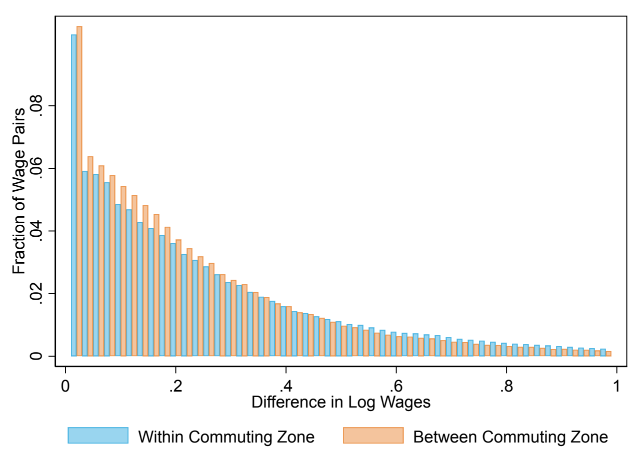
Notes: The figure illustrates the economic sector distributions within each LEDH-ACS sample, utilizing the nine primary industry sectors from the North American Industry Classification System (NAICS). The figure's labels describe each broad economic sector. "Agriculture" also encompasses farming, hunting, and forestry. "Trade Transportation" includes wholesale and retail trade, along with transportation and warehousing services. "Information Finance" spans diverse fields such as information, finance, insurance, real estate, and professional services. "Education Healthcare" involves educational and social assistance services. "Arts Hospitality" covers arts, recreation, and accommodation/food services. "Other Services" encapsulates miscellaneous sectors.

Figure A5: Distribution of Wage Comparisons Between and Within Firms in the LEHD-ACS: Salaried Workers

(a) Across Locations: Between Firms vs Within Firms

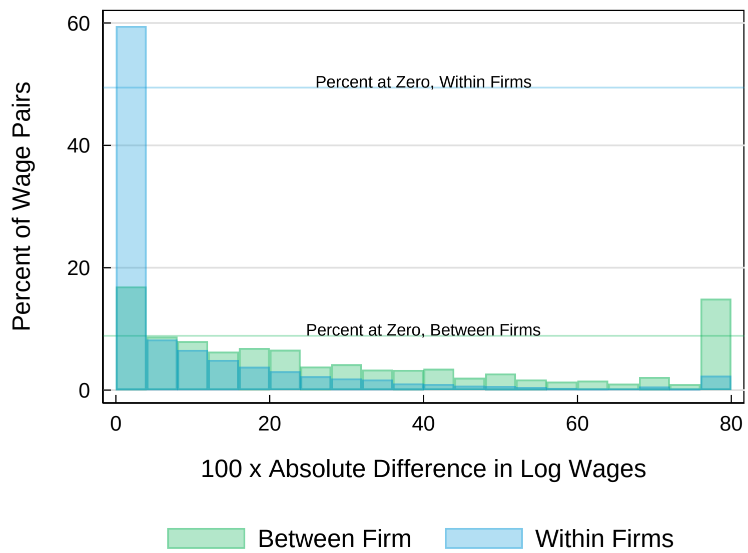


(b) Within Firm: Within vs Between Locations



Notes: Panel A plots the distribution of differences in log quarterly earnings between pairs of identical occupation–year observations located in two different counties using the LEHD-ACS, restricting to salaried workers. The blue histogram shows "within-firm" pairs (same firm, different county); the green histogram shows matched "between-firm" pairs (different firm in the same 4-digit NAICS industry). Between-firm pairs are matched to the within-firm comparison on gender, race (white/non-white), 5-year age bin, and four education bins. Panel B repeats the exercise within firms, again using salaried workers, comparing earnings gaps for pairs of workers in the same county ("within location", blue) with gaps for pairs in different counties ("across locations", green). Differences are expressed in log points and binned into intervals of 0.002 (0.2 percentage points).

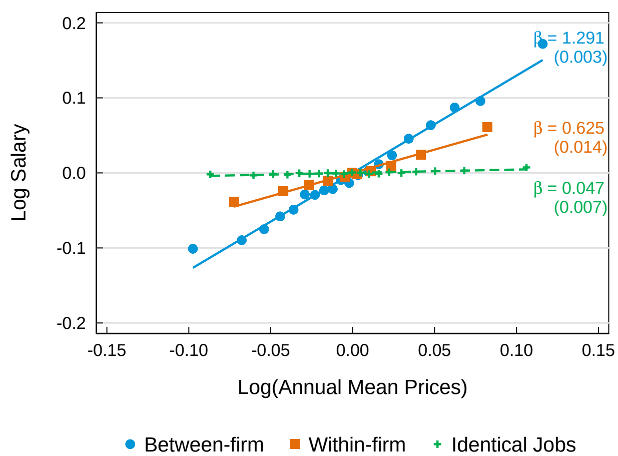
Figure A6: Identical Wage Setting: Firms with At Least 10 Establishments



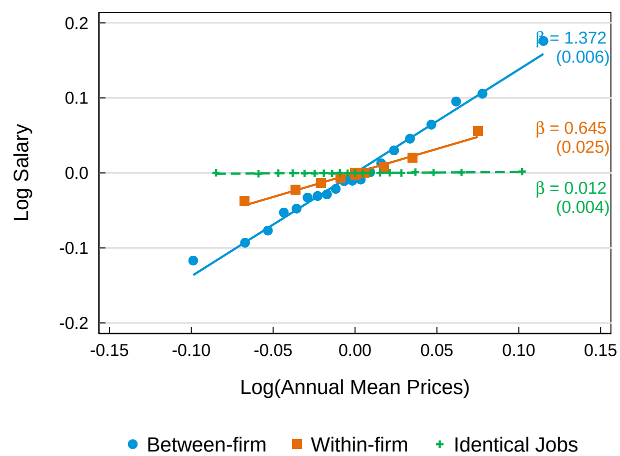
Notes: This figure uses Burning Glass data to replicate Figure 3. We limit to firms that have at least ten establishments. The blue and green lines indicate the fraction of job-pairs for which there is no difference in the absolute wage when looking at job-pairs within firms (blue line) and between firms (green line).

Figure A7: Posted Wages and Local Prices—Robustness to Wage Ranges and Occupation Weighting

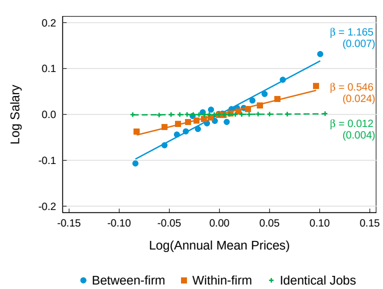
A. Adding Salary Ranges



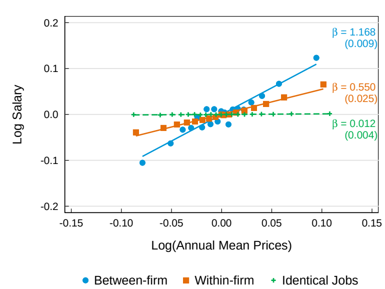
B. Reweighting Occupations



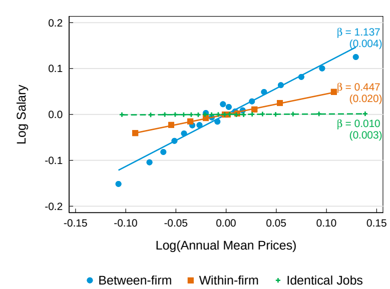
C. Firms with ≥ 5 Establishments



D. Firms with ≥ 10 Establishments

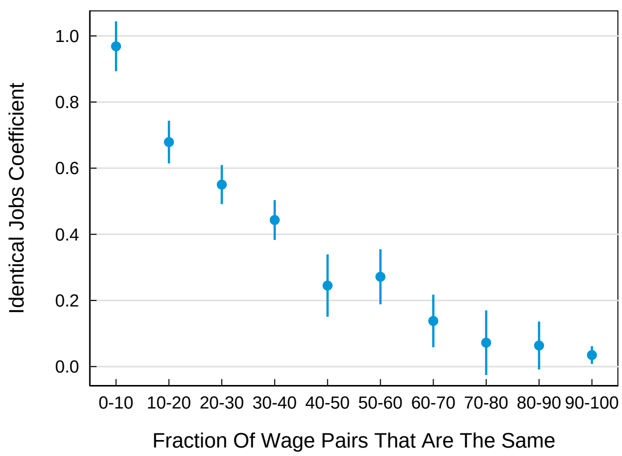


E. Simple OLS



Notes: These figures use data from Burning Glass. In all panels, the binned scatterplot shows the relationship between the local price index and the log wage using the same procedure as the main text. The local price index is instrumented by county-level home prices in all panels except Panel E. In Panel A, the sample includes all jobs with posted wages, including those that point wage ranges. For jobs with posted wage ranges, we take the midpoint of the range. The blue line and circles correspond to Equation (6) and the orange line and squares correspond to Equation (5). In Panel B, we include only point wages, as in the baseline sample, but we re-weight the observations to match the 6-digit occupation distribution in the OES. In Panel C, we restrict the data to include only firms with at least 5 locations, and in Panel C, we restrict to only firms with at least 10 locations. In Panel E, we include only point wages, as in the baseline sample, but we do not instrument the local price index. All regressions include job and year fixed effects, and the orange regressions include firm fixed effects as well. Because of the fixed effects, both the y-axis and x-axis are demeaned in all panels. Standard errors, in parentheses, are clustered by firm.

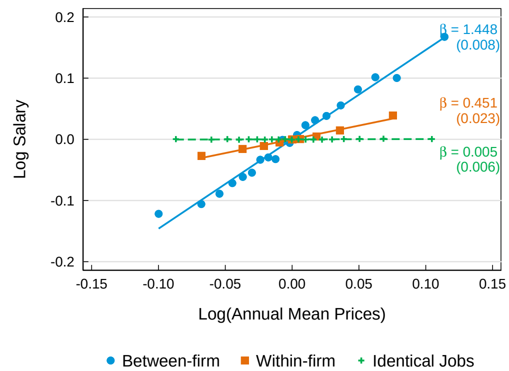
Figure A8: Identical Jobs Coefficient



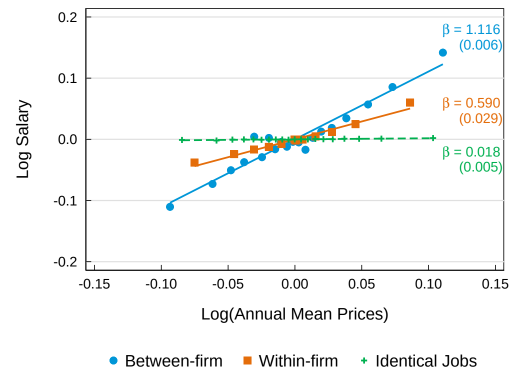
Notes: The figure uses data from Burning Glass to show the relationship between the within-firm regression coefficients in equation 5 (y-axis) and the fraction of jobs within a firm by occupation that have the same wage.

Figure A9: Wages and Local Prices: Heterogeneity

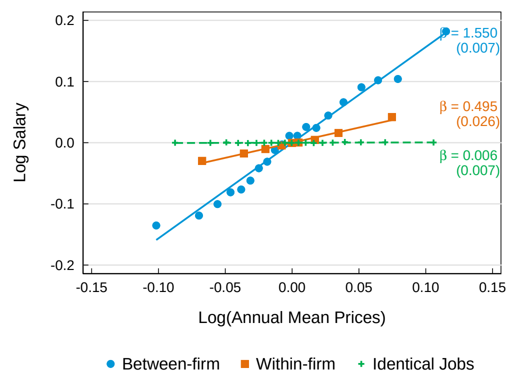
(a) High Wage Occupations



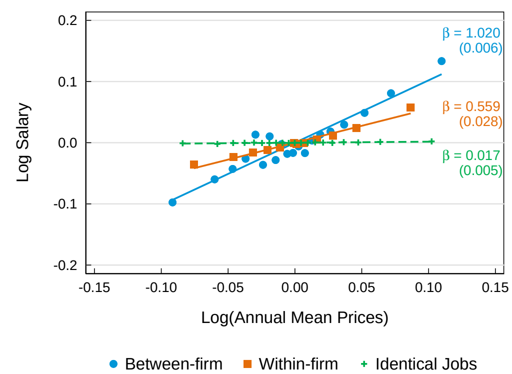
(b) Low Wage Occupations



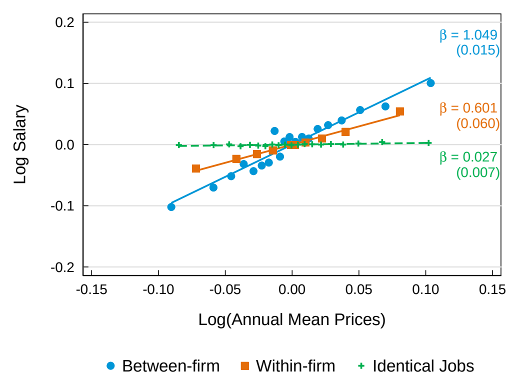
(c) Tradable Occupations



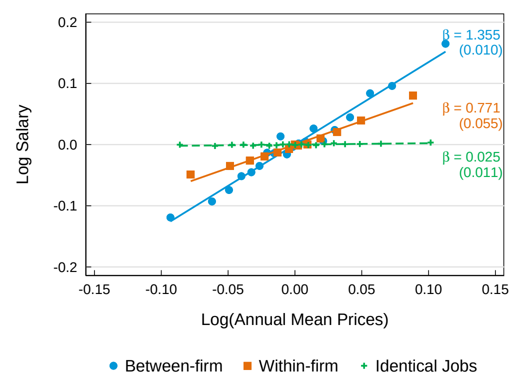
(d) Non-Tradable Occupations



(e) Tradable Industries

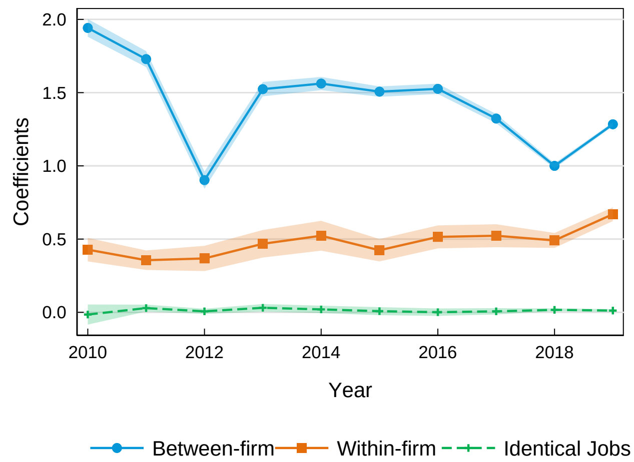


(f) Non-Tradable Industries



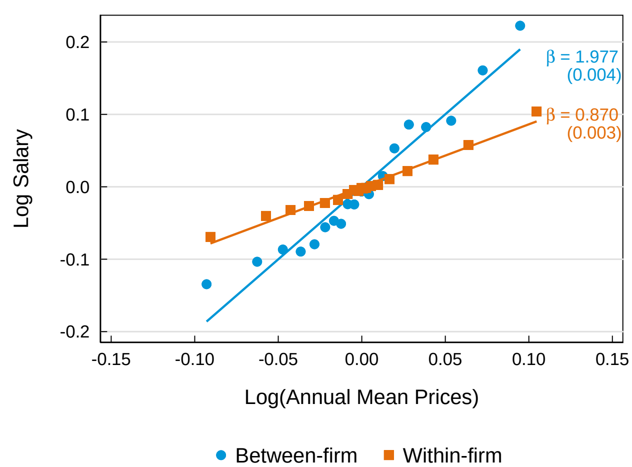
Notes: High-wage occupations are defined as those with an OES wage that is above the median in the sample. We define a tradable occupation as one that can be done remotely following Dingel and Neiman (2020). We define tradable and non-tradable industries following Chodorow-Reich et al. (2021). In all panels, blue dots represent estimates of Equation (6) and orange circles represent estimates of Equation (5), standard errors clustered by firm are in parentheses. Data is from Burning Glass

Figure A10: Wage compression from 2010 to 2019



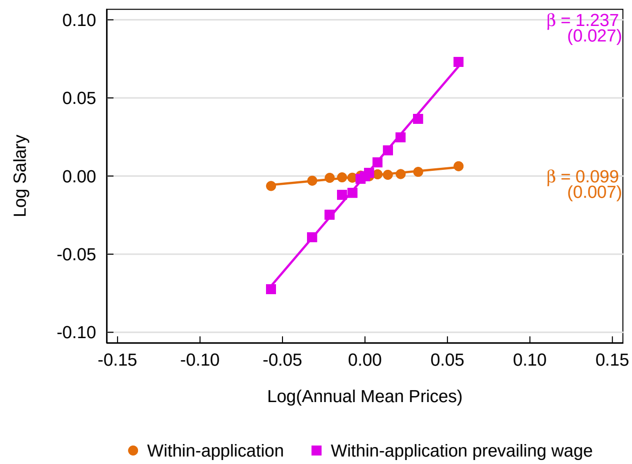
Notes: We estimate the regression coefficients separately for each year of the data. The blue line and circles correspond to Equation (6) and the orange line and squares correspond to Equation (5). The dashed green line and crosses correspond to Equation 5, but we run this regression restricting to national occupations. The shaded areas are 95% confidence intervals, associated with standard errors that are clustered by firm. National occupations are those occupations by firms for which 80% of job pairs have identical wages. All regressions include job and year fixed effects, and the green and orange regressions include firm fixed effects as well.

Figure A11: Nominal Wages and Local Prices Using LCA Data



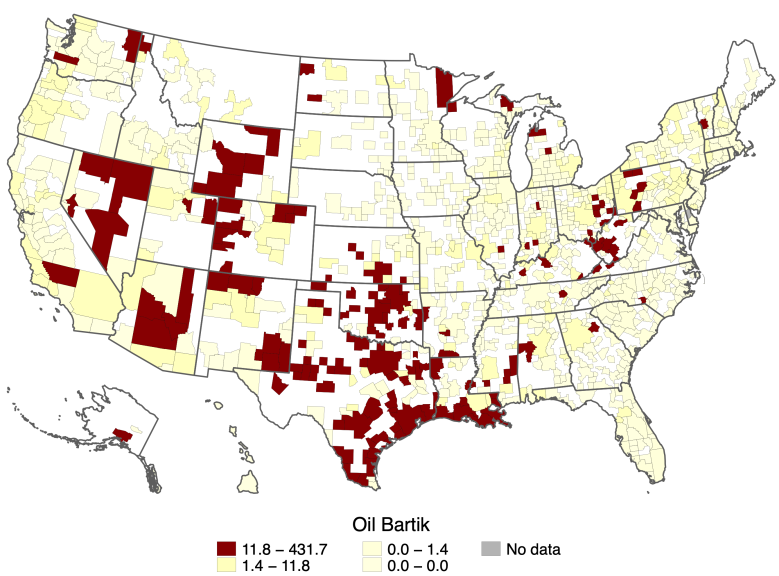
Notes: Data is from all years (2010-2019) in the LCA data. Non-certified and withdrawn visa applications are included. Wages/salaries are annualized. In each regression, we instrumented local price indices with county-level home prices. Controls are included for the year and whether the wage is annual or hourly, along with firm-by-occupation fixed effects (within-firm regressions) or occupation fixed effects (between-firm regressions). Standard errors, clustered by firm, are in parentheses.

Figure A12: Within-Worker Sensitivity of Reported Wages to Local Prices



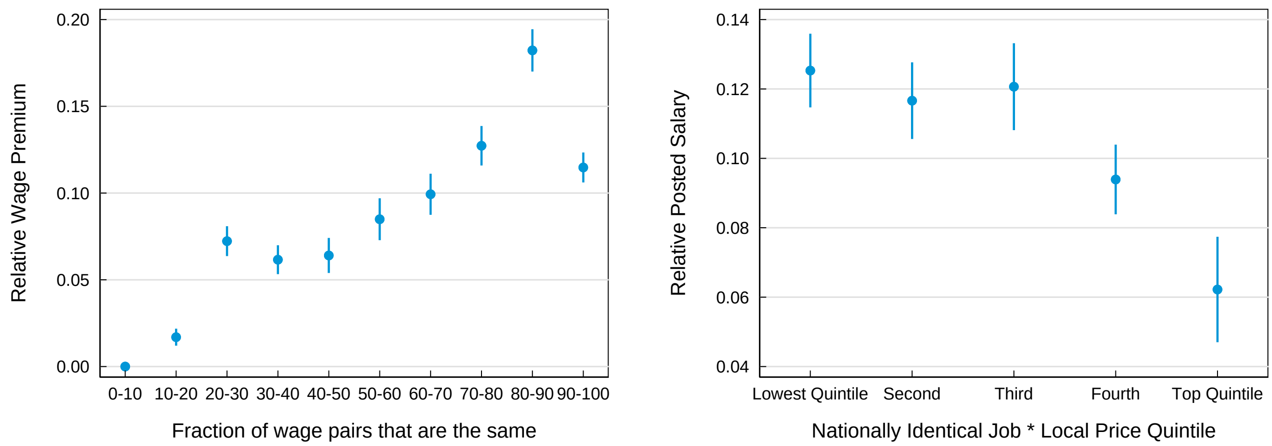
Notes: The sample includes the set of applications with wages posted for at least 2 worksites, and which are for only 1 worker. Non-certified and withdrawn visa applications are included. The sample for these regressions represents 4,128 applications/workers and includes 9,133 observations (worker-worksites). The regression includes controls/fixed effects for the application, occupation, and whether the position is hourly or annual. Standard errors, clustered by firm, are in parentheses.

Figure A13: Regional Exposure to Natural Resources Instrument



Notes: This figure presents a heat map showing the geographic distribution of natural resource shocks in the U.S., measured in 2012, by county. The map is constructed by grouping counties into ten deciles and shading such that lighter colors correspond to lower rates of natural resource demand. The natural resource instrument is defined as in Section 4, Equation (**??**).

Figure A14: Relative Wages of National Wage Setters

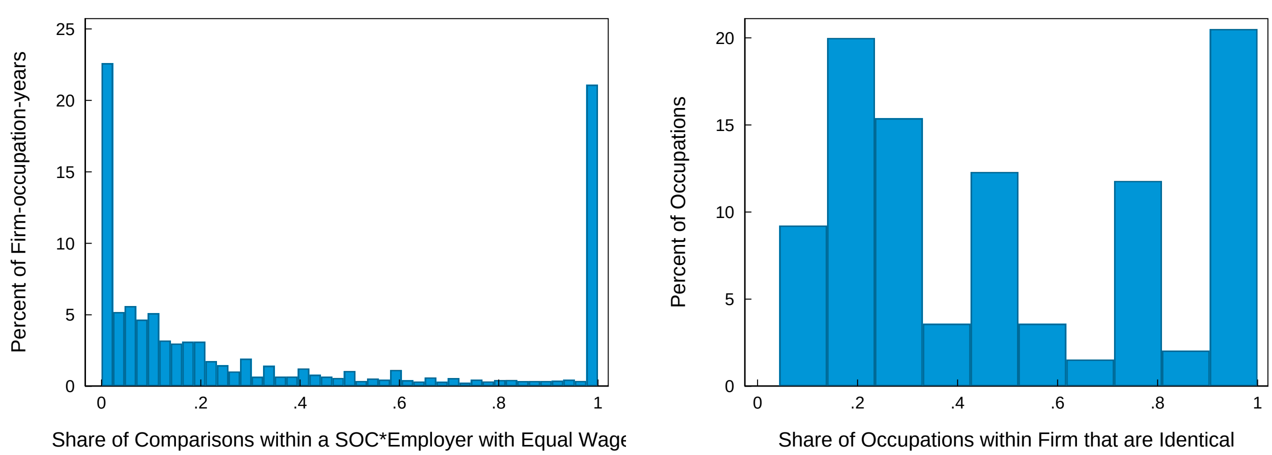


Notes: This figure uses data from Burning Glass. The left panel shows the relationship between the relative wage premium (y-axis) and the fraction of jobs within a firm by occupation that have the same wage. All coefficients are plotted relative to the 0-10 bin. The regression includes soc by year by county by 2-digit industry fixed effects, and a quadratic in establishment size and firm size. The right panel shows the average wage premium by the local price of an area. The regression includes an indicator for whether the job has a nationally set wage, interacted with an indicator for the price quintile of the county. The regression also includes a quadratic in establishment size, a firm fixed effect, and fixed effects for job by county by industry by year, so that the wage premium is measured within the firm, between identical and non-identical occupations. Nationally identical jobs are defined as those jobs paying the modal wage in occupation by firm by year cells in which at least 80% of wage pairs are the same. The sample in both panels includes all firm-job pairs present in at least 2 establishments in that year.

Figure A15: Prevalence of Identical Wages Within the Firm

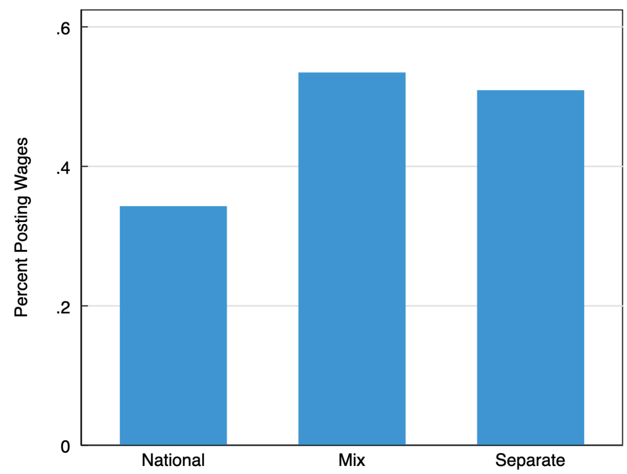
(a) Within job, across locations

(b) Within firm, across occupations



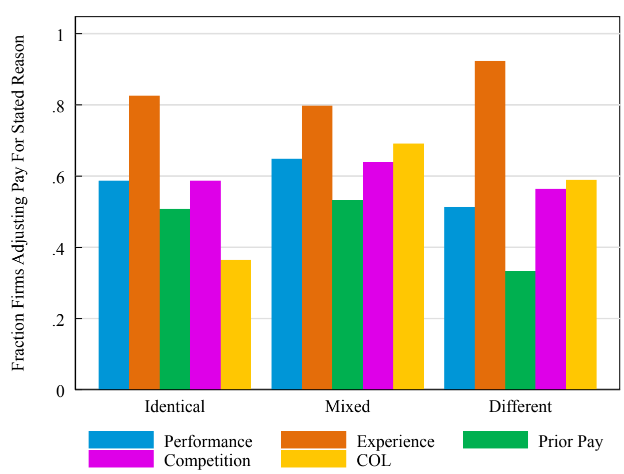
Notes: In the left panel, the sample excludes job cells where there are fewer than 5 within-firm pairs. This results in 7,880 firms. In the right panel, we further condition the sample to include the set of firms with at least 1 national occupation and at least 3 occupations. National occupations are defined as those where at least 80% of wage pairs are the same. Data is from Burning Glass

Figure A16: Fraction of Firms Posting Wages by Wage Setting Policy



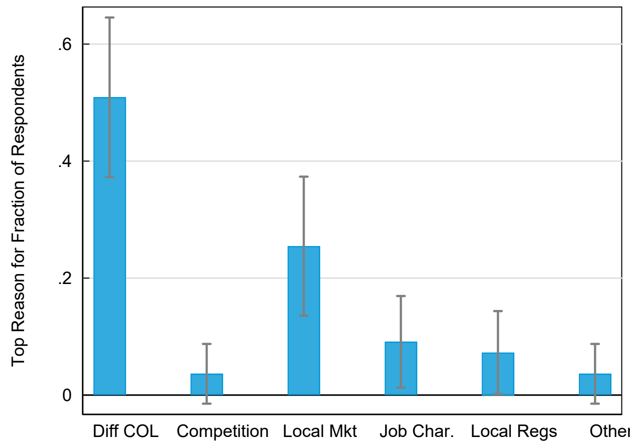
Notes: This figure shows the fraction of survey respondents who state that their firm posts wages or salary bands on the majority of their job vacancies. "National" means that a respondent stated that pay bands (wages) are set identically across establishments so that workers with the same job title face the same pay band. "Mix" means that a respondent stated that pay bands (wages) are sometimes determined separately, but not always. "Separate" means that a respondent stated that pay bands (wages) are determined separately for each establishment/plant/store. The exact question asked is shown in the online survey appendix.

Figure A17: Reasons for Adjusting Pay within Bands



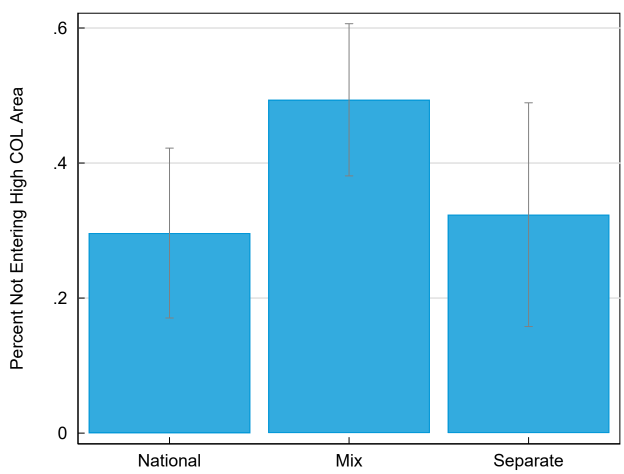
Notes: This figure shows the fraction of firms that state that they adjust pay within bands for the five provided reasons. "Identical" refers to firms that set identical pay bands in all of their establishments, "Mixed" are firms that use identical pay bands for some jobs across establishments but not all, and "Different" are firms that use different pay bands across establishments.

Figure A18: Reasons Firms Pay Differently across Geographies



Notes: This figure presents survey responses to the question: "You have mentioned that you set wages or pay bands separately across locations for some of the jobs in your firm. Why does your company choose to set separate wages or pay bands for those jobs?" The sample consists of respondents who state that they work at a firm that sets pay separately by region. "Diff. Cost of Living" means that the firm operates in regions with a different cost of living. "Local Competition" means that the firm follows what their competitors do. "Local Markets" means that the firm hires on a local market. "Job Characteristics" means that the firm is hiring for a specific type of job. "Local Regulations" means that the firm is constrained by local regulations, such as minimum wages.

Figure A19: National Wage Setting and Entering High Cost of Living Regions

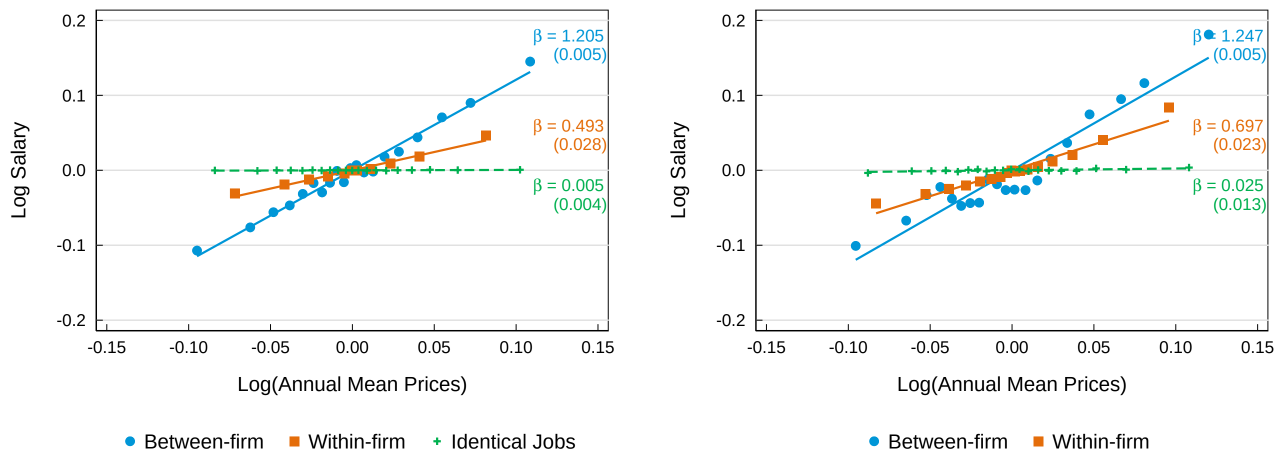


Notes: This figure shows the fraction of respondents who state that their firm would not enter a high cost of living area due to their decision to adopt a national pay structure.

Figure A20: Posted Wages and Local Prices: Different Levels of Aggregation

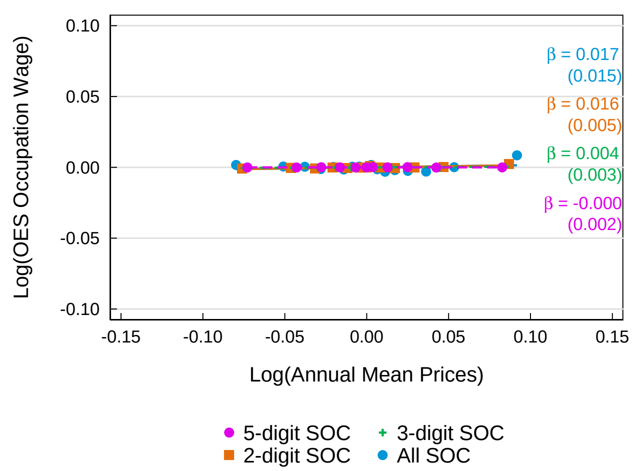
(a) Within Job Titles

(b) Across all occupations



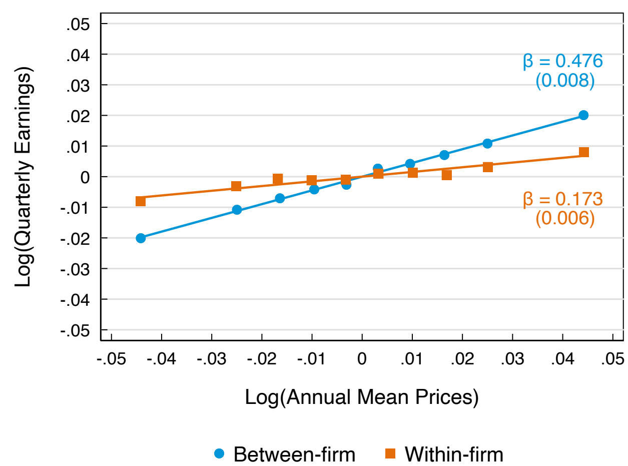
Notes: In the left panel, the unit of observation is the job title, and in the right panel, the unit of observation is the occupation. In both panels, the blue circles show the between-firm regression as in Equation 6, but replacing occupation fixed effects (θ_{ot}) with job-title in the left panel and removing them altogether in the right panel. Similarly, in both panels, the orange diamonds show the within-firm regression as in Equation 5, but replacing occupation by firm fixed effects (θ_{oit}) with job title by firm fixed effects in the left panel and firm fixed effects in the right panel. The sample in the left panel includes 10,376 distinct job titles.

Figure A21: Occupation Selection and Prices



Notes: Each specification shows an estimation of Equation 5 that replaces the posted wage for each job with the wage for that 6-digit occupation in the OES. Each regression line differs in the level of the fixed effects. Specifically, the purple circles include firm by 5-digit occupation fixed effects, the green crosses include firm by 3-digit occupation fixed effects, the orange circles include firm by 2-digit occupation fixed effects, and the blue circles include firm fixed effects. All regressions include year fixed effects. In each regression, the county-price-level (on the x-axis) is instrumented with the county-home-price-index. Because of the fixed effects, both the y-axis and x-axis are demeaned.

Figure A22: Within- and Between-Firm Relationship Between Prices and Wages with Job Switchers



Notes: This binned scatterplot shows the relationship between the local price index and the log wage using data from a sample of job switchers within the firm (orange) and a sample of job switchers between firms (blue). The data source is the LEHD (not merged to the ACS). We instrument for local prices with county-level home prices, by regressing prices on house prices and the other variables of the regression, and then using the fitted value of prices in the scatter, while partialling out all control variables. Standard errors, in brackets, are clustered by firm.

Tables

Table A1: Comparing Median Wages in OES and Burning Glass

	Annual Basepay	Hourly Basepay	Annual Total	Hourly Total
	(1)	(2)	(3)	(4)
Posted Wages	1.064	1.125	1.049	1.127
	(0.027)	(0.011)	(0.028)	(0.013)
Observations	19,888	37,674	18,451	30,917

Notes: We regress Burning Glass occupation by MSA log median hourly wages on Occupational Employment Statistics' occupation by MSA log median wages, both at the 6-digit occupation level and averaged over 2010-2019. To mitigate attenuation bias, a split-sample instrumental variable is used. The Burning Glass data is randomly divided into two samples, utilizing the occupation by MSA log median wages of one of the sub-samples to instrument for the occupation by MSA log median wage of the other sub-sample. In the first column, the Burning Glass wage is annual base pay. In the second column, the wage is hourly base pay; in the third, annual total pay; and in the fourth column, hourly total pay. The observations are weighted by occupation by MSA employment over 2010-2019. Robust standard errors are reported in parentheses.

Table A2: Comparing OES and Burning Glass Wages Across the Distribution

	10th (1)	25th (2)	Median (3)	75th (4)	90th (5)
Posted Wages	0.892 (0.009)	1.050 (0.010)	1.125 (0.011)	1.075 (0.011)	0.944 (0.011)
Observations	37,697	37,694	37,674	37,595	37,358

Notes: In each column, we examine the dependent variable, representing the specified moment of occupation by MSA hourly wages sourced from Occupational Employment Statistics. The independent variable corresponds to the equivalent moment in the posted wage distribution within Burning Glass data. Both variables are in logs, and the analysis focuses on wages averaged over 2010-2019 at the 6-digit occupational level. To mitigate attenuation bias, a split-sample instrumental variable is used. The Burning Glass data is randomly divided into two samples, utilizing the specified moment of the occupation by MSA log median wages of one of the sub-samples to instrument the specified moment for the occupation by MSA log median wage of the other sub-sample. In all columns, the Burning Glass wage is hourly base pay. The observations are weighted by occupation by MSA employment over 2010-2019. Robust standard errors are reported in parentheses.

Table A3: Determinants of Wage Posting

	Outcome: Percentage Chance of Posting a Wage					
Regressor:	Median Hourly OES Occupation Wage	Posted Education	Posted Experience	Firm # of Establishments	Consumer Prices	Superstar City
	(1)	(2)	(3)	(4)	(5)	(7)
Specification:						
No Controls	-2.29	-2.30	-1.40	-1.14	-0.50	-1.25
	(0.40)	(0.35)	(0.22)	(0.56)	(0.12)	(0.74)
Firm x Year Fixed Effects	-2.55					
	(0.27)					
Firm x Year x SOC Fixed Effects		-0.40	-0.47		-0.06	-0.20
		(0.03)	(0.02)		(0.07)	(0.44)
Observations	220,411,774	145,512,272	109,034,578	233,035,488	209,877,404	233,035,488

Notes: The sample contains the same restriction as in row 4 of Table 2 except observations with missing wages are included (we treat observations posting wage ranges or commission pay as missing wages). The dependent variable is the percentage chance of posting a wage (0 to 100). The regressor is divided through by its standard deviation in columns 1-7, there is an indicator variable for whether the observation is in New York, Los Angeles, San Francisco, or Washington D.C. (column 8). Standard errors are clustered at the detailed occupation level in column 1-4 and the county level in columns 5-7.

Table A4: Robustness to Different Price Measures (LEHD-ACS)

	Panel A						
Price Variable:	IV			Local prices		House prices	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Average Local Price for Firm	1.567		1.583	1.433		0.180	
	(0.044)		(0.061)	(0.038)		(0.007)	
Local Price		0.818			0.759		0.091
		(0.041)			(0.037)		(0.006)
Specification	Between	Within	Between (Within Sample)	Between	Within	Between	Within
Observations	36,560,000	27,710,000	27,710,000	36,560,000	27,710,000	36,560,000	27,710,000
	Panel B						
Price Variable:		Post-2008 Reg. prices		2008 Reg. prices		Avg. annual earnings	
		(8)	(9)	(10)	(11)	(12)	(13)
Average Local Price for Firm		1.493		1.386		0.537	
		(0.041)		(0.037)		(0.012)	
Local Price			0.818		0.718		0.255
			(0.045)		(0.036)		(0.015)
Specification		Between	Within	Between	Within	Between	Within
Observations		22,790,000	17,060,000	36,560,000	27,710,000	36,560,000	27,710,000

Notes: This table shows the results from estimating equations (5) and (6) using the LEHD-ACS. Columns 1-2 show the baseline results. In column 3, we estimate equation (6) using the sample of firms used in column 2. Columns 4-5 do not instrument for local prices with housing prices. Columns 6-7 show the results using house prices as the main independent variable, obtained from Zillow. Columns 8-9 use the post-2008 regional price, and columns 10-11 use the 2008 regional price. Columns 12-13 use the average annual earnings in a county, calculated using the LEHD, as the independent variable. The sample is held fixed across columns, and counts of observations are rounded to pass disclosure review. we restrict to the fourth quarter of each year for computational tractability. Standard errors, in brackets, are clustered by firm.

Table A5: Robustness to Different Earnings and Wage Measures (LEHD-ACS)

	Panel A					
Dependent Variable:	Avg. Occupation Wage		Implied Wage		Weekly Hours	
	(1)	(2)	(3)	(4)	(5)	(6)
Local prices	0.178	0.158		0.806		0.012
	(0.001)	(0.001)		(0.043)		(0.006)
Average Local Price for Firm (EIN)			1.632		-0.066	
			(0.048)		(0.011)	
Specification	Between	Within	Between	Within	Between	Within
Observations	36,560,000	27,720,000	36,560,000	27,720,000	36,560,000	27,720,000
Included Sample			Imputed Match	Imputed Match	Imputed Match	Imputed Match

	Panel B					
Dependent Variable:	Quarterly Earnings		Implied Wage		Weekly Hours	
	(7)	(8)	(9)	(10)	(11)	(12)
Local prices		0.745		0.727		0.012
		(0.060)		(0.062)		(0.014)
Average Local Price for Firm (EIN)	1.494		1.583		-0.089	
	(0.037)		(0.039)		(0.010)	
Specification	Between	Within	Between	Within	Between	Within
Observations	923,000	281,000	923,000	281,000	923,000	281,000
Included Sample	Exact Match	Exact Match	Exact Match	Exact Match	Exact Match	Exact Match

	Panel C					
Dependent Variable:	ACS Reported Wage		Quarterly Earnings (SEIN)		Quarterly Earnings (Firm ID)	
	(13)	(14)	(15)	(16)	(17)	(18)
Local prices		0.752		0.641		0.940
		(0.056)		(0.034)		(0.039)
Average Local Price for Firm (EIN)	1.541					
	(0.034)					
Average Local Price for Firm (State-EIN)			1.438			
			(0.032)			
Average Local Price for Firm (FIRMID)					1.605	
					(0.049)	
Specification	Between	Within	Between	Within	Between	Within
Observations	923,000	281,000	36,560,000	25,000,000	36,560,000	25,000,000
Included Sample	Exact Match	Exact Match	SEIN	SEIN	FIRMID	FIRMID

Notes: This table shows the results from estimating equations (5) and (6) on the LEHD-ACS sample using different wage and earnings measures as outcomes, and when varying our definition of a firm. In Panel A, the outcome in columns 1-2 is the average occupation wage, estimated in the LEHD. Columns 3-4 show the results using implied wages as the outcome. Implied wages are calculated as quarterly earnings with imputed average weekly hours times 13. Columns 5-6 study weekly hours from the ACS as the outcome. In Panel B and columns 13-14 of Panel C, we estimate the equations on the subsample containing quarters that match exactly between the LEHD and the ACS. The outcomes are quarterly earnings from the LEHD, implied wages imputed using LEHD earnings and weekly hours from the ACS, weekly hours from the ACS, and usual hourly wages from the ACS. In Panel C, columns 15-18, we re-estimate the equations using two other definitions of the firm: either the State Employer Identification Number (SEIN) or the FIRMID, which is more aggregated. We restrict to the fourth quarter of each year for computational tractability. The sample is held fixed across columns, and counts are rounded to pass disclosure review. Standard errors, in brackets, are clustered by firm.

Table A6: Sensitivity of Posted Wages to Local Conditions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Average Local Price for Firm	1.137						1.284	
	(0.027)						(0.031)	
Local Price		0.446						0.538
		(0.020)						(0.023)
Average Local House Price for Firm			0.136					
			(0.003)					
Local House Price				0.051				
				(0.002)				
Local Income for Firm					0.389			
					(0.010)			
Local Income						0.123		
						(0.006)		
Specification	OLS	OLS	OLS	OLS	OLS	OLS	IV	IV
Observations	3,525,351	1,617,884	3,681,306	1,853,545	3,695,553	1,876,240	3,521,841	1,612,813
Firms	341,809	54,651	364,748	58,741	366,418	59,235	341,427	54,537
Fixed-Effects:								
Year	✓	✓	✓	✓	✓	✓	✓	✓
Occupation	✓	✓	✓	✓	✓	✓	✓	✓
Firm x Occupation		✓		✓		✓		✓

Notes: Standard errors are clustered at the firm level. All coefficients are estimated using OLS, other than the last two columns, which instrument for local prices with local house prices. Local prices come from the Bureau of Labor Statistics. Local House Price indices come from Zillow. Average local incomes are computed from Occupational Employment Statistics (OES).

Table A7: Heterogeneity in the Sensitivity of Wages to Local Prices (LEHD-ACS)

Variable:	High Tenure		Above Median Occ. Wage		Old Worker Age		Large Firm Size		Tradable Industry	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Avg. Local Price For Firm (EIN) x I(Variable = 0)	1.561		1.549		1.482		1.556		1.572	
	(0.045)		(0.056)		(0.044)		(0.046)		(0.252)	
Avg. Local Price For Firm (EIN) x I(Variable = 1)	1.584		1.580		1.636		1.568		1.428	
	(0.045)		(0.042)		(0.049)		(0.045)		(0.079)	
Local Prices x I(Variable = 0)		0.809		0.765		0.706		0.839		0.602
		(0.038)		(0.043)		(0.045)		(0.057)		(0.082)
Local Prices x I(Variable = 1)		0.835		0.870		0.917		0.816		0.856
		(0.037)		(0.041)		(0.042)		(0.044)		(0.080)
Specification	Between	Within	Between	Within	Between	Within	Between	Within	Between	Within
Observations	36,560,000	27,710,000	36,560,000	27,710,000	36,560,000	27,710,000	36,560,000	27,710,000	36,560,000	27,710,000

Notes: This table presents the results from estimating equations (5) and (6), interacting prices with various worker, industry, and firm characteristics. In each case, the variable that interacts with the regressor is in the first row of the table. We study worker tenure, the median wage of their occupation, their age, their firm size, and whether they are in a tradable industry. In all but the last category, we split into above and below median categories; in the last category, we use the tradable industry definition of Chodorow-Reich et al. (2021). The sample is held fixed across columns, and observations are rounded for disclosure review. We restrict to the fourth quarter of each year for computational tractability. Standard errors, clustered by firm, are in parentheses.

Table A8: Wage Growth in Burning Glass, 2 Years Between Vacancies

Dependent Variable:	Growth In Posted Wages					
	(1)	(2)	(3)	(4)	(5)	(6)
Avg. Growth In Posted Wages In County	0.077	0.045	0.046	0.059		
	(0.020)	(0.018)	(0.020)	(0.017)		
Avg. Growth In Posted Wages In Other Establishments Within Firm	0.370	0.328	0.329			
	(0.075)	(0.066)	(0.060)			
Avg. Growth In Posted Wages In County (By Occ)					0.004	0.019
					(0.015)	(0.017)
Avg. Growth In Posted Wages In Other Establishments Within Firm (By Occ)					0.399	0.366
					(0.049)	(0.065)
I(National Occ.) x Avg. Growth In Posted Wages In County (By Occ)						-0.052
						(0.035)
I(National Occ.) x Avg. Growth In Posted Wages In Other Establishments Within Firm (By Occ)						0.288
						(0.095)
Observations	54,558	53,059	48,214	75,570	16,261	14,454
Fixed-Effects:						
OccupationxYear		✓				
2-Digit-IndustryxYear		✓				
Occupationx2-Digit-IndustryxYear			✓	✓	✓	✓

Note: this table relates annual wage growth for workers, at the occupation, region, firm and year level, to: average wage growth in the region, calculated over workers in all other firms in the region; and average wage growth in the firm, calculated over workers in all other regions. The table studies outcomes in Burning Glass and restricts to data with a 2-year gap between vacancy postings. The first column has no controls. The second adds occupation by year and 2-digit industry by year fixed effects. Columns 3-5 have occupation by 2-digit industry by year fixed effects. Column 4 drops average growth in earnings from the rest of the firm. Column 5 averages earnings within firm-occupation and region-occupation cells. Column 6 interacts both regressors with an indicator for whether, in the initial period, the job is a national occupation—where at least 80% of wage pairs for the same job, across regions, are the same in the initial period. Firm clustered standard errors are in parentheses.

Table A9: Robustness of Natural Resources Shock Wage Pass-Through in LEHD

	Nontradable Ind.		Nontradable Occ.		Large Firms		Firm FE	Reweighted	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta \log w_{iofr't}$	0.781	0.332	0.789	0.400	0.841	0.154		0.598	0.273
	(0.147)	(0.112)	(0.143)	(0.157)	(0.172)	(0.082)		(0.141)	(0.244)
$\Delta \log w_{iofr't}$ NWS							0.786		
							(0.152)		
$\Delta \log w_{iofr't}$ NoNWS							0.413		
							(0.126)		
Observations	663,000	2,361,000	536,000	470,000	524,000	1441,000	3,258,000	720,000	2,538,000
First-Stage F-stat	24.6	30.49	20.53	4.8	20.75	52.27	12.81	21.62	9.51
Included Sample	NWS	No NWS	NWS	No NWS	NWS	No NWS		NWS	No NWS

Notes: This table presents the results from regressing earnings growth in the firm's second establishment on earnings growth in the firm's first establishment within a pair, instrumenting to earnings growth in the first establishment with the natural resources shock. Columns 1-2 restrict to nontradable industries, and columns 3-4 to nontradeable occupations. In columns 5-6, we restrict to firms with more than 10 establishments. Column 7 includes firm fixed effects, and columns 8-9 reweighting so that the occupation distribution in our sample better matches the actual occupation distribution in the full LEHD, as opposed to the subsample of the LEHD that merges to the ACS.

Table A10: Pass Through of Natural Resources Shock to Wages in other Establishments in Burning Glass

	First Stage			Reduced Form			IV		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta\text{Shock}_{j,t}$	1.25	0.80	1.28	-0.17	0.66	-0.24			
	(0.62)	(0.17)	(0.66)	(0.13)	(0.12)	(0.13)			
$\Delta \log w_{oij't}$							-0.15	0.83	-0.20
							(0.11)	(0.12)	(0.12)
Observations	2,406,079	448,045	1,958,034	2,569,225	458,228	2,110,997	2,406,079	448,045	1,958,034
First-Stage F-stat							4.11	22.85	3.77
Included Sample	All	Identical	Different	All	Identical	Different	All	Identical	Different

Notes: This table uses pairwise data to examine the impact of a natural resource-induced shock on establishment wages across a firm. Natural resources industries are NAICS sectors 11 and 21, and we measure employment in each county using the Quarterly Census of Employment and Wages. The regression sample excludes public sector firms, firms in national resources (NAICS industry 21), establishment pairs that are located within 100 miles of one another, and non-exposed observations in counties with more than 1% employment in mining. All variables are demeaned using unexposed observations (those with an absolute value of the natural resource shock that is below the 25th percentile). The outcome in columns 1-3 is 100 $\times$ the change log of the exposed establishment's wage. The outcome in columns 4-9 is 100 $\times$ the change log of the unexposed establishment's wage. In columns 7, 8, and 9, we instrument for the exposed establishment's wage growth with the natural resources instrument. In columns 2, 5, and 8, we show the results when the specification is run on the sample of pairs that had identical wages in the prior period. Columns 3, 6, and 9 show the results run on the sample of pairs that had different wages in the prior period. Standard errors are clustered at the level of the exposed county. The Kleibergen-Paap F-statistic associated with columns 7 through 9 are listed below the regressions.

Table A11: Relative Wages, Education Requirements and Experience Requirements of National Firms

	Outcome				
	Log Salary			Experience	Education
	(1)	(2)	(3)	(4)	(5)
National Job	0.12	0.17	0.11	0.09	-0.60
	(0.00)	(0.01)	(0.00)	(0.02)	(0.03)
National Job x Urban		-0.06			
		(0.01)			
National Firm			0.01		
			(0.00)		
Observations	1,426,576	1,419,492	1,426,576	573,872	978,075

Notes: Regressions in all columns include a quadratic in establishment size and a quadratic in firm size, both measured by vacancies, and fixed effects for job by county by industry by year. National jobs are defined as those jobs paying the modal wage in occupation by firm by year cells in which at least 80% of wage pairs are the same. The sample includes all firm-job pairs present in at least 2 establishments in that year. The average SOC wage is defined using the median wage in the OES data in a given year. Standard errors are clustered at the county level. A national firm is one in which at least 50% of the occupations are nationally wage set.

Table A12: Characteristics of National Wages Setters in Linked Compustat Subsample

	$\frac{\text{Log Revenue}}{\text{Emp}}$	$\frac{\text{Log R\&D}}{\text{Emp}}$	Log Employment	$\frac{\text{Log Revenue}}{\text{Emp}}$	$\frac{\text{Log R\&D}}{\text{Emp}}$	Log Employment
	(1)	(2)	(3)	(4)	(5)	(6)
National Firms	0.062	0.868	0.281	0.082	0.860	0.378
	(0.072)	(0.242)	(0.133)	(0.068)	(0.253)	(0.131)
Avg. Fraction of Identical Jobs	0.143	1.198	-0.824	0.183	1.185	-0.666
	(0.116)	(0.319)	(0.204)	(0.113)	(0.345)	(0.199)
Avg. Fraction of Identical Occupations	0.147	1.208	-0.751	0.204	1.192	-0.606
	(0.108)	(0.309)	(0.195)	(0.103)	(0.320)	(0.191)
Fixed Effects:						
Industry				✓	✓	✓
Dependent Mean	13	9	9	13	9	9
No. Observations	684	208	685	683	207	684

Notes: Fixed effects are five industry groups (NAICS first digit 1,2, 3, 4, and 5-8). For firms with industrial and financial service data in Compustat, we keep industrial observations. For each Compustat firm that merges to Burning Glass, we take the mean across all years. Each row is from a separate regression, considering a different measure of national wage setting. In all rows, nationally identical occupations are defined as those occupations by firm by year cells in which at least 80% of wage pairs are the same. In row 1, we define a firm as national if at least 50% of its occupations are classified as national in any year of the sample. In row 2, “Avg. Fraction of Identical Jobs” is the fraction of jobs in an occupation that have identical wages, averaged over all occupations and years. In row 3, “Avg. Fraction of Identical Occupations” is the fraction of occupations that meet the criteria to be defined as national, averaged over all years.

Table A13: Franchise Analysis

	(1)	(2)	(3)	(4)
Panel A	Outcome: Δ Log Salary			
Franchise	0.057	0.074	0.057	0.074
	(0.036)	(0.039)	(0.035)	(0.038)
Observations	57,090,600	57,090,600	57,074,284	57,074,284
Fixed Effects:				
Year x Industry	✓	✓	✓	✓
Job		✓		✓
Region			✓	✓
Panel B	Outcome: Log Salary			
Log Prices	1.264	0.489	0.690	0.529
	(0.031)	(0.020)	(0.074)	(0.070)
Observations	3,538,187	2,191,341	152,393	298,796
Sample	All Firms	All Firms	Franchises	Non-Franchises
Fixed Effects:				
Year	✓	✓	✓	✓
Job	✓			
Firm X Job		✓	✓	✓

Notes: The unit of observation on Panel A is a job pair within the firm (i.e. the same job in different locations within the firm). The dependent variable is the log absolute difference in the posted salary, and the indicator for franchise is an indicator for whether the firm is franchised. The sample includes all 337 firms that are classified as either franchised or not franchised. Panel B relates posted wages to prices as in Table A6. Column 1 is the between-firm relationship for all firms in the baseline sample (i.e. Equation 6), column 2 is the within-firm relationship for all firms in the baseline sample (i.e. Equation 5), column 3 is the within-firm relationship for the 337firms in our sample that are franchises, and column 4 is for the set of firms that are not franchises. In both Panel A and B, standard errors clustered at the firm level are reported in parentheses.

B1 Survey Appendix

The survey was run with a large HR association. The association is designed to bring together HR professionals at annual meetings, and to provide support in the form of training and mentorship. Members of the association include individuals working in an array of HR positions. We targeted people who work in management level positions or higher. Individuals received a $15 gift card if they participated in the 10-minute survey.

Because we are interested in how firms set pay across geographies, we limit our sample to respondents working at firms that are located in more than one city. Panel A of Appendix Figure B4 shows the distribution of the number of cities in which the respondents' employers operate. Roughly 18% of respondents say that they operate in a firm that only operates in one city. Panel B shows the number of states that the firms operate in. For our entire analysis, we drop the 18% of respondents who state that their firm operates in one city, but include respondents with firms operating in only one state.

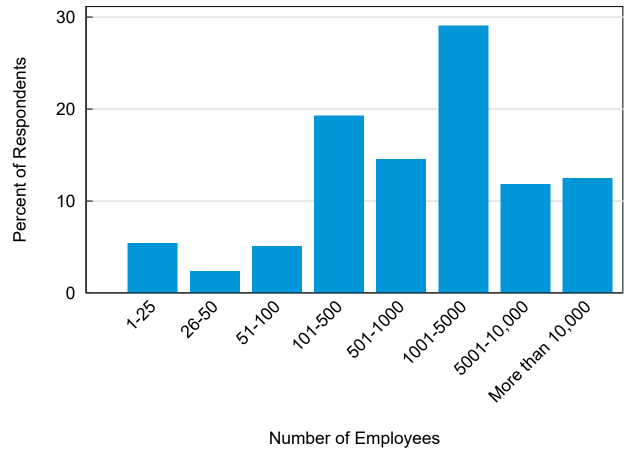
Figure B3 displays the job titles of respondents. To standardize titles, we allowed respondents to write in their title and then aggregated them. The majority of respondents work as HR managers or executives. In column 1 of Appendix Table B1, we provide additional information on the respondents and the types of firms they work for. Over 60% of respondents are directly involved in setting pay. On average, they have been working in their current position for 6.8 years. Respondents report working at firms in which an average of 55% of employees are salaried (as opposed to paid hourly), and roughly 80% of the firms use pay or salary bands rather than posting a single wage. Respondents tend to work at large firms. Nearly 70%. of respondents work at a firm that employs over 500 workers (Figure B1). Respondents work in a variety of sectors, as shown in Figure B2.

Table B1: Survey Summary Statistics

	Full Sample (1)	Flexible Pay (2)	Some or All Identical Pay (3)
Sets pay	0.609	0.672	0.592
	[0.489]	[0.473]	[0.493]
Yrs. experience	6.858	7.340	6.720
	[6.620]	[6.739]	[6.598]
Firm posts wage	0.465	0.509	0.453
	[0.500]	[0.505]	[0.499]
% salaried empl.	55.48	53.57	56.025
	[29.14]	[29.32]	[29.13]
Uses pay bands	0.802	0.672	0.841
	[0.399]	[0.473]	[0.367]
Observations	282	58	224

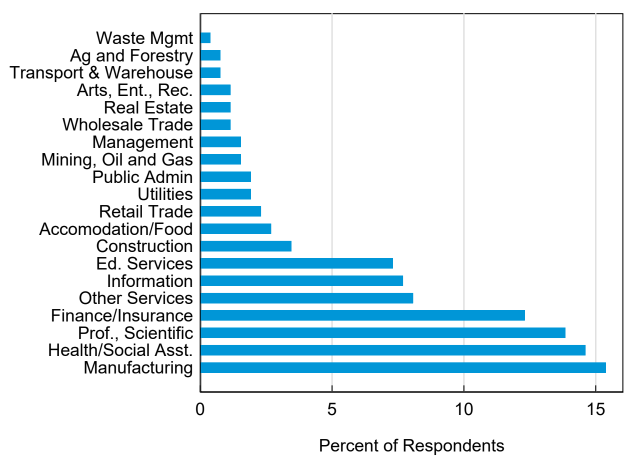
Notes: This table presents summary statistics for the set of survey respondents working at firms that operate in more than one city. Column 2 restricts to the sample of respondents who state that they work at a firm that does not set identical wages for jobs across locations. Column 3 restricts to the sample of individuals who report paying identical wages for some or all of their jobs. "Sets pay" is an indicator that takes the value one if the respondent is directly involved in setting pay within the firm. "Firm posts wages" is an indicator that the firm posts wages or salary bands on their job advertisements. "% salaried empl." is the fraction of employees who are salaried rather than paid hourly. "Uses pay bands" indicates that the firm uses pay bands for the majority of their employees.

Figure B1: Number of Employees



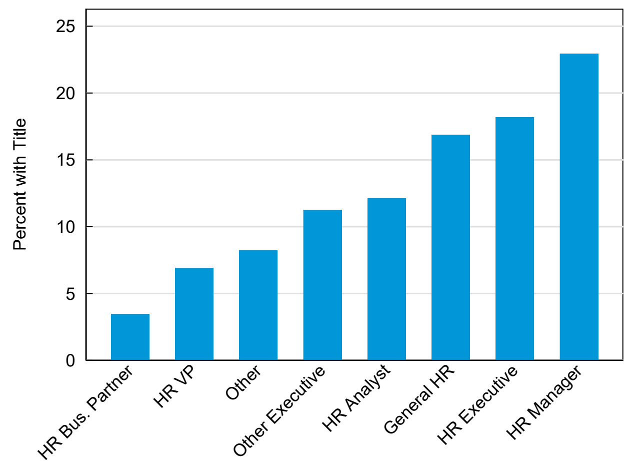
Notes: This figure shows the distribution of firm size (in terms of number of employees) among survey respondents.

Figure B2: Sector Representation of Survey Respondents



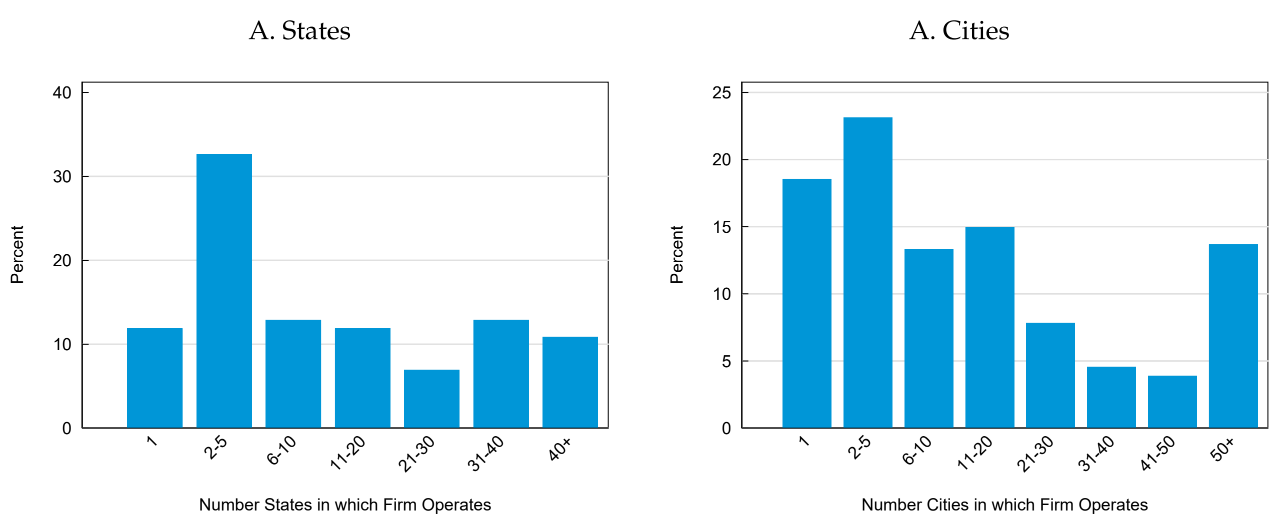
Notes: This figure shows the percent of survey respondents who work at a firm in each of the industries represented on the y-axis.

Figure B3: Respondent Job Titles



Notes: This figure shows the percent of survey respondents whose job title falls under one of the categories on the x-axis. Respondents typed in their own job titles, which were then grouped into one of the above categories.

Figure B4: Number of Cities and States in which Firms Operate



Notes: This figure shows the fraction of respondents working in firms that operate in the given number of states (Panel A) and cities (Panel B).

C1 Model Appendix

C1.1 Model Setup

In Section 2, we briefly described out a model. This subsection explains the model in detail.

Model Setup. In our setting, there are $r = 1, ..., R$ regions and a unit measure of workers. In each region, there is a single sector producing non-tradable goods. There are $f = 1, ..., F$ firms that hire workers in all regions. Specifically, in each region r, firm f operates an establishment that posts wages and employs workers.

Establishments have heterogeneous productivity $A_{rf} = A_f \times A_r$. The establishment has a wage W_{rf}, which it then pays to all its workers. Given employment L_{rf}, the establishment operates a decreasing returns to scale production function $F(L_{rf})$ and produces output $Y_{rf} = A_{rf} F(L_{rf})$ sold in a competitive market. Goods are sold at a price P_r that varies by region.

There is a unit continuum of ex-ante identical agents consuming goods and supplying labor, which we index by $k \in [0, 1]$. Each agent has idiosyncratic, nested logit preferences for working at each establishment rf, that depends on both the identity f of the firm and on the region r. We denote the value of agent k's idiosyncratic taste for establishment rf by ε_{rfk}, and their indirect utility from working in this establishment by V_{rfk}. If agent k works in establishment rf, they consume C_{rfk} of the non-tradable good, over which they have logarithmic utility.

Labor Supply. The agent's problem is to choose the establishment with the highest utility. They solve $\max_{rf} V_{rfk}$, where indirect utility is defined by $V_{rfk} = \max_{C_{rfk}} [\log C_{rfk} + \varepsilon_{rfk}]$, subject to a budget constraint $P_r C_{rfk} \leq W_{rfk}$. We assume that the distribution of idiosyncratic preferences is nested logit, where the nests correspond to locations and establishments within a location. That is, workers have preferences first over locations and then establishments within a location. Therefore, the distribution of workers' idiosyncratic preferences has distribution $F(\{\varepsilon_{rf}\}) = e^{-\sum_{r\in R}\left(\sum_{f\in F} e^{-\rho_r \varepsilon_{rf}}\right)^{\frac{\eta}{\rho_r}}}$, where M is the set of firms in the economy across both sectors, and $\rho_r \geq \eta$. As in the canonical Rosen-Roback model, workers supply labor across markets in order to maximize their utility. Mobility across markets depends on η, which parametrizes the dispersion of idiosyncratic tastes for different markets by each worker k, and governs how substitutable different regions are from the worker's perspective.

Workers also supply labor within markets to different establishments. Mobility within markets across establishments depends on ρ_r. This parameter is the dispersion of idiosyncratic tastes for different establishments within region r, and it governs how substitutable establishments in region r are from the worker's perspective. We can interpret ρ_r as the ability of workers to reallocate between establishments, and we allow ρ_r to exogenously vary across regions. In the next section, we show that the labor supply curve facing each establishment is

$$L_{rf} = W_{rf}^{\rho_r} P_r^{-\eta} \left(\sum_{k \in F} W_{rk}^{\rho_r} \right)^{\frac{\eta - \rho_r}{\rho_r}} \kappa, \tag{13}$$

where κ is an aggregate variable that does not vary by region or firm. Therefore, the endogenous region specific variable κ_r from the main text is defined as $\kappa_r \equiv P_r^{-\eta}\left(\sum_{k\in F} W_{rk}^{\rho_r}\right)^{\frac{\eta-\rho_r}{\rho_r}}$. This expression highlights that ρ_r is also the labor supply elasticity to the establishment.[51]

C1.2 Deriving Equations in the Main Text

The household's budget constraint implies that consumption satisfies

$$C_{rfk} = \frac{W_{rfk}}{P_r}.$$

Therefore, the consumer problem simplifies to

$$\max_{rf} \log C_{rfk} + \varepsilon_{rfk} = \max_{rf} \log \frac{W_{rfk}}{P_r} + \varepsilon_{rfk}.$$

A well known result (e.g. Verboven, 1996, Berger et al., 2022) is that since ε_{rfk} has a nested logit distribution, the probability that agent k chooses establishment rf is

$$\begin{aligned}
Pr_{rf} &= \frac{\left(\frac{W_{rf}}{P_r}\right)^{\rho_r}}{\sum_{k\in F}\left(\frac{W_{rk}}{P_r}\right)^{\rho_r}} \left(\sum_{k\in F}\left(\frac{W_{rk}}{P_r}\right)^{\rho_r}\right)^{\frac{\eta}{\rho_r}} \kappa \\
&= W_{rf}^{\rho_r} P_r^{-\eta} \left(\sum_{k\in F} W_{rk}^{\rho_r}\right)^{\frac{\eta-\rho_r}{\rho_r}} \kappa
\end{aligned}$$

where κ is a constant whose value does not depend on regional variables. Integrating over agents k, it follows that

$$L_{rf} = W_{rf}^{\rho_r} P_r^{-\eta} \left(\sum_{k\in F} W_{rk}^{\rho_r}\right)^{\frac{\eta-\rho_r}{\rho_r}} \kappa$$

as in equation (2) in the main text.

We next turn to the problem of the establishment of a local wage setter. In each sector and region, the establishment solves

$$\max_{W_{rf}, L_{rf}} P_r A_{rf} F(L_{rf}) - W_{rf} L_{rf} \quad \text{subject to } L_{rf} = (W_{rf})^{\rho_r}\kappa_r, \quad \kappa_r = P_r^{-\eta}\left(\sum_{k\in F} W_{rk}^{\rho_r}\right)^{\frac{\eta-\rho_r}{\rho_r}} \kappa, \tag{14}$$

which has first order condition

$$P_r A_{rf} F'\left(L_{rf}\right) \rho_r \left(W_{rf}\right)^{\rho_r - 1} \kappa_r - \left(1+\rho_r\right)\left(W_{rf}\right)^{\rho_r} \kappa_r = 0$$

[51] For simplicity, we do not allow multiple occupations in the model. We can think of an establishment in this model as corresponding to an establishment by occupation observation in the data. Alternatively, we could add another "nest" to the labor supply function, to let the representative worker reallocate across occupations within a region.

$$\implies P_r A_{rf} F'(L_{rf})\, \rho_r (W_{rf})^{-1} - (1+\rho_r) = 0$$

$$\implies W_{rf} = \frac{\rho_r}{1+\rho_r} P_r A_{rf} F'(L_{rf})$$

which is equation (3) from the main text.

C1.3 Higher Local Consumer Prices Raise Establishment Wages

This subsection shows that in partial equilibrium, all else equal, higher local consumer prices generally raise establishment wages for local wage setters. The exception to this result is the knife-edge case where there is constant returns to scale in establishment level production, meaning that establishment labor demand is infinitely elastic.

We study the partial equilibrium problem of a single local wage setting establishment and ask what happens to establishment wages when local consumer prices rise. From the wage setting equation (3), we have

$$W_{rf} = \frac{\rho_r}{1+\rho_r} P_r A_{rf} (1-\alpha) L_{rf}^{-\alpha}$$

and from the labor supply equation (2) we have

$$L_{rf} = W_{rf}^{\rho_r} P_r^{-\eta} \tilde{\kappa}_r \quad \tilde{\kappa}_r \equiv \left(\sum_{k \in F} W_{rk}^{\rho_r} \right)^{\frac{\eta-\rho_r}{\rho_r}} \kappa.$$

Substituting equation (2) into (3) implies

$$\begin{aligned} W_{rf} &= \frac{\rho_r}{1+\rho_r} P_r A_{rf} (1-\alpha) \left(W_{rf}^{\rho_r} P_r^{-\eta} \tilde{\kappa}_r \right)^{-\alpha} \\ &= \frac{\rho_r}{1+\rho_r} P_r A_{rf} (1-\alpha) W_{rf}^{-\alpha\rho_r} P_r^{\alpha\eta} \tilde{\kappa}_r^{-\alpha} \end{aligned}$$

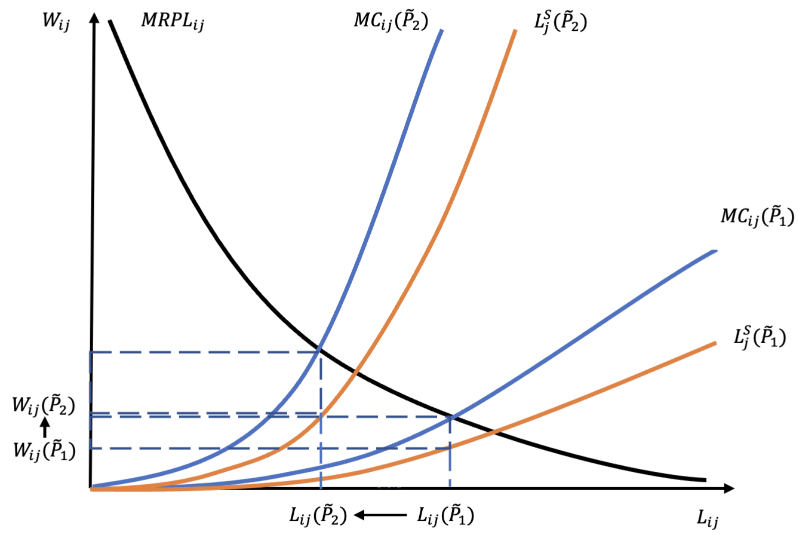
$$\implies W_{rf}^{1+\alpha\rho_r} = \frac{\rho_r}{1+\rho_r} P_r A_{rf} (1-\alpha) P_r^{\alpha\eta} \tilde{\kappa}_r^{-\alpha}$$

$$\begin{aligned} \implies W_{rf} &= \left[\frac{\rho_r}{1+\rho_r} P_r A_{rf} (1-\alpha) P_r^{\alpha\eta} \tilde{\kappa}_r^{-\alpha} \right]^{\frac{1}{1+\alpha\rho_r}} \\ &= \left[\frac{\rho_r}{1+\rho_r} P_r A_{rf} (1-\alpha) \tilde{\kappa}_r^{-\alpha} \right]^{\frac{1}{1+\alpha\rho_r}} P_r^{\frac{\alpha\eta}{1+\alpha\rho_r}}. \end{aligned}$$

We now consider a partial equilibrium exercise, in which we study the response of establishment wages W_{rf} to a change in local consumer prices P_r, holding other variables fixed. We have

$$\log W_{rf} = \frac{1}{1+\alpha\rho_r} \log \left[\frac{\rho_r}{1+\rho_r} P_r A_{rf} (1-\alpha) \tilde{\kappa}_r^{-\alpha} \right] + \frac{\alpha\eta}{1+\alpha\rho_r} \log P_r$$

Figure C1: Effect of Consumer Prices on Establishment Wages in Partial Equilibrium



Notes: The graph plots the marginal revenue product of the establishment, which is its labor demand curve. The graph also plots the labor supply curve and the marginal cost curve of the establishment. We consider cases where local consumer prices are a low value of $\tilde{P}_1$ and a high value of $\tilde{P}_2$.

$$\implies \frac{\partial \log W_{rf}}{\partial \log P_r} = \frac{\alpha\eta}{1+\alpha\rho_r} \geq 0$$

Therefore, in partial equilibrium, increases in local consumer prices strictly increase establishment wages, except in the knife-edge case where $\alpha = 0$, which corresponds to an infinitely elastic labor demand curve, or constant returns to labor in production, or $\eta = 0$, meaning there is no mobility across locations. Note that the labor supply function depends on local prices because workers will move to areas with lower prices, all else equal, and increase the supply of labor. The wage depends on labor supply when there are decreasing returns to scale in production. Existing evidence suggests that $\alpha > 0$ for most establishments, that is, there is decreasing returns to labor (see, e.g., Lamadon et al., 2022).

Intuitively, an increase in local prices means that a given nominal wage affords workers less real consumption. So workers migrate away from the region. Therefore, overall labor supply to the region falls, meaning labor supply to the establishment falls. As a result, the establishment hires fewer workers—raising the marginal product of labor, and, therefore, the wage paid to each worker. We illustrate this logic with a standard diagram of a monopsonistic firm.

C1.4 Calculating Fraction of National Wage Setters Using Fact 2

We now discuss the degree of national wage setting implied by our estimates. We use an alternative strategy compared to the main text. There, we used Fact 1—the dispersion of wages within and between firms—to measure the fraction of national wage setters. This section instead uses Fact 2—how wages vary with prices within and between firms and across space. We calculate that at least 36% of employment is in firms that set wages nationally.

Using the simple model of Section 2, we develop a simple rule of thumb to convert between the within- and between-firm regression coefficients, and the degree of national wage setting. Under some assumptions that we discuss shortly, the ratio of the between firm and the within firm regression coefficients is an upper bound for the share of local wage setters. The most important of these assumptions is that high productivity firms do not sort into high productivity regions. This assumption is unlikely to be exactly correct, but allows us to gauge national wage setting in a simple way that differs from the main text.[52] In the LEHD-ACS and across various specifications, the ratio of regression coefficients is around 40%, suggesting that the share of national wage setters in the LEHD-ACS is at least 60%. As we discussed in Section 4 of the main text, our LEHD-ACS sample restricts to multi-establishment firms only, which constitute roughly 60% of employment (Carballo, Mansfield, and Pfander, 2024). Therefore the share of employment in firms that set wages nationally is at least $60\% \times 60\% = 36\%$.

Now, we explain the assumptions under which the within- and between-firm regression coefficients identify the fraction of national wage setters, and then derive the result.

First, we state the assumptions:

1. On average, high productivity firms do not sort into high productivity areas
2. There is constant returns to scale and constant labor market power across space
3. Establishment productivity takes the form $A_{rf} = A_r A_f$ where A_r and A_f are the regional and firm level components of productivity
4. Different from the main text, firm f operates establishments in only a subset of the regions, but the share of national and local wage setters in each region is $\mathcal{N}$
5. The mean wage of a national wage setter, W_f, and a local wage setter, $W_{f'}$, who operate in same regions satisfies $W_f / W_{f'} = A_f / A_{f'}$. That is, the mean wage of national and local wage setters is proportionate to their relative productivities.

As we have discussed, we view the first of these assumptions as the most substantive. This assumption is likely not correct—nevertheless, by making it, we are able to arrive at a useful way to compare the magnitudes of estimates in the two datasets. In what follows, we will use lower case variables to denote the logarithm of upper case variables. We also note that the result only holds to a first order.

We now derive the result linking the ratio of regression coefficients to national wage setting. From equation (3) the wage for local wage setters is

$$W_{rf}^L = \frac{\rho}{1+\rho} P_r A_r A_f$$

[52] We are unaware of direct evidence on whether high productivity firms sort to high productivity regions, because of the difficulty of disentangling the two components of productivity.

$$\implies w_{rf}^{L} = \log\left(\frac{\rho}{1+\rho}\right) + p_r + a_r + a_f$$
$$= \mu_f + p_r + a_r \quad \mu_f \equiv \log\left(\frac{\rho}{1+\rho}\right) + a_f. \tag{15}$$

We can write $a_r = a(p_r)$, where $a(\cdot)$ is a function which acknowledges that regional productivity and regional prices are jointly determined in equilibrium. Let $\bar{a}$ and $\bar{p}$ be the log of mean productivity and mean prices across all regions. Correspondingly, let

$$\bar{a}_f \equiv \log\left(\frac{\sum_{r\in R_f} A_{rf}}{R_f}\right) \quad \bar{p}_f \equiv \log\left(\frac{\sum_{r\in R_f} P_{rf}}{R_f}\right)$$

denote the log mean price and log mean productivity across the regions R_f in which firm f operates establishments. Then, to a first order in the neighborhood of $\bar{a}$, we have

$$a_r = \bar{a}_f + a'(\bar{p})(p_r - \bar{p}_f), \tag{16}$$

which implies from equation (15) that the local wage setter's log wage is

$$w_{rf}^{L} = \mu_f + p_r + \bar{a}_f + a'(\bar{p})(p_r - \bar{p}_f)$$
$$= \mu_f + \bar{a}_f - a'(\bar{p})\bar{p}_f + \left(1 + a'(\bar{p})\right)p_r \tag{17}$$

Next, we solve for the mean wage of national and local wage setters. englishThe mean wage for local wage setters, averaging across their establishments, is

$$w_f^{L} = \mu_f + \bar{p}_f + \bar{a}_f \tag{18}$$

The mean wage for national wage setters, according to assumption (5) above, also satisfies

$$w_f^{N} = \mu_f + \bar{p}_f + \bar{a}_f. \tag{19}$$

That is, the national and local wage setters' wage are proportionate to their relative productivity, provided that they operate in the same region.

The definition of national wage setting from the main text implies

$$|W_{rf} - W_f^{N}| < |\frac{\rho}{1+\rho}P_r A_r A_f - W_f^{N}|,$$

that is, the wage for a national wage setter in a given region is closer to the mean wage of the national wage setter, than would be their frictionless wage absent national wage setting.

Combining the definition of national wage setting and equation (17) implies that, to a first order, the wage of a national wage setter satisfies

$$w_{rf}^{N} = \mu_f + \bar{a}_f - a'(\bar{p})\,\bar{p}_f + \alpha\left(1 + a'(\bar{p})\right)p_r$$

for $\alpha \in (0,1)$, i.e. the response of wages to prices for a national wage setter is lower than it would be for the corresponding local wage setter.

Therefore, given productivity and prices, but averaging over the shares $\mathcal{N}$ and $1-\mathcal{N}$ of national and local wage setters, the conditional expected wage is

$$\begin{aligned}
E\left[w_{rf}|\mu_f, \bar{a}_f, \bar{p}_f, p_r\right] &= \mathcal{N} w_{rf}^{N} + (1-\mathcal{N})\, w_{rf}^{L} \\
&= \mathcal{N}\left(\mu_f + \bar{a}_f - a'(\bar{p})\,\bar{p}_f + \alpha\left(1 + a'(\bar{p})\right)p_r\right) + (1-\mathcal{N})\left(\mu_f + p_r + \bar{a} + a'(\bar{p})\,(p_r - \bar{p})\right) \\
&= \mu_f + \bar{a}_f - a'(\bar{p})\,\bar{p}_f + \left[\mathcal{N}\alpha + (1-\mathcal{N})\right]\left(1 + a'(\bar{p})\right)p_r
\end{aligned}$$

Therefore, a regression of wages on firm fixed effects and local prices implies a regression coefficient on local prices given by

$$\frac{\partial E\left[w_{rf}|\mu_f, \bar{a}_f, \bar{p}_f, p_r\right]}{\partial p_r} = \left[\mathcal{N}\alpha + (1-\mathcal{N})\right]\left(1 + a'(\bar{p})\right), \tag{20}$$

The conditional mean firm wage, averaging across national and local wage setters in equations (18) and (19), and given productivity and prices, is

$$\begin{aligned}
E\left[w_f|\mu_f, \bar{p}_r, \bar{a}_r\right] &= \mu_f + \bar{p}_f + \bar{a}_f \\
&= \mu_f + \bar{p}_f + \bar{a} + a'(\bar{p})\,(\bar{p}_f - \bar{p})
\end{aligned}$$

where the second line substitutes equation (16). Therefore, the regression coefficient from regressing mean firm wages on the mean price of the firm is

$$\frac{\partial E\left[w_f|\mu_f, \bar{p}_r, \bar{a}_r\right]}{\partial \bar{p}_f} = \frac{\partial \mu_f}{\partial \bar{p}_f} + 1 + a'(\bar{p})\,.$$

Our assumption (1) that high productivity firms do not sort to regions with high prices implies $\partial\mu_f/\partial\bar{p}_f = 0$ which implies

$$\frac{\partial E\left[w_f|\mu_f, \bar{p}_r, \bar{a}_r\right]}{\partial \bar{p}_f} = 1 + a'(\bar{p})\,. \tag{21}$$

Equation (20) defines the within firm coefficient from a regression of wages on prices. Equation (21) defines the between firm regression coefficient. The ratio of these two regression coefficients, R, therefore satisfies

$$\begin{aligned}
R &= \frac{\left[\mathcal{N}\alpha + (1-\mathcal{N})\right]\left(1 + a'(\bar{p})\right)}{1 + a'(\bar{p})} \\
&= \mathcal{N}\alpha + (1-\mathcal{N})
\end{aligned}$$

$$\implies \mathcal{N} = \frac{1-R}{1-\alpha} \geq 1 - R.$$

Therefore, one minus the ratio of the within to the between regression coefficients is a lower bound for the fraction of national wage setters, as we claimed.

C1.5 Extending the Model to Tradeable Production

The model in the main text studies a firm that produces non-tradeable goods in multiple locations, and defines a "frictionless wage" for these firms. In the main text, we assert that firms producing tradeable goods set the same frictionless wage in all regions, provided that labor market power does not vary across regions. We now provide a simple extension of the benchmark model, to allow for tradeable firms, in order to formalize this statement.

To allow for tradeables, we modify the benchmark model in two ways. First, firms sell goods at a single national price P, which does not vary across regions. Second, there is no longer an establishment-level production function. Instead, there is a firm-level production function, in which firms produce output using the sum of labor input across the various locations in which they operate establishments, according to the production function $F\left(\sum_{r \in R} L_{rf}\right)$. In these two senses, the firm is tradeable—there is no local variation in prices and production is aggregated across the locations of the firm. The labor supply block of the model remains the same as in the baseline model.

With these modifications, the firm-level profit function is

$$\Pi_f = PF\left(\sum_{r \in R} L_{rf}\right) - \sum_{r \in R} W_{rf} L_{rf}. \tag{22}$$

As before, worker-level labor supply to the establishment is

$$L_{rf} = \kappa_r W_{rf}^{\rho_r}, \tag{23}$$

where κ_r is an endogenous constant that the firm takes as given.

Now, we solve the model in order to show that tradeable firms set the same frictionless wage in all establishments. To do so, we assume that the firm maximizes profits (22) subject to labor supply (23).

The first order condition is

$$\frac{\partial \Pi_f}{\partial W_{rf}} = 0$$

$$\implies PF'\left(\sum_{r \in R} L_{rf}\right) \frac{\partial L_{rf}}{\partial W_{rf}} - \frac{\partial}{\partial W_{rf}} \left[\kappa_r W_{rf}^{1+\rho_r}\right] = 0$$

$$\implies PF'\left(\sum_{r \in R} L_{rf}\right) \kappa_r \rho_r W_{rf}^{\rho_r - 1} - \kappa_r \left(1 + \rho_r\right) W_{rf}^{\rho_r} = 0$$

$$\implies PF'\left(\sum_{r\in R} L_{rf}\right)\rho_r W_{rf}^{-1} - (1+\rho_r) = 0$$

$$\implies W_{rf} = \frac{\rho_r}{1+\rho_r} PF'\left(\sum_{r\in R} L_{rf}\right). \tag{24}$$

Therefore, in the tradeable model, firms set wages as a markdown of marginal revenue product $PF'\left(\sum_{r\in R} L_{rf}\right)$, which varies at the firm level but not at the regional level. $\rho_r/(1+\rho_r)$ is a measure of regional labor market power. Suppose that labor market power does not vary, that is, $\rho_r/(1+\rho_r) = \rho/(1+\rho)$ where ρ is a national variable. Then, equation (24) shows that the frictionless wage does not vary across establishments for tradeable firms.

We now show in this model that, in the tradeable production model, an increase in local prices in one region r , raises the equilibrium frictionless wage $W_{r'f}$ in any other region r'.

Substitute equation (24) into the labor supply equation to write

$$L_{sf} = \kappa_s \Big(\frac{\rho_s}{1+\rho_s} PF'(L_f)\Big)^{\rho_s}.$$

Thus total labor satisfies the fixed-point equation

$$L_f = \sum_{s\in R} \kappa_s \Big(\tfrac{\rho_s}{1+\rho_s} PF'(L_f)\Big)^{\rho_s}, \tag{25}$$

where $L_f \equiv \sum_{s\in R} L_{sf}$. Equation (25) implicitly defines L_f as a function of all $\{\kappa_s\}$.

Next, we differentiate (25) with respect to κ_r. Let

$$G(L_f;\kappa) = \sum_{s\in R} \kappa_s C_s^{\rho_s} [F'(L_f)]^{\rho_s} - L_f, \quad C_s = \tfrac{\rho_s}{1+\rho_s} P.$$

At equilibrium, $G = 0$. By the implicit function theorem:

$$0 = \frac{\partial G}{\partial \kappa_r} + \frac{\partial G}{\partial L_f}\frac{\partial L_f}{\partial \kappa_r}.$$

We have

$$\frac{\partial G}{\partial \kappa_r} = C_r^{\rho_r}[F'(L_f)]^{\rho_r}, \quad \frac{\partial G}{\partial L_f} = \sum_s \kappa_s \rho_s C_s^{\rho_s} [F'(L_f)]^{\rho_s} \frac{F''(L_f)}{F'(L_f)} - 1.$$

Since $F' > 0, F'' < 0$, it follows that $\partial G/\partial L_f < 0$. Hence,

$$\frac{\partial L_f}{\partial \kappa_r} = -\frac{C_r^{\rho_r}[F'(L_f)]^{\rho_r}}{\partial G/\partial L_f} > 0.$$

Next, we note that from equation (24), $W_{r'f} = C_{r'} F'(L_f)$. Thus,

$$\frac{dW_{r'f}}{dL_f} = C_{r'} F''(L_f) < 0.$$

Combining both results via the chain rule, we have

$$\frac{\partial W_{r'f}}{\partial \kappa_r} = \frac{dW_{r'f}}{dL_f} \times \frac{\partial L_f}{\partial \kappa_r} < 0.$$

Therefore, higher κ_r lowers wages in another region r'. Finally, higher prices lower κ_r, according to the definition of κ_r (e.g. equation 14).

C1.6 Change in Profits due to National Wage Setting

This subsection uses the simple model of Section 2 to calculate the change in establishment profits due to national wage setting. We calculate this change under the assumption that labor supply elasticities do not vary across space, and assuming an isoelastic production function.

First, we write profits as a function of wages only, substituting out labor and, for simplicity, ignoring variation in prices P_r. From equation (1), profits are

$$\Pi_{rf} = A_{rf} L_{rf}^{\alpha} - W_{rf} L_{rf}$$

and from equation (2), labor supply to the firm is

$$L_{rf} = \kappa_r W_{rf}^{\rho},$$

which implies

$$\Pi_{rf} = A_{rf} \kappa_r^{\alpha} W_{rf}^{\alpha\rho} - \kappa_r W_{rf}^{1+\rho}.$$

Define $w_{rf} \equiv \log W_{rf}$ and $\pi_{rf} = \log \Pi_{rf}$, with asterisks corresponding to optimized values. Then we can write log profits as a function of the wage, as

$$\pi_{rf} = \pi\left(w_{rf}\right) = \log\left[\kappa_r^{\alpha} A_{rf} e^{\alpha\rho w_{rf}} - \kappa_r e^{(\rho+1) w_{rf}}\right].$$

At the optimum choice of wage w_{rf}^*, we must have $\pi'\left(w_{rf}^*\right) = 0$. Some algebra implies $\pi''\left(w_{rf}^*\right) = -\alpha\rho\left(1+\rho\right)$. A second order expansion of $\pi\left(w_{rf}\right)$ yields

$$\pi\left(w_{rf}\right) \approx \pi\left(w_{rf}^*\right) + \frac{1}{2}\pi''\left(w_{rf}^*\right)\left(w_{rf}^* - w_{rf}\right)$$

$$\implies \pi_{rf} - \pi_{rf}^* = -\frac{\alpha\rho\left(1+\rho\right)}{2}\left(w_{rf}^* - w_{rf}\right)^2 \tag{26}$$

as required.

C1.6.1 Mapping LEHD-ACS Statistics into Profit Loss

This subsection shows how to map the statistics that we have estimated from the LEHD-ACS into equation (12) from the main text, in order to calculate the counterfactual profit of national wage setters were they to set wages locally.

In the LEHD-ACS, we measure the following statistic:

$$\mathrm{Q}_{f,r,r'}\left[\left|w^L_{rf} - w^L_{r'f}\right| - \left|w_{rf} - w_{r'f}\right|\right] = Z_{f,r,r'} \tag{27}$$

where $\left|w_{rf} - w_{r'f}\right|$ is the absolute log difference of wages for national wage setter f across regions r and r', $\left|w^L_{rf} - w^L_{r'f}\right|$ is the absolute log difference of wages for a local wage setter matched to national wage setter f across regions r and r',, and $Q_{f,r,r'}$ denotes a quantile (in practice the median) after sorting the distribution of $\left|w^L_{rf} - w^L_{r'f}\right| - \left|w_{rf} - w_{r'f}\right|$ by r, r' and f.

In order to map this statistic to our expression for profits, we must make three assumptions:

1. Each firm only operates in two regions, r and r'
2. The log mean wage for a national wage setter, w_f, equals the counterfactual log mean wage that the national wage setter would have had if they set wages locally, w^*_f.
3. Productivity has the form $A_{rf} = A_r A_f$.

The first assumption is necessary in order to match the model with our statistics, which are estimated using pairwise comparisons. The second assumption is innocuous, and places a minimal structure on the mean wage of national wage setters. The third assumption states that productivity is multiplicative in firm- and region-specific factors.

In order to proceed, we will have to prove the following statement: $\left|w^L_{rf} - w^L_{r'f}\right| = \left|w^*_{rf} - w^*_{r'f}\right|$. That is, the difference across regions of log wages for the matched local wage setter, is the same as the counterfactual difference for the national wage setter. Intuitively, the national wage setter and the matched local wage setter differ only in terms of their firm-wide productivity, which is differenced out in the pairwise comparison. Formally, equations (2) and (3) from the main text imply

$$W^L_{rf} = \frac{\rho}{1+\rho} A_f A_r L^{-\alpha}_{rf}$$

and

$$L_{rf} = \kappa_r \left(W^L_{rf}\right)^{\rho}.$$

Substituting and taking logs implies

$$w^L_{rf} - w^L_{r'f} = \frac{(a_r + \rho\kappa_r) - (a_{r'} - \rho\kappa_{r'})}{1+\alpha\rho} = w^*_{rf} - w^*_{r'f}. \tag{28}$$

Our definition of national wage setting implies that to a first order, and for some $\alpha \in (0,1)$, we have

$$w_{rf} - w_f = \alpha\left(w^*_{rf} - w^*_f\right), \tag{29}$$

that is, the gap between the log wage and its mean value for a national wage setter is smaller than the gap between the benchmark equivalents. Rearranging and using assumption (2) implies

$$w_{rf} = \alpha w^*_{rf} + (1-\alpha)\, w^*_f \tag{30}$$

and

$$w_{rf} - w_{r'f} = \alpha \left(w^*_{rf} - w^*_{r'f} \right). \tag{31}$$

Then the quantile statistics (27), imply

$$\begin{aligned} Z_{f,r,r'} &= \mathrm{Q}_{f,r,r'} \left[\left| w^L_{rf} - w^L_{r'f} \right| - \left| w_{rf} - w_{r'f} \right| \right] \\ &= \mathrm{Q}_{f,r,r'} \left[\left| w^*_{rf} - w^*_{r'f} \right| - \alpha \left| w^*_{rf} - w^*_{r'f} \right| \right] \\ &= (1-\alpha)\, \mathrm{Q}_{f,r,r'} \left[\left| w^*_{rf} - w^*_{r'f} \right| \right] \end{aligned}$$

where we substitute into the second line equations (28) and (31).

We also have

$$\begin{aligned} w^*_{rf} - w_{rf} &= w^*_{rf} - \left[\alpha w^*_{rf} + (1-\alpha)\, w^*_f \right] \\ &= \frac{1-\alpha}{2} \left(w^*_{rf} - w^*_{r'f} \right) \end{aligned}$$

$$\begin{aligned} \implies \mathrm{Q}_{f,r,r'} \left[\left| w^*_{rf} - w_{rf} \right| \right] &= \mathrm{Q}_{f,r,r'} \left[\left| \frac{1-\alpha}{2} \left(w^*_{rf} - w^*_{r'f} \right) \right| \right] \\ &= \frac{1-\alpha}{2} \mathrm{Q}_{f,r,r'} \left[\left| \left(w^*_{rf} - w^*_{r'f} \right) \right| \right] \\ &= \frac{Z_{f,r,r'}}{2} \end{aligned} \tag{32}$$

where we use equation (30) in the second equality.

The profit function (12) from the main text is

$$\left| \pi_{rf} - \pi^*_{rf} \right| = \frac{\alpha\rho\,(1+\rho)}{2} \left(w^*_{rf} - w_{rf} \right)^2.$$

Taking quantiles implies

$$\begin{aligned} \mathrm{Q}_{f,r,r'} \left[\left| \pi_{rf} - \pi^*_{rf} \right| \right] &\approx \mathrm{Q}_{f,r,r'} \left[\left| \frac{\alpha\rho\,(1+\rho)}{2} \left(w^*_{rf} - w_{rf} \right)^2 \right| \right] \\ &= \frac{\alpha\rho\,(1+\rho)}{2} \mathrm{Q}_{f,r,r'} \left[\left| \left(w^*_{rf} - w_{rf} \right)^2 \right| \right] \\ &= \frac{\alpha\rho\,(1+\rho)}{2} \left(\mathrm{Q}_{f,r,r'} \left[\left| w^*_{rf} - w_{rf} \right| \right] \right)^2 \\ &= \frac{\alpha\rho\,(1+\rho)}{2} \left(\frac{Z_{f,r,r'}}{2} \right)^2 \end{aligned}$$

where the final equality uses equation (32). The left hand side of the equality is the object of interest—quantiles of the deviation of profits from the frictionless value. The right hand side is a function only of the labor supply elasticity and $Z_{f,r,r'}$, which we measured from the LEHD-ACS.

C1.7 Wage Premia for National Wage Setters

This subsection explores why national wage setters might pay a wage premium relative to other firms, according to the benchmark model of Section 2 and Appendix Section C1.1. We identify two reasons. First, national wage setters might be more productive than other firms, perhaps as a consequence of adopting national wage setting and other productivity enhancing management practices. Section 5 presents evidence consistent with this view. Second, national wage setters pay a premium if high wage areas tend to also have high labor supply.

We now derive an expression for the wage premium of national wage setters. To do so, we make several simplifying assumptions within the baseline model. We assume that establishment production has constant returns to scale, that labor supply elasticities to the establishment are constant across space, and that establishment productivity has a firm and region component so that $A_{rf} = A_r A_f$. Under these assumptions, the wage paid by a national wage setter simplifies from equation (**??**) of the main text to yield

$$\begin{aligned} W_f^* &= \sum_{r \in R} \omega_{rf} W_{rf}^* \\ &= \sum_{r \in R} \frac{(1+\rho) L_{rf}}{\sum_{k \in R} (1+\rho) L_{kf}} W_{rf}^* \\ &= \sum_{r \in R} \frac{(1+\rho) \kappa_r W_f^{*\rho}}{\sum_{k \in R} (1+\rho) \kappa_k W_f^{*\rho}} \frac{\rho}{1+\rho} A_r A_f \\ &= \frac{\rho}{1+\rho} A_f \sum_{r \in R} \frac{\kappa_r}{\sum_{k \in R} \kappa_k} A_r \end{aligned}$$

where the first equality is equation (**??**) of the main text; the second equality substitutes in the definitions of the weights ω_{rf}; the third equality substitutes in labor supply to the establishment (2), and the optimal wage of a local wage setter (3); and the final equality simplifies. Recall from Appendix Section C1.1 that $\kappa_r \equiv P_r^{-\eta} \left(\sum_{k \in M} W_{rk}^{\rho} \right)^{\frac{\eta - \rho}{\rho}}$ is a composite parameter capturing labor supply to the region.

The wage of a local setter, averaged across its regions, is

$$\begin{aligned} \bar{W}_f &= \frac{1}{R} \sum_{r \in R} W_{rf}^* \\ &= \frac{1}{R} \sum_{r \in R} \frac{\rho}{1+\rho} A_r \tilde{A}_f \\ &= \frac{\rho}{1+\rho} \tilde{A}_f \frac{1}{R} \sum_{r \in R} A_r \end{aligned}$$

where $\tilde{A}_f$ is the productivity of the local wage setter, potentially different from the national wage setter's productivity A_f; and the second line substitutes in the wage-setting equation of local wage setters (3).

Therefore, the wage premium of a national wage setter relative to a local wage setter is

$$\begin{aligned} W_f^* - \bar{W}_f &= \frac{\rho}{1+\rho} A_f \sum_{r \in R} \frac{\kappa_r}{\sum_{k \in R} \kappa_k} A_r - \frac{\rho}{1+\rho} \tilde{A}_f \frac{1}{R} \sum_{r \in R} A_r \\ &= \frac{\rho}{1+\rho} \left(A_f \sum_{r \in R} \frac{\kappa_r}{\sum_{k \in R} \kappa_k} A_r - \tilde{A}_f \frac{1}{R} \sum_{r \in R} A_r \right). \end{aligned} \tag{33}$$

Equation (33) suggests two reasons for a premium. First, national wage setters could be more productive. Clearly, if the productivity of the national wage setter (A_f) is much greater than the productivity of the local wage setter ($\tilde{A}_f$) then there is a premium.

Second, more subtly, there is a premium if high productivity areas also tend to have high regional labor supply. To see this point, suppose that national wage setters do not have higher productivity (so $\tilde{A}_f = A_f$). Then the expression for the premium simplifies to

$$W_f^* - \bar{W}_f = \frac{\rho}{1+\rho} A_f \sum_{r \in R} \left(\frac{\kappa_r}{\sum_{k \in R} \kappa_k} A_r - \frac{A_r}{R} \right).$$

There is a premium for national wage setters if the term inside the brackets is positive, which in turn requires that κ_r and A_r are positively correlated. In other words, high productivity regions (high A_r) must also have high labor supply (high κ_r).

What is the intuition for this result? High productivity areas also pay high nominal wages. If these areas have high labor supply, then national wage setters will reallocate employment towards these areas. If so, the national wage is disproportionately influenced by high wage areas. As a result the national wage will be higher on average than equivalent, locally set wages.

It is certainly plausible that high productivity areas have high regional labor supply. From the definition of regional labor supply, $\kappa_r r^{-\eta} \left(\sum_{k \in M} W_{rk}^{\rho} \right)^{\frac{\eta-\rho}{\rho}}$, areas with high nominal wages and low local consumption prices P_r will have high regional labor supply. Plausibly, productive areas pay high wages and also supply local consumption goods relatively cheaply. However, one cannot analytically prove whether high productivity is positively related to high labor supply. General equilibrium forces may operate in other directions. For instance, high nominal wages may increase population and raise non-tradeable prices by enough to lower real wages and reduce labor supply. A full numerical exploration of this issue seems beyond the scope of the paper.