National Wage Setting*

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Abstract

How do firms set wages across space? Using job-level vacancy data and a survey of HR managers, we show that 40-50% of a job's posted wages are identical across locations within a firm. Moreover, nominal posted wages within the firm vary relatively little with local prices, a pattern we verify with other measures of job level wages. Using the co-movement of wage growth across establishments, we argue these patterns reflect *national wage setting*—a significant minority of firms choose to set the same nominal wage for a job across all their establishments, despite varying local labor market conditions.

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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. As such, while the concentration of employment across firms in local labor markets has fallen in recent decades, the concentration of employment nationally has risen (Autor et al., 2020; Rossi-Hansberg et al., 2021). How do these large national firms set wages? The answer matters for many phenomena, such as wage inequality, the growth of labor market power, 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 whether national firms strengthen or weaken the inequality in place.

This paper investigates how firms set wages across space. To fix ideas, we start with a benchmark framework for how multi-establishment firms set wages across space, integrating standard models of imperfect labor market competition and spatial equilibrium. In this standard 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 a constraint that nominal wages be the same across the firm's locations, regardless of how local labor market conditions vary. The main contribution of this paper is to show, empirically, that a substantial minority of firms are best characterized as national wage setters.

The primary dataset we use to establish this result contains online job vacancies provided by 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 5% of the Burning Glass sample that provide posted point wages for detailed occupations across establishments within a firm.[1] Investigating national wage setting with standard administrative datasets is difficult for two reasons. First, without detailed information on job titles, changing job composition within a firm across regions may mask national wage setting. For example, even if CVS pays the same wage to both low wage cashiers and high wage managers in Cincinnati and San Francisco, average wages will be lower in the Cincinnati store if CVS hires more cashiers relative to managers there. Second, most administrative datasets measure earnings and not wages, which in this example could mask national wage setting if workers

[1] We define a job in a firm as the detailed occupation, measured using 6-digit SOC codes, combined with the pay frequency of the job (e.g. annual or hourly) and pay type in the posting (e.g. base pay or commission). We define an establishment of the firm as the combination of the firm name and the county in which they post the vacancy.

in San Francisco work longer hours. The Burning Glass data allows us to overcome these challenges. First, the data contains detailed job level information, meaning we can directly control for changes in job composition across regions. Second, vacancies include hourly wages for non-salaried workers and annual wages for salaried workers, which allows us to distinguish between wages and earnings (i.e. the product of wages and hours worked).

We complement the data on posted wages with three additional datasets. First, we conducted a survey of human resources (HR) managers and executives. We asked questions about how firms set wages and why they adopt their wage setting policy. The survey data allows us to test whether pay structures show similar patterns to posted wages, to explore whether our findings are similar for firms outside of our Burning Glass sample, and to explain why firms choose to set wages nationally. Second, we use data on self-reported wages and other forms of compensation from Payscale, a salary comparison service, to test whether workers' realized wages are also compressed across space and specifically explore the extent to which bonus pay may offset this compression. Lastly, we analyze worker-level wage information provided in Labor Condition Applications (LCAs), which are mandatory reports from firms applying for select visas for foreign workers, such as the H1B visa. This unique dataset, which includes information on worker wages, occupations, worksites, and firms, allows us to validate the patterns using both within-firm and within-worker variation.

We organize the patterns in the data into four descriptive facts about wage setting across space. First, we find a large amount of wage compression within the firm across space. This wage compression is most starkly illustrated by the finding that 40-50% of postings for the same job in the same firm but in different locations have exactly the same wage. Second, we find that identical wage setting is a choice made by firms for each occupation—for a given occupation, some firms set identical wages across *all* their locations, while the remaining firms set different wages across most of their locations. Third, we show that within firms, nominal wages are relatively insensitive to local prices. Fourth, we show that firms setting identical wages pay a wage premium. Although selection in posting wages in Burning Glass is not random, a battery of robustness tests suggests that selection does not account for our findings about wage compression. These facts are in line with HR professionals' survey responses and with patterns for realized wages in both Payscale and the LCA data.

We then argue that these identical wages across space are due to *national wage setting*. We provide two pieces of evidence. First, we compare wage growth in the same job across different establishments. Jobs that initially pay identical wages across locations have strongly correlated future wage growth across locations, while jobs that initially pay different wages across locations have weakly correlated future wage growth. Second, we study a local shock to wages based on the demand for natural resources, which raises wages for establishments located in natural resource-intensive regions but not operating in the natural resource sector. We find that firms initially setting identical wages pass local resource shocks through to wages in the rest of the firm, while those with initially different wages do not.

Next, we use our survey to ask *why* firms choose to set wages nationally. We find that firms set national wages for a range of reasons, including hiring on a national market, simplifying management, and adhering to within-firm fairness norms. Government policies such as minimum wages do not appear to drive national wage setting. These reasons point to a mix of firm and occupation specific factors that matter more for higher wage workers, and suggest that nominal pay comparisons matter to workers.

We next carry out a simple, model-based exercise to measure the profits at stake from setting wages nationally. To do so, we benchmark the wage dispersion that would have been observed for national wage setters had they chosen to vary wages flexibly across regions. For this estimate, we assume that observably similar firms, who do not set identical wages across space, provide a reasonable counterfactual for the distribution of wages across locations of national wage setters. We find that in the absence of national wage setting, wages for national wage setters would vary across establishments by a median of 6.1%, and profits would be between 3 and 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.

We close the paper with some broader consequences. A comprehensive examination is beyond the scope of the paper and instead, we briefly touch on three implications of national wage setting. First, a back-of-the-envelope exercise suggests national wage setting reduces aggregate nominal wage inequality by roughly 5% by compressing nominal wages across space. Second, merging in establishment-level employment data from Dun and Bradsheet, we find evidence national wage setting raises employment in low-wage areas, consistent with a simple model of labor supply. As such, national wage setters seem to reduce aggregate wage and earnings inequality without disemployment effects, through raising wages in low wage regions. Lastly, we explore how national wage setting affects the response of local economies to shocks, and find national wage setting raises regional nominal wage rigidity.

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 et al. (2014) show that global retailers set the same price for the same product in different countries of the same currency union.[2] We complement these papers by studying wage setting instead of price setting, by studying the entire economy beyond the specific setting of the retail sector, and by combining survey and micro data to understand the reasons why firm behavior responds little to local conditions.

A second literature studies the firm-level determinants of worker pay. Evidence suggests that different firms often pay similar workers different wages (Card et al., 2013; Song et al., 2019). There are a range of explanations for this phenomenon, including amenities (Sorkin, 2018; Lamadon et al., 2022), rent sharing of firm productivity (Card et al., 2018), and variation in firms' wage setting power due to their market share (Berger et al., 2022a; Jarosch et al., 2019). National wage setting policies are another reason that different firms may pay workers performing the same job in the same location different wages.

Our paper also relates to a growing literature seeking to understand why firms adopt certain pay policies. For example, several papers show that fairness norms constrain wages within an establishment (Bewley, 1999; Card et al., 2012; Saez et al., 2019; Dube et al., 2019). Relative to these papers, we provide evidence that fairness norms affect how firms set wages *across* establishments. More broadly our paper contributes to growing evidence that firms' wage policies are "clunky" and hard to square with fine-grained optimization (Dube et al., 2020; Cullen et al., 2022).

Several recent papers share our specific focus on how within-firm pay varies across space. Hjort et al. (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 international data on wages paid in different currencies. Our setting allows us to shed more light on the nature of firm

[2] Nakamura (2008), Hitsch et al. (2019) and Cavallo (2018), amongst others, also 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.

wage setting and highlight reasons why a particular subset of firms sets wages nationally. In another related paper, Derenoncourt et al. (2021) study the consequences for local labor markets of four large firms' national minimum wage policies.[3]

Finally, a third literature studies the spatial determinants of pay and other local labor market conditions.[4] For instance Card et al. (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 and across firms, we focus on differences in wages across space but within firms.[5]

2 A Simple Model of Wage Setting Across Space

We begin by developing a simple framework to clarify how firms set wages across multiple establishments in a benchmark model. Specifically, we combine a standard model of imperfect labor market competition, as in Card et al. (2018), with a standard Rosen-Roback model of spatial equilibrium (e.g., Moretti, 2011). We include imperfect labor market competition to have a notion of heterogeneous firms, and a model of spatial equilibrium to have a notion of heterogeneous regions. We show that in this benchmark model, firms set identical wages across space only if the marginal revenue product of labor is the same across establishments. We also define the concept of national wage setting, wherein certain firms choose to pay the same nominal wage across establishments, even if marginal products vary.

Model Setup. In our setting, there are $j = 1, ..., J$ regions and a unit measure of workers. There are two sectors, producing either tradable or non-tradable goods. In each sector $S \in \{N, T\}$, there are $i = 1, ..., M_S$ firms who hire workers in all regions. Specifically, in each region j, firm i operates an

[3]Four 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 and 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 et al. (2021), who report survey evidence that multinational corporations partly pay high wages overseas to ensure cross-country pay fairness; and Boeri et al. (2021), who study the effect of national wage setting among unions in Italy, compared with flexible wage setting among unions in Germany, on regional outcomes in each country. Also related is Giupponi and Machin (2021), who document uniform wage setting across workers of different ages performing the same job, within the English residential care home sector.

[4]See Moretti (2011) for a survey of this vast literature, or recent contributions by Caliendo et al. (2018), Hornbeck and Moretti (2022), Schoefer and Ziv (forthcoming) or Brinatti et al. (2021).

[5]A closely related finding to ours is Bilal (2021), who documents firm wide uniformity in separation rates across space.

establishment that posts wages and employs workers.

Establishments in sector S have heterogeneous productivity $A_{ij}^S = A_i^S \times A_j^S$, where A_i^S and A_j^S are drawn from distributions that can vary by sector. The establishment posts a wage W_{ij}^S, which it then pays to all its workers. Given employment L_{ij}^S, the establishment operates a decreasing returns to scale production function $F\left(L_{ij}^S\right) = (L_{ij}^S)^{1-\alpha}$ and produces output $Y_{ij}^S = A_{ij}^S F\left(L_{ij}^S\right)$ sold in a competitive market. Goods in the tradable sector are sold at a price that does not vary by region and which, without loss of generality, we normalize to 1. Goods in the non-tradable sector are sold at a price P_j^N 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 ij, that depends on both the identity i of the firm and on the region j. We denote the value of agent k's idiosyncratic taste for establishment ij by ε_{ijk}, and their indirect utility from working in this establishment by V_{ijk}. If agent k works in establishment ij, they consume C_{ijk}^N of the non-tradable good and C_{ijk}^T of the tradable good. Agents derive utility from a homothetic aggregator across consumption $C_{ijk} = C\left(C_{ijk}^N, C_{ijk}^T\right)$, and have logarithmic utility in C_{ijk}.

Labor Supply. The agent's problem is to choose the establishment with the highest utility. They solve $\max_{ij} V_{ijk}$, where indirect utility is defined by $V_{ijk} = \max_{C_{ijk}} [\log C_{ijk} + \varepsilon_{ijk}]$, subject to a budget constraint $C_{ijk}^T + P_j^N C_{ijk} \leq W_{ijk}$. We assume that the distribution of idiosyncratic preferences is nested logit, with distribution $F\left(\{\varepsilon_{ij}\}\right) = e^{-\sum_{j\in N}\left(\sum_{i\in M} e^{-\rho_j \varepsilon_{ij}}\right)^{\frac{\eta}{\rho_j}}}$, where M is the set of firms in the economy across both sectors, and $\rho_j \geq \eta$. 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_j. This parameter is the dispersion of idiosyncratic tastes for different establishments within region j, and it governs how substitutable establishments in region j are from the worker's perspective. We can interpret ρ_j as the ability of workers to reallocate between establishments, and we allow ρ_j to exogenously vary across regions. Appendix Section C1 shows that the labor supply curve facing each establishment is

$$L_{ij} = W_{ij}^{\rho_j} \tilde{P}_j^{-\eta} \left(\sum_{k \in M} W_{kj}^{\rho_j} \right)^{\frac{\eta - \rho_j}{\rho_j}} \kappa, \tag{1}$$

where $\tilde{P}_j$ is the local consumer price index, defined as the ideal price index associated with the homothetic consumption aggregate C_{ij} and κ is an aggregate constant. This expression highlights that ρ_j is also the labor supply elasticity to the establishment.[6]

Wage Setting in the Benchmark Model. Firm i in sector S solves a separate problem in each labor market j, aiming to maximize each establishment's profits

$$\max_{W_{ij}^S, L_{ij}^S} P_j^S A_{ij}^S F(L_{ij}^S) - W_{ij}^S L_{ij}^S \tag{2}$$

given the establishment labor supply curve (equation 1). In the equilibrium of the model, each agent maximizes utility by choosing a region, establishment, and consumption bundle according to their nested logit preferences. Each establishment maximizes profits according to equation (2) and goods markets clear in the tradable and non-tradable sector of each region.

The first order condition of the firm's problem (2) implies

$$W_{ij}^{*\,S} = \underbrace{\frac{\rho_j}{1+\rho_j}}_{\text{markdown}} \overbrace{P_j^S A_{ij}^S F'\left(L_{ij}^S\right)}^{\substack{\text{marginal revenue} \\ \text{product}}} \tag{3}$$

for each establishment j of the firm i. The result is standard: establishments set nominal wages as a markdown of nominal marginal revenue product, where the markdown depends on the labor supply elasticity to the establishment. Nominal marginal revenue product can vary due to workers' productivity A_{ij}, producer prices P_j, and the optimal scale of the firm given by its productivity, L_{ij}^S. Separate from producer prices, higher local consumer prices also raise wages by causing workers to migrate out of the region, reducing labor supply to the region, lowering L_{ij}^S, and thus raising the marginal revenue

[6]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.

product.[7] In this simple framework, the markdown $\rho_j/(1+\rho_j)$ varies exogenously across regions, though richer models endogenize markdowns as a function of establishments' market share (Berger et al., 2022a).

Firms pay the same nominal wage in two establishments if the establishments have the same marginal revenue product and markdown. Evidence suggests a great deal of dispersion in both productivity and local competition. For example, Kehrig and Vincent (2019) find that most of the dispersion of productivity within U.S. manufacturing occurs within firms across their establishments; Schoefer and Ziv (forthcoming) show that, overall, local productivity varies substantially across places; Macaluso et al. (2019) estimate a great deal of variation in labor markdowns, even within narrowly defined industries; and there is substantial dispersion of local consumer prices across space (Moretti, 2013; Diamond, 2016, Card et al., 2021; Diamond and Moretti, 2021). Moreover, various realistic features that are not included in our model—such as regional amenities, use of land in production, or differing worker composition across regions—would further increase dispersion in the labor market conditions that matter for wage setting.

National Wage Setting. In the following sections, we will argue that the empirical evidence is inconsistent with this benchmark model for a substantial minority of firms. Instead, we will suggest that a fraction of firms set wages nationally—these firms pay the same nominal wage everywhere, regardless of local conditions. To formalize this notion, consider an extension of the benchmark model where a share of firms in sector S must pay the same wage W_i in all establishments, meaning that they sum across establishments to maximize firm profits

$$\max_{W_i^S, L_{ij}^S} \sum_{j \in N} \left[P_j^S A_{ij}^S F(L_{ij}^S) - W_i^S L_{ij}^S \right] \tag{4}$$

again given each establishment's labor supply curve.[8] The constraint affects only a subset of firms, but affects all locations within these firms. The first order condition implies

$$W_i^{*S} = \sum_{j \in N} \omega_{ij} W_{ij}^{*S}, \tag{5}$$

[7] In Appendix Section C1, we formally show that in partial equilibrium, higher consumer prices raise the wages paid by an establishment, unless the establishment's labor demand curve is infinitely elastic. Existing evidence suggests establishments' labor demand is far from infinitely elastic (see, e.g., Lamadon et al., 2022).

[8] In this framework, firms that set wages nationally can have higher productivity and pay higher wages on average. As such, national wage setting could raise productivity and offset the cost of setting suboptimal wages, so that some firms might prefer to set wages nationally. In Appendix Section C1.3, we extend our model to formalize this argument.

where $\omega_{ij} = (1+\rho_j) L^S_{ij} / \sum_{k \in N} \left[(1+\rho_k) L^S_{ik}\right]$ is a weight for each location. These firms set wages as a *weighted average* of marked-down revenue product in each location, with weights that depend on labor supply elasticities and employment in each region. The remaining share of firms, who we refer to as "local wage setters," behave as in the benchmark model.[9]

3 Data Description

The main dataset we use comes from Burning Glass Technologies, a company that scrapes online job postings. Throughout the paper, we complement these data with a survey that we ran with HR managers and executives; with data on self-reported wages from Payscale, a salary comparison service; and with workers' wages from Labor Condition Applications (LCAs), which are mandatory filings from firms seeking certain visas for foreign workers.

3.1 Job Level Data from Burning Glass

Our main data source is an establishment-level dataset of job vacancies covering 2010-2019. 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 vacancies in the United States (Carnevale et al., 2014). However, only 5% of vacancies in Burning Glass include point wages, meaning that the subset of vacancies that include point wages is roughly 3% of total U.S. vacancies. We exclude jobs posting wage ranges from our analysis, but we show the robustness of the main findings to including those observations and taking the midpoint of the range.

For those vacancies that include wage information, 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). We define the wage as the annual earnings for that job. Appendix Table A1 shows that point wages are more likely to be posted at smaller firms, in occupations

[9]Our model does not allow rationing by labor demand—workers are always on the establishment labor supply curve. In section 8 we find evidence consistent with this assumption, using information on establishment employment from Dun & Bradstreet. Moreover in section 7, when we benchmark the effects of national wage setting on profits, we extend the model to allow for rationing by labor demand, and the results change little. Our model also abstracts from establishment entry and capital. In section 8 we discuss how establishment entry affects our findings; and in section 7, how capital affects our findings.

that have lower wages, and for jobs with lower education and experience requirements. In all cases the magnitudes are relatively small—for instance an occupation with a 1 standard deviation higher wage lowers its probability of posting a wage by 0.016.[10]

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 worker side, the vacancy includes information on required years of education or years of experience. On the job side, the language of the job posting reveals an occupation, which Burning Glass codes into a six-digit (SOC) occupation code.[11] In a given year, the average firm posts 2.8 vacancies per occupation. Throughout the analysis, we define a job as the combination of the occupation, salary type, and pay frequency (e.g. pest control workers with hourly base pay).[12] Lastly, in addition to detailed occupations, we explore alternate specifications defining jobs using the standardized job titles included in the vacancy data.

Burning Glass also assigns a firm name and county to each vacancy, which allows us to define establishments. We cleaned firm names using a deduplication procedure outlined in Appendix Section A1.1. We define an establishment of a firm as the collection of vacancies assigned to a firm within a county.[13] 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.

One important feature of the Burning Glass data is that it provides measures of posted wages, not the realized wages paid to workers. Appendix Figure A1 plots the tight positive relationship between the median posted wage in Burning Glass in each 6-digit occupation within a metro area against the corresponding measure from the Occupational Employment Statistics (OES) data—when Burning Glass wages are 1% higher, occupation wages from the OES are also roughly 1% higher. We more extensively

[10] Appendix Table A1 also shows that there is no clear relation between whether firms are more likely to post wages in areas with high cost of living, moreover the magnitudes of any relationship are small. For instance, within a firm, a county with a 1 standard deviation higher house price level raises its probability of posting by 0.0013; whereas a county with a 1 standard deviation higher consumer price level has a probability of posting that is lower by 0.0003. These statistics suggest that the strategic posting of wages across locations is unlikely to meaningfully affect our estimates of national wage setting.

[11] Six-digit occupation codes are highly granular, including occupations such as pest control worker, college professor in physics, and home health aide.

[12] We define the job using salary type and pay frequency since it is challenging to make wage comparisons across those categories. We find that, within an occupation, firms rarely post vacancies with different salary types, and pay frequencies, with only 1.8% of occupation and firm pairs posting multiple salary types across locations within a year and .8% posting multiple pay types. This small dispersion suggests that firms do not strategically vary the structure of pay across locations and therefore, 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.

[13] We also make use of Burning Glass' firm level industry information. Vacancies are assigned 2 and 3 digit industry codes in Burning Glass when industry information is available in the text of the vacancy. We assign to each firm the industry in which it posts the most vacancies.

probe this relationship and show in Appendix Table A2 that all types of posted wages in Burning Glass closely track realized wages in the OES data and show in Appendix Table A3 that the tight relationship in Figure A1 applies not only to median wages but also to other points in the distribution.

Lastly, for our main analysis, we make several sample restrictions, summarized in Appendix Table A4. 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. 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.[14] In Appendix Figures A2, we document how well the resulting sample represents employment in overall U.S. economy. We over-represent 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. Throughout, we show robustness with data re-weighted to match the occupation distribution in the OES.

3.2 Survey of HR Professionals

We supplement our analysis of job vacancies with a survey that we administered 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. We have a particularly large number of respondents from 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, since we are interested in the behavior of firms that operate in multiple regions. The majority of respondents are HR managers or executives who are directly involved in setting pay (Appendix Figure B3). More details on

[14] This averaging potentially causes a downward bias in our measure 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. Our measure would show no wage compression even though, in this example, it exists.

the sample and survey design are provided in Appendix Section B1 and the online survey appendix.

3.3 Additional Salary Data: Payscale and Labor Condition Application (LCA) Data

We also use two additional datasets with worker wages. First, we use data from Payscale, a salary comparison company that aims to provide both employees and employers with accurate information on job market compensation. One way it does so is by having current job-holders fill out their compensation information, including their current salary or wage, the average number of hours they work per week, and information on bonuses and benefits. The dataset we received contains the self-reported information that job-holders enter. Specifically, we have information on the individual's current firm and job title, her wage/salary, bonuses and other forms of compensation, hours worked, and other individual-level characteristics such as age and gender. Pooling data from 2011-2018, the dataset covers 3.22 million individuals.[15] For our purposes, the key limitation of the Payscale data is that it is sampled at the worker, rather than firm, level. Therefore, only 26% of the sample works in a job that is present in multiple establishments of the firm. This additional restriction distorts the sample, tilting it heavily towards the finance, insurance, and healthcare sectors.

Second, we use data from Labor Condition Applications (LCA), 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),[16] 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. While these wages are not realized wages, the wage reported in the LCA application is likely close to the wages that workers eventually receive, as it is costly for employers to change the wage after the application.

The DOL has made these applications available for each fiscal year from 2010 to 2021, and we use

[15]We restrict attention to workers between the ages of 20 and 65 with positive reported earnings, leaving 2.55 million workers in the sample, 56% of whom work in salaried occupations. Details on the industry and occupation representation are discussed in Appendix Section A1.

[16]Firms are allowed to list many potential worksites for each worker, and about 2% of the sample reports more than 1. In the main analysis, we use the wage for the primary worksite, but also explore patterns in wages across worksites for a given worker in the appendix.

data from 2010-2019 to match the Burning Glass sample. The program is large, with an average of 460,000 job applications per year, including both certified and uncertified applications. These jobs are highly concentrated in a subset of high-skill occupations, geographically dispersed, with nearly 70% of primary worksites outside the 10 biggest cities in the U.S., and dominated by a handful of large firms.[17] Therefore, although this sample is unique, the fact that it is concentrated in certain occupations and firms while being geographically diverse makes it well suited for an analysis of wage setting patterns within the firm locations for the same job.

4 Descriptive Facts on Wages within the Firm Across Space

This section presents four descriptive findings on wage compression within the firm across regions. In section 5, we will argue that the compression in wages is due to national wage setting.

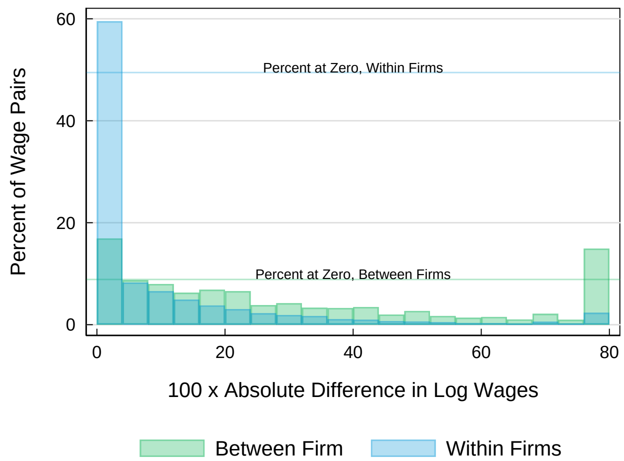
Fact 1: A large share of wages are set identically within firms across locations.

We begin by showing that there is a large amount of wage compression within the firm across locations. This is most starkly exemplified by the large fraction of posted wages that are exactly identical across locations. Specifically, we calculate the difference in the posted wage for within-firm job pairs, which we define as postings within the same year in the same job and the same firm but in different counties (e.g. postings for administrative assistants at Deloitte in Boston and San Francisco in 2019). For each of these pairs, we construct a corresponding between-firm pair for the same job in the same locations but with the job in the second location being in a randomly selected different firm in the same industry (e.g. postings for administrative assistants at Deloitte in Boston and administrative assistants at Ernst & Young in San Francisco in 2019). Figure 1 shows the distribution of wage differences for the within-firm pairs (blue) and the corresponding between-firm pairs (green). 49% of within-firm pairs post *exactly* the same wage, while only 8.9% of between-firm pairs post the same 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.[18]

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

[18] We can also reweight 6-digit occupations in this figure to match the occupation distribution within the OES. In this case, 11% of between-firm pairs at identical while 30% of within firm pairs are identical.

Figure 1: Distribution of Wage Comparisons Between and Within Firms



Notes: The figure shows the distribution of wage differences for within- and between-firm pairs. 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.

Our survey results closely mirror these patterns within job postings. Figure 2 shows responses to the question "Which of the following describes how your firm sets pay bands (wages) across locations for the majority of your workers?"[19] Respondents could choose one of three options: pay bands (wages) are determined separately for each establishment, are set identically so that workers with the same job title face the same pay band (wage), or sometimes separately but not always. Nearly 30% of respondents state that they work at firms that set wages identically across establishments ("Identical"). An additional 45% of firms set pay identically for some, but not all, of their jobs ("Mix"). Only around 25% of respondents report working at a firm that sets different wages for workers with the same job title, but who are working in different establishments ("Separate").

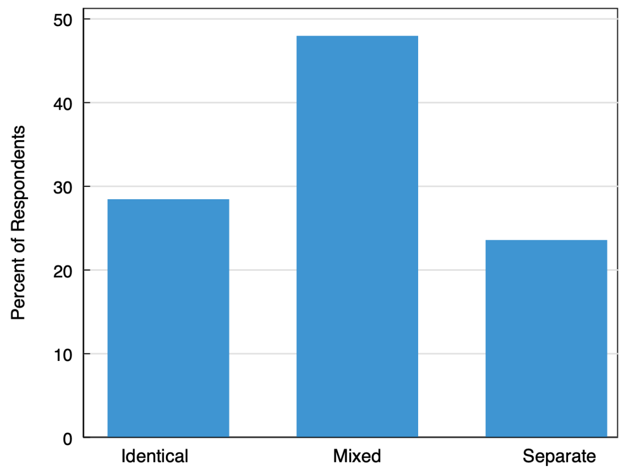
Fact 2: Identical wages are a characteristic of occupations within firms.

The compression of wages within the firm could result either from certain firms setting identical wages for all of their jobs, or a larger set of firms setting identical wages for a subset of their jobs. We find evidence for the latter.

First, we find that for a given job within a firm, firms either set wages identically across all locations,

[19]Earlier in the survey, we ask respondents whether their firm primarily uses pay bands, where workers face a minimum and maximum wage, or wages, where workers are offered a single wage.

Figure 2: Survey Responses: Method of Setting Wages



Notes: This figure shows survey responses to a question asking how the respondent's firm sets pay bands/wages across locations for the majority of its workers. "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 online survey appendix.

or vary wages across their locations.[20] It is rare to see a job pay identical wages in certain locations, but then vary the wages for the same job in other locations. Indeed, among those jobs where at least 20% of the job pairs were the same, 71% were identical across all locations. Consistent with this fact, Appendix Figure A3 shows that county-level variables are relatively weak predictors of identical wages—we describe how we estimate predictors of identical wages, using dyadic regressions, in Appendix Section A2.1. Specifically, we find that within the firm, the probability that posted wages are the same across pairs is decreasing in the geographic distance between the establishments, decreasing in the differences in price levels, and increasing the average unemployment rate of the counties. However, the magnitude of these relationships are small—for example, a one standard deviation increase in the difference in price levels across counties decreases the probability of posting identical wages within the firm relative to between firms by only 0.02, relative to an average difference of 0.55.

Second, firms do not tend to set identical wages for all of their jobs. Specifically, we find that while roughly 20% of firms set nationally identical wages for all occupations, the majority of firms setting

[20] Appendix Figure A4 shows the fraction of establishment pairs with wages that are identical for each occupation and firm. We find a clear bimodal distribution, with many occupations within firms having less than 10% of pairs being identical, many having all pairs being identical, and very few having between 50 and 95% of pairs being identical.

national wages do so for only a subset of their occupations (See Appendix Figure A4). Third, not all firms choose to set national wages for the same occupations. Appendix Figure A3 shows that identical wages are more common in high-wage or tradable occupations, which we define as those that can be done remotely (Dingel and Neiman (2020)).[21] Identical wages are also less common in firms with fewer occupations or in tradable industries.

In sum, setting identical wages across space is not a characteristic of the firm (e.g. it is not the case that CVS always sets identical wages and Walgreens does not), the location (e.g. it is not the case that CVS sets identical wages in Austin and Dallas, but not in NYC and Boston), or the occupation (e.g. all firms set identical wages for cashiers). Rather, identical wages is a choice made by the firm for each occupation (e.g. CVS sets identical wages for pharmacists across all locations, but varies wages for cashiers).

Fact 3: Within firms, nominal wages are relatively insensitive to local prices

We now show that wages within the firm are relatively insensitive to local labor market conditions. Specifically, we explore how wages vary with local prices by estimating the within-firm relationship between wages and local prices as

$$\log w_{ijot} = \beta \text{price level}_{jt} + \theta_{oi} + \theta_t + \varepsilon_{ijot} \tag{6}$$

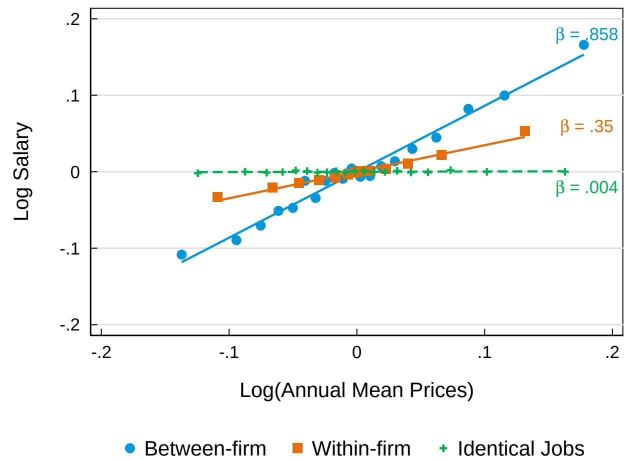
where $\log w_{ijot}$ is the posted wage in occupation o in firm i in county j in year t. Price level$_{jt}$ represents a local price index for the county, sourced from the Bureau of Economic Analysis.[22] θ_t are year fixed effects, which control for differences in posted wages over time. Including job-by-firm fixed effects (θ_{oi}) means we estimate the correlation between nominal wages and prices within the firm. To account for measurement error in the local price indices, we instrument the local price index with county-level home price indices from Zillow.[23]

[21] One possible explanation for these patterns is that low-wage occupations are bound by the minimum wage. This would induce compression in wages both within and across firms, making the relative within-firm compression less stark. However, we find similar cross-occupation patterns even when we exclude all pairs where one of the observations is at the binding minimum wage for that state (i.e. the maximum of the state minimum wage and the federal minimum wage) or when looking only at within-firm differences across the wage distribution, suggesting that the minimum wage is not driving these patterns.

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

[23] In Appendix Table A5, we show similar results using Zillow home price indices directly or using measures of average local nominal incomes. In this table, we also report the non-instrumented version of the regressions in Figure 3.

Figure 3: Sensitivity of Nominal Wages to Local Prices



Notes: This binned scatterplot shows the relationship between the local price index, instrumented by county-level home prices, and the log wage. The blue line and circles correspond to Equation 7 and the orange line and squares correspond to Equation 6. The dashed green line and crosses correspond to Equation 6 but we run this regression restricting to national firms. National firms are those firms for which 50% of their jobs are national (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. See Appendix Figure A5 for a version including jobs that post salary ranges.

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

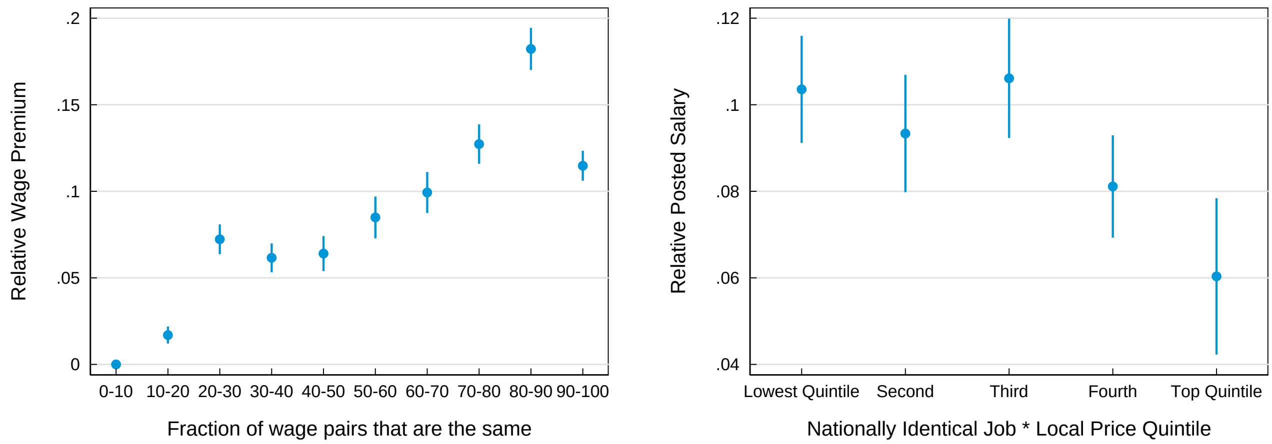
$$\log w_{ijot} = \gamma \overline{\text{price level}}_{it} + \theta_o + \theta_t + \epsilon_{ijot} \tag{7}$$

where $\overline{\text{price level}}_{it}$ is the average value of local prices for all counties in which the firm operates.[24] The between firm variation is by construction not affected by wage setting within firms across establishments.

Figure 3 plots binned scatter plots, with orange squares corresponding to the within firm and occupation regression (6) and blue circles corresponding to the between firm regression (7). The within-firm coefficient is low, both in absolute terms and when compared to the between-firm coefficient. The slope of the orange line, representing β, is positive, implying that within the firm, nominal wages are higher in counties with higher prices. However, the coefficient is less than 0.4—within the firm, a job in a county with 1% higher prices tends to pay a nominal wage that is only .35% higher. By contrast, the estimate of

[24] Using the average price level in the firm instead of the price level in location j purges the within-firm variation and isolates the between-firm relationship.

Figure 4: Relative Wages of National Wage Setters



Notes: 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 the an indicator for the price quintile of the county. The regression also includes a quadratic in establishment size, a quadratic in firm 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.

γ is closer to 1: a 1% higher price level is associated with .86% higher nominal wages.[25,26]

The within-firm slope is flat because firms compress their wages across locations. However, firms compressing or setting identical wages might only operate in areas with similar labor market conditions. To test for this possibility, the dashed green line in Figure 3 shows equation (6) estimated on the sample of identical wage setting firms. The slope is close to zero by construction. However, the range of prices that identical wage setting firms face is similar to the range of prices faced by other firms, suggesting that firms compressing wages across space do not sort into areas with similar prices.

Fact 4: Firms setting identical wages pay a wage premium.

The left panel of Figure 4 plots the estimated wage premium for jobs by the extent of wage uniformity within the firm. Specifically, these are the coefficients from a regression of log posted wages on occu-

[25] If we estimate the between-firm regression (Equation 7) using only the subset of observations included in the within-firm regression (Equation 6), the between-firm slope falls slightly to .7.

[26] Appendix Figure A6 shows these specifications for various subsets of the data—tradable and non-tradable industries and occupations, and high and low wage occupations—and demonstrates that the pattern is widespread. Appendix Figure A5 shows that the results are nearly identical when re-weighting 6-digit occupations to match the OES distribution.

pation by year by county by industry fixed effects and dummies for the fraction of the establishments in that occupation within the firm that have the same wage. The fixed effects included in the regression control for differences in wages that stem from the different distribution of nationally identical jobs across labor markets. Additionally, since large firms tend to pay higher wages on average, we also include in the regression a quadratic in establishment size and a quadratic in firm size, both measured by vacancies. We see that the relative wage is increasing with the fraction of wages within the firm that are identical, and that jobs for which 80-90% of the wages are identical pay almost 20% more on average than similar jobs in firms where fewer than 10% of establishments have identical wages. Appendix Table A6 summarizes these patterns with regressions, showing in that those jobs in firms where at least 80% of the jobs have identical wages pay 12% more than other comparable jobs within their markets. Table A6 also shows 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.[27]

The right panel of Figure 4 explores the relative wage by the price level of the area for identical wage setters. Unsurprisingly, the wage premium is decreasing in the price level of the area, but interestingly, the wage premium is positive everywhere—firms with identical wages are paying a wage premium even in the highest cost of living areas. We find no evidence that firms accompany this posted wage premium with higher requirements for education and experience. Specifically, Appendix Figure A7 shows the same specification as in the right panel of Figure 4, but using education and experience requirements instead of the posted salary. We find that there is no slope with respect to the local price index.

One possible reason for this pay premium is that firms with nationally identical wages 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 nationally uniform wages have higher output per worker and more R&D spending per worker (See Appendix Table A7).

4.1 Discussion of Descriptive Facts

In this section, we discuss the interpretation of our finding that firms compress wages across space.

[27]While the sample in the LCA data is too small to entirely replicate that analysis, in Appendix Figure A8, we show the relationship between the difference between the paid wage and the prevailing wage (i.e. the firm's reported wage less the firm's own reported prevailing wage) against the local price of the area. We also see that the wage premium is declining in the local price of the area and that workers in the lowest cost areas are seeing the largest wage premium.

Posted Wages vs. Realized Wages: One key feature of the job vacancy data is that we have information on the posted, rather than the realized, wage. However, based on several pieces of additional evidence, we do not believe that our results are driven by our use of posted wages. First, we find a similar, if not higher, share of firms that do not vary nominal pay across space in our survey data (Figure 2). Our estimates of identical wage setting are also strikingly similar to what large compensation consulting companies have found in their surveys. For example, Empsight, a salary survey company that works with Fortune 500 firms, found in their 2018 survey that 30% of firms do not adopt geographically differentiated compensation policies (Empsight International LLC (2018)).

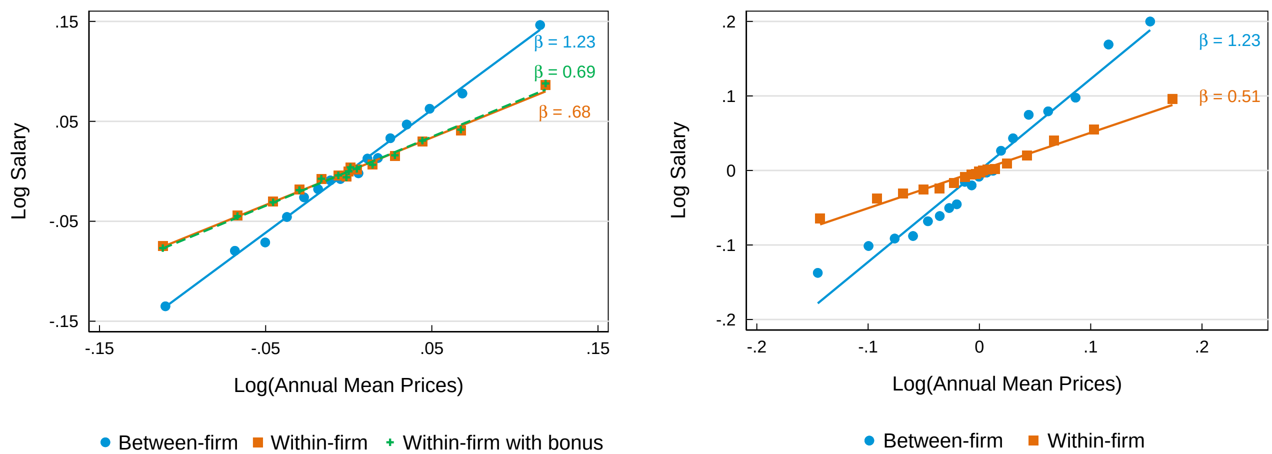
Second, we do not find evidence that selection into posting wages is likely to upward bias our results. While posted point wages are less likely in higher-wage occupations, we do not find that firms vary the likelihood of posting wages on their vacancies across areas—specifically, for a given job, they are not meaningfully less likely to post wages in areas with high prices, high house prices, or in "superstar" cities like New York or San Francisco (See Table A1). We also explored in our survey the extent to which firms setting nationally identical wages may be more likely to post wages on their vacancies than other firms. As in the Burning Glass data, 10% of survey respondents state that they work for a firm that posts wages. However, we find that if anything, firms with nationally identical wages are *less* likely to post wages on their job ads (See Appendix Figure A9).

Third, we use two additional data sources—Payscale and work visa application data—to confirm the findings using different wage measures. Specifically, we use the Payscale data to show that the wage compression that we document in the Burning Glass data is not undone by bonuses and bargaining during the hiring process. Specifically, we follow the analysis in Section 4 and estimate Equation (6) and (7) using base pay reported in Payscale. For this analysis, we define a unique job as the combination of pay frequency (salaried or hourly), occupation, education, and worker age.[28] The left panel of Figure 5 visualizes the results. We see in the blue circles that between firms, there is a strong positive relationship between earnings and prices. However, within firms, that slope is substantially attenuated and is around half of the between-firm slope, roughly the same pattern as for posted wages in Figure 3. Moreover, the green line shows the estimated relationship when we include reported bonuses in annual compensation.

[28] We include worker age in order to crudely account for differences in worker experience at the firm (e.g. differences in pay between an assistant professor and a tenured professor) and we include education to control for well-known differences in pay for similar jobs with different terminal degrees.

Figure 5: Nominal Wages and Local Prices Using Alternate Wage Measures

(a) Payscale Database (b) LCA Data



Notes: Data in the left panel is from Payscale and the unit of observation is the individual. The blue circles show a binscatter with 20 bins for Equation 7. The orange squares show the binscatter with 20 bins for Equation 6. The green circles include reported bonuses in total compensation. In each regression, we instrumented local price indices with county-level home prices. We define a job as the combination of pay frequency, salary type, age, and education level. Each regression includes year fixed effects. All three regressions are restricted to include the same sample of 109,021 observations. See Table A8 for additional details. Data in the right panel 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).

The within-firm slope is nearly indistinguishable, suggesting that bonuses do not moderate the wage compression that we observe in the Burning Glass data.[29]

As a second source of validation, we repeat the exercise within the H1-B visa applications data. The right panel of Figure 5 again shows the estimates for Equation (6) and (7). As in the other data sources, we find that that the between-firm slope is twice as large as the within-firm slope.

Location-specific Firm Amenities: While Figure 5 showed that bonuses do not offset these differences, it is possible that firms pay a similar nominal wages across space but compensate workers in high cost of living areas by offering them other location-specific amenities. We investigate this possibility using the Payscale data, where survey respondents are asked whether they are satisfied working for their current

[29] Appendix Table A8 reports the regressions underlying Figure 5 and presents additional results. We find that the within-firm slope is around half of the between-firm slope when using OLS (i.e not instrumenting local price indices with house house prices) and when restricting to either just hourly or just salaried workers.

employer.[30] Specifically, we relate worker satisfaction to local prices, as in our third descriptive fact, to test whether workers are equally satisfied across locations, and whether this relationship differs between and within firm. We find that within a firm, workers in high price areas are less satisfied than workers in low price areas, but there is no statistically significant relationship when looking between firms (See Appendix Table A9). These results loosely suggest that firms are not providing amenities in high price regions that offset the differences in real wages coming from national wage setting.

Worker Composition Across Locations: While we find that nominal wages vary little across space within a job, firms' marginal cost of labor could still vary within a firm across locations because of worker composition. For instance, suppose an accounting firm pays identical wages in Cleveland and New York. That firm might attract higher quality accountants in Cleveland, which would lower its marginal costs despite fixed nominal wages. Though this possibility is difficult to measure directly, two pieces of evidence suggest worker composition does not play a large offsetting role. First, we use the information within the job posting on education and experience requirements to see whether firms are explicitly recruiting workers with higher education or more experience in high-cost areas. We see no evidence that this is the case (See Figure A7).

Second, 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 the patterns in Appendix Figure A10 show that even when the prevailing wages are very different, firms report that they would pay that worker the same nominal wage across locations (we describe the construction of this figure in Appendix Section A2.3).

Incumbent Workers: While most of our analysis focuses on posted wages, we find similar patterns for within-firm wage compression for incumbent workers. Specifically, within the the Payscale database, we show patterns very similar to those in Figure 5 when restricting to only those workers who have been with their current employers for at least 4 years. As such, there do not seem to be meaningful differences in wage tenure profiles for the same job across space.

[30]Respondents are not required to answer this questions, leaving us with a relatively small sample size. There could also be selection into answering the question, so these results should be interpreted with caution.

Relabelling Job Titles: 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 analysis to account in part for this margin of adjustment. However, we also present two pieces of evidence that demonstrate that this margin is not quantitatively meaningful. First, Appendix Figure A11 explores the robustness of the patterns in Figure 3 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 A12, we explicitly test for this by estimating Equation (6) 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.

5 Evidence for National Wage Setting

So far we have documented wage compression within firms across space. This compression concentrates in a subset of jobs that pay identical wages across all locations. In this section, we argue that this subset of jobs have national wages—firms choose to pay the same wage everywhere, even if conditions are different. We provide two pieces of evidence for this. First, we compare wage growth across different locations of the same job. Jobs that initially pay identical wages across locations tend to subsequently have strongly correlated wage growth, whereas jobs that initially pay different wages across locations tend to have weakly correlated wage growth. Second, shocks to wages in a single establishment increase wages throughout the firm for jobs that initially set identical wages, but not for other jobs.

5.1 Co-movement of Wages Across Locations

To start, consider the predictions of national wage setting for the co-movement of wages within a job across locations. Jobs that initially pay identical 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 using the paired, within-firm and across-location job data from Section 4. We estimate the regression

$$\Delta \log w_{oijt} = \beta_1(\Delta \log w_{oij't} \times \text{Equal}_{oij,t-1}) + \beta_2(\Delta \log w_{oij't} \times \text{Diff}_{oij,t-1}) + \beta_3 \text{Equal}_{oij,t-1} + \theta_o + \theta_t + \varepsilon_{oijt} \quad (8)$$

where the outcome, $\Delta \log w_{oijt}$, is the growth in the wage that firm i pays for occupation o in county j.[31] We relate this wage to the growth in the wage at that firm for the same occupation in another county, j'. $\text{Equal}_{oij,t-1}$ is an indicator that the occupation had identical wages in $t-1$ and $\text{Diff}_{oij,t-1}$ is an indicator that the occupation did not have identical wages. We also control for occupation (θ_o) and year (θ_t) fixed effects. We are interested in the estimates of β_1 and β_2 which capture to comovement of wages within the firms for different types of jobs.

Estimates of equation (8) are reported Table 1. In the baseline estimates in the first column, we find a strong co-movement of wages for jobs with initially identical wages: a 1% increase in the wage growth in one establishment predicts 0.64% higher growth for the other establishment. The elasticity is much weaker, at only 0.16, for jobs that do not have initially identical wages.[32] These patterns are consistent with our hypothesis that jobs which initially pay identical wages are setting wages nationally.[33]

However, there is an identification concern—shocks to wages that are correlated across establishments could also explain these patterns.[34] To reproduce the patterns, these shocks must be particularly correlated in jobs which initially pay identical wages. We partially weigh against this alternative by es-

[31] To improve precision, we treat differences as follows. First, we take the mean wage across observations in consecutive years (for instance, taking the mean across observations in 2010 and 2011, or in 2012 and 2013), so that t refers to consecutive two-year intervals. Then, we take differences across four year intervals. See Appendix Table A10, column 1, for similar specifications without this averaging.

[32] We find further evidence that a change in one establishment at a firm affects wages in other establishments in our survey. We asked respondents at firms setting identical wages for some or all of their jobs whether their firm would change its wages in response to a shock that forced the firm to change its wages in a single establishment. The responses are summarized in Appendix Figure A13. Half of respondents state that a wage change in one establishment would impact the wages that they pay in other establishments (combining the first two bars).

[33] In Appendix Table A10, we show that there is no evidence that firms respond by altering the number of jobs they post. Specifically, we find that when wages grow in the establishment in county j', there is no change in the probability of posting a job with a wage in county j or in the number of vacancies posted within a year. This alleviates a concern the estimates in Table 1 are biased by firms either not posting or not post vacancies with wages in response to wage growth elsewhere in the firm.

[34] In the simple model of Section 2, wages will comove across different establishments of the same firm if shocks to nominal marginal revenue product are correlated across these establishments.

Table 1: Co-movement of Wages within a Firm Across Counties

	Baseline (1)	County Pair (2)	Excluding Tradable Industries (3)	Nontradable Occupations (4)	OES Occupation Weights (5)
$\Delta \log w_{oij't} \times \text{Equal}_{oij,t-1}$	0.634	0.628	0.626	0.625	0.556
	(0.071)	(0.058)	(0.079)	(0.083)	(0.115)
$\Delta \log w_{oij't} \times \text{Diff}_{oij,t-1}$	0.155	0.173	0.151	0.152	0.063
	(0.038)	(0.029)	(0.043)	(0.039)	(0.026)
Observations	6,506,438	4,583,928	4,317,084	5,753,522	6,506,438
Fixed Effects:					
Occupation	✓	✓	✓	✓	✓
Year	✓		✓	✓	✓
County Pair x Year		✓			

Notes: This table shows estimates of Equation (8). An observation is a job pair within the same firm but in two different counties. Standard errors are clustered at the county j' and firm level. Column 3 excludes tradable industries, which are defined following tradable occupation as one that can be done remotely following Mian and Sufi (2014a). Specifically, industries that engage in global trade are classified as tradable. Column 4 excludes tradable occupations, which we define as those that can be done remotely, following Dingel and Neiman (2020). In column 5, we weight observations so that the sample matches the 6-digit occupation distribution in the OES.

timating variants of regression equation (8) in subsequent columns of Table 1. We show in Column 2 that results are similar in a regression with county-pair by year fixed effects, which identifies β_1 and β_2 using cross-occupation and cross-firm variation within county pairs. These fixed effects absorb common shocks across the counties in which the job locates. In Columns 3 and 4, we restrict to non-tradable industries or occupations. Firms selling tradable goods may initially pay identical wages across space, and product demand shocks will be the same for all establishments in the firm.[35] However, the results remain similar even excluding these firms or jobs. Finally, column 5 shows estimates re-weighting occupations to match the 6-digit occupation distribution in the OES. The results are again very similar.

5.2 Pass Through of Local Shocks

In this subsection, we instrument for wages using local shocks to show a causal relationship between wages across establishments. We instrument for $\Delta \log w_{oij't}$ in Equation (8) with a shock to wages in county j'. The shock we use comes from national booms and busts in demand for natural resources employment demand, driven in large part by a boom and bust in global oil prices between 2010 and

[35]In our simple model, these firms have identical nominal marginal revenue product in different locations.

2019 (see Hazell and Taska (2022) for a discussion). This shock is appealing because natural resource employment is highly localized and therefore likely to directly affect only some establishments within the firm (See Appendix Figure A14 for a map). Specifically, we construct a shift-share instrument that measures a county's exposure to natural resource shocks as:

$$\text{Shock}_{j,t} = 100 \times \frac{\text{Natural resources employment}_{j,2009}}{\text{Total employment}_{j,2009}} \times \log(\text{Natural resources employment}_{-j,t}) \quad (9)$$

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).

For the instrument to be valid in equation (8), the natural resource shock should raise establishment wages in exposed county j', but not affect wages in the paired establishment j of the firm through other channels. We take three 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. Second, to avoid geographic spillovers, we only study establishments j located more than 100 miles from the exposed establishment j'. Third, we add to equation (8) job by county by year fixed effects (γ_{ojt}) to account for market-level effects of the natural resources shock, such as migration across regions or market level supply shocks.

This regression raises the challenge of selecting "clean controls", emphasized by Cengiz et al. (2019), Borusyak et al. (2022), and the literature estimating two way fixed effects regressions. By adding the fixed effects γ_{ojt}, 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 j that are not exposed to natural resources shocks in their paired establishment j'. However, an establishment in the control group of this regression might still be exposed to natural resource shocks, via a third establishment j'' in the same firm, located in an exposed area. If so, then the control establishments have been treated, which biases our estimates. Therefore we refine our regression to select a "clean" control group.[36] Specifically, we define unexposed observations as those

[36]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 2: Pass Through of Natural Resources Shock to Wages in other Establishments

	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	2406079	448045	1958034	2569225	458228	2110997	2406079	448045	1958034
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), and establishment pairs that are located within 100 miles of one another. 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, an 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. All regressions include unexposed county $\times$ year $\times$ occupation fixed effects, calculated using unexposed observations (described in detail in Appendix A2.4). The Kleibergen-Paap F-statistic associated with columns 7 through 9 are listed below the regressions.

for which the maximum absolute value of the natural resources shock is below the 25th percentile, taking the maximum across all establishments and years within the firm. Unexposed observations form the control group. As such, all variables in Equation 8 are demeaned using unexposed observations.[37]

Column 1 of Table 2 shows the first stage result from regressing the natural resources shock in the second establishment on the wage in that establishment. A 1% increase in exposure leads to a 1.25% increase in posted wages. Columns 2 and 3 show that the wages in exposed counties respond similarly to a shock regardless of whether wages are set identically in the initial period. Pairs with identically-set wages respond somewhat less, which is expected if national wage-setters have more rigid pay policies and are less able to respond to local shocks. Columns 4-6 show reduced form estimates consistent with national wage setting. On average, there is no significant impact of a natural resources shock on wages in unexposed counties (column 4). However this average effect masks an important heterogeneity, which columns 5 and 6 reveal. Jobs that initially set identical wages have a high pass through of the local shock into other establishments (column 5). Jobs that initially set different wages do not show any significant

[37]We have verified that our results are insensitive to varying the thresholds for defining exposed firms (See Appendix Table A11). More details on this method as well as an example are provided in Appendix A2.4.

pass-through (column 6). We see the same pass-through of wages in the IV estimates (columns 7-9): an increase in the wages in an establishment in an exposed county passes through to wages in unexposed establishments, if and only if the job sets wages identically in the initial period. The magnitude of the coefficient on wage growth in column 8 implies that when establishments initially setting identical wages raise wages by 1% in one location, they raise wages by an average of 0.83% in the second. In Appendix Table A11, we show that the results are robust to clustering by county and year (columns 1-2), restricting to cases where the exposed establishment is larger than the unexposed establishment (columns 3-4), changing the exposure thresholds (columns 5-6), and that the results are not driven by tradable occupations or firms operating in tradable industries (columns 7-10).

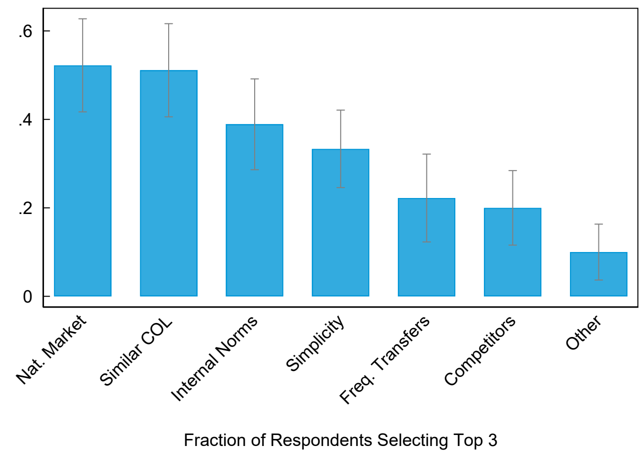
Our pass through results tentatively suggest that jobs setting identical wages across establishments are national wage setters—for these jobs, shocks to a single establishment raise wages everywhere, whereas jobs setting different wages do not pass the shock through. However, we note two caveats. First, our empirical results are narrow in scope because we focus on a particular shock affecting only a subset of firms, who 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 jobs that pay identical wages.

6 Reasons for National Wage Setting

We now turn to understanding why some firms practice national wage setting while others set wages flexibly across space. 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 the free-form answers into seven reasons. In the full survey, we asked respondents whose firms do not vary the nominal wages of at least some jobs to rank those reasons in order of importance. Figure 6 shows the fraction of HR managers that report each reason as one of the top three. While there was support for many different explanations, several patterns emerge.

One pattern that emerges is that many firms set national wages to simplify management. Around 35% of respondents report that they set national wages in part because it is administratively costly to

Figure 6: Reasons firms do not vary nominal wages across space—survey evidence



Notes: Sample is restricted to the set of respondents working at firms that set identical pay for some or all of their jobs. The blue bars represent firms that set national pay for the majority of their jobs. The orange bars represent firms that set national pay for roughly half of their jobs. *Nat. Market* means that the firm hires on a national market. *Internal Norms* is the selection "We want workers performing the same job to be paid the same wage." *Similar 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." *Frequent 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.

tailor the wage to each location. This finding echoes earlier results from DellaVigna and Gentzkow (2019) that suggest that firms set uniform prices across space to simplify management. This policy only benefits the firm, on net, when the costs of setting identical 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. In areas with similar cost of living, optimal wages are similar, in which case the benefits of a more sophisticated pay structure that depends on location will be small. These findings are echoed in the job vacancy data, where we find that firms operating in cities with similar economic conditions tend to have more national wage setting, although geographic variation explains only a small amount of the variation in the data (See Figure A3).[38]

A second pattern is that some firms set identical nominal wages across space in order to adhere to fairness norms. Almost 40% of survey respondents cited internal norms as a reason for national wage setting. Importantly, these internal norms seem to matter for *nominal* and not real wages across establish-

[38]Of course, 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, the firm may decide not to open up establishments in high cost of living areas. However, we found limited evidence in our survey that national wage setting affects where firms locate (see Appendix Figure A15).

ments. We found anecdotal support for this view from industry professionals. A human resources executive at a nationally wage setting firm told us that that paying workers within the same job lower wages outside the headquarters would "*penalize*" these workers, making them feel like "*second class citizens*" and harming the "*pay culture*" of the firm. Fairness concerns were more important for the relatively high wage workers that this executive termed "*culture carriers*".[39] These workers reportedly communicate with or work in multiple locations of the firm, they are more likely to know pay in other locations, and would be demotivated by differences in pay. According to this executive, fairness concerns across locations mattered less for lower wage workers.

Third, we find more national wage setting in occupations with more mobile workers. In the survey, the second most commonly cited reason for setting national wages is hiring on a national labor market—that is, firms set national wages when they employ workers who could move throughout the country for a job. Notably, hiring nationally mobile workers seems to cause firms to equalize nominal and not real wages across space. Indeed, the same 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. These concerns reportedly mattered less for less mobile occupations, who tended to be lower wage.[40]

Three points about these results stand out. First, national wage setting is caused by a mix of firm and occupation characteristics. Some factors leading to national wage setting, such as managerial simplicity, may depend on firm characteristics. Firms that have invested in the infrastructure to set wages locally for some occupations (e.g. subscribing to data from compensation consulting firms) can presumably set wages locally for other occupations with little additional difficulty. Other factors leading to national wage setting, such as worker mobility, depend on occupation characteristics, and explain why firms might choose to set national wages for certain types of jobs. Factors such as fairness norms could depend on both firm and occupation characteristics. Fairness norms seem to depend in part on pay culture, a firm specific characteristic that applies across across many occupations, but these norms also seem to matter more in higher wage occupations, where there is more communication across locations.

Second, the results suggest that nominal pay comparisons, including comparisons across space, mat-

[39] Quotations are from a personal Zoom interview with the authors, 26th January 2021.

[40] 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 A16).

ter to workers. This result might be surprising—after all, comparisons of real wages across space might be more relevant to workers' welfare. Nevertheless, according to the survey, fairness norms and workers' location choices do relate to nominal wages.

Third, some factors that could potentially lead to national wage setting are notable by their absence from both the pilot and the free-form answer. Specifically, respondents did not mention government policies, such as minimum wages, as a source of national wage setting. Instead, the reasons for national wage setting seem to relate to higher wage workers, who are unaffected by the minimum wage.[41]

7 Measuring the Effect of National Wage Setting on Profits and Wages

Having demonstrated the prevalence of national wage setting, we return to our simple model from Section 2 to benchmark the effect that national wage setting has on profits. In particular, we approximate how firms would have set wages in the absence of national wage setting and then, using our model, provide a back of the envelope estimate of the profits foregone by firms due to national wage setting. It is possible that setting wages nationally increases worker productivity and maximizes profits—recall from Section 4 that 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, perhaps used in combination with other productivity enhancing management practices (Bloom and Van Reenen, 2010).

We assume that jobs paying identical wages everywhere, as measured in Section 4, are setting wages nationally. We start with simple estimates of what wage dispersion would have been for these jobs, if they had not chosen to set wages nationally. We calculate two benchmarks intended to be a lower and an upper bound for this counterfactual wage dispersion. First, for each location in which the nationally wage set job operates, we calculate the average wage in that location and occupation for other establishments in the same industry that are not doing national wage setting. This "between-firm" match captures the market-level average wage paid by similar establishments for exactly the same occupation. In our simple model, this benchmark is the counterfactual wage dispersion of national wage setters as long as the local elasticity of labor supply and the local component of productivity is the same for the

[41]One reason for national wage setting that respondents did not mention, but which may still be important, is that firms might want to constrain the discretion of local managers with regard to pay. In support of this reason, survey respondents are more likely to set wages nationally if pay and management is centralized (Appendix Table A12). Also, in the Burning Glass data, national wage setting is less likely for franchised firms, who have greater discretion by local managers (Appendix Section A2.2).

Table 3: Effect of National Wage Setting on Establishment Profits

	Between-Firm Benchmark			Within-Firm Benchmark		
	25th	Median	75th	25th	Median	75th
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Percent Difference in Wages					
	10	24	53	2.2	6.1	13
	Panel B: Percent Difference in Profits					
$\rho = 4$, CRS	9.9	45	227	.46	3.6	17
$\rho = 2$, CRS	3.1	16	73	.14	1.1	5.2
$\rho = 6$, CRS	20	75	744	.96	7.4	33
$\rho = 4$, DRS	6.8	32	133	.31	2.4	11
$\rho = 4$, Rationing	6.8	24	59	.31	2.4	10

Notes: The sample includes the set of firm and job cells that we have identified as identical wage setters, meaning that at least 80% of job pairs across locations are identical. We restrict the between-firm difference to be no more than 50%. In the calibration with decreasing returns to labor, the exponent on labor is 0.66.

various establishments. We consider this an upper bound, since, despite our matching procedure, there are likely unobserved factors that will contribute to between-firm differences in wages.

We construct an alternative benchmark wage difference using within-firm differences across locations for the set of jobs that do *not* set wages nationally. Specifically, for each location pair in which a national wage setter is hiring, we calculate the average percent difference in the wage across those two locations *within firms that are not setting wages nationally*, matching firms by location and occupation.[42] Through the lens of the simple model, this is the correct counterfactual if productivity differences across space are the same for these two firms (i.e. for firms i and k and locations j and j' we have $A_{ij}/A_{ij'} = A_{kj}/A_{kj'}$) and all firms within a market face the same labor supply elasticity. Here, we classify only firms setting identical wages across space as national wage setters. Since national wage setting may lead to some compression in wages within the firm even for those that do not set identical wages, this benchmark likely understates the true dispersion in wages that we would expect in the absence of national wage setting.

Panel A of Table 3 shows the results. The median absolute differences between the actual wage, and the wage suggested by the between-firm and within-firm benchmarks, are 24% and 6.1%, respectively. Even according to the more conservative within-firm benchmark, 25% of the national jobs set wages

[42]For example, if local wage setters 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 that operate across those two locations would similarly have wages 7% apart in the absence of the national wage setting constraint.

more than 13% different from the benchmark. This confirms that 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 profits affected by national wage setting.[43] This allows us to derive a simple formula for the reduction in profits from national wage setting. Specifically, for the version of our model with constant returns to scale in labor, we have

$$\frac{\Pi_{ij}^{*}-\overline{\Pi}_{ij}}{\Pi_{ij}^{*}}=1-(1+\rho)\left(\frac{\overline{W}_{i}}{W_{ij}^{*}}\right)^{\rho}+\rho\left(\frac{\overline{W}_{i}}{W_{ij}^{*}}\right)^{1+\rho} \tag{10}$$

where $\overline{W}_i$ and $\overline{\Pi}_i$ are the actual wages and profits of national wage setters, whereas W_{ij}^{*} and Π_{ij}^{*} are the wages and profits in the counterfactual. We derive this expression, as well as a version with decreasing returns to scale in labor, in Appendix Section C1.4. Under the assumption that the two empirical benchmarks described above provide an estimate for W_{ij}^{*}, we can calculate the profit loss from national wage setting for given a value of ρ, without measuring other objects such as local productivity.[44]

Panel B of Table 3 presents the estimated change in profits from national wage setting. The numbers reported in this table are the average percent increase in profits that a national job would receive from setting wages locally, holding constant other factors. The baseline estimate in Row 1 assumes constant returns to scale in production (CRS) 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). Rows 2 and 3 maintain constant returns to scale but consider a labor elasticity of 2 and 6, respectively. Row 5 assumes decreasing returns to scale (DRS) with an exponent on labor of 0.66. Row 6 allows for rationing as well as decreasing returns to scale. Specifically, we modify the model to allow establishments to employ the number of workers implied by their labor demand curves whenever labor supply exceeds labor demand at the nationally set wage.[45] While these simple calculations abstract from porentially important productivity or general equilibrium effects due to national wage setting, the baseline within-firm counterfactual estimate implies that the median job is 3.6% less profitable than it would be with flexible wage setting.

[43]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.

[44]We do not model other inputs such as capital directly. However, in Appendix Section C1.4, we show that a model with fully variable capital is isomorphic to our model with constant returns to scale in production, while a model with fixed capital is isomorphic to our model with decreasing returns to scale.

[45]We show how to calculate profit losses in this case in Appendix Section C1.4.

8 Consequences of National Wage Setting

We end by considering some broader consequences of national wage setting. Comprehensively examining these consequences is beyond the scope of the paper. Instead, we briefly touch on three key areas: aggregate wage inequality, the distribution of employment across space, and nominal wage rigidity.

Aggregate Wage Inequality: Since national wage setting compresses the distribution of nominal wages across space, it likely dampens aggregate wage inequality. We gauge the size of this effect using a back of the envelope exercise. We start with a simple variance decomposition. Our summary measure of aggregate nominal wage inequality—including variation both within and between regions—is the variance of log nominal wages $Var\left[w_{ioj}\right]$, where w_{ioj} is the log nominal wage paid in an establishment ij and occupation o. We can decompose nominal wage inequality into its within and between firm components:

$$Var\left[w_{ioj}\right] = Var\left[w_{ioj} - \bar{w}_{io}\right] + Var\left[\bar{w}_{io}\right] \tag{11}$$

where $\overline{w}_{io}$ is a mean of log wages within a firm and occupation across locations. The first component is the variance of wages within a firm and occupation but across regions; whereas the second component is the variance of wages between firms and occupations, which excludes regional variation.

National wage setting lowers aggregate nominal wage inequality by reducing the within firm component. Since national wage setters pay the same nominal wage across space, the contribution of national wage setters to nominal wage inequality within firms is zero. As in section 7, we explore a benchmark in which national wage setters vary pay similarly to local wage setters. Specifically, we set the variance of wages within firms for national wage setter to be equal to the variance of wages within firms for local wage setters, holding the variance of wages between firms constant. Notably, this implies that the counterfactual does not change the wage premium for national wages that we documented in Section 4.

Table 4 reports the increase in aggregate wage inequality in this counterfactual, as well as the variance decomposition of wage inequality in the data. The results suggest national wage setting is important for aggregate wage inequality. Row 1 is our baseline estimate. Column 1 reports the share of total nominal wage inequality explained by the within-firm, within-occupation component, which is 8%. Column 2 reports the growth in nominal wage inequality in the counterfactual, which is 4.3%. In rows 2-4 of Table

Table 4: Effect of National Wage Setting on Wage Inequality

	Estimated % Share of Wage Inequality Within Firms	Counterfactual % Increase in Wage Inequality
Nominal wages	8.0	4.3
Nominal wages, unweighted	9.8	5.3
Nominal wages, trimmed	8.0	4.3
Nominal wages, ≥5 observations per firm	8.5	4.6

Notes: The sample is defined as in Figure 3. We study the mean wage at the establishment by pay frequency by salary type by occupation level. In rows 1-4, the share of the variance of nominal wages explained by the between firm by occupation component is the R^2 from a regression of nominal wages on firm by occupation by pay frequency by salary type fixed effects, weighted by vacancies. The remaining variance in wages is the within variation of local wage setters, V_{within}. The growth in wage inequality in the counterfactual is $N/(1-N) \times V_{\text{within}}$, where N is the share of national wage setters, set to 0.35 in all counterfactuals.

4, we estimate counterfactual increases in a range of 4-5%, from unweighted specifications, specifications that trim wages, and specifications that drop firms with fewer than 5 establishments.[46]

While we are conservative in assuming that only firms setting identical wages across space are compressing wages due to national wage setting, we caution that this back of the envelope exercise is illustrative and ignores several important issues. For instance, we do not study real wages, though nominal and real wages across space display different patterns (Moretti, 2013; Diamond, 2016; Card et al., 2021; Diamond and Moretti, 2021). We believe that measurement error in the Bureau of Economic Analysis' measure of local prices precludes a similar exercise here that studies the variance of real wages. Moreover our counterfactual ignores general equilibrium responses to national wage setting.

Geographic Distribution of Employment: National wage setting should have consequences for the geographic distribution of employment as those firms do not vary wages even as labor supply changes across space. This section studies employment across space by merging Burning Glass with establishment-level employment from Dun and Bradstreet.[47] We then explore the within-firm relationship between establishment employment and local prices, separately for national and non-national wage setters.

[46]Reassuringly, our baseline estimates of the standard deviation of log nominal wages is 0.61 — similar to measures from other datasets (e.g. Figure 1 of Hoffmann et al. (2020) finds a standard deviation of log annual earnings for full time workers equal to 0.65 over 2010-2019, using the Current Population Survey).

[47]Hazell and Taska (2022) describes and studies the same merged dataset, and validates the Dun and Bradstreet information against official data sources.

The simple model in Section 2 predicts that national wage setters should be relatively large in low price areas. In our model, workers are on their labor supply curves. National wage setters pay relatively high wages in low price areas compared with local wage setters, leading to an increase in relative labor supply for national wage setters. However, modifying the model to let establishments ration labor, when supply exceeds demand at the nationally set wage, may predict the opposite. If so, then employment is determined by labor demand and not labor supply. National wage setters may be relatively small in low price areas under rationing, because higher wages reduce labor demand.[48]

Our estimates find that, compared with local wage setters, national wage setters are relatively large in low price areas, consistent with the model of labor supply of Section 2. Appendix Figure A17 displays the result. We find that both national and local wage setters have a positive relationship between wages and employment, meaning that establishments are bigger in higher-prices areas. However, the slope is more shallow for the national wage setter—inconsistent with rationing according to labor demand.

While national wage setters might adjust employment in each establishment on the intensive margin, these firms do not seem to enter different areas. In particular, we showed in Figure 3 that national jobs are in similar locations to other jobs, suggesting that the extensive margin of establishment entry does not differ for national firms. This result might seem puzzling, since a fixed national wage might be particularly costly in very high or low wage areas. In Appendix Section C1.5, we resolve this puzzle in a version of our model that endogenizes establishment entry. In the model extension, national wage setting can increase productivity. If the productivity gap is sufficiently large, national wage setters choose to enter all regions since competition from local wage setters is weak. Consistent with this possibility, we showed in Section 4 that national wage setters pay higher wages and have higher sales per worker than other firms.

Our finding that national wage setters are relatively large in low price areas has several tentative implications. First, all else equal, national wage setting redistributes employment towards low price areas—according to our model, the effect comes from tilting labor supply towards these areas. Second, the employment response should amplify the effects of national wage setting on earnings, relative to wage, inequality.

[48]Intuitively, for a given establishment of a national wage setter, there is a "self imposed minimum wage". In canonical models, raising minimum wages has ambiguous effects. If the minimum wage is initially high, an increase will lower employment due to labor demand rationing. If it is initially low, an increase raises employment via labor supply (Berger et al., 2022b).

Wage Rigidity: Lastly, we find that national wage setting policies increase nominal wage rigidity at the local level. This finding is expected: firms setting wages nationally do not vary wages in response to regional shocks. Indeed, Appendix Table A13 shows that firms are about 40% less likely to change wages over time for those jobs that are nationally identical. This is true after controlling for the occupation, the industry and even when looking within the firm across occupations. Moreover, national wage setters are about half as likely to change wages in response to regional shocks to wages, compared with other jobs.[49] By raising regional wage rigidity, national wage setting should amplify the effect of local shocks on employment through standard channels (Hall, 2005). As such, national wage setting should have raised the impact of regional shocks such as the 2007-2009 housing crisis (Mian and Sufi, 2014b), and may increase local fiscal multipliers (Nakamura and Steinsson, 2014).

9 Conclusion

This paper demonstrates the prevalence of national wage setting. We first demonstrated, descriptively, that there is substantial wage compression within the firm across locations. The most extreme illustration of this is the finding that a significant minority of firms often set exactly the same nominal wage for the same job in different locations. We find that this leads to a substantial dampening of the relationship between wages and prices within the firm. Using the co-movement of wages over time within the firm, we demonstrated that the bulk of this compression is the result of national wage setting, meaning that firms choose to pay the same nominal wage in all of the regions in which they operate. We found that firms adopt these national wage setting practices for several reasons, including that it simplifies management, it accords with firms sense of fairness, and it attracts mobile workers who make nominal, rather than real, wage comparisons across locations. Lastly, we briefly explored some consequences of national wage setting. At the establishment level, the profits at stake seem substantial. At the level of the broader economy, national wage setting may have important effects for wage inequality, nominal wage rigidity and the distribution of employment across space.

[49]This pattern potentially contrasts with findings in Butters et al. (2022), who find that national and local chains both adjust prices in response to local cost shocks.

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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 labelling 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 on to 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 precleaned 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 Additional Information on Payscale Data

The Payscale data contains data on individuals' self-reported salaries/wages, bonus and other non-salary benefits, other personal characteristics such as age and gender, and current firm/job title. Payscale harmonizes jobs across firms by mapping job titles to O*NET "Detailed Occupation" categories, which are roughly similar to SOC-6 codes.[50] Throughout our analysis, we use the O*NET Detailed Occupation codes.

[50] A crosswalk can be found at https://www.onetcenter.org/taxonomy/2019/soc.html

Appendix Figure A18 shows the industry and broad occupation representation in the data. Appendix Table A14 shows how well the data tracks the distribution of wages reported in the Occupation Employment Data (OES) at the occupation by MSA level. Overall, the data is less nationally representative than the Burning Glass data (Figure A18) but tracks OES wages moderately well, especially towards the top of the wage distribution.

Since our goal in the analysis is to uncover differences in wages across locations within the firm, we define the annual salary of hourly workers by multiplying the hourly rate by 2000 (50 weeks per year at 40 hours per week). For salaried workers, we use the reported base salary as our main measure of annual earnings.

In terms of bonuses, we find that within the database, 27% of the workers report bonuses, the average size of which is 2.5% of base earnings, very similar to the magnitudes found in Grigsby et al. (2021) using the ADP payroll data. Like in Grigsby et al. (2021), we find that bonuses are a larger part of compensation for workers at the top of the income distribution (See Appendix Figure A19).

A2 Additional Empirical Results

A2.1 Predictors of National Wage Setting

To complement the reasons for national wage setting reported in the survey in Section 6, we also analyze which occupation, county, and industry-level characteristics most strongly predict national wage setting using the Burning Glass data. We pay specific attention to variables that relate to the survey findings, such as a proxy for fairness norms or managerial simplicity.

We begin by exploring occupation-level predictors using a pairwise dyadic regressions. Specifically, we include all within and between firm pairs from Figure 1 and estimate:

$$\text{Same}_{i',jj'ot} = \beta \mathbb{1}_{i=i'} + \alpha \mathbb{1}_{i=i'} \times X_{o,t} + \omega X_{ot} + \gamma_{j,-j} + \gamma_i + \gamma_t + \epsilon_{ijot} \tag{12}$$

where $\text{Same}_{i',jj'ot}$ is an indicator for both wages in the pair of counties j and j' being identical ($w_{ijot} = w_{ij'ot}$). The indicator $\mathbb{1}_{i=i'}$ is a dummy variable capturing whether the observation is a within-firm pair, and $X_{o,t}$ are characteristics for the occupation (o) pair. The firm (γ_i), county-pair ($\gamma_{j,-j}$), and year (γ_t) fixed effects soak up other dimensions that differ across the pair. Given the stark patterns in Figure 1, we expect β to be large and positive—wages are more likely to be identical across locations within the firm than between firms. We are interested here in the estimate of α, which shows how this probability varies with characteristics of the occupation. A positive value for α indicates more within-firm wage compression in jobs with that characteristic.

We explore heterogeneity along geographic- or firm-level variables with regressions similar to Equation 12 but that have different variables in X and different fixed effects. Specifically, when looking at geographic variation in X, we replace $\gamma_{j,-j}$ with occupation fixed effects and when looking at firm-level variation in X, we replace firm fixed effects with occupation fixed effects. This combination of controls partials out other sources of variation across pairs and focuses on just the variation of interest.

The blue circles in Figure A3 show the estimates of α for several occupation-level variables, the orange squares that for several county-level variables, and the pink triangles for several firm-level variables. We see that national wage setting is more common in higher-wage occupations and those that are tradable, which we define as those that can be done remotely (Dingel and Neiman, 2020). We see that firms operating in cities with similar economic conditions and that are closer together physically tend to have more identical wages, although these variables explain a small amount of the variation in the data. We also see that national wages are more likely when the unemployment rate is higher. In terms of firm characteristics, the pink diamonds in Figure A3 show that firms with more vacancies and firms in tradable industries have less geographically compressed wages on average. Firms that are more geographically concentrated with a large HQ and dispersed and smaller branches are no more likely to set identical wages than those in less dispersed locations.

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 franchised or not-franchised. Appendix Table A15 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 Additional Results with LCA data

We found in the Burning Glass data that firms setting national wages were paying a wage premium that was largest in the lowest-cost areas (See Figure 4). While the sample in the LCA data is too small to entirely replicate that analysis, in Figure A8, we show the relationship between the difference between the paid wage and the prevailing wage (i.e. the firm's reported wage less the firm's own reported prevailing wage) against the local price of the area. Unsurprisingly, since firms are filling out the LCA to demonstrate that they are paying at least the prevailing wage, we see that the premium is positive everywhere. However, we also see that the wage premium is declining in the local price of the area and that workers in the lowest cost areas are seeing the largest wage premium.

Additionally, throughout the analysis using the LCA data, we utilized information on wages in the worker's primary worksite, which is defined as the physical location where the work will be performed. However, in some years, employers can report multiple possible worksites (up to 10) for workers along with the wage that they would pay in each worksite. Using within-worker variation for this sample, we can trace out the wage setting policy of the firm, understanding how the firm plans to vary the wage for exactly the same worker as they move locations within the firm. Specifically, we estimate:

$$w_{kij} = \beta_1 p_j + \gamma_k + \epsilon_{kij}$$

where w_{kij} is a measure of the wage for worker k in firm i in county j and γ_k is a worker fixed effect. β_1 captures the relationship between wages and prices across worksites for a given worker. We consider regressions where the dependent variable is either the reported prevailing wage or the reported actual wage. Figure A10 shows the results. The pink line shows the within-worker across-worksite slope of the prevailing wage. We see here that, even for the same worker, the data spans worksites with very different local price levels. Moreover, the slope of the prevailing wage with respect to the price is 0.80. This strongly contrasts with the reported wage for the workers across worksites, which is shown in the orange line, and is nearly zero—in this sample, firms report paying nearly identical wages for the same worker across multiple locations, even in places where they recognize that the prevailing wage is very different. This within-worker pattern is robust to restricting the sample to the subset of occupations that are less tradable (i.e. education or healthcare).

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 un-treated "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 A14 shows that there is a relatively small number of counties that are heavily exposed to natural resource shocks.

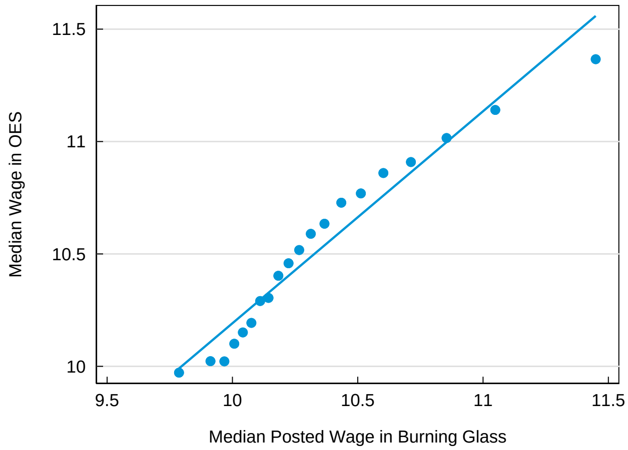
In our regression, the "treatment" group is firms that have one establishment in a county exposed to a natural resource shock and one establishment in a county with no exposure. For example, take an accounting firm with an establishment in Houston (exposed) and an establishment in Chicago (unexposed). 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 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

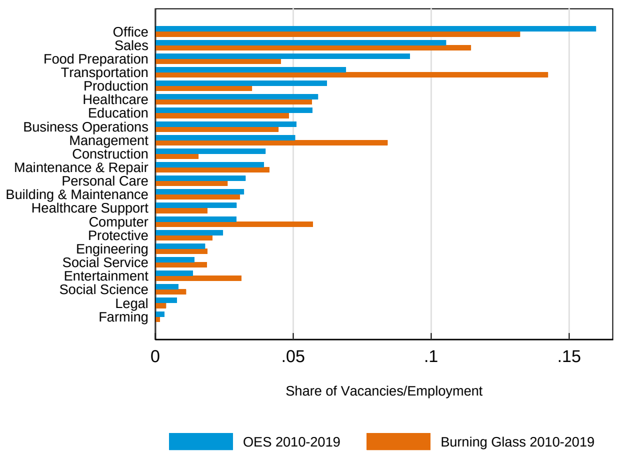
Figure A1: Distribution of Median Wages in Burning Glass and Occupational Employment Statistics



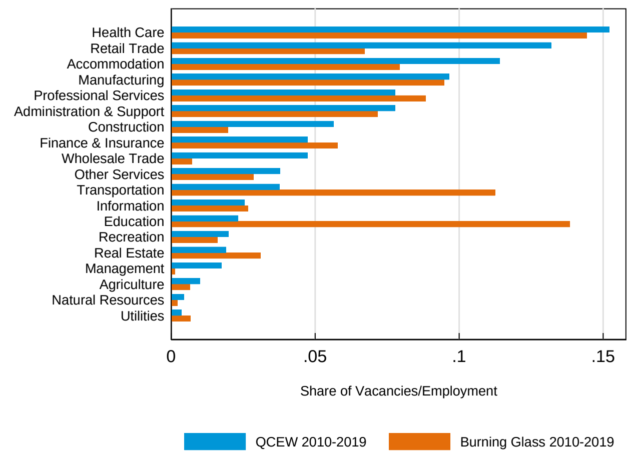
Notes: The OES wage on the y-axis is the log of the occupation by MSA median hourly wages from the Occupational Employment Statistics. The x-axis is the log median wages from Burning Glass for all jobs posting hourly basepay. In both cases, we study the wage averaged over 2010-2019. In both datasets, 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 A2, Column 2.

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

(a) Occupation

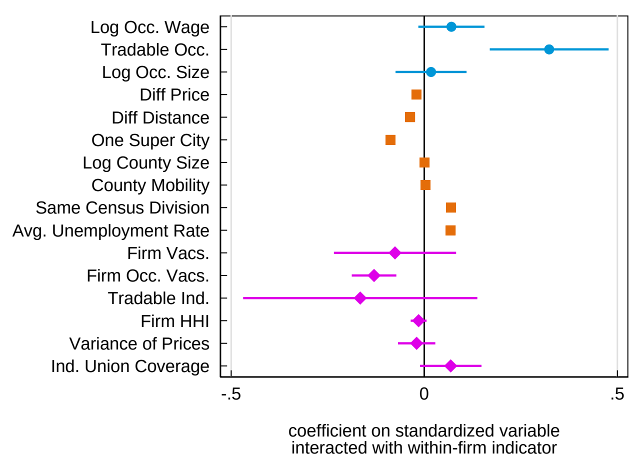


(b) Industry



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. Sample includes the set of vacancies including a posted point wage (See Table A4, row 5).

Figure A3: Predictors of National Wage Setting

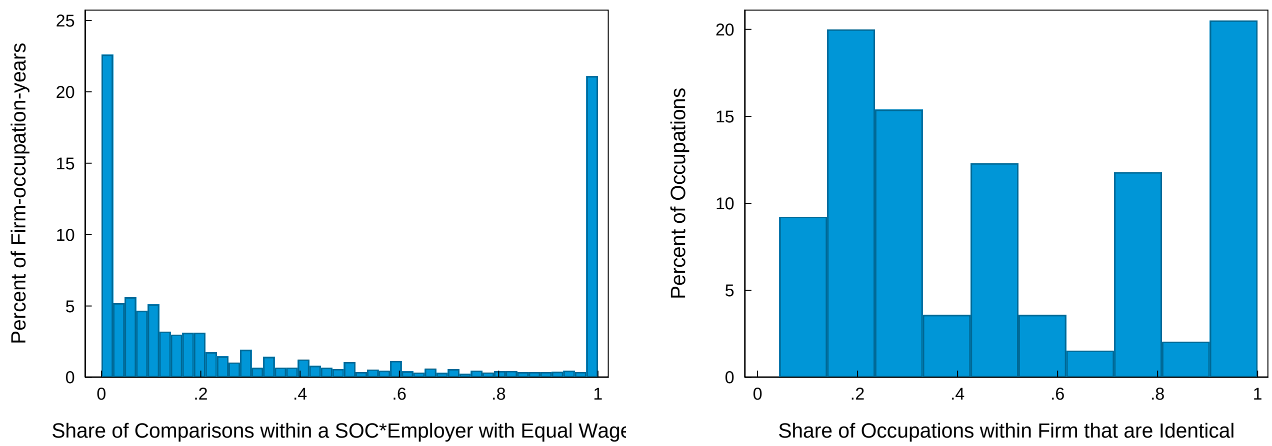


Notes: All coefficients are the interaction between the noted variable and an indicator for whether the pair is within the firm (i.e. α from Equation 12). The blue dots show occupation-level variables, the orange squares show geographic variables, and the purple diamonds show firm-level variables. The estimates shown with blue dots include fixed effects for the year and county of each establishment and the firm by year. The estimates shown with orange squares include fixed effects for the firm by year and the occupation by year. The estimates shown with pink diamonds include fixed effects for the year and county of each establishment and the occupation by year. All continuous variables are converted to z-scores so that the coefficients reflect a 1 standard deviation increase. Standard errors are clustered at the occupation-level for the blue dots, at the county-pair level for the orange squares and at the firm level for the pink diamonds. See Appendix Tables A16, A17, and A18 for the underlying regression details.

Figure A4: Prevalence of Identical Wages Within the Firm

(a) Within job, across locations

(b) Within firm, across occupations

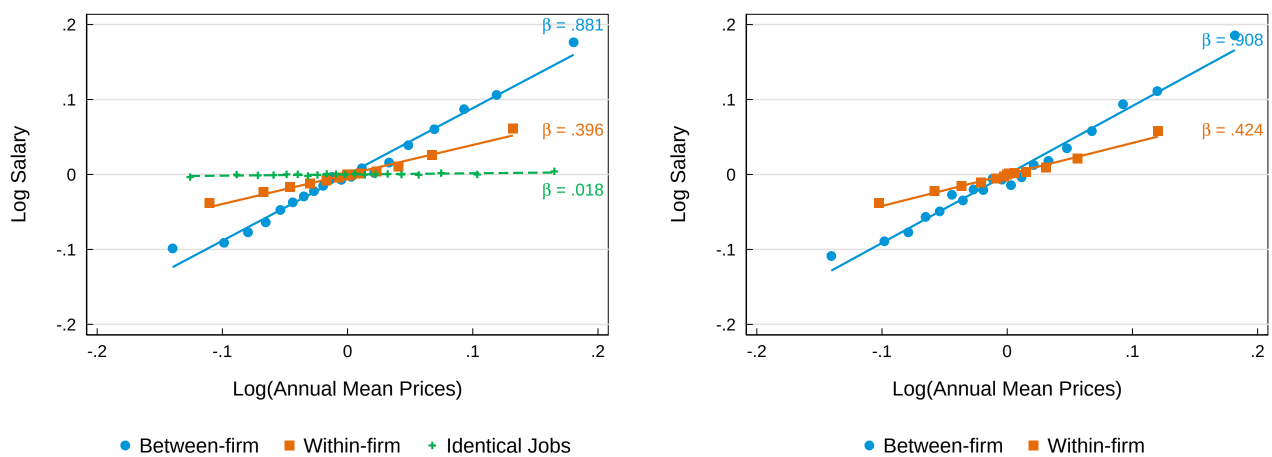


Notes: In the left panel, the sample excludes job cells where there are fewer than 5 within-firm pairs. This results in 7,880 firms. In the right panel, we further condition the sample to include the set of firms with at least 1 national occupation and at least 3 occupations. National occupations are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

Figure A5: Posted Wages and Local Prices: Robustness to Wage Ranges and Occupation Weighting

(a) Adding Salary Ranges

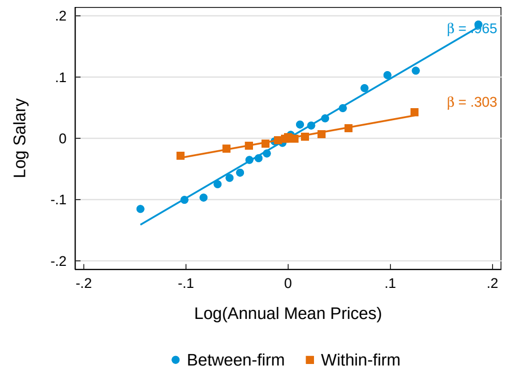
(b) Reweighting Occupations



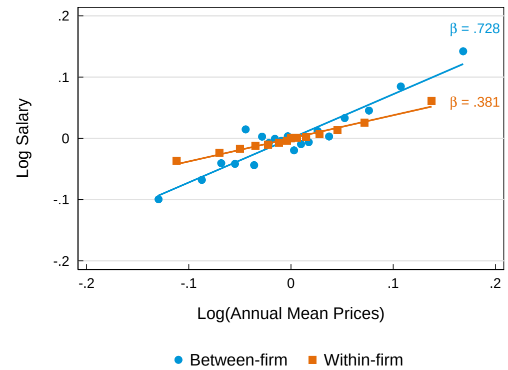
Notes: In both panels, the binned scatterplot shows the relationship between the local price index, instrumented by county-level home prices, and the log wage. In the left, the sample includes all jobs with posted wages, including those that point wage ranges. For jobs with posted wage ranges, we take the midpoint of the range. The blue line and circles correspond to Equation 7 and the orange line and squares correspond to Equation 6. The blue points include 6,130,262 observations and the orange points include 3,788,286 observations. In the right panel, 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. 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 both panels.

Figure A6: Wages and Local Prices: Heterogeneity

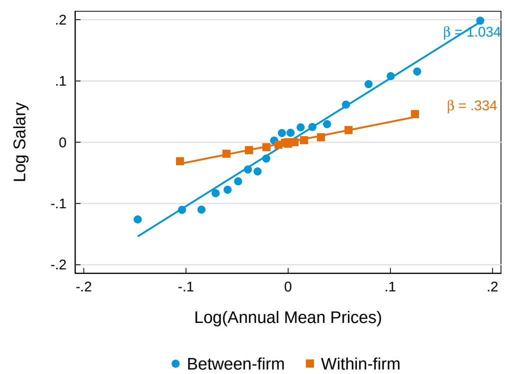
(a) High Wage Occupations



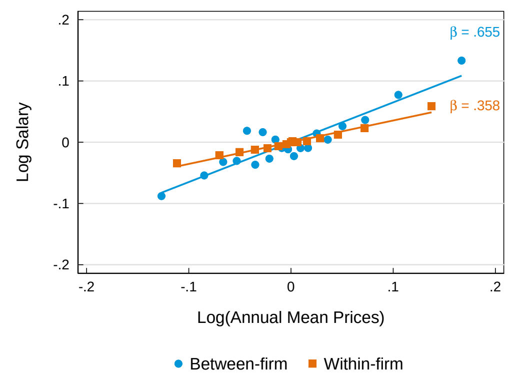
(b) Low Wage Occupations



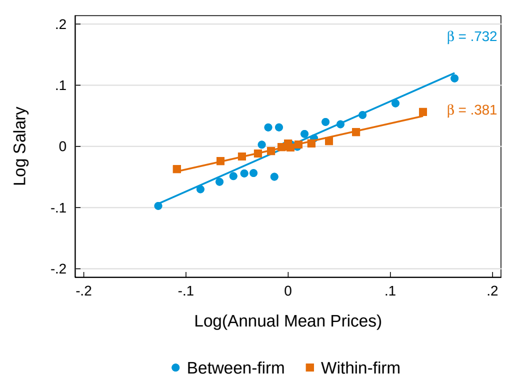
(c) Tradable Occupations



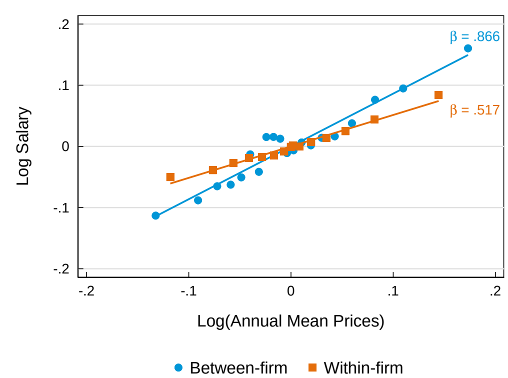
(d) Non-Tradable Occupations



(e) Tradable Industries



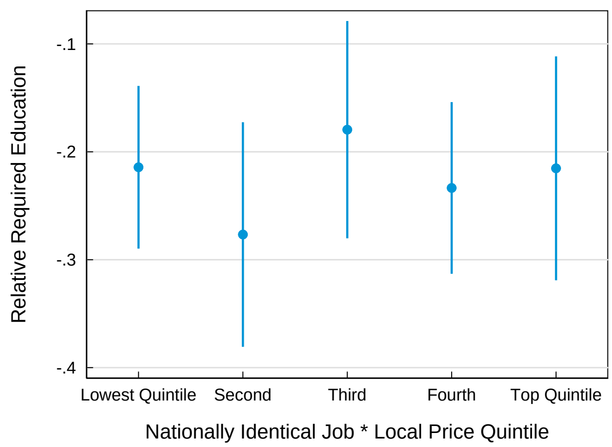
(f) Non-Tradable Industries



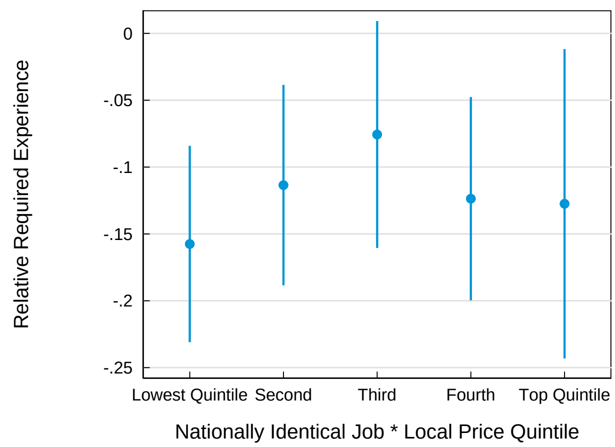
Notes: High-wage occupations are defined as those with an OES wage that is above the median in the sample (which we find to be 11). We define a tradable occupation as one that can be done remotely following Dingel and Neiman (2020). We define tradable and non-tradable industries following Mian and Sufi (2014a). Specifically, industries that engage in global trade are classified as tradable and retail trade (NAICS 44-45) and accommodation/food services (NAICS 72). All other industries are unclassified. In all panels, blue dots represent estimates of Equation 7 and orange circles represent estimates of Equation 6.

Figure A7: Relative Education and Experience by Local Price Level

(a) Required Education

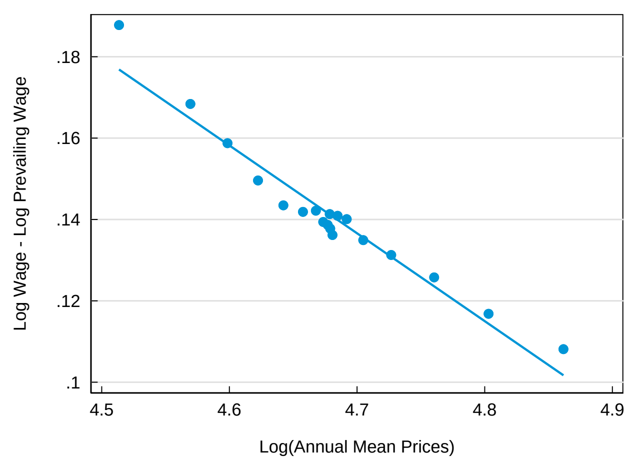


(b) Required Experience



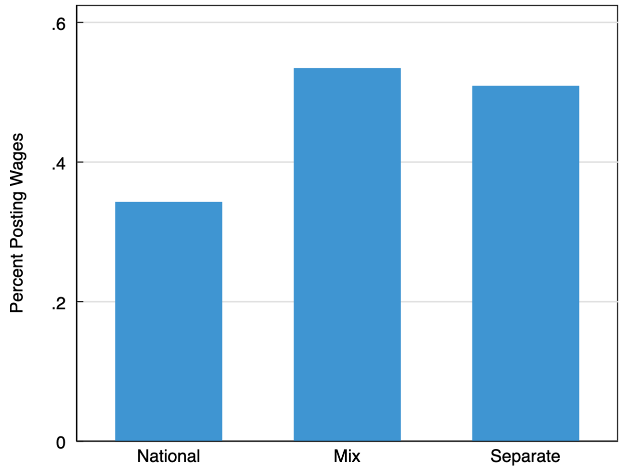
Notes: Each regression includes a quadratic in establishment size, a quadratic in firm size, and fixed effects for job by county by industry by year. Nationally identical jobs are defined as those jobs paying the modal wage in occupation by firm by year cells in which at least 80% of wage pairs are the same. Sample includes all firm-job pairs present in at least 2 establishments in that year.

Figure A8: Wage Premium in LCA by local prices



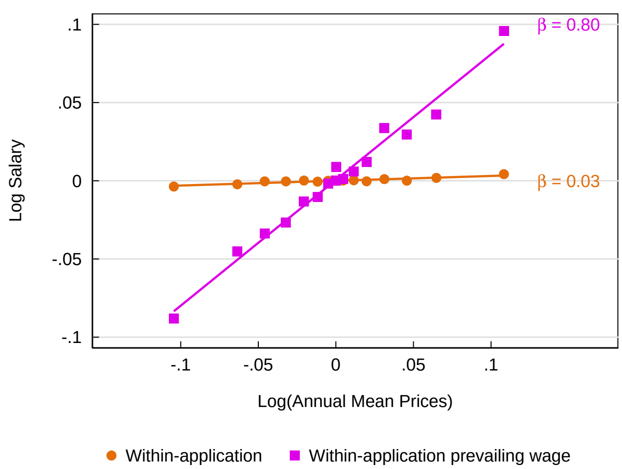
Notes: The y-axis is the log of the reported (annualized) wage minus the log of the reported (annualized) prevailing wage. Non-certified and withdrawn visa applications are included. The sample includes 3,446,546 observations. The regression includes controls for firm, occupation, year, and whether the salary is hourly or annual.

Figure A9: Fraction of Firms Posting Wages by Wage Setting Policy



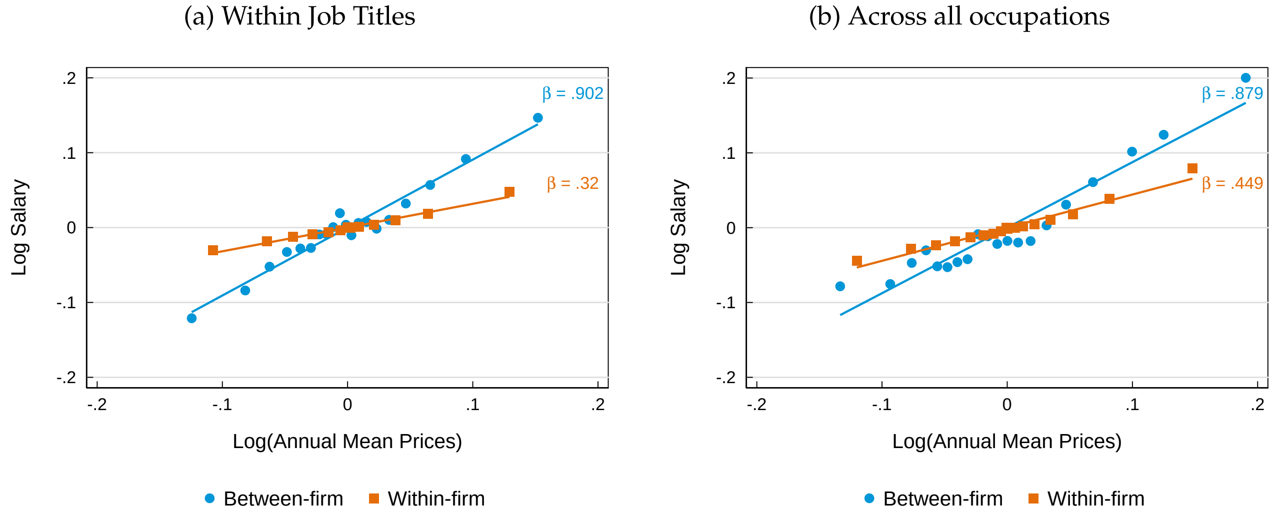
Notes: This figure shows the fraction of survey respondents who state that their firm posts wages or salary bands on the majority of their job vacancies. "National" means that a respondent stated that pay bands (wages) are set identically across establishments so that workers with the same job title 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 A10: Within-Worker Sensitivity of Reported Wages to Local Prices



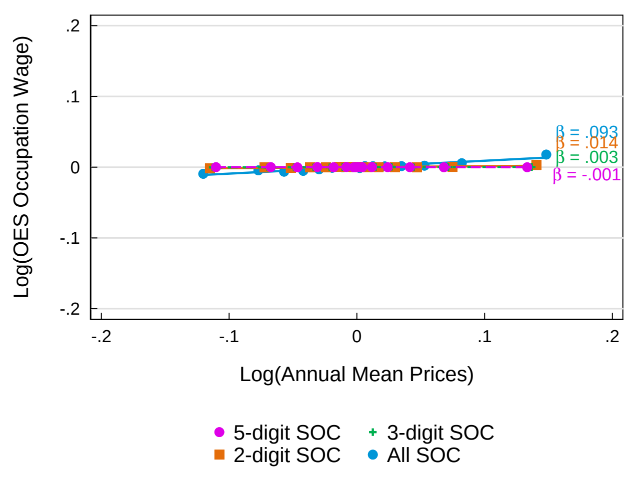
Notes: The sample includes the set of applications with wages posted for at least 2 worksites, and which are for only 1 worker. Non-certified and withdrawn visa applications are included. The sample for these regressions represents 4,128 applications/workers and includes 9,133 observations (worker-worksites).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

Figure A11: Posted Wages and Local Prices: Different Levels of Aggregation



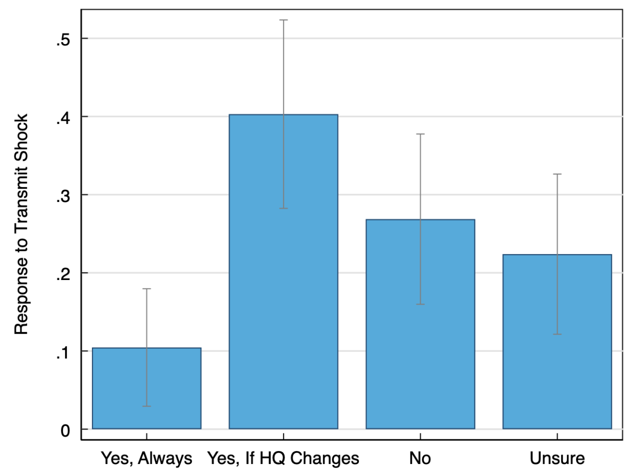
Notes: In the left panel, the unit of observation is the job title and in the right panel, the unit of observation is the occupation. In both panels, the blue circles show the between-firm regression as in Equation 7, but replacing occupation fixed effects (θ_{ot}) with job-title in the left panel and removing them altogether in the right panel. Similarly, in both panels, the orange diamonds show the within-firm regression as in Equation 6, 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 right panel. The sample in the left panel includes 10,376 distinct job titles.

Figure A12: Occupation Selection and Prices



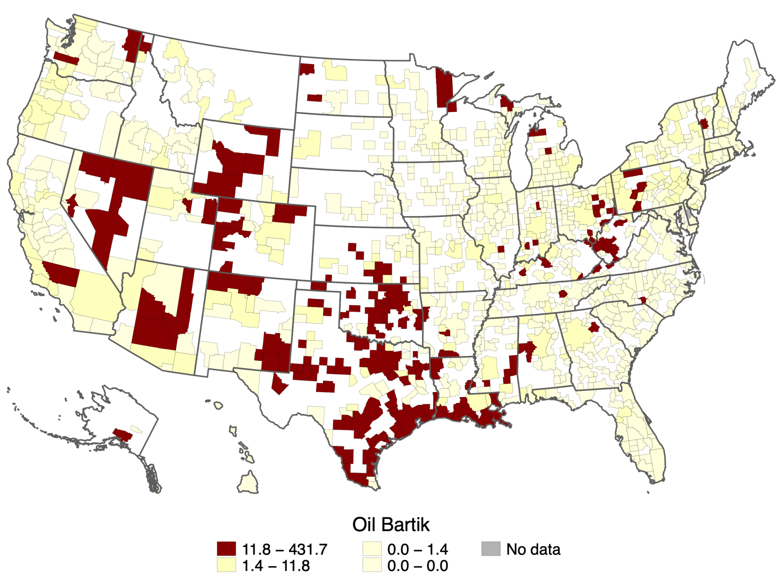
Notes: Each specification shows an estimation of Equation 6 that replaces the posted wage for each job with the wage for that 6-digit occupation in the OES. Each regression line differs in the level of the fixed effects. Specifically, the purple circles include firm by 5-digit occupation fixed effects, 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 A13: Impact of Wage Change in A Single Establishment on Other Establishments



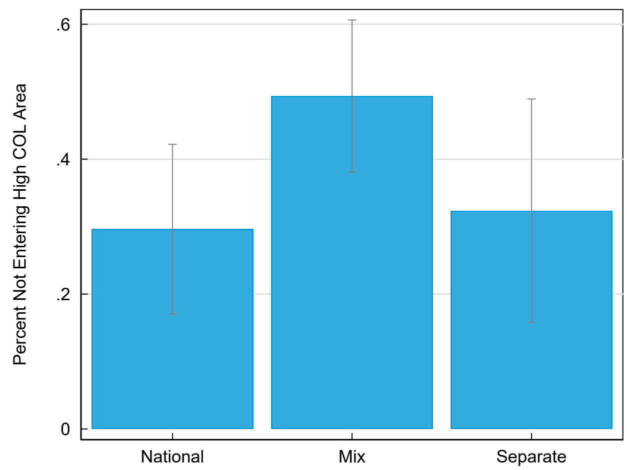
Notes: This figure shows survey responses to the question: "Say an establishment in your company located in City A had to change its wage or pay bands to keep up with local competition. Would other establishments/plants/stores in your firm located in cities B and C also then change their wage or pay bands?" The sample consists of respondents who report working at firms that set identical pay for some or all of their jobs.

Figure A14: Regional Exposure to Natural Resources Instrument



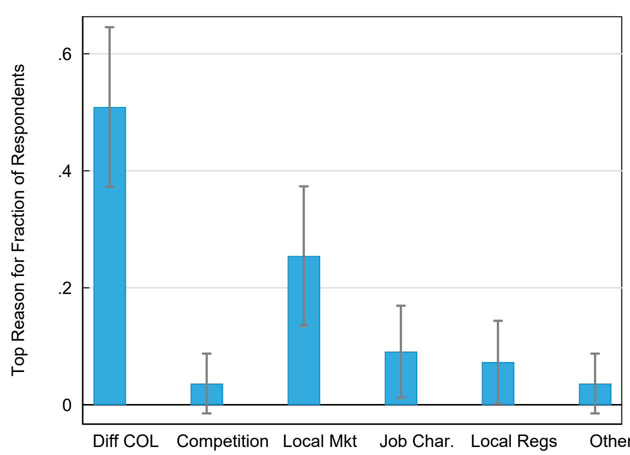
Notes: This figure presents a heat map showing the geographic distribution of natural resource shocks in the U.S., measured in 2012, by county. The map is constructed by grouping counties into ten deciles and shading such that lighter colors correspond to lower rates of natural resource demand. The natural resource instrument is defined as in Section 5, Equation (9).

Figure A15: 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 A16: Reasons Firms Pay Differently across Geographies



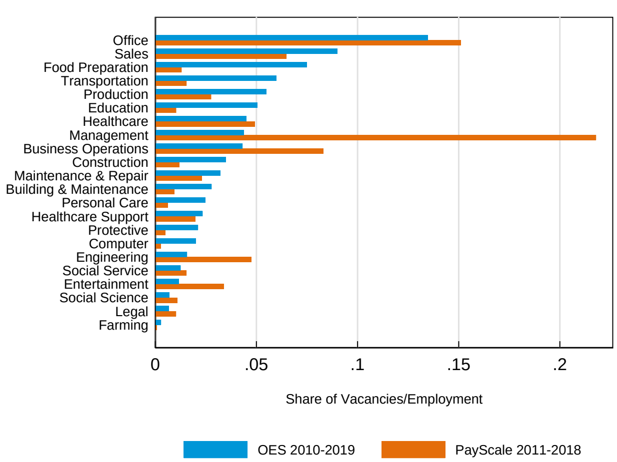
Notes: This figure presents survey responses to the question: “You have mentioned that you set wages or pay bands separately across locations for some of the jobs in your firm. Why does your company choose to set separate wages or pay bands for those jobs?” The sample consists of respondents who state 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 A17: Geographic Distribution of Employment: Effect of National Wage Setting

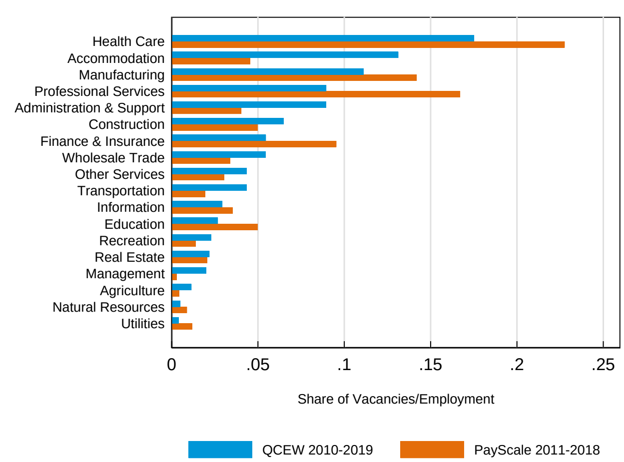
Notes: This binned scatterplot shows the relationship between the local price index and log of employment in the establishment. Annual establishment-level employment comes from Dun and Bradstreet. The orange line and squares includes firms that are national wage setters, defined as in Section 4 as those where at least 50% of their occupations have identical wages in at least 80% of establishments. The blue line and circles includes all other firms. All regressions include firm and year fixed effects. Because of the fixed effects, both the y-axis and x-axis are demeaned. The regression includes all establishments and years for the firms in the D&B sample, not restricting to those establishments that appear in the Burning Glass sample. We restrict the sample to those firms with at least 5 establishments in the Burning Glass sample.

Figure A18: Occupation and Industry Distribution of Payscale Data

(a) Occupation

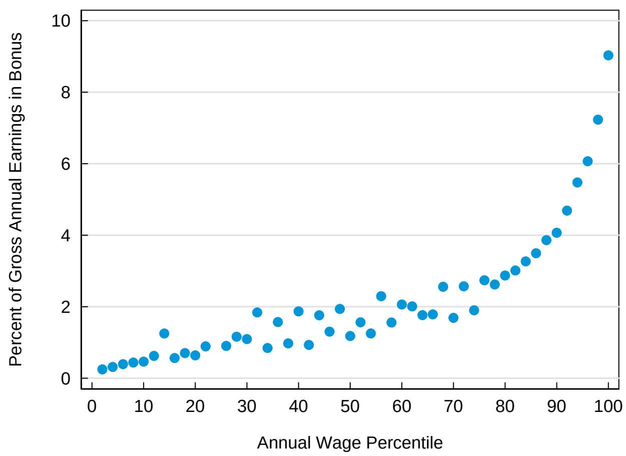


(b) Industry



Notes: Shares are calculated using the total number of workers summed across 2010-2019. In the left panel, benchmark employment is from the 2010-2019 Occupational Employment Statistics, by broad occupation. In the right panel, benchmark employment is by broad industry from the Quarterly Census of Wages and Employment.

Figure A19: Bonuses as a fraction of total pay in Payscale data



Notes: This figure shows reported bonuses as a percentile of reported base pay for each part of the wage distribution. The y-axis is the fraction of total compensation that comes from bonuses. Each dot represents 2% of the data. The x-axis shows the wage percentile, calculated over the entire sample period. The sample includes both hourly and salaried workers.

Table A1: Determinants of Wage Posting

Regressor:	Median Hourly OES Occupation Wage	Posted Education	Posted Experience	Firm # of Establishments	Consumer Prices	Superstar City
	Outcome: Percentage Chance of Posting a Wage					
	(1)	(2)	(3)	(4)	(5)	(7)
Specification:						
No Controls	-1.62	-2.36	-1.15	-0.22	-0.51	-1.12
	(0.36)	(0.44)	(0.22)	(0.65)	(0.07)	(0.41)
Firm x Year Fixed Effects	-1.25	-1.09	-0.56			
	(0.10)	(0.12)	(0.05)			
Firm x Year x SOC Fixed Effects					-0.03	-0.05
					(0.01)	(0.03)
Observations	145891980	102505082	74181070	148211982	112194747	148211982

Notes: The sample contains the same restriction as in row 4 of Table A4 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 detailed occupation level in column (1)-(4) and the county level in columns (5)-(7).

Table A2: Comparing Median Wages in OES and Burning Glass

	Annual Basepay	Hourly Basepay	Annual Total	Hourly Total
	(1)	(2)	(3)	(4)
Posted Wages	0.698	0.934	0.618	0.861
	(0.014)	(0.007)	(0.015)	(0.007)
Observations	48,142	76,300	43,245	65,418

Notes: We regress occupation by MSA log median hourly wages from the Occupational Employment Statistics, on occupation by MSA log median wages from Burning Glass. In both cases, we study the wage averaged over 2010-2019. In both datasets, occupations are at the 6 digit level. 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 A3: Comparing OES and Burning Glass Wages Across the Distribution

	10th (1)	25th (2)	Median (3)	75th (4)	90th (5)
Posted Wages	0.450	0.614	0.769	0.798	0.695
	(0.006)	(0.009)	(0.010)	(0.010)	(0.009)
Observations	72,514	72,514	72,490	72,342	71,935

Notes: In each column, the dependent variable is the specified moment of the occupation by MSA hourly wages from the Occupational Employment Statistics. The independent variable is the same moment of the posted wage distribution in the Burning Glass data. In both cases, we take logs and study the wage averaged over 2010-2019. In both datasets, occupations are at the 6 digit level. 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 A4: Summary Statistics on Sample Formation

	Vacancies (1)	Firms (2)	Establishments (3)	Counties (4)
Full 2010-2019 data	239,029,970	2,742,556	9,117,553	3,224
Drops missing wages, includes ranges	40,625,295	1,267,504	3,529,713	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. 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 fifth row is the main sample for our analysis. 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.

Table A5: Sensitivity of Posted Wages to Local Conditions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Average Local Price for Firm	0.768						0.858	
	(0.020)						(0.024)	
Local Price		0.301						0.350
		(0.015)						(0.018)
Average Local House Price for Firm			0.136					
			(0.003)					
Local House Price				0.055				
				(0.002)				
Local Income for Firm					0.389			
					(0.010)			
Local Income						0.135		
						(0.006)		
Specification	OLS	OLS	OLS	OLS	OLS	OLS	IV	IV
Observations	2527527	1581958	3687032	2532913	3695553	2552794	2525390	1577323
Firms	248892	63900	365414	96631	366418	97058	248662	63802
Fixed-Effects:								
Year	✓	✓	✓	✓	✓	✓	✓	✓
Occupation	✓	✓	✓	✓	✓	✓	✓	✓
Firm x Occupation		✓		✓		✓		✓

Notes: Standard errors are clustered at the firm level. All coefficients are estimated using OLS. 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 A6: 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. Sample includes all firm-job pairs present in at least 2 establishments in that year. 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 A7: Characteristics of National Wages Setters in Linked Compustat Subsample

	$\frac{\text{Log Revenue}}{\text{Emp}}$	$\frac{\text{Log R\&D}}{\text{Emp}}$	Tobin's Q	$\frac{\text{Log Revenue}}{\text{Emp}}$	$\frac{\text{Log R\&D}}{\text{Emp}}$	Tobin's Q
	(1)	(2)	(3)	(4)	(5)	(6)
National Firms	0.075	0.771	-0.032	0.092	0.764	-0.032
	(0.072)	(0.243)	(0.094)	(0.068)	(0.252)	(0.096)
Avg. Fraction of Identical Jobs	0.173	1.105	0.034	0.203	1.088	0.034
	(0.116)	(0.318)	(0.140)	(0.111)	(0.341)	(0.143)
Avg. Fraction of Identical Occupations	0.176	1.123	0.023	0.225	1.105	0.011
	(0.108)	(0.308)	(0.140)	(0.103)	(0.317)	(0.140)
Outcome Mean	13	9	2	13	9	2
Observations	685	208	669	684	207	668
Fixed Effects:						
Industry				✓	✓	✓

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 occupation 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 occupations that have identical wages, averaged over all occupation 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. In terms of the fields within compustat, Tobin's Q is defined as (($prcc_f \times$ csho) + at - ceq)/at

Table A8: Sensitivity of Nominal Wages in Payscale to Local Conditions

	OLS		IV		Hourly Workers		High-tenure Workers		Including Bonuses	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Average Local Price for Firm		1.094		1.231		1.272		1.269		1.273
		(0.045)		(0.050)		(0.110)		(0.057)		(0.054)
Local Price	0.592		0.676		0.668		0.679		0.691	
	(0.028)		(0.026)		(0.038)		(0.028)		(0.027)	
Observations	109196	109196	109021	109021	47822	47822	88379	86230	109021	109021
Firms	16354	16354	16340	16340	6766	6766	13388	13200	16340	16340
Fixed-Effects:										
Year	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Job		✓		✓		✓		✓		✓
Job×Employer	✓		✓		✓		✓		✓	

Notes: Data is from Payscale and the unit of observation is the individual. In each regression, we define a job as the combination of pay frequency, salary type, age, and education level. Each regression includes year fixed effects. High-tenure workers are those who report having been at their firm for at least 4 years. Only 30% of the sample reports their firm tenure.

Table A9: Worker Satisfaction and Local Prices

	Worker Satisfaction		Fair Pay	
Outcome Variable:	(1)	(2)	(3)	(4)
Average Local Price for Firm		-0.121		-0.590
		(0.358)		(0.518)
Local Price	-0.555		-0.036	
	(0.215)		(0.298)	
Observations	8862	8862	5176	5176
Firms	2659	2659	1702	1702
Fixed-effects				
Year	✓	✓	✓	✓
Job		✓		✓
Job×Employer	✓		✓	

Notes: Workers rank their satisfaction ("I am satisfied with my employer") according to a 5-point Likert scale, where responses range from Strongly Disagree (1) to Strongly Agree (5). We convert this ranking into a z-score. Therefore, the units of the outcome variable are scaled as standard deviations from the mean. Local prices come from the Bureau of Labor Statistics.

Table A10: Effects of wage growth on job postings in other establishments

Dependent Variable:	Wage Growth (1)	Indicator for Posting (2)	Vacancy Growth (3)	Combined vacancy growth (4)
Δ log $w_{oij't}$ x Equal	0.714	-0.011	0.272	0.036
	(0.044)	(0.057)	(0.168)	(0.104)
Δ log $w_{oij't}$ x Diff	0.181	0.042	0.293	0.154
	(0.039)	(0.038)	(0.137)	(0.120)
Observations	3752422	7971358	3752422	7971358
Fixed Effects:				
Occupation	✓	✓	✓	✓
Year	✓	✓	✓	✓

Notes: The sample includes job pairs within the firm (i.e. same occupation within the firm in different counties) that both posted wages in year $t-1$ and at least 1 job within the pair also posted wages in year t. In column 1 and 3, the sample further restricts to those pairs where both posted wages in year t. In all columns, the regressors are wage growth in the second establishment of the job, interacted with an indicator for whether wages in the first and second job were equal in the initial period. In column 1, the dependent variable is the change in the log wage in the first establishment of the firm ($\Delta \log w_{oijt}$). In column 2, the dependent variable is an indicator for whether the firms posts a vacancy with a wage in year t for that job in establishment 1. In column 3, the dependent variable is the change in log of the number of vacancies posted in establishment 1 between year $t-1$ and t. In column 4, the dependent variable is the change in the number of vacancies (v_{oijt}) posted between year $t-1$ and t, defined as $\frac{v_{oijt}-v_{oijt-1}}{\frac{1}{2}(v_{oijt}+v_{oijt-1})}$. This specification includes both the intensive and extensive margin of posting behavior. All observations are unweighted and standard errors are twoway clustered at the firm and the location of the second establishment.

Table A11: Robustness of Pass Through of Natural Resources Shock

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Alternate Clusters		Primary Estab. Sample		Strict Unexposed		Nontradable Occ.		Excluding Tradable Ind.	
Δ Natural Resources	0.57	-0.11	0.73	-0.32	0.47	-0.95	0.93	-0.29	0.24	-0.60
	(0.38)	(0.16)	(0.19)	(0.25)	(0.24)	(0.22)	(0.25)	(0.14)	(0.13)	(0.14)
Observations	458228	2110997	196458	883500	305199	1439505	265353	1930300	408332	1542219
Included Sample	Identical	Different	Identical	Different	Identical	Different	Identical	Different	Identical	Different

Notes: In columns 1 and 2 we show the estimates from the reduced form specification for equation (9) when performing twoway clustering at the county and firm levels. In columns 3 and 4 we restrict the sample to job pairs for which the exposed job belongs to an establishment that is larger than the establishment to which the unexposed job belongs. Columns 5 and 6 classify unexposed firms as those in the bottom 10^{th} percentile of shock exposure. Column 6 further restrict to exposed firms in the top 25% percentile of exposure. Column 7 shows the reduced form results from interacting wage growth with an indicator for whether an occupation had equal wages in the prior period and for whether the occupation is classified as tradable. Column 8 shows the reduced form results from interacting wage growth with an indicator for whether the firm is in a tradable industry. In all columns we instrument for the change in wage growth using the natural resources Bartik instrument. All regressions include variables that are demeaned by the unexposed firms, as described in Appendix A2.4.

Table A12: Correlates of National Wage Setting

	More than 500 Employees (1)	More than 50% Empl. Salaried (2)	Pay Determined Centrally (3)	Centralized Hiring (4)
National Firm	0.064	0.020	0.306	0.072
	(0.079)	(0.081)	(0.069)	(0.074)
Mixed Pay Firm	0.139	-0.032	0.096	0.083
	(0.072)	(0.074)	(0.072)	(0.068)
Mean of outcome for firms with no national pay	0.574	0.485	0.574	0.279
Observations	298	298	298	297

Notes: The dependent variable in column 1 is an indicator that the respondent works at a firm employing more than 500 workers; in column 2 it is an indicator that more than 50% of the firm's employees are salaried (as opposed to hourly) employees; in column 3 it is an indicator that the firm's pay structure is determined by central management; and in column 4 it is an indicator that hiring is done by centralized management.

Table A13: National Wage Setting and Wage Rigidity

	(1)	(2)	(3)	(4)	(5)	(6)
Nationally Wage Set Job	-48.917	-48.178	-34.606	-48.639	-47.907	-34.644
	(0.203)	(0.207)	(0.303)	(0.294)	(0.299)	(0.424)
Shock x Non-nationally wage set job				0.234	0.230	0.161
				(0.039)	(0.039)	(0.031)
Shock x Nationally wage set job				0.032	0.051	0.077
				(0.028)	(0.028)	(0.025)
Observations	583,367	583,367	555,384	575,300	575,300	547,442
Fixed Effects:						
Occupation x Year	✓	✓	✓	✓	✓	✓
Industry x Year		✓	✓		✓	✓
Firm			✓			✓

Notes: The dependent variable is an indicator for whether the wage changes between $t-1$ and t and includes all job postings that are posted with wages in consecutive years. The dependent variable is multiplier by 100. The shock is the change in the average change in log wages for jobs posted in the county by other firms and that are outside the 2-digit occupation. This is intended to capture general wage pressure in a county. Nationally wage set jobs are defined as those where at least 80% of counties in which the firm is posting in a given occupation pay exactly the same wage. This is defined in the period $t-1$ for those jobs with at least 2 establishments in that period. Standard errors in columns 4 through 6 are clustered at the county level.

Table A14: Comparing OES and Payscale Wages Across the Distribution

	10th (1)	25th (2)	Median (3)	75th (4)	90th (5)
Posted Wages	0.450	0.614	0.769	0.798	0.695
	(0.006)	(0.009)	(0.010)	(0.010)	(0.009)
Observations	72,514	72,514	72,490	72,342	71,935

Notes: In each column, the dependent variable is the specified moment of the occupation by MSA hourly wages from the Occupational Employment Statistics. The independent variable is the same moment of the wage distribution in the Payscale data. In both cases, we take logs and study the wage averaged over 2010-2018. In both datasets, occupations are at the 6 digit level. In all columns, the Payscale data is annual base pay for hourly workers only. The observations are weighted by occupation by MSA employment over 2010-2018. Robust standard errors are reported in parentheses.

Table A15: 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	0.865	0.309	0.415	0.368
	(0.024)	(0.016)	(0.052)	(0.055)
Observations	2,541,299	1,542,150	107,455	206,918
Fixed Effects:				
Year	✓	✓	✓	✓
Job	✓			
Firm x Job		✓	✓	✓
Sample	All Firms	All Firms	Franchises	Non-Franchises

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 log absolute difference in the posted salary and 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 A5. Column (1) is between-firm relationship for all firms the baseline sample (i.e. Equation 7), column (2) is within-firm relationship for all firms in the baseline sample (i.e. Equation 6), column (3) is with 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.

Table A16: Dyadic Regressions - Location Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Within Ind.	0.554	0.495	0.497	0.487	0.489	0.482	0.495
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ Price	0.003						
	(0.000)						
Δ Price x Within	-0.020						
	(0.000)						
Δ Distance		0.006					
		(0.000)					
Δ Distance x Within		-0.037					
		(0.000)					
One Super City			0.019				
			(0.000)				
One Super City x Within			-0.087				
			(0.001)				
Log County Size				-0.002			
				(0.000)			
Log County Size x Within				0.001			
				(0.000)			
County Mobility					0.005		
					(0.000)		
County Mobility x Within					0.003		
					(0.000)		
Same Census Division						-0.006	
						(0.000)	
Same Census Division x Within						0.069	
						(0.000)	
Average Unemployment Rate							-0.028
							(0.000)
Average Unemployment Rate x Within							0.068
							(0.000)
Outcome Mean	0.303	0.271	0.271	0.271	0.271	0.271	0.271
Observations	91857320	228952020	228973712	113323000	176821048	228973712	228914744

Notes: Each regression includes fixed effects for the firm of the first establishment in the pair, occupation, and year. The outcome variable is an indicator for whether wages in the pair are equal. Half of the pairs are within firms and half of the pairs are between firms. Standard errors are clustered at the county pair level. Figure A3 shows the coefficients of the characteristics interacted with the within-firm indicator. Column 1 looks at the difference in the price index between the 2 counties in the pair, constructed as the difference in the log of the price index. Column 2 looks at the geographic distance in miles between the 2 counties in the pair. Column 3 looks at an indicator for whether 1 county in the pair is in a superstar city, which we define to be LA, San Francisco, NYC, or Washington DC. Column 4 relates the wage difference to the difference in the size of the counties in the pair, measured as the difference in the log of total employment in each county, measured within the OES. Column 4 looks at county mobility, measured as the fraction of moves out of county 1 that go to county 2. This data comes from the Census J2J Origin Destination statistics. Column 6 looks at an indicator for whether the counties are in the same census division. Column 7 looks at the average unemployment rate across the 2 counties. All continuous variables are converted to z-scores so that the coefficients reflect a 1 standard deviation increase.

Table A17: Dyadic Regressions - Occupation Characteristics

	(1)	(2)	(3)
Within Ind.	0.533	0.430	0.533
	(0.041)	(0.058)	(0.044)
Log Occ. Wage	-0.028		
	(0.022)		
Log Occ. Wage x Within	0.070		
	(0.044)		
Tradable Occ.		-0.140	
		(0.041)	
Tradable Occ. x Within		0.323	
		(0.078)	
Log Occ. Size			-0.014
			(0.022)
Log Occ. Size x Within			0.018
			(0.047)
Outcome Mean	0.288	0.270	0.288
Observations	174681756	227318776	174686096

Notes: Each regression includes fixed effects for the firm of the first establishment in the pair, the county pair, and year. The outcome variable is an indicator for both jobs in the pair having identical wages. Half of the pairs are within firms and half of the pairs are between firms. Standard errors are clustered at the occupation level. Figure A3 shows the coefficients of the characteristics interacted with the within-firm indicator. Column 1 looks at average wage of the occupation, measured within the OES. Column 2 looks at an indicator for whether the occupation is tradable, measured as those that can be done remotely (Dingel and Neiman, 2020). Column 3 looks at occupation size, measured as the log of total employment in that occupation, measured in the OES. All continuous variables are converted to z-scores so that the coefficients reflect a 1 standard deviation increase.

Table A18: Dyadic Regressions - Firm Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
Within Ind.	0.495	0.495	0.508	0.495	0.544	0.495
	(0.043)	(0.043)	(0.046)	(0.045)	(0.051)	(0.046)
Firm Vacs.	-0.009					
	(0.010)					
Firm Vacs. x Within	-0.076					
	(0.081)					
Firm Occ. Vacs.		0.004				
		(0.012)				
Firm Occ. Vacs. x Within		-0.130				
		(0.029)				
Tradable Ind.			0.032			
			(0.035)			
Tradable x Within			-0.166			
			(0.155)			
Firm HHI				0.004		
				(0.005)		
Firm HHI x Within				-0.015		
				(0.010)		
Variance of Prices					-0.011	
					(0.013)	
Variance of Prices x Within					-0.020	
					(0.025)	
Ind. Union Coverage						-0.027
						(0.020)
Ind. Union Coverage x Within						0.068
						(0.041)
Dependent Mean	0.271	0.271	0.271	0.271	0.294	0.271
Observations	228973712	228973712	228973712	228973712	183598568	228973712

Notes: Each regression includes fixed effects for the occupation, the county pair, and year. The outcome variable is an indicator for both jobs in the pair having identical wages. Half of the pairs are within firms and half of the pairs are between firms. Standard errors are clustered at the firm level. Figure A3 shows the coefficients of the characteristics interacted with the within-firm indicator. Column 1 looks firm size, measured as the total number of vacancies posted in all occupations over the entire sample period. Column 2 looks at firm size measured as the number of occupations in which the firm posts vacancies over the entire sample period. Column 3 looks at an indicator for whether the firm is in a tradable industry, measured following Mian and Sufi (2014a). Specifically, industries that engage in global trade are classified as tradable and retail trade (NAICS 44-45) and accommodation/food services (NAICS 72). All other industries are unclassified. Column 4 looks at the geographic HHI of the firm, measured using the share of total vacancies at the firm in the entire sample period that are in a given county. A high HHI indicates 1 large establishment and several smaller establishments. Column 5 looks at the variance of local prices across establishments of the firm. Column 6 looks at the fraction of workers in an industry that are covered by a union contract, measured as in Hirsch and MacPherson (2003). All continuous variables are converted to z-scores so that the coefficients reflect a 1 standard deviation increase.

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.

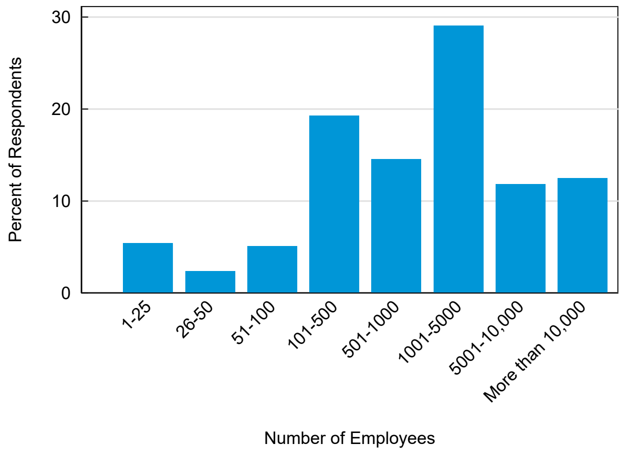
Figure B3 displays the job titles of respondents. To standardize titles, we allowed respondents to write in their title and then aggregated them. The majority of respondents work as HR managers or executives. In column 1 of Appendix Table B1, we provide additional information on the respondents and the 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

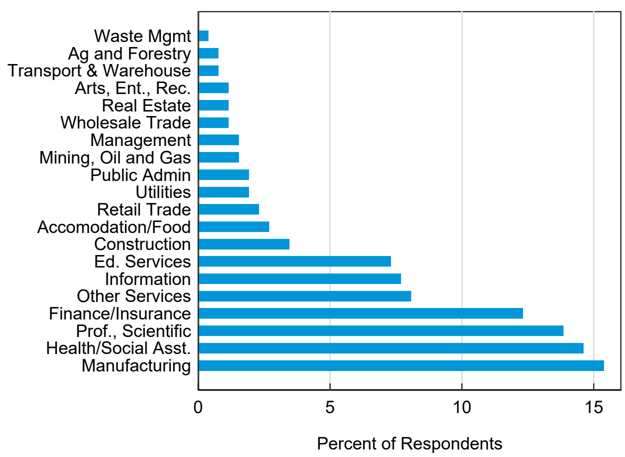
Notes: This table presents summary statistics for the set of survey respondents working at firms that operate in more than one city. Column 2 restricts to the sample of respondents who state that they work at a firm that does not set identical wages for jobs across locations. Column 3 restricts to the 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



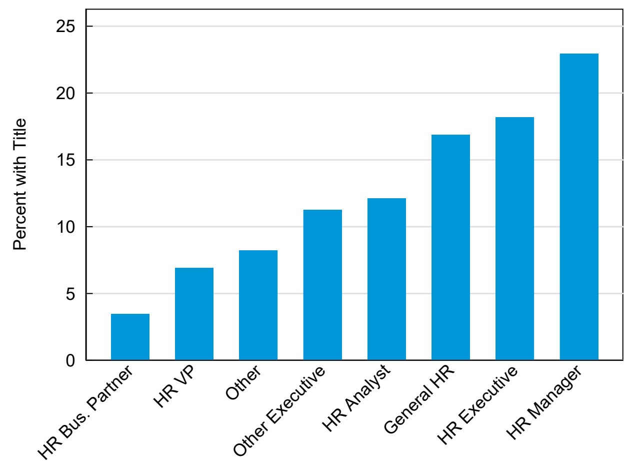
Notes: This figure shows the distribution of firm size (in terms of number of employees) among survey respondents.

Figure B2: Sector Representation of Survey Respondents



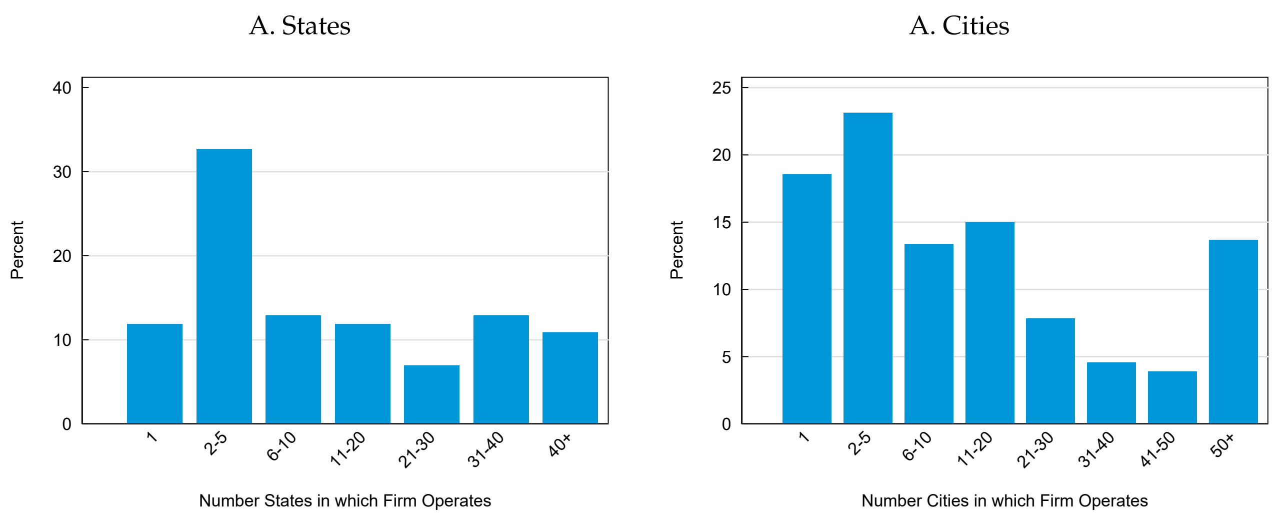
Notes: This figure shows the percent of survey respondents who work at a firm in each of the industries represented on the y-axis.

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 Deriving Equations in the Main Text

We start by solving for the value of each household's consumption aggregate, C_{ijk}. The household solves the sub-maximization problem

$$\max_{C^N_{ijk}, C^T_{ijk}} C_{ijk} = C\left(C^N_{ijk}, C^T_{ijk}\right)$$

subject to

$$C^T_{ijk} + P^N_j C^N_{ijk} \leq W_{ijk}.$$

This implies that

$$C_{ijk} = \tilde{C}\left(P^N_j, W_{ijk}\right)$$

where $\tilde{C}$ is optimal consumption. By homotheticity, we have

$$C_{ijk} = \frac{W_{ijk}}{\tilde{P}_j}$$

where $\tilde{P}_j$ is the ideal consumer price index. Therefore the consumer problem simplifies to

$$\max_{ij} \log C_{ijk} + \varepsilon_{ijk} = \max_{ij} \log \frac{W_{ijk}}{\tilde{P}_j} + \varepsilon_{ijk}.$$

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

$$\begin{aligned} P_{ij} &= \frac{\left(\frac{W_{ij}}{\tilde{P}_j}\right)^{\rho_j}}{\sum_{k\in M}\left(\frac{W_{kj}}{\tilde{P}_j}\right)^{\rho_j}} \left(\sum_{k\in M}\left(\frac{W_{kj}}{\tilde{P}_j}\right)^{\rho_j}\right)^{\frac{\eta}{\rho_j}} \kappa \\ &= W_{ij}^{\rho_j} \tilde{P}_j^{-\eta} \left(\sum_{k\in M} W_{kj}^{\rho_j}\right)^{\frac{\eta-\rho_j}{\rho_j}} \kappa \end{aligned}$$

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

$$L_{ij} = W_{ij}^{\rho_j} \tilde{P}_j^{-\eta} \left(\sum_{k\in M} W_{kj}^{\rho_j}\right)^{\frac{\eta-\rho_j}{\rho_j}} \kappa$$

as in equation (1) 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

$$\max_{W_{ij}^S, L_{ij}^S} P_j^S A_{ij}^S F(L_{ij}^S) - W_{ij}^S L_{ij}^S \quad \text{subject to } L_{ij}^S = \left(W_{ij}^S\right)^{\rho_j} \kappa_j, \quad \kappa_j = \tilde{P}_j^{-\eta} \left(\sum_{k \in M} W_{kj}^{\rho_j}\right)^{\frac{\eta-\rho_j}{\rho_j}} \kappa,$$

which has first order condition

$$P_j^S A_{ij}^S F'\left(L_{ij}^S\right) \rho_j \left(W_{ij}^S\right)^{\rho_j - 1} \kappa_j - (1+\rho_j)\left(W_{ij}^S\right)^{\rho_j} \kappa_j = 0$$

$$\implies P_j^S A_{ij}^S F'\left(L_{ij}^S\right) \rho_j \left(W_{ij}^S\right)^{-1} - (1+\rho_j) = 0$$

$$\implies W_{ij}^S = \frac{\rho_j}{1+\rho_j} P_j^S A_{ij}^S F'\left(L_{ij}^S\right)$$

which is equation (3) from the main text.

National wage setters solve

$$\max_{W_i^S, L_{ij}^S} \sum_{j \in N} \left[P_j^S A_{ij}^S F(L_{ij}^S) - W_i^S L_{ij}^S\right] \quad \text{subject to } L_{ij}^S = \left(W_i^S\right)^{\rho_j} \kappa_j$$

$$\implies \max_{W_i^S} \sum_{j \in N} \left[P_j^S A_{ij}^S F(\left(W_i^S\right)^{\rho_j} \kappa_j) - W_i^S \left(W_i^S\right)^{\rho_j} \kappa_j\right]$$

$$\implies \max_{W_i^S} \sum_{j \in N} \left[P_j^S A_{ij}^S F(\left(W_i^S\right)^{\rho_j} \kappa_j) - \left(W_i^S\right)^{1+\rho_j} \kappa_j\right]$$

which has first order condition

$$\sum_{j \in N} \left[P_j^S A_{ij}^S F'(L_{ij}^S) \rho_j \left(W_i^S\right)^{\rho_j - 1} \kappa_j - (1+\rho_j)\left(W_i^S\right)^{\rho_j} \kappa_j\right] = 0$$

$$\implies \sum_{j \in N} \left[P_j^S A_{ij}^S F'(L_{ij}^S) \rho_j \left(W_i^S\right)^{\rho_j} \left(W_i^S\right)^{-1} \kappa_j - (1+\rho_j)\left(W_i^S\right)^{\rho_j} \kappa_j\right] = 0.$$

Substituting in $L_{ij}^S = \left(W_{ij}^S\right)^{\rho_j} \kappa_j$, this becomes

$$\implies \sum_{j \in N} \left[P_j^S A_{ij}^S F'(L_{ij}^S) \rho_j \left(W_i^S\right)^{-1} L_{ij}^S - (1+\rho_j) L_{ij}^S\right] = 0$$

$$\implies \sum_{j \in N} \left[P_j^S A_{ij}^S F'(L_{ij}^S) \rho_j \left(W_i^S\right)^{-1} L_{ij}^S\right] = \sum_{j \in N} \left[(1+\rho_j) L_{ij}^S\right]$$

$$
\begin{aligned}
\implies W_i^S &= \sum_{j\in N} \frac{\rho_j L_{ij}^S}{\sum_{k\in N}\left[(1+\rho_k)\, L_{ik}^S\right]} P_j^S A_{ij}^S F'(L_{ij}^S) \\
&= \sum_{j\in N} \frac{(1+\rho_j)\, L_{ij}^S}{\sum_{k\in N}\left[(1+\rho_k)\, L_{ik}^S\right]} \frac{\rho_j}{1+\rho_j} P_j^S A_{ij}^S F'(L_{ij}^S) \\
&= \sum_{j\in N} \omega_{ij} \frac{\rho_j}{1+\rho_j} P_j^S A_{ij}^S F'(L_{ij}^S),
\end{aligned}
$$

where $\omega_{ij} = (1+\rho_j)\, L_{ij}^S / \sum_{k\in N}\left[(1+\rho_k)\, L_{ik}^S\right]$. We have derived equation (5) from the main text.

C1.2 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

$$
W_{ij} = \frac{\rho_j}{1+\rho_j} P_j A_{ij}\,(1-\alpha)\, L_{ij}^{-\alpha}
$$

and from the labor supply equation (1) we have

$$
L_{ij} = W_{ij}^{\rho_j} \tilde{P}_j^{-\eta} \tilde{\kappa}_j \quad \tilde{\kappa}_j \equiv \left(\sum_{k\in M} W_{kj}^{\rho_j}\right)^{\frac{\eta-\rho_j}{\rho_j}} \kappa.
$$

Substituting equation (1) into (3) implies

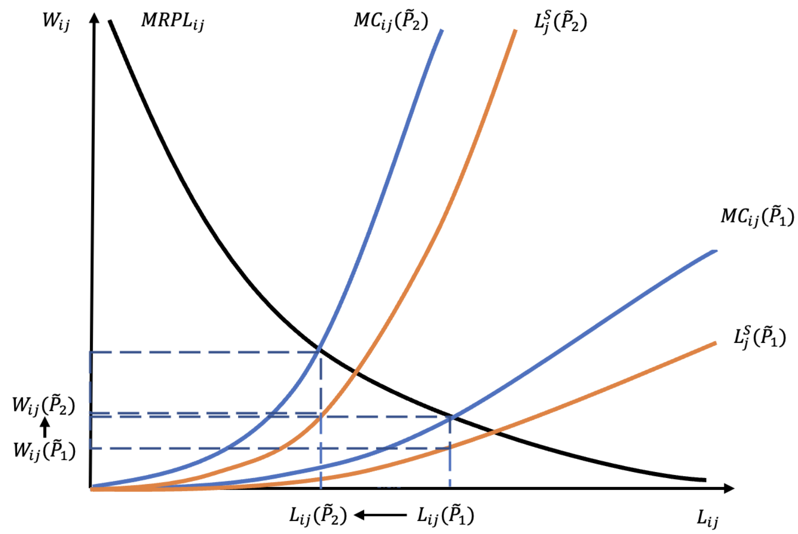
$$
\begin{aligned}
W_{ij} &= \frac{\rho_j}{1+\rho_j} P_j A_{ij}\,(1-\alpha)\left(W_{ij}^{\rho_j} \tilde{P}_j^{-\eta} \tilde{\kappa}_j\right)^{-\alpha} \\
&= \frac{\rho_j}{1+\rho_j} P_j A_{ij}\,(1-\alpha)\, W_{ij}^{-\alpha\rho_j} \tilde{P}_j^{\alpha\eta} \tilde{\kappa}_j^{-\alpha}
\end{aligned}
$$

$$
\implies W_{ij}^{1+\alpha\rho_j} = \frac{\rho_j}{1+\rho_j} P_j A_{ij}\,(1-\alpha)\, \tilde{P}_j^{\alpha\eta} \tilde{\kappa}_j^{-\alpha}
$$

$$
\begin{aligned}
\implies W_{ij} &= \left[\frac{\rho_j}{1+\rho_j} P_j A_{ij}\,(1-\alpha)\, \tilde{P}_j^{\alpha\eta} \tilde{\kappa}_j^{-\alpha}\right]^{\frac{1}{1+\alpha\rho_j}} \\
&= \left[\frac{\rho_j}{1+\rho_j} P_j A_{ij}\,(1-\alpha)\, \tilde{\kappa}_j^{-\alpha}\right]^{\frac{1}{1+\alpha\rho_j}} \tilde{P}_j^{\frac{\alpha\eta}{1+\alpha\rho_j}}.
\end{aligned}
$$

We now consider a partial equilibrium exercise, in which we study the response of establishment wages

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 $\tilde{P}_2$.

W_{ij} to a change in local consumer prices $\tilde{P}_j$, holding other variables fixed. We have

$$\log W_{ij} = \frac{1}{1+\alpha\rho_j} \log\left[\frac{\rho_j}{1+\rho_j} P_j A_{ij} (1-\alpha) \tilde{\kappa}_j^{-\alpha}\right] + \frac{\alpha\eta}{1+\alpha\rho_j} \log \tilde{P}_j$$

$$\implies \frac{\partial \log W_{ij}}{\partial \log \tilde{P}_j} = \frac{\alpha\eta}{1+\alpha\rho_j} \geq 0$$

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.

C1.3 Endogenizing the Share of National Wage Setters

This subsection considers a two stage game that endogenizes $\mathcal{N}$, the share of wage setters subject to rigidity. We allow firms to choose whether to set national wages. If firms choose to set national wages, they receive a productivity benefit, which they balance against the cost of paying the same nominal wage across all their labor markets. We show that when the productivity benefits of national wage setting are at an moderate level, some firms will find national wage setting optimal and others will prefer local wage setting. In equilibrium, there can be a mix of national and local wage setters as is the case in the data.

C1.3.1 Model Setup

Consider the following stage game that extends our baseline model.

- **Stage 1.** Firms draw a *national wage setting shock* A_{iF}, from a continuous distribution with mean μ_F and support $\left[\underline{A}, \overline{A}\right]$. Then firms choose whether to be national or local wage setters. If firms choose to be national wage setters, then their productivity increases by a factor A_{iF}, but they must pay the same nominal wage everywhere. Otherwise, firms choose to be local wage setters. They can pay different wages in different regions, but forgo the productivity gain of national wage setting.
- **Stage 2**. Depending on their choice in Stage 1, firms are either national or local wage setters. Then firms set wages as in our benchmark model. For brevity, we do not repeat the model equations here. We make three simple modifications of the benchmark model for this extension. First, we assume $P_j = 1,$ i.e. prices are fixed. Second, we assume there is a unit mass of firms, instead of a discrete number as in the main section. Third, we assume that the labor supply elasticity to the establishment, ρ_j, does not vary across regions.

We solve for the subgame perfect equilibrium of this two stage game and study properties of the equilibrium share of national wage setters $\mathcal{N}^*$.

C1.3.2 Discussion

In this extension, firms choose whether to set rigid wages given a trade-off. They may increase their productivity, and hence their profits, by setting wages nationally. But firms may also lose profits because they must set the same wage in all labor markets while conditions differ. Alternatively, firms can tailor wages in each labor market to forgo this trade-off. Firms with high values of the national wage setting shock will find national wage setting more attractive.

Consider some examples of factors behind the national wage setting shock. Firms could be motivated to set national wages in order to improve morale from internal equity and therefore raise productivity across the firm. Alternatively, firms might attract higher quality workers from occupations that "set wages nationally". These high quality workers would be averse to taking nominal pay cuts to work in low nominal wage regions but would accept jobs that pay the same nominal wage as in higher nominal wage regions. Finally, firms might enjoy a reduction in costs—isomorphic to a productivity gain—from only employing human resource workers in their headquarters. However, these firms would then have to pay the same nominal wage everywhere—even in the low nominal wage regions.

This model is consistent with our empirical facts 2 and 5**:**

- **Fact 2: Identical wages are a characteristic of occupations within firms** National wage setters pay the same nominal wage across all establishments, local wage setters can vary nominal wages across establishments.
- **Fact 4: Firms setting identical wages pay a wage premium.**. If $\mu_F > 1$ (on average there is a productivity gain from national wage setting), then national wage setters will pay a premium.

C1.3.3 Proposition and Discussion

Proposition. *For all values $\mathcal{N}^* \in (0,1)$, there exists a value of μ_N such that $\mathcal{N}^*$ is the equilibrium outcome.*

This proposition shows that for any given fraction of firms setting wages nationally $\mathcal{N}$, there exists a productivity gain from national wage setting that leads to $\mathcal{N}$ as an equilibrium outcome.

Intuitively, firms balance the productivity gains from adopting national wage setting against the costs of setting the same wage everywhere. Of course, if the gains from national wage setting are massive or tiny for all firms, either all or none of the firms will choose to be national wage setters.

But suppose that the value of μ_F is intermediate. Then some firms will be nearly indifferent between national and local wage setting. At the market level, different firms will choose either form of wage setting. Firms with a high value of the "national wage setting shock" will find it optimal to set wages nationally. Firms with a low value of this shock will set wages locally. So, with an intermediate value of μ_F, there can be a mix of national and local wage setters, as in our empirics. As μ_F grows, but remains in an intermediate range, the equilibrium share of national wage setters will also grow.

Proof available on request.

C1.4 Change in Profits due to National Wage Setting

This subsection uses the simple model of Section 2, to calculate change in establishment profits due to national wage setting. We calculate this change under three assumptions: (i) constant returns to scale in labor, (ii) decreasing returns to scale in labour, and (iii) decreasing returns to scale with rationing by labor demand. In the process, we show that models with fully variable or fully fixed capital are isomorphic to our model with either constant or decreasing returns to scale.

C1.4.1 Change in Profits with Constant Returns to Scale

To simplify the algebra, assume: $A_{ij} = A_i A_j$, and define the labor supply curve, equation (1), as $L_{ij} = \kappa_j W_{ij}^{\rho}$, where $\kappa \equiv \tilde{P}_j^{-\eta} \left(\sum_{k \in M} W_{kj}^{\rho_j}\right)^{\frac{\eta-\rho_j}{\rho_j}} \kappa$. Finally assume constant returns to scale in production, so that we have $Y_{ij} = A_i A_j L_{ij}$. Appendix Section C1 shows that the optimal counterfactual wage, absent national wage setting, is

$$W_{ij}^* = \frac{\rho}{1+\rho} A_i A_j.$$

In general, establishment profits are

$$\Pi_{ij} = A_i A_j L_{ij} - W_{ij} L_{ij} = \left(A_i A_j - W_{ij}\right) \kappa_j W_{ij}^{\rho}.$$

Therefore profits under local wage setting are

$$\Pi_{ij}^* = \left(A_i A_j - W_{ij}^*\right) \kappa_j W_{ij}^{*\rho}$$

and profits under national wage setting are

$$\Pi_{ij}^c = \left(A_i A_j - \bar{W}_i\right) \kappa_j \bar{W}_i^{\rho}.$$

With some simple algebra, the change in profits is

$$\frac{\Pi_{ij}^* - \Pi_{ij}^c}{\Pi_{ij}^*} = 1 - \frac{\left(A_i A_j \bar{W}_i^{\rho} - \bar{W}_i^{\rho+1}\right)}{\left(A_i A_j W_{ij}^{*\rho} - W_{ij}^{*\rho+1}\right)}. \tag{13}$$

We can rewrite establishment TFP in terms of wages, using

$$W_{ij}^* = \frac{\rho}{1+\rho} A_i A_j \implies A_i A_j = W_{ij}^* \frac{1+\rho}{\rho}. \tag{14}$$

We can substitute equation (14) into equation (13) to get

$$\begin{aligned}
\frac{\Pi_{ij}^* - \Pi_{ij}^c}{\Pi_{ij}^*} &= 1 - \frac{\left(W_{ij}^* \frac{1+\rho}{\rho} \bar{W}_i^{\rho} - \bar{W}_i^{\rho+1}\right)}{\left(W_{ij}^* \frac{1+\rho}{\rho} W_{ij}^{*\rho} - W_{ij}^{*\rho+1}\right)} \\
&= 1 - (1+\rho)\left(\frac{\bar{W}_i}{W_{ij}^*}\right)^{\rho} - \rho \left(\frac{\bar{W}_i}{W_{ij}^*}\right)^{1+\rho},
\end{aligned}$$

which is equation (10) from the main text.

C1.4.2 Change in Profits with Decreasing Returns to Scale

Now, suppose that the establishment production function has decreasing returns to scale

$$Y_{ij} = A_i A_j \bar{K}^{\alpha} L_{ij}^{1-\alpha}$$

where $\bar{K}$ is a fixed, exogenous constant, which may represent a fixed stock of capital. Then the local wage setter solves

$$\max_{W_{ij},L_{ij}} A_i A_j \bar{K}^{\alpha} L_{ij}^{1-\alpha} - W_{ij} L_{ij}$$

$$= \max_{W_{ij}} A_i A_j \bar{K}^{\alpha} \left(\kappa_j W_{ij}^{\rho}\right)^{1-\alpha} - \kappa_j W_{ij}^{1+\rho},$$

where the second line substitutes in the establishment's labor supply curve. The first order condition is

$$A_i A_j \bar{K}^{\alpha} (1-\alpha) \left(\kappa_j W_{ij}^{\rho}\right)^{-\alpha} \kappa_j \rho W_{ij}^{\rho-1} - (1+\rho) \kappa_j W_{ij}^{\rho} = 0$$

$$\implies W_{ij}^{*1+\alpha\rho} \frac{1+\rho}{\rho} \frac{1}{1-\alpha} \kappa_j^{\alpha} = A_i A_j \bar{K}^{\alpha}. \tag{15}$$

Profits under optimality for the local wage setter are then

$$\Pi_{ij}^{*} = A_i A_j \bar{K}^{\alpha} \left(\kappa_j W_{ij}^{*\rho}\right)^{1-\alpha} - \kappa_j W_{ij}^{*1+\rho}$$

$$\begin{aligned} \implies \Pi_{ij}^{*} &= W_{ij}^{*1+\alpha\rho} \frac{1+\rho}{\rho} \frac{1}{1-\alpha} \kappa_j^{\alpha} \left(\kappa_j W_{ij}^{*\rho}\right)^{1-\alpha} - \kappa_j W_{ij}^{*1+\rho} \\ &= \left[W_{ij}^{*1+\alpha\rho} \frac{1+\rho}{\rho} \frac{1}{1-\alpha} W_{ij}^{*\rho(1-\alpha)} - W_{ij}^{*1+\rho} \right] \kappa_j, \end{aligned}$$

where we have used equation (15) in the second line. Profits under national wage setting are

$$\Pi_{ij}^{c} = A_i A_j \bar{K}^{\alpha} L_{ij}^{1-\alpha} - \bar{W}_i L_{ij}$$

$$\begin{aligned} \implies \Pi_{ij}^{c} &= A_i A_j \bar{K}^{\alpha} \left(\kappa_j \bar{W}_i^{\rho}\right)^{1-\alpha} - \kappa_j \bar{W}_i^{1+\rho} \\ &= \left[W_{ij}^{*1+\alpha\rho} \frac{1+\rho}{\rho} \frac{1}{1-\alpha} \bar{W}_i^{\rho(1-\alpha)} - \bar{W}_i^{1+\rho} \right] \kappa_j, \end{aligned}$$

where again we have used equation (15) in the second line. Then the difference in profits due to national wage setting are

$$\begin{aligned} \frac{\Pi_{ij}^{*} - \Pi_{ij}^{c}}{\Pi_{ij}^{*}} &= 1 - \frac{\Pi_{ij}^{c}}{\Pi_{ij}^{*}} \\ &= 1 - \frac{W_{ij}^{*1+\alpha\rho} \frac{1+\rho}{\rho} \frac{1}{1-\alpha} \bar{W}_i^{\rho(1-\alpha)} - \bar{W}_i^{1+\rho}}{W_{ij}^{*1+\alpha\rho} \frac{1+\rho}{\rho} \frac{1}{1-\alpha} W_{ij}^{*\rho(1-\alpha)} - W_{ij}^{*1+\rho}}, \end{aligned} \tag{16}$$

Note that this calculation does not depend on $\bar{K}$, hence, our estimates of the change in profits with decreasing returns to scale do not depend on the level of fixed capital.

C1.4.3 Change in Profits with Rationing

In this section, we will allow establishments to ration labor according to labor demand, when labor supply exceeds labor demand. We have

$$\Pi_{ij}^{*} = A_i A_j L_{ij}^{*1-\alpha} - W_{ij}^{*} L_{ij}^{*}$$

which implies

$$MRPL\left(L_{ij}\right) = A_i A_j \left(1-\alpha\right) L_{ij}^{*-\alpha},$$

where $MRPL$ stands for the nominal marginal revenue product of labor. Then we know that local wage setters set optimal wages as a markdown of marginal revenue product, which implies

$$\begin{aligned} W_{ij}^{*} &= \frac{\rho}{1+\rho} MRPL\left(L_{ij}^{*}\right) \\ &= \frac{\rho}{1+\rho} A_i A_j \left(1-\alpha\right) L_{ij}^{*-\alpha} \end{aligned}$$

$$\implies \left(\frac{1+\rho}{\rho} W_{ij}^{*} \frac{1}{A_i A_j \left(1-\alpha\right)}\right) = L_{ij}^{*-\alpha}$$

$$\implies L_{ij}^{*} = \left(\frac{1+\rho}{\rho} W_{ij}^{*} \frac{1}{A_i A_j \left(1-\alpha\right)}\right)^{-\frac{1}{\alpha}}.$$

Therefore profits for local wage setters are

$$\begin{aligned} \Pi_{ij}^{*} &= A_i A_j L_{ij}^{*1-\alpha} - W_{ij}^{*} L_{ij}^{*} \\ &= \left(A_i A_j\right)^{\frac{1}{\alpha}} \left[\left(\frac{1+\rho}{\rho} W_{ij}^{*} \frac{1}{\left(1-\alpha\right)}\right)^{-\frac{1-\alpha}{\alpha}} - W_{ij}^{*} \left(\frac{1+\rho}{\rho} W_{ij}^{*} \frac{1}{\left(1-\alpha\right)}\right)^{-\frac{1}{\alpha}}\right]. \end{aligned}$$

Temporarily, suppose that the establishment has a national wage $\bar{W}_i$, and rations employment according to labor demand. Then the establishment has employment L_{ij} satisfying

$$\bar{W}_i = MRPL\left(L_{ij}\right)$$

$$\implies \bar{W}_i = A_i A_j \left(1-\alpha\right) L_{ij}^{-\alpha}$$

$$\implies L_{ij} = \left(\frac{\bar{W}_i}{\left(1-\alpha\right) A_i A_j}\right)^{-\frac{1}{\alpha}},$$

which implies profits under rationing are

$$\begin{aligned}
\Pi_{ij}^R &= A_i A_j L_{ij}^{1-\alpha} - \bar{W}_{ij} L_{ij} \\
&= (A_i A_j)^{\frac{1}{\alpha}} \left[\left(\frac{\bar{W}_i}{(1-\alpha)} \right)^{-\frac{1-\alpha}{\alpha}} - \bar{W}_{ij} \left(\frac{\bar{W}_i}{(1-\alpha)} \right)^{-\frac{1}{\alpha}} \right].
\end{aligned}$$

Then the percentage difference between Π_{ij}^R and Π_{ij}^* is

$$\begin{aligned}
\frac{\Pi_{ij}^R}{\Pi_{ij}^*} &= \frac{(A_i A_j)^{\frac{1}{\alpha}} \left[\left(\frac{\bar{W}_i}{(1-\alpha)} \right)^{-\frac{1-\alpha}{\alpha}} - \bar{W}_{ij} \left(\frac{\bar{W}_i}{(1-\alpha)} \right)^{-\frac{1}{\alpha}} \right]}{(A_i A_j)^{\frac{1}{\alpha}} \left[\left(\frac{1+\rho}{\rho} W_{ij}^* \frac{1}{(1-\alpha)} \right)^{-\frac{1-\alpha}{\alpha}} - W_{ij}^* \left(\frac{1+\rho}{\rho} W_{ij}^* \frac{1}{(1-\alpha)} \right)^{-\frac{1}{\alpha}} \right]} \\
&= \frac{\bar{W}_i^{-\frac{1-\alpha}{\alpha}} \left(\frac{1}{(1-\alpha)} \right)^{-\frac{1}{\alpha}} \left[\left(\frac{1}{(1-\alpha)} \right)^{1-\alpha} - 1 \right]}{W_{ij}^{*-\frac{1-\alpha}{\alpha}} \left(\frac{1+\rho}{\rho} \frac{1}{(1-\alpha)} \right)^{-\frac{1}{\alpha}} \left[\left(\frac{1+\rho}{\rho} \frac{1}{(1-\alpha)} \right)^{1-\alpha} - 1 \right]}.
\end{aligned}$$

Define the wage at which the establishment's labor demand and labor supply intersect by $\tilde{W}_i$. The establishment will ration labor if $\bar{W}_i > \tilde{W}_i$, i.e. labor supply exceeds labor demand at the nationally set wage. Hence the establishment will have a profit change $\frac{\Pi_{ij}^R}{\Pi_{ij}^*}$ in this region, and otherwise will have a profit change $\frac{\Pi_{ij}^c}{\Pi_{ij}^*}$ as defined in equation (16).

We cannot directly measure $\tilde{W}_i$ without further assumptions on both $A_i A_j$, the parameters of labor demand, and of κ_j, the parameters of labor supply. We cannot easily measure these parameters. Therefore we approximate $\tilde{W}_i$ as $\tilde{W}_i = W_i^* \frac{1+2\rho}{2\rho}$. This approximation is exactly correct when the labor supply and labor demand curves have the same magnitude slope in the region of $\tilde{W}_i$.

C1.4.4 Model with Variable Capital

We now introduce variable capital into our model, and show that the change in profits due to national wage setting is isomorphic. This model leads to an identical counterfactual calculation to the model without capital. In particular, suppose that we have output

$$Y_{it} = A_i A_j K_{ij}^{\alpha} L_{ij}^{1-\alpha}$$

and labor supply curve

$$L_{ij} = \kappa_j W_{ij}^{\rho},$$

where K_{ij} is rented at cost r and κ_j is defined by equation (1). Then the local wage setter solves

$$\max_{W_{ij}, L_{ij}, K_{ij}} A_i A_j K_{ij}^{\alpha} L_{ij}^{1-\alpha} - W_{ij} L_{ij} - r K_{ij}$$

The first order condition with respect to capital is

$$A_i A_j \alpha K_{ij}^{\alpha-1} L_{ij}^{1-\alpha} - r = 0$$

$$\implies K_{ij}^{*} = \left(\frac{\alpha A_i A_j}{r}\right)^{\frac{1}{1-\alpha}} L_{ij}.$$

Then we can rewrite the local wage setter's problem as

$$\max_{W_{ij}, L_{ij}} A_i A_j K_{ij}^{*\alpha} L_{ij}^{1-\alpha} - W_{ij} L_{ij} - r K_{ij}^{*}$$

$$= \max_{W_{ij}, L_{ij}} \left((A_i A_j)^{\frac{1}{1-\alpha}} \left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha}} - \left[W_{ij} + r^{-\frac{\alpha}{1-\alpha}} (\alpha A_i A_j)^{\frac{1}{1-\alpha}} \right] \right) L_{ij}$$

so profits under optimality are

$$\left((A_i A_j)^{\frac{1}{1-\alpha}} \left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha}} - \left[W_{ij}^{*} + r^{-\frac{\alpha}{1-\alpha}} (\alpha A_i A_j)^{\frac{1}{1-\alpha}} \right] \right) \kappa_j W_{ij}^{*\rho}.$$

Then note that the optimal wage is

$$\frac{d}{dW_{ij}^{*}} \left((A_i A_j)^{\frac{1}{1-\alpha}} \left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha}} - \left[W_{ij}^{*} + r^{-\frac{\alpha}{1-\alpha}} (\alpha A_i A_j)^{\frac{1}{1-\alpha}} \right] \right) \kappa_j W_{ij}^{*\rho} = 0$$

$$\implies \frac{1+\rho}{\rho} W_{ij}^{*} = \left((A_i A_j)^{\frac{1}{1-\alpha}} \left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha}} - r^{-\frac{\alpha}{1-\alpha}} (\alpha A_i A_j)^{\frac{1}{1-\alpha}} \right).$$

The corresponding problem for the establishment of a national wage setter is

$$\max_{L_{ij}, K_{ij}} A_i A_j K_{ij}^{\alpha} L_{ij}^{1-\alpha} - \bar{W}_{ij} L_{ij} - r K_{ij}.$$

The first order condition for the national wage setter is

$$A_i A_j \alpha K_{ij}^{\alpha-1} L_{ij}^{1-\alpha} - r = 0$$

$$\implies K_{ij}^{*} = \left(\frac{\alpha A_i A_j}{r}\right)^{\frac{1}{1-\alpha}} L_{ij}$$

which simplifies the problem to

$$\max_{L_{ij}, K_{ij}} A_i A_j K_{ij}^{\alpha} L_{ij}^{1-\alpha} - \bar{W}_{ij} L_{ij} - r K_{ij}$$

$$= \max_{L_{ij}} (A_i A_j)^{\frac{1}{1-\alpha}} \left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha}} L_{ij} - \left[\bar{W}_{ij} + r^{-\frac{\alpha}{1-\alpha}} (\alpha A_i A_j)^{\frac{1}{1-\alpha}} \right] L_{ij}.$$

Therefore profits with national wage setting are

$$\left((A_i A_j)^{\frac{1}{1-\alpha}} \left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha}} - \left[\bar{W}_{ij} + r^{-\frac{\alpha}{1-\alpha}} \left(\alpha A_i A_j\right)^{\frac{1}{1-\alpha}} \right] \right) \kappa_j \bar{W}_{ij}^{\rho}.$$

The profit loss is then

$$\begin{aligned} \frac{\Pi_{ij}^{*} - \Pi_{ij}^{c}}{\Pi_{ij}^{*}} &= 1 - \frac{\Pi_{ij}^{c}}{\Pi_{ij}^{*}} \\ &= 1 - \frac{\left(\frac{1+\rho}{\rho} W_{ij}^{*} - \bar{W}_{ij}\right) \bar{W}_{ij}^{\rho}}{\left(\frac{1+\rho}{\rho} W_{ij}^{*} - W_{ij}^{*}\right) W_{ij}^{*\rho}}, \end{aligned}$$

which is identical to the case without capital and constant returns to scale.

C1.5 Model Extension with Endogenous Entry

This subsection considers an extension of our model with endogenous entry, in order to study how national wage setting affects establishments' entry decisions. We find that if national wage setters are sufficiently more productive than local wage setters, then they will enter all locations. This result is consistent with the descriptive findings from Section 4 that (i) national wage setters pay higher wages and have higher productivity than local wage setters, and (ii) national wage setters tend to enter similar areas to local wage setters.

The intuition is that when national wage setters have sufficiently high productivity, they can afford to pay higher wages than local wage setters in all regions, even those with very high wages, and still make a profit. Therefore they enter everywhere.

C1.5.1 Model Setup

We augment the baseline model by modelling entry into each region. National and local wage setters must pay a fixed cost F to have positive employment in an establishment/region. National wage setters must only set identical wages across establishments with positive employment. There is a fixed measure $\mathcal{N}$ of national wage setters. There is a large measure $\mathcal{L}$ of local wage setters in each region (large enough to exhaust ex ante profits for local wage setters).

We also simplify the baseline model along several dimensions. These assumptions are innocuous and simplify the algebra. The simplifications are: (i) no worker mobility across regions (ii) all production is non-tradeable (iii) there is constant returns to scale in establishment employment (iv) establishment productivity is A_{Lj} for all local wage setters in region j, and $A_N A_j$ for all national wage setters in region j (v) the labor supply elasticity is the same everywhere (vi) regions are "small" within the country in the sense that wage changes in an individual region have a negligible effect on the aggregate wage index.

With these assumptions, the problem for the national wage setter is

$$\max_{W_i, L_{ij}} \sum_{j \in N} \left[A_N A_j L_{ij} - W_i L_{ij} - F\right] \times I\left(L_{ij} > 0\right)$$

where $I\left(L_{ij} > 0\right)$ is an indicator variable for whether the establishment has positive employment in region j, F is a fixed cost of entry into the region. The national wage setter can choose to operate only in a subset of establishments. Though their wage does not vary across establishments it must only be equal across the establishments with positive employment.

The local wage setter's problem is the same as in our baseline model, i.e. they set wages

$$W_{ij}^{*} = \frac{\rho}{\rho + 1} A_{ij},$$

if they choose to operate an establishment in region j, which requires a fixed cost of entry F.

C1.5.2 Result

Proposition. *In the equilibrium of the model, national wage setters have positive employment in all regions, so* $L_{ij} > 0$ *for all* j*, if (i)* A_{Lj} *is sufficiently small in all regions* j *and (ii)* ρ *is sufficiently small.*

The interpretation of this result is that national wage setters will operate in every region provided they have a sufficiently large productivity advantage over local wage setters in all regions, as well as an appropriate degree of labor market power.

The intuition for the result is as follows. Condition (i) is intuitive. Suppose that A_N is much larger than A_L. Then national wage setters have a productivity advantage relative to local wage setters. Therefore they can pay higher wages than local wage setters in all markets, even those with very high wages, and employ enough workers to make profits everywhere. Therefore they will enter all markets because they can "out compete" local wage setters everywhere.

Condition (ii) is less obvious. This condition requires markdowns to be "large enough". Why? For national wage setters to enter everywhere, we need them to make profits even in regions with low productivity, since they must pay a relatively high wage in these regions. National wage setters can still make a profit in low productivity regions provided they have large enough markdowns on workers' marginal product, to compensate for the low regional productivity.

Proof available on request.