National Wage Setting*

Jonathon Hazell
LSE

Christina Patterson
Chicago Booth & NBER

Heather Sarsons
UBC & NBER

Bledi Taska
Burning Glass Technologies

March 2024

Abstract

How do firms set wages across space? We document four facts using job-level vacancies and matched employer-employee data. First, firms rather than locations explain most of the variation in wages within a job. Second, nominal wages within the firm vary little with local prices. Third, firms most strongly influence wage growth across locations. Fourth, local wage shocks impact wages in the rest of the firm, but only for jobs that initially pay identical wages. We argue these patterns indicate *national wage setting*, in which firms choose to set the same nominal wage for a job across all their establishments.

JEL Codes: J24, J45, J33, H56

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

1 Introduction

In the U.S., big firms have grown in large part by expanding into new regions (Hsieh and Rossi-Hansberg, 2021). As a result, local labor markets have become dominated by a small number of large firms that operate in many regions. Therefore, while the concentration of employment across firms in local labor markets has fallen in recent decades, the concentration of employment nationally has risen (Autor 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 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 that integrates standard models of imperfect labor market competition and spatial equilibrium. In the 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 local labor market conditions. We then show, empirically, that a large minority of firms are best characterized as national wage setters.

We establish this result using two datasets that measure wages with firm, occupation, and location information. The first is a dataset containing 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 approximately 3% of Burning Glass, or 2% of total US vacancies, that provide posted point wages for detailed occupations with firm and location information.[1] The second is a merge between the Longitudinal Employer-Household Dynamics (LEHD), a linked employer-employee database sourced from state unemployment insurance programs in 27 states; and the American Community Survey (ACS), a large representative survey of U.S. households.

Each dataset provides a distinct advantage in identifying national wage setting. Burning Glass provides detailed information on occupations; and measures hourly wages for non-salaried workers and annual wages for salaried workers, allowing us to distinguish between wages and earnings (i.e. the

[1] We define an occupation as the occupation's 6-digit SOC code, combined with the pay frequency of the job (e.g. annual or hourly), full-time/part-time status, 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.

product of wages and hours worked). Most administrative datasets lack these features. However, we only see firms that post wages, raising concerns about sample selection and differences between posted and realized wages. The LEHD linked with the ACS (LEHD-ACS) measures quarterly earnings for workers in the same occupation but different locations of the same firm. There is some information on hours worked but it is limited, meaning a noisier measure of wages. That said, the LEHD-ACS contains a nationally representative sample of firms, avoiding selection concerns; and measures realized earnings and wages for both continuing workers as well as new hires. We supplement our analysis with a third dataset of worker-level wage information provided in Labor Condition Applications (LCAs). LCAs are mandatory reports that firms applying for select visas for foreign workers, such as the H1B visa, fill. These data contain salaries, net of hours, as well as occupation, location, and firm information. The chief advantage of this dataset is a measure of post bargaining salaries, which is not contaminated by hours worked. Lastly, we fielded a survey of human resources (HR) managers and executives, and asked questions about how firms set wages and why they adopt their wage setting policy.

We document four facts about wage setting across space that together indicate national wage setting. First, we show substantial compression in the level of wages within firms across space. Using both the LEHD-ACS and Burning Glass, we find that the clear majority of variation in wages for a given job is explained by the firm rather than geographic location. Furthermore, using Burning Glass we find that wage compression concentrates in a subset of jobs and locations paying identical wages— 40-50% of vacancy postings for the same job in the same firm, but in different locations, pay exactly the same wage.[2] Second, we show in both datasets that wages within the firm and across locations are relatively insensitive to local prices. This insensitivity holds even when firms operate in regions with a wide range of prices, for a variety of occupations and industries, and for both new and incumbent workers. The implied degree of national wage setting is similar across the two datasets. Third, in both datasets, wage *growth* is more strongly influenced by firm-level factors than by geographic factors. Fourth, to rule out explanations for wage compression other than national wage setting, we study the pass through of local wage shocks into the rest of the firm in Burning Glass. After shocks to wages in a single location, jobs that initially set identical wages in Burning Glass—whom we hypothesize to be national wage setters—increase wages in their other unaffected establishments. By studying local wage shocks, we avoid confounding factors

[2]This statistic is less meaningful in the LEHD-ACS given its noisier measure of wages.

such as firm-wide productivity shocks, which could lead wage growth to comove within the firm even in the absence of national wage setting. Comparing across our facts and datasets, we conservatively estimate that 40% of multi-establishment firms set wages nationally.

We then attempt to explain when and why national wage setting occurs. Using the Burning Glass data, we find that geographic and firm-level factors are weak predictors of national wage setting. In fact, national wages are a characteristic of specific jobs within firms, meaning that a firm will set a national wage for some jobs but not all. However, these jobs are paid a national wage in *all* of the firm's locations. Jobs with national wages are paid a premium over similar jobs without national wages, even in high wage labor markets. We supplement these findings with our survey of HR professionals. We find suggestive evidence that firms are more likely to engage in national wage setting when workers are mobile (hired on a national market), when firms have fairness norms that constrain nominal wages, and when it may be beneficial for productivity and profits, such as by reducing managerial costs.

We also find that firms set national wages even though there are profits at stake. We carry out a suggestive, model-based exercise with Burning Glass data. 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 a brief discussion of the consequences of geographic wage compression on aggregate wage inequality. A back-of-the-envelope exercise suggests national wage setting reduces aggregate nominal wage inequality by roughly 5%, through compressing nominal wages across space.

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.[3] We complement these papers by studying wage setting instead of price setting, by studying the entire economy beyond the specific

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

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., 2022; Jarosch et al., 2019).[4] National wage setting policies are another reason why different firms may pay workers performing the same job in the same location different wages. As such, our paper contributes to growing evidence that firms' wage policies are hard to reconcile with fine-grained optimization (Dube et al., 2020; Cullen et al., 2022).

Several recent papers share our specific focus on how pay varies within firms and 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 wage setting and highlight reasons why a particular subset of firms sets wages nationally.[5]

2 A Simple Framework for Wage Setting Across Space

We begin with a simple framework to clarify how firms set wages across space. We recover a standard result: firms set identical wages across space only if the product of markdowns and the marginal revenue product of labor is the same across establishments. We then define a concept of national wage setting.

Since our model ingredients are standard, we outline them in the main text and leave the formal details to Appendix Section C1.1. There are R regions, and a unit measure of workers. Each region

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

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

contains a discrete number of firms, who hire workers in all regions, meaning that in region r, firm f operates an establishment.

Establishments have productivity A_{rf}, and pay a nominal wage W_{rf} to all their workers. Given employment L_{rf}, the establishment operates a decreasing returns to scale production function $F\left(L_{rf}\right)$ and produces non-tradeable and region specific output $A_{rf}F\left(L_{rf}\right)$, sold in a competitive market at a price P_r which varies by region. Establishment profits are

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

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

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

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

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

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

Therefore establishments set nominal wages as a markdown $\rho_r/(1+\rho_r)$ of nominal marginal revenue product $P_r A_{rf} F'\left(L_{rf}\right)$, where the markdown depends on the labor supply elasticity to the establishment.

Nominal marginal revenue product can vary due to workers' productivity A_{rf}, producer prices P_r, and the optimal scale of the firm, L_{rf}. Separate from producer prices, higher local consumer prices will also raise wages by causing workers to migrate out of the region, reducing labor supply to the region via the κ_r term in the labor supply equation (2), lowering L_{rf}, and thus raising the marginal revenue product.[6] In this simple framework, the markdown $\rho_r/(1+\rho_r)$ varies exogenously across regions, though richer models endogenize markdowns as a function of establishments' market share (Berger et al., 2022).

Equation (3) shows that firms pay the same nominal wage in two establishments if the establishments have the same product of marginal revenue product and markdown. Existing evidence suggests a great deal of dispersion in both productivity and local competition, meaning the benchmark model predicts meaningful wage dispersion within the firm.[7] Nevertheless, firms will not vary wages across space if the product of marginal revenue products and labor market power does not vary. For instance, certain firms with national span might have the same productivity and labor market power in all of their locations. Or, firms might sell purely tradeable goods.[8]

National Wage Setting. In the following sections, we will argue that the empirical evidence is inconsistent with the benchmark model for a substantial minority of firms. Instead, we will suggest that a fraction of firms set wages nationally. These firms must pay the same nominal wage W_f in all establishments, regardless of the revenue product or markdown of the establishment.[9] The constraint affects only a subset of firms, but affects all locations within these firms. The remaining firms, who we refer to as "local wage setters", behave as in the benchmark model.

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

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

[8]In Appendix Section C1.4 we extend the model to show that if labor market power does not vary across space, then purely tradeable firms (who aggregate output across establishments and sell to a national product market) pay the same wage in all locations.

[9]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 C1.7 we consider a specific model that determines the wage W_f, in which firms maximize profits subject to the constraint of setting equal wages everywhere.

3 Data Description

Our two main datasets are online vacancies from Burning Glass Technologies, and a merge between the Longitudinal Employer-Household Dynamics (LEHD) dataset and the American Community Survey (ACS). The LEHD is a linked employer-employee database sourced from state level unemployment insurance programs. The ACS is a large representative survey of households. Our main datasets provide us with posted wages (in Burning Glass) and realized earnings with some information on hours (in the LEHD-ACS), in both cases with occupation, firm, and location information. The datasets have complementary advantages that together address various measurement concerns. Posted wages in Burning Glass are not affected by hours worked, but suffer from selection concerns. Measures of occupations and wages are noisier in the LEHD-ACS, but there is no concern about sample selection. We supplement our main datasets with a survey of HR managers and executives and with wages from mandatory filings for foreign workers' visas.

3.1 Burning Glass Data

Our first main data source is a dataset of vacancies covering 2010-2019, with firm, occupation and location information. The dataset was developed by Burning Glass Technologies. Burning Glass collects data from roughly 40,000 company websites and online job boards, with no more than 5% of vacancies from any one source. They then apply a deduplication algorithm and convert the vacancies into a form amenable to data analysis. In total, Burning Glass covers around 70% of vacancies in the United States (Carnevale et al., 2014). However, only 3% of vacancies in Burning Glass, or approximately 2% of total US vacancies, include point wages and the other variables necessary for our analysis. 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.[10]

For those vacancies that include a wage, we have detailed information on the wage, including the pay frequency of the contract (e.g., whether pay is annual or hourly) and the type of salary (e.g. whether compensation includes a bonus). Appendix Table A3 shows that point wages are more likely to be posted at smaller firms, in occupations that have lower wages, and for vacancies with lower education

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

and experience requirements. In all cases the magnitudes are relatively modest—for instance, firms are 2.3 percentage points less likely to post a wage for occupations with wages 1 standard deviation above the mean.[11] These statistics suggest that the strategic posting of wages across locations is unlikely to meaningfully affect our estimates of national wage setting.

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, we see the firm name, industry, county, and occupation, which Burning Glass codes into a six-digit (SOC) occupation code.[12,13] We cleaned firm names using a deduplication procedure outlined in Appendix Section A1.1, and we define an establishment as a county-by-firm observation, aggregating observations within counties. Using this definition, 75% of employers only have vacancies within a single establishment in a given year, but among those firms with multiple locations, the average number of establishments is 8.6. In our Burning Glass analysis, we will use the term "occupation" to refer to the combination of the occupation, salary type, and pay frequency (e.g. pest control workers with hourly base pay) and the term "job" to refer to an occupation within a firm (e.g. a pest control worker with hourly base pay, within a specific company).[14]

Table 1 summarizes how the main sample that we use for the analysis changes with our restrictions. In addition to the restrictions discussed above, we exclude the public sector, military occupations and all jobs with commission pay. It is important to note that these restrictions lead to a very large reduction in sample size, which raises additional concerns about sample selection. Our main sample includes only those vacancies with non-missing wage, occupation, industry, and location information, in the private

[11] Appendix Table A3 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 consumer price level has a probability of posting that is lower by 0.06. Appendix Table A3 also indicates that there is no strong connection between firms being more likely to post wages in areas with a high cost of living.

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

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

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

Table 1: Summary Statistics on Sample Formation

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

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

sector, not in a military occupation, and without commission pay. This sample, in Row 4 of the table, is 2.8% of total Burning Glass vacancies. In Row 5, we collapse to have one observation per year in each establishment, occupation and pay group (e.g. hourly base pay) and take the average salary across vacancies.[15] In Appendix Figure 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.

Burning Glass is useful because it contains detailed occupations and wages, which are typically not observed in administrative datasets. However, there are two limitations. First, Burning Glass provides posted wages, which might differ from realized wages paid to workers. Second, the main Burning Glass sample only contains jobs that post point wages, raising selection concerns related to firms' decisions about whether to post wages.

We provide some tests to assuage these primary concerns. In Appendix Figure A3 and Appendix Tables A1 and A2 we show that Burning Glass wages closely track realized wages from official sources, at

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

a granular region-by-occupation level.[16] In particular, a region-by-occupation cell with a 1% higher wage in Burning Glass, also has approximately a 1% higher wage in official sources (1.06%-1.13% depending on the wage measure). If posted wages systematically differed from realized wages across certain locations or occupations, then one would expect a coefficient significantly different from 1. For instance, if posted wages tend to be similar in high and low wage regions, while realized wages differ greatly due to ex post bargaining, regressions would produce a coefficient far greater than 1.[17] We also show in Appendix Table A3 that within firms, selection into posting wages is uncorrelated with local prices, local high prices, or being in a "superstar city" like New York or San Francisco. Nevertheless, we stress that sample selection concerns are difficult to rule out completely and therefore we supplement this data with several additional data sources.

3.2 Longitudinal Employer-Household Dynamics and American Community Survey

Our second main dataset is a merge between the LEHD, a linked employer-employee dataset, and the ACS, a large survey of households. This merge contains realized earnings with firm, occupation, location and hours information, for a representative sample of workers from 2000-2019.

The LEHD is a census of workers covered by state unemployment insurance programs in 27 states.[18] State unemployment insurance covers roughly 95% of workers, and the states in our subsample of the LEHD covers 48% of total US employment. The LEHD measures workers' quarterly earnings, which are the product of total earnings per hour and hours worked. Earnings includes gross wages and salaries, bonuses, stock options, tips, other gratuities, and the value of meals and lodging. The LEHD contains a firm identifier, 6-digit NAICS industry information, and the estimated commuting zone where the

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

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

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

worker is employed.[19] Therefore, our notion of a region in the LEHD is a commuting zone. We define an establishment as a commuting zone-by-firm observation. Throughout the analysis, our baseline definition of a firm is the firm's EIN number.[20]

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

Merging the LEHD and ACS at the worker level thus produces a dataset of workers' quarterly earnings, usual weekly hours, occupation, location, and firm information. This combination of information is unique among currently available nationally representative administrative datasets within the United States.[21] We merge observations from the ACS to the LEHD in the quarter in which the household is surveyed. In all baseline specifications, we maximize our sample by assuming that the worker's occupation does not change within an employment spell. Specifically, while we link ACS respondents only to the LEHD in the quarter in which they are surveyed, we impute occupation for all quarters in which the worker stays in the same state and employer. We do not impose that the occupation remain constant once the worker transitions to another employer or state. In referring to the LEHD-ACS, we use "job" to refer to a firm by occupation (e.g. a pest control worker at a specific company). We call this merged sample the LEHD-ACS.

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

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

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

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

by the ACS at some point during their job spell. The second and third measures are available only for the quarter in which a worker from the LEHD is interviewed for the ACS.

We make several additional restrictions to form our main sample for analysis. First, we restrict attention to the fourth quarter of each year.[22] Second, we restrict to commuting zones for which we observe local prices (from the Bureau of Economic Analyis) and local house prices (from Zillow). This drops only small commuting zones and is consistent with the sample restrictions that we make in our analysis using the Burning Glass data. Third, to limit the influence of outliers, we drop workers whose quarterly earnings are above the 99th percentile in a given commuting zone by year. Fourth, we exclude workers in public administration (NAICS code beginning with 9). Fifth, we restrict to workers in firms with at least 2 establishments in our 27 state sample of the LEHD. Sixth, we restrict to workers who hold only 1 job in the month in which they are sampled in the ACS. This increases our confidence that the reported occupation corresponds to the matched job within the LEHD. Lastly, we exclude all workers in the ACS who do not report the usual hours that they work in a week or who report usually working 0 hours in a week; drop the first and last quarters of each worker's employment spell with each firm; and study workers who earn more than the full time federal minimum wage in any given quarter.

Table 2 shows several summary statistics for the main LEHD-ACS sample. Panel A shows the number of commuting zones, firms, occupations, or workers for the different subsamples we use throughout our analysis. Panel B presents worker-level demographic information.

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

The summary statistics suggest several points. First, firms in the LEHD-ACS matched sample of column (2) are bigger than in the overall LEHD sample in column (1), in terms of the number of estab-

[22]Since the identifying variation for the analysis comes from cross-worker comparisons, this restriction reduces the computational burden of the analysis while maintaining the maximal cross-sectional variation.

Table 2: Summary Statistics in the LEHD-ACS

	Panel A: Sample Information				
Sample:	10% of LEHD	Full LEHD-ACS	LEHD-ACS Subsample	Full LEHD-ACS ACS Quarters	LEHD-ACS Subsample ACS Quarters
	(1)	(2)	(3)	(4)	(5)
Number of CZ in Firm x Year in sample	3.41	2.19	1.59	2.95	2.80
Number of Firms	278,000	208,000	109,000	87,500	14,000
Number of CZ in Firm x Year in full LEHD	5.03	6.37	12.70	9.65	35.75
Number of workers	6,921,000	4,961,000	910,000	3,790,000	278,000
Total LEHD Employment in Firm x Year	150	200	750	450	3,500

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

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

lishments (Panel A, Row 3) and in terms of total employment (Panel A, Row 5). Second, the LEHD-ACS merged sample remains large in absolute terms—for instance, there are almost as many firms and workers in the merged sample, as in the 10% sample of the entire LEHD (Panel A, Row 4). Third, the LEHD-ACS sample is similar to the full LEHD in terms of workers' demographics and earnings. None of age, college education, earnings per worker or fame share differ greatly across the samples. Appendix Figure A4 shows the industry composition for the samples in Columns 1, 2 and 3 in Table 2. We see that the distributions are largely similar but slightly over-represent trade, transport, education and healthcare and under-represent information and finance.

There are two key advantages of the LEHD-ACS with respect to Burning Glass. First, the LEHD-ACS is close to being representative, being the product of administrative earnings records and a representative survey. The main LEHD-ACS sample differs from the full LEHD only by restricting to large multi-establishment firms and geographically dispersed occupations—necessary restrictions in order to focus on the population potentially affected by national wage setting. Second, the LEHD-ACS contains information about realized workers' wages and earnings, as opposed to posted wages, and therefore assuages concerns about selection and ex post negotiation of posted wages. However, the LEHD-ACS also has important limitations with respect to Burning Glass. Surveys like the ACS often code occupations with measurement error (e.g. Kambourov and Manovskii, 2013). Moreover the wage measures of the LEHD-ACS have limitations. Quarterly earnings (measured in the LEHD) contains variation in both hourly wages and hours worked. Weekly hours from survey data (measured in the ACS) typically includes measurement error (e.g. Bound and Krueger, 1991) and is only available for the LEHD in the quarters that match to the ACS.

3.3 Additional: Survey of HR Professionals and Labor Condition Application (LCA) Data

We supplement our main data sources with two additional datasets. The first is a survey 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. The HR association is one of the two largest in the United States, suggesting a broad sample of firms. However we note that the survey sample is skewed towards manufacturing, professional and scientific industries, and finance (Appendix Figure B2). For our analysis, we drop all respondents who work at firms operating in only one city, since we are interested in the behavior of firms that operate in multiple regions.[23] The majority of respondents are HR managers or executives who are directly involved in setting pay (Appendix Figure B3). More details on the sample and survey design are provided in Appendix Section B1 and the online survey appendix.

Our second supplementary dataset includes wages from Labor Condition Applications (LCAs) submitted to the Department of Labor (DOL). An LCA is a requirement for a firm's application for an H1-B, H1-B1, or E-3 visa. The goal of this document is to ensure that employers will pay the foreign worker at

[23]Our survey does not select only national firms, since 18% of respondents do not operate in multiple cities.

least the prevailing wage for the occupation in the area of employment. As such, employers are required to submit information about the worker (i.e. their occupation (6-digit SOC code), work location of the employee (state and county), and wage for the worker (either as range or as a point) as well as information about the prevailing wage for that specific job, which is defined by the DOL to be the average wage paid to similarly employed workers in a specific occupation in the area of intended employment. 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. We use data from 2010 to 2019. The program is large, with an average of 460,000 job applications per year, including both approved and unapproved applications. These jobs are highly concentrated in a subset of high-skill occupations.[24] However the jobs are geographically dispersed, with nearly 70% of primary worksites outside the 10 biggest cities in the U.S., and dominated by large firms.

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

4 Evidence for National Wage Setting

This section presents four facts that together indicate national wage setting. First, firms compress the level of wages across space, and a sizeable minority of firms set identical wages across locations. Second, within firms, nominal wages are relatively insensitive to local prices. Third, firms compress wage growth across space. Finally, firms that initially set identical wages across space pass local shocks through to wages in their other locations.

Fact 1: Wage Levels within Firms are Compressed Across Space

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

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

We implement this idea following Nakamura (2008) and DellaVigna and Gentzkow (2019). We regress the log wage for occupation o in firm f on a region fixed effect, γ_r, and a firm fixed effect, γ_f:

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

We then run the same regression while dropping either firm or region fixed effects. The reduction in the adjusted R-squared from dropping firm fixed effects measures the marginal contribution of firm level factors to explaining wages; likewise, dropping region fixed effects measures their marginal contribution. We calculate the difference in the adjusted R-squared from dropping either region or firm fixed effects, separately for each occupation, and plot the distributions in Figure 1. Panel A shows the results from the Burning Glass data, with job-level wages as the outcome variable. Panel B shows the LEHD-ACS results, with worker-level quarterly earnings as the outcome variable.[25]

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

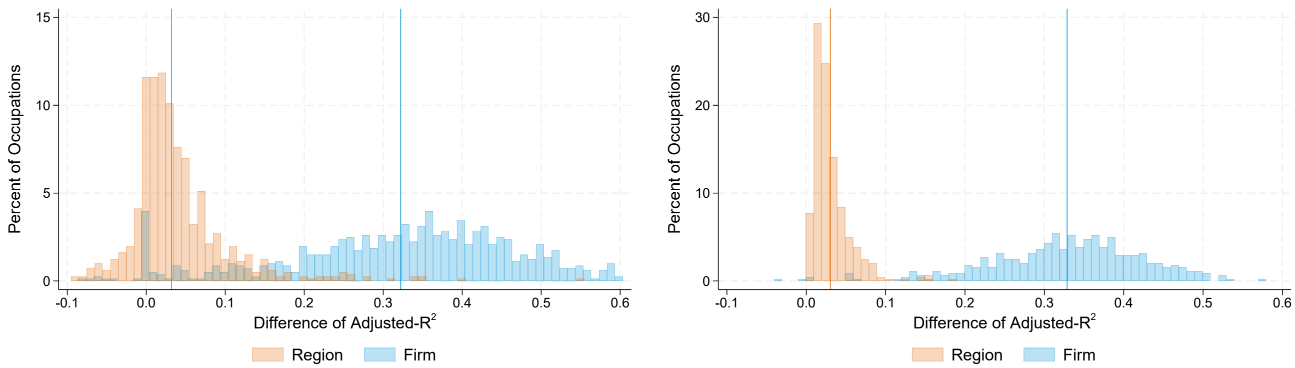
One possible explanation for the patterns in the LEHD-ACS is compression of hours, rather than wages. We explore this by re-estimating regression (4), pooled across all occupations, with reported hourly wages as the outcome variable; this variable is available only in the quarters in which workers appear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

Wage compression within the firm could take various forms. For instance, all jobs and locations could be compressing wages to a similar extent. Alternatively, wage compression might concentrate

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

Figure 1: Variation in Wages is Explained by the Firm

(a) Burning Glass (b) LEHD

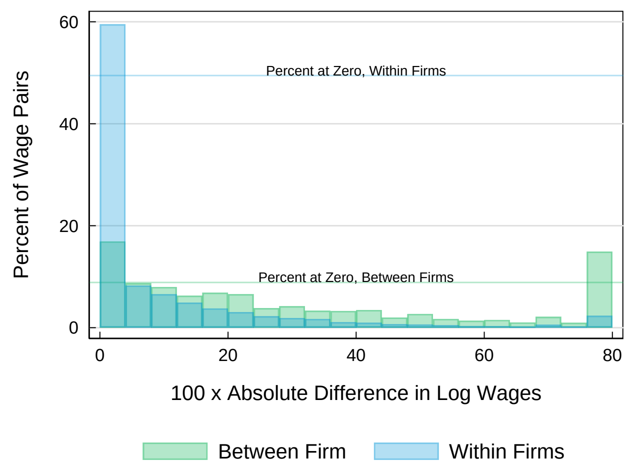


Notes: Each panel plots the share of wage variation explained by either the region or the firm, for each occupation; and then plots the distribution across occupations. In Panel A, the data range has been truncated to a minimum value of -0.1 and a maximum of 0.6, which excludes 3.12% and 3.48% of the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

in a particular set of jobs and locations. We can discriminate between these two possibilities using the Burning Glass data, where we can calculate the exact difference in posted wages between two jobs. 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 occupation in the same locations, but with the second location containing 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). We also match each firm to another in the same quintile of the size distribution, proxied by firm vacancies.

We find that a large minority of jobs and locations pay *identical* wages, consistent with wage compression being concentrated among a particular set of jobs/locations. Figure 2 shows the distribution of wage differences for the within-firm pairs (blue) and the corresponding between-firm pairs (green). 49% of within-firm pairs have *exactly* the same posted wage, while only 8.9% of between-firm pairs have the same posted wage. That number rises to 52% if we consider all within-firm wage pairs rather than just those with a between-firm match. Moreover, 62% of within-firm pairs are within 5% of each other, while only 19% of between-firm pairs are within that same band. We can also reweight 6-digit occupations in

Figure 2: Distribution of Wage Comparisons Between and Within Firms



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

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.[26,27]

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

We have shown that wages are compressed within the firm. However wages might be compressed simply because firms locate in regions with similar labor market conditions. Our next fact shows that, to the contrary, firms set similar wages even across locations with different conditions.

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

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

where $\log w_{ofrt}$ is the wage in occupation o in firm f in region r in year t. Price level$_{rt}$ represents a local price index for the region (i.e. a county in Burning Glass, or a commuting zone in the LEHD).[28] Including occupation-by-firm fixed effects (θ_{oft}) means we estimate the correlation between nominal wages and

[26] In Appendix Figure A5, we reproduce Figure 2 but restrict the sample to firms that have at least ten establishments.

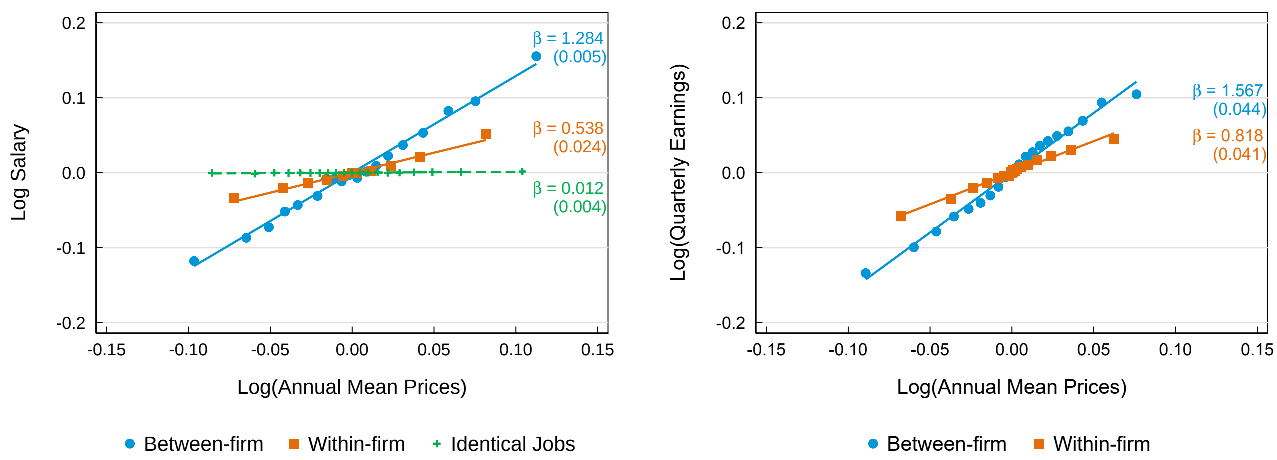
[27] In Appendix Section A2.1 we show that identical wages are less common among franchised firms.

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

Figure 3: Sensitivity of Nominal Wages to Local Prices

(a) Burning Glass

(b) LEHD



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

prices within the firm, and also hold fixed trends in wages over time. To account for measurement error in local price indices, we instrument the local price index with region-level home price indices from Zillow.

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

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

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

Panel A of Figure 3 plots binned scatter plots using the Burning Glass data, with orange squares corresponding to the within-firm and occupation regression (equation 5) and blue circles corresponding to the between-firm regression (equation 6). The within-firm coefficient is low, compared to the between-firm coefficient. The slope of the orange line is positive, implying that within the firm, nominal wages are higher in counties with higher prices. However, the coefficient is 0.54—within the firm, a job in a county with 1% higher prices tends to pay a nominal wage that is only 0.54% higher. By contrast, the estimate of γ is much higher: a 1% higher price level is associated with 1.3% higher nominal wages.[29]

Panel B of Figure 3 shows similar results using the LEHD-ACS. We estimate equations (5) and (6) but use quarterly earnings as an outcome variable, and include demographic and industry controls to account for sorting of workers across space. Specifically, we control for gender, race, and age dummies, all interacted with year; and we include 6-digit industry-by-year fixed effects for the between-firm regression in equation (6). Again, the within-firm slope is relatively low, with a value of 0.8. The between firm slope is significantly higher, with a value of 1.57. Hours variation across space does not account for these results: Appendix Table A6 shows that the results are similar using weekly wages from the ACS or quarterly earnings from the LEHD divided by usual weekly hours from the ACS; moreover hours vary little across space within the firm.[30]

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

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, we again exploit that in Burning Glass, one can detect which jobs pay identical

[29]In Appendix Table A4, we report the main specification, show similar results using Zillow home price indices directly or using measures of average local nominal incomes, and report the non-instrumented version of the regressions. In all cases the between firm coefficient is roughly twice as large as the within firm coefficient. Additionally, Panel A of Appendix Figure A6 shows that the results are robust to including salary ranges in Burning Glass. Panel B shows that the results are nearly identical when re-weighting 6-digit occupations to match the OES distribution, while panels C and D show robustness to limiting our sample to firms with at least five and ten establishments respectively. Finally, Panel E illustrates that the results are robust to using local prices without instrumenting with housing prices. Appendix Section A2.2 discusses how relabelling of job titles in Burning Glass might affect our result.

[30]In Appendix Table A5, we report the main specification and also show that the results are robust to using local prices without instrumenting with housing prices, using other measures of prices, using average earnings, and restricting the between-firm sample to be the same set of firms as the within-firm sample. In all cases the between firm coefficient is roughly twice as large as the within firm coefficient. Appendix Table A6 also shows that results are similar with two other firm definitions from the Census Bureau; and shows that the average occupation wage varies similarly across space, within versus between firms, suggesting occupation composition cannot explain the results.

wages across locations. The dashed green line in Panel A of Figure 3 shows Equation (5) estimated on the sample of occupations and firms where at least 80% of the postings for that occupation pay the same wage. The slope is close to zero by construction, but the range of prices that the firms face is similar to the range of prices faced by other firms. Therefore, firms with identical wages operate in areas that have very different local prices.[31]

Insensitivity of wages to prices within the firm is widespread in both main datasets. For Burning Glass, Appendix Figure A8 estimates equations (5) and (6) 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 present for many types of jobs. Appendix Figure A9 demonstrates that the degree of wage compression is similar in each year of the sample. In the LEHD-ACS, we study heterogeneity in the sensitivity of wages to local conditions by worker tenure, age, the average occupation wage, firm size, and industry type—again finding that wage compression is pervasive (see Appendix Table A7). The within-firm coefficients are consistently half the magnitude of the between-firm coefficients. Notably, there is wage compression in the LEHD-ACS even for workers with long tenure at the firm, a rather different sample than the new hires' wages that are contained in Burning Glass. In addition, we see substantial wage compression in non-tradable industries, suggesting that the results are not driven by a common production function.

We have shown wage compression when using posted wages and realized earnings as outcomes. We conduct a final test of wage compression using the LCA dataset of visa applications, which contains information on realized salaries net of hours. We repeat the analysis with the LCA, shown in Appendix Figure A10. We again find that the between-firm slope is twice as large as the within-firm slope, indicating significant wage compression of comparable magnitude to the other datasets. Morever, using a unique feature of the visa applications data, we can look at the change in the wage for a *given* worker across locations within the firm. Specifically, firms can list the wages that they would pay a given worker at up to 10 different worksites. This is admittedly a very selected sample, but the patterns in Appendix Figure A11 show that even when the prevailing wages are very different, firms report that they would pay that worker the same nominal wage across locations.

[31] Appendix Figure A7 shows the within firm slope rises for jobs with fewer pairs of identical wages.

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

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

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

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

We implement this test with a regression

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

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

Table 3 presents the main results. Panel A studies the LEHD-ACS. In column (1), we regress wage growth in the job on average wage growth in the rest of the firm, and in the rest of the region. A 1% increase in regional wage growth associates with a 0.14% increase in the wage growth of the job; whereas a 1% increase in firm wage growth associates with a 0.87% increase in the wage growth of the job—

Table 3: Firm versus Regional Factors and Wage Growth

	Panel A: LEHD-ACS					
Dependent Variable:	Growth In Individual Quarterly Earnings					
	(1)	(2)	(3)	(4)	(5)	
Avg. Growth In Earnings In Community Zone	0.135	0.122	0.120	0.185		
	(0.029)	(0.027)	(0.027)	(0.042)		
Avg. Growth In Earnings In Other Establishments Within Firm	0.873	0.852	0.844			
	(0.019)	(0.015)	(0.014)			
Avg. Growth In Earnings In Community Zone-Occupation					0.018	
					(0.008)	
Avg. Growth In Earnings In Other Establishments Within Firm-Occupation					0.387	
					(0.014)	
Observations	15,060,000	15,060,000	15,060,000	15,060,000	15,060,000	
	Panel B: Burning Glass					
Dependent Variable:	Growth In Posted Wages					
	(1)	(2)	(3)	(4)	(5)	(6)
Avg. Growth In Posted Wages In County	0.065	0.049	0.051	0.059		
	(0.017)	(0.015)	(0.015)	(0.014)		
Avg. Growth In Posted Wages In Other Establishments Within Firm	0.462	0.429	0.368			
	(0.083)	(0.074)	(0.052)			
Avg. Growth In Posted Wages In County-Occupation					0.051	0.071
					(0.014)	(0.017)
Avg. Growth In Posted Wages In Other Establishments Within Firm-Occupation					0.576	0.632
					(0.050)	(0.055)
I(National Occ.) x Avg. Growth In Posted Wages In County (By Occ)						-0.064
						(0.016)
I(National Occ.) x Avg. Growth In Posted Wages In Other Establishments Within Firm (By Occ)						0.281
						(0.061)
Observations	405,047	398,799	389,330	552,231	144,566	128,566
Fixed-Effects:						
OccupationxYear		✓				
2-Digit-IndustryxYear		✓				
Occupationx2-Digit-IndustryxYear			✓	✓	✓	✓

Note: this table relates annual wage growth for workers, at the occupation, region, firm and year level, to: average wage growth in the region, calculated over workers in all other firms in the region; and average wage growth in the firm, calculated over workers in all other regions. In Panel A, the data is from the LEHD-ACS. All columns control for demographics (dummies for age, gender and race). The sample is held constant across columns and observations are rounded, to pass disclosure review. Panel B studies outcomes in Burning Glass, and restricts to data with a 1 year gap between vacancy postings. Panel B, Column 6 interacts both regressors with an indicator for whether, in the initial period, the job is a national occupation—where at least 80% of wage pairs for the same job, across regions, are the same in the initial period. Firm clustered standard errors are in parentheses.

roughly 8 times larger. The coefficients are unchanged as we add in occupation by year, industry by year and occupation by industry by year fixed effects. In column 4, we drop the firm wage growth regressor. In column 5 we calculate wage growth at the region by occupation level, and the firm by occupation level. Again, the firm level factor associates much more strongly with wage growth at the job level.[32] Panel B studies Burning Glass, with similar results. Again, in column 1, the comovement between firm wage growth and job level wage growth is much higher than between regional wage growth and job level wage growth. Results remain similar as we include the same additional specifications as Panel

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

A.[33] Again, we caution that the magnitudes are not strictly comparable, given that the wage concept is different across the two datasets.

Finally, we show that the importance of firm level factors again concentrates in a subset of jobs paying identical wages across some of their locations. To make this point, we again exploit that in Burning Glass, we can measure whether firms set identical wages across locations. We consider regression (7) separately for firms that set identical wages in the initial period for most of their jobs, and firms that do not set identical wages for most of their jobs. Specifically, we distinguish between jobs that pay identical wages in at least 80% of their locations, versus other jobs. Column (6) of Panel B in Table 3 shows that for firms that initially set identical wages, the co-movement between the establishment wage and the rest of the firm is high, whereas the co-movement with local factors is low. For firms that initially do not set identical wages, the pattern reverses. In particular, row 3 of column 6 shows that for jobs that do not set identical wages initially, 1% higher wage growth in the county-occupation associates with 0.07% higher wage growth in the job. The sum of row 3 and row 5 indicates that for jobs initially setting identical wages, wage growth in the county-occupation does not associate with wage growth in the job. The final row of column 6 shows that when wages in the firm-occupation increase by 1%, wage growth in the job is 0.28% higher if the job initially set identical wages.

Fact 4: National Wage Setters Pass Through Local Shocks

Our evidence so far suggests national wage setting, but is not conclusive. Jobs that compress the level and growth of wages might be those jobs for which labor productivity varies little across space. According to our simple framework, these jobs will compress wages even without national wage setting. An example could be a firm producing purely tradeable output, sold at a nation-wide price. Even if tradeable prices and productivity vary over time, they may not vary across space within the firm, meaning the firm compresses the level and growth of wages absent national wage setting.[34] In this section, we provide a sharp test of national wage setting using the pass-through of local wage shocks.

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

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

[34]In Appendix Section C1.4 we extend the baseline model to show that if labor market power does not vary across space, then purely tradeable firms pay the same wage in all locations.

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 dataset from Burning Glass, described in the first fact of this section. We implement this test within Burning Glass since we do not have a good firm- or job-specific measure of national wage setting within the LEHD-ACS.[35]

We consider the regression

$$\Delta \log w_{ofrt} = \beta_1(\Delta \log w_{ofr't} \times \text{Equal}_{ofr,t-1}) + \beta_2(\Delta \log w_{ofr't} \times \text{Diff}_{ofr,t-1}) + \beta_3 \text{Equal}_{ofr,t-1} + \gamma_{ort} + \varepsilon_{ofrt} \tag{8}$$

where the outcome, $\Delta \log w_{ofrt}$, is the growth in the wage that firm f pays for occupation o in county r.[36] We relate this wage to the growth in the wage at that firm for the same occupation in another county, j'. $\text{Equal}_{ofr,t-1}$ is an indicator that the occupation had identical wages in $t-1$ and $\text{Diff}_{ofr,t-1}$ is an indicator that the occupation did not have identical wages. We also control for occupation by year by region fixed effects (γ_{ort}).

National wage setting predicts that β_1 is much larger than β_2. However, there is an identification concern—shocks to labor productivity that are correlated across establishments could also explain these patterns, even absent national wage setting. Therefore we instrument for wage growth, $\Delta \log w_{oir't}$ in Equation (8), with a purely local shock to wages in county r'. For this instrument to be valid in equation (8), the natural resource shock should raise establishment wages in exposed county r'. However conditional on the fixed effect γ_{ort}, the shock cannot particularly affect wages in a paired establishment r with identical wages, through channels other than national wage setting. For instance, the instrument is invalid if it raises productivity in establishment r by more than other establishments in the same region and occupation, and also differentially affects jobs that set identical wages. Appendix Section C1.5 formalizes this discussion, by deriving regression equation (8) using the baseline model—in order to define

[35]Measures of wage compression from the LEHD-ACS, such as firm-specific estimates of β in Equation (5), are subject to incidental parameter biases and parameter uncertainty that prevent them from being combined with the methods in this subsection.

[36]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.

the exclusion restriction of the instrument and interpret the regression coefficients in terms of structural parameters.

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 2019. After a boom, certain areas that concentrate in natural resources have reason to pay higher wages, including in sectors that do not produce natural resources. Other areas, without natural resource employment, will be relatively unaffected. This shock is appealing because natural resource employment is highly localized. Therefore natural resource booms are likely to directly affect certain establishments, with minimal effects on the rest of the firm (see Appendix Figure A12 for a map). For instance, consider a retail firm employing workers in Houston and New York. After a natural resources boom, overall wages will rise in Houston—meaning the retail firm has reason to pay higher wages in Houston but not necessarily New York.

Importantly, we account for the market-level effects of the natural resources shock with the occupation by county by year fixed effects (γ_{ort}) in equation (8). For instance, natural resource shocks will affect all establishments in a given region, even if the shock does not directly affect that region, through forces such as migration across regions or market level supply shocks. However the fixed effect γ_{ort} absorbs this market level variation.

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

We construct a shift-share instrument that measures a county's exposure to natural resource shocks as Natural resources employment$_{r,2009}$/Total employment$_{r,2009} \times \log($Natural resources employment$_{-r,t})$. This instrument measures a county's predicted exposure to aggregate changes in natural resource demand using county j's employment share in natural resources measured in 2009, the year before our sample period, and the growth in all other counties' employment in natural resource industries. We take the difference of the instrument over time, in line with equation (8).

Table 4: 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	2,406,079	448,045	1,958,034	2,569,225	458,228	2,110,997	2,406,079	448,045	1,958,034
First-Stage F-stat							4.11	22.85	3.77
Included Sample	All	Identical	Different	All	Identical	Different	All	Identical	Different

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

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_{ort}, this regression assigns to the "treatment group" establishments who are exposed to the natural resource shock in their paired establishments, whereas the regression assigns to the "control group" establishments in county r that are not exposed to natural resources shocks in their paired establishment r'. However, an establishment in the control group of this regression might still be exposed to natural resource shocks, via a third establishment r'' in the same firm, located in an exposed area. If so, then the control establishments have been treated, which would bias our estimates. Therefore we refine our regression to select a "clean" control group.[37] Specifically, we define unexposed observations as those 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. More details on this method as well as an example are provided in Appendix A2.3.

[37]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.

Column 1 of Table 4 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 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 A9, 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.[38] However, we note three 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.

[38] Appendix Section C1.5 formalizes this point. We show that through the lens of the model, our regression estimates imply that the share of jobs with identical wages that set wages nationally, is statistically indistinguishable from 1.

Third, our analysis exclusively relies on data from Burning Glass, rather than the LEHD-ACS, because we cannot reliably detect jobs setting identical wages in the latter dataset.

Discussion of Magnitudes

We close this section by discussing the degree of national wage setting implied by our estimates. Across our facts and datasets, we find that at least 40% of jobs that employ workers in multiple regions set wages nationally. To arrive at this conclusion, recall Fact 1, which shows that in Burning Glass 40-50% of jobs that post vacancies in multiple regions set identical wages. Later, in Fact 4, we find that the jobs setting identical wages are likely national wage setters. 40% seems like a lower bound for the share of national wage setters, given that some firms might not set identical wages but might still compress wages across locations due to national wage setting.

Our second fact suggests a similar degree of national wage setting, with consistency across Burning Glass and the LEHD-ACS. The second fact presents the within- and between-firm relationship between prices and wages. We develop a simple rule of thumb to convert between these relationships and the implied degree of national wage setting. We use the structure of the simple model of Section 2. In Appendix Section C1.8, we show that under some assumptions, the ratio of the between firm and the within firm regression coefficients measures the share of firms that do not set wages nationally. The most important of these assumptions is that high productivity firms do not sort into high productivity regions. This assumption is heroic and unlikely to be exactly correct, but allows us to compare magnitudes in the LEHD and Burning Glass in a simple way.[39] Even if this assumption fails, comparing magnitudes in Burning Glass and the LEHD-ACS is still useful if the degree of firm sorting is similar across the two datasets. In the LEHD-ACS and Burning Glass regressions, the ratio of regression coefficients is 40% and 51%, suggesting that the share of national wage setters is 60% and 49% respectively. Given that Burning Glass and the LEHD-ACS contain different measures of wages, with different shortcomings, their agreement about national wage setting is reassuring. Likewise, the variation that we use to measure national wage setting is quite different for Facts 1 and 2, but we arrive at reassuringly similar results.[40]

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

[40]Our survey of human resources executives suggests a similar degree of national wage setting (see Appendix Figure A16).

5 Characteristics of National Wage Setters

We now turn to understanding the characteristics of national wage setters, which we identify using Burning Glass. To begin, we use the Burning Glass data to identify correlates of national wage setting, finding limited evidence that location and firm-level variables predict national wages. Instead, firms set wages nationally for a subset of their occupations, but for all locations of these occupations. Occupations that can be done remotely are more likely to have national wages. Occupations with national wages also tend to earn a premium over occupations that set wages locally, perhaps because firms setting national wages are more productive. Our survey with HR managers suggests that firms set national wages when they help simplify management, or when workers are geographically mobile or concerned about pay fairness in nominal terms. However, we stress that these results are suggestive.

5.1 Predictors of National Wage Setting

We use the Burning Glass data to estimate pairwise dyadic regressions to identify occupation, geographic, and firm-level variables that predict national wage setting. For the occupation-level predictors, we include all within and between firm pairs from Figure 2 and estimate:

$$\text{Same}_{f',rr'ot} = \beta \mathbb{1}_{f=f'} + \alpha \mathbb{1}_{f=f'} \times X_{o,t} + \omega X_{ot} + \gamma_{r,-r} + \gamma_f + \gamma_t + \epsilon_{frot} \tag{9}$$

$\text{Same}_{f',rr'ot}$ is an indicator for both wages in the pair of counties r and r' being identical ($w_{frot} = w_{fr'ot}$), $\mathbb{1}_{f=f'}$ 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_f), county-pair ($\gamma_{r,-r}$), and year (γ_t) fixed effects soak up other dimensions that differ across the pair. Given the stark patterns in Figure 2, 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 in 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 (9) but that have different variables in X and different fixed effects. Specifically, when looking at geographic variation in X, we replace $\gamma_{r,-r}$ 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.

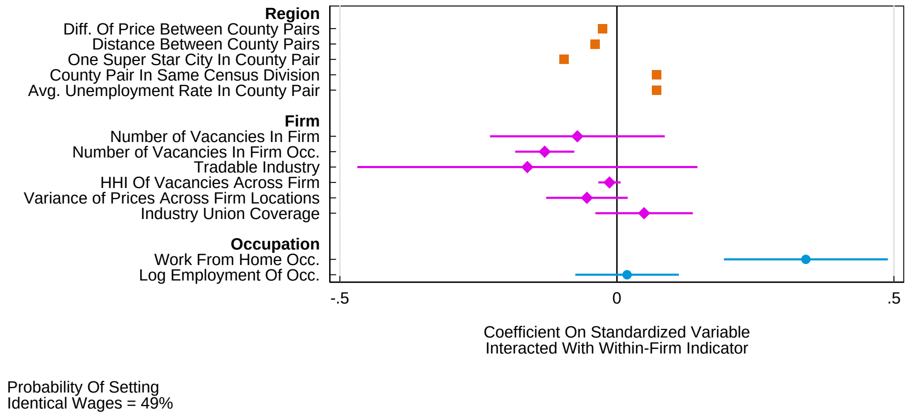
The blue circles in Figure 4 show the estimates of α for occupation-level variables, the orange squares for county-level variables, and the pink triangles for firm-level variables. Several patterns emerge. First, county-level variables are relatively weak predictors of national wages. Within the firm, the probability that posted wages are the same across pairs is decreasing in the geographic distance between the establishments, decreasing in the difference in price levels, and increasing the average unemployment rate of the counties. Jobs are more likely to set identical wages if pairs are in the same census division or outside "superstar cities" such as New York or San Francisco. However, these magnitudes 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, firm-level variables are similarly weak predictors of national wage setting. National wages are slightly less common in firms with more occupations and more vacancies (i.e. larger firms), and are less likely in tradable industries. The share of unionization in the industry does not affect national wage setting. There is no relationship between national wage setting and the degree to which firm employment is spread out evenly across space, as measured by the Herfindahl Index of firm vacancies across locations ("Firm HHI"). Nor is national wage setting related to the variance of prices across the locations of the firm. These findings weigh against the hypothesis that firms only set wages nationally when the costs to doing so are low, since firms are similarly likely to set wages nationally even when employment is decentralized across space and in labor markets with diverse local conditions.

Firm and location variables do not predict national wage setting because firms set wages nationally for a subset of their occupations, but for all locations of these occupations. Appendix Figure A13 shows that the majority of firms setting identical wages for some occupations do so for only a subset. Only 20% of firms set national wages for all occupations. Appendix Figure A13 also shows that within a firm and occupation with *some* identical wages, there is typically identical wages across all locations. We find that many jobs have less than 10% of pairs being identical, many jobs have all pairs being identical, and very few jobs between 50 and 95% of pairs being identical.

Therefore there is heterogeneity in which occupations have identical wages. Turning to occupation-level determinants, the strongest predictor of national wage setting is the ability for an occupation to

Figure 4: Predictors of National Wage Setting



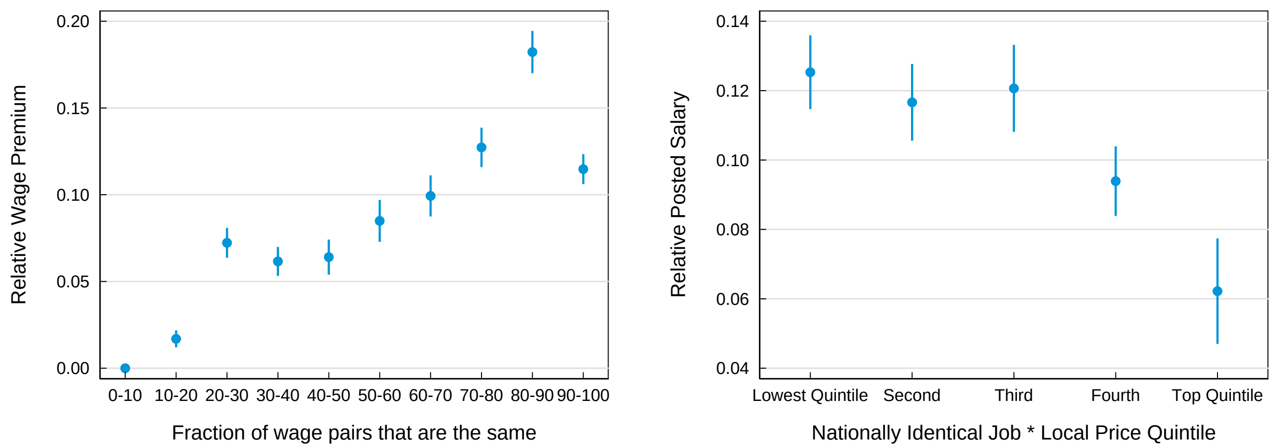
Notes: All coefficients are the interaction between the noted variable and an indicator for whether the pair is within the firm (i.e. α from Equation 9). The blue dots show occupation-level variables, the orange squares show geographic variables, and the purple diamonds show firm-level variables. he 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 A10, A11, and A12 for further details on the underlying regressions.

be done remotely (Dingel and Neiman (2020)). Remote work might increase the likelihood of national wages for a variety of reasons. For example, marginal products might be more equal across locations for these jobs, or certain pay norms that lead to national wage setting might be particularly strong for remote jobs. Given that national wages are a characteristic of occupations within firms, we next explore the pay of jobs with national wages.

5.2 The Pay of Nationally Wage Set Jobs

While firm and location are relatively weak predictors of national wage setting, a prominent feature of jobs with national wages is that they earn a premium. This is shown in the left panel of Figure 5, where we use the Burning Glass data to plot the estimated wage premium for jobs by the extent of wage uniformity within the firm. Specifically, we plot the coefficients from a regression of log posted wages on occupation 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

Figure 5: 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 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.

identical jobs across labor markets. 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 A13 summarizes these patterns with regressions, showing jobs in firms where at least 80% of the jobs have identical wages pay 12% more than other comparable jobs within their markets. Appendix Table A13 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.

The right panel of Figure 5 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.[41]

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 A14, which also finds no clear relationship of national wage setting to total firm employment). Consistent with this evidence, the simple framework of Section 2 predicts that national wage setters pay a wage premium if they are more productive than local wage setters, as we establish formally in Appendix Section C1.9.[42]

5.3 Survey Evidence: Motivations for National Wage Setting

We now turn to our survey evidence to understand why, according to HR managers, there is national wage setting. This evidence is again suggestive. Appendix Figure A15 establishes that many of our respondents work at firms that set national wages. The figure shows responses to the question "Which of the following describes how your firm sets wages (pay bands) across locations for the majority of your workers?"[43] Respondents could choose one of three options: wages (pay bands) are determined separately for each establishment, are set identically so that workers with the same job title face the same wage (pay bands), or sometimes separately but not always. Panel A shows the results for firms that use point wages and Panel B shows the results for those firms using pay bands. Just under 15% of firms that set point wages work at firms that set identical wages across establishments and over 30% of those using pay bands do. Consistent with our results in Burning Glass, nearly 50% using point wages or pay bands state that they set wages identically for some jobs but not all. Of course, firms could be making adjustments within pay bands based on geographic factors. Appendix Figure A17 asks firms that use pay bands whether they adjust pay within a band for any of the following reasons: to reward worker performance, based on a worker's experience, based on a worker's prior pay, based on workers receiving

[41] Appendix Figure A14 shows the same specification as in the right panel of Figure 5, but using education and experience requirements instead of the posted salary. There is no slope with respect to the local price index.

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

[43] Earlier in the survey, we ask respondents whether their firm primarily uses pay bands or a point wage.

outside offers, and the local cost of living. Cost of living is chosen the least among firms that set identical bands across space. Therefore, while firms may adjust wages across space within pay bands, it does not appear to happen within the majority of firms.

In our survey, we asked respondents whose firms do not vary the nominal wages of at least some jobs to rank seven reasons for not doing so.[44] Appendix Figure A19 shows the fraction of HR managers that report each reason as one of the top three. The most commonly cited reason for setting national wages is hiring on a national labor market—that is, firms set national wages when they hire across the country for all of their establishments, meaning that the workers who take these jobs are more likely to be geographically mobile. Notably, hiring nationally mobile workers seems to cause firms to equalize nominal and not real wages across space. Indeed, a human resources executive told us that paying a national wage was important for "*attracting and retaining talent*" in low wage locations of the firm, since the company was "*competing in a national labor market*" for relatively mobile and high wage occupations.[45]

Many firms also set national wages to simplify management. Around 35% of respondents report that they set national wages in part because it is administratively costly to tailor the wage to each location. This policy only benefits the firm, on net, when the costs of 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.[46] Finally, nearly 40% of survey respondents cited internal fairness norms as a reason for national wage setting. These internal norms again seem to matter for *nominal* and not real wages across establishments. Workers may communicate with others or work in multiple locations of the firm, making them more likely to know pay in other locations. This again could explain why national wages are more common in job-pairs that are geographically close.

Overall, our results do not point strongly to any one reason that firms set national wages. We do find that geographic and firm-level factors matter little in explaining the prevalence of national wage setting, and that national wages are instead a characteristic of specific jobs within firms. The Burning Glass and survey data provide suggestive evidence that occupations with more geographically mobile, high-wage

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

[45] Consistent with this view, survey respondents who do *not* set wages nationally in some or all jobs report hiring on a local market as an important reason (see Appendix Figure A20).

[46] It is possible that firms operate in areas with a similar cost of living *because* they adopt rigid pay structures. For example, if a firm cannot or chooses not to vary nominal pay across establishments, it may decide not to open up establishments in high cost of living areas. However, we found limited evidence in our survey that national wage setting affects where firms locate (see Appendix Figure A21).

workers are more likely to have national wages.[47]

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

How much is at stake for the firms that choose to set wages nationally? In this section, we make simple assumptions about how firms would have set wages in the absence of national wage setting and then, using the model in Section 2, provide a back of the envelope estimate of the profits at stake from national wage setting. It is possible that setting wages nationally increases worker productivity and maximizes profits, since firms setting national wages pay a premium and are slightly more productive. If so, our benchmark reflects the increase in firm profits due to national wage setting, perhaps used in combination with other productivity enhancing management practices. Given the simplicity of the model, the results of this section are suggestive.

We assume that jobs paying identical wages everywhere, as measured in Section 4 in the Burning Glass dataset, are setting wages nationally. We attempt to provide a lower bound for what wage dispersion would have been for these jobs, had they not chosen to 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.[48] According to the simple framework and equation (3), this is the correct counterfactual if (i) productivity differences across space are the same for these two firms (i.e. for firms f and k and locations r and r' we have $A_{fr}/A_{fr'} = A_{kr}/A_{kr'}$), (ii) all firms within a market face the same labor supply elasticity and (iii) there is constant returns to scale in labor. 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 5 shows the results. The median absolute difference between the actual wage and the wage suggested by the within-firm benchmark is 6.1%. Even according to this conservative benchmark,

[47] Some factors that could lead to national wage setting are notable by their absence from the pilot and the free-form answers. Specifically, respondents did not mention government policies, such as minimum wages, as a source of national wage setting.

[48] 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.

Table 5: Effect of National Wage Setting on Establishment Profits

	25th	Median	75th
	(4)	(5)	(6)
		Panel A: Percent Difference in Wages	
	2.2	6.1	13
		Panel B: Percent Difference in Profits	
$\rho = 4$, CRS	0.46	3.6	17
$\rho = 2$, CRS	0.14	1.1	5.2
$\rho = 6$, CRS	0.96	7.4	33
$\rho = 4$, DRS	0.31	2.4	11
$\rho = 4$, Rationing	0.31	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. In the calibration with decreasing returns to labor, the exponent on labor is 0.66.

25% of the national jobs set wages more than 13% different from the benchmark. Therefore firms engage in national wage setting even across markets that have meaningful dispersion in wages.

We combine these empirical benchmarks with the structure of the simple model in Section 2 to provide an estimate for the share of profits affected by national wage setting.[49] Specifically, for the version of our model with constant returns to scale in labor, we combine the definition of establishment profits given by equation (1) and the labor supply curve to the establishment given by equation (2). Some algebra implies

$$\frac{\Pi^*_{rf} - \overline{\Pi}_{rf}}{\Pi^*_{rf}} = 1 - (1+\rho)\left(\frac{\overline{W}_f}{W^*_{rf}}\right)^{\rho} + \rho\left(\frac{\overline{W}_f}{W^*_{rf}}\right)^{1+\rho} \tag{10}$$

where $\overline{W}_i$ and $\overline{\Pi}_i$ are the actual wages and profits of national wage setters, W^*_{rf} and Π^*_{rf} are the wages and profits in the counterfactual of local wage setting, and ρ is the labor supply elasticity to the establishment. We derive this expression in Appendix Section C1.6, which presents additional results for models with capital, decreasing returns to labor and labor rationing. Under the assumption that the two empirical benchmarks described above provide an estimate for W^*_{rf}, we can calculate the profit loss from national wage setting for given a value of ρ, without other hard-to-measure objects such as local productivity.

[49]For this back of the envelope, we additionally assume that the labor supply elasticity is the same in all markets for all firms (i.e. $\rho_j = \rho$ for all j). This assumption is innocuous, since differences in local productivity and markdowns are not separately identified by our model.

The profits at stake from national wage setting seem to be moderately large, though a range of values are possible depending on the calibration of the model. Panel B of Table 5 presents this result. 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 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 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. While these simple calculations abstract from potentially 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.

Given the simplicity of the exercise, our findings are only illustrative. Nevertheless they are a useful lower bound on the profits at stake from national wage setting. As robustness, we consider a second counterfactual. 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. We consider this second counterfactual an upper bound, since, despite our matching procedure, there are likely unobserved factors that will contribute to between-firm differences in wages. Appendix Table A15 calculates profits at stake from national wage setting from the between-firm match, and finds they are significantly larger than the baseline.

7 Consequence of National Wage Setting for Wage Inequality

Comprehensively examining the consequences of national wage setting is beyond the scope of the paper. We therefore end by considering one key consequence: aggregate wage inequality. Since national wage setting compresses the distribution of nominal wages across space, it likely dampens aggregate wage inequality. We gauge the rough 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 is the

Table 6: 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, $\geq$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.

variance of log nominal wages $Var\left[w_{for}\right]$, where w_{for} is the log nominal wage paid in an establishment fr and occupation o. Aggregate nominal wage inequality includes variation both within and between regions, occupations, and firms. The component of aggregate nominal wage inequality that is affected by national wage setting is the component of the variance arising within a firm and occupation, and across regions. We can decompose nominal wage inequality into its within and between firm-occupation components:

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

where $\overline{w}_{fo}$ 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 first, within-firm-and-occupation component. Since national wage setters pay the same nominal wage across space within the firm and occupation, the contribution of national wage setters to nominal wage inequality within firms and occupations is zero. As in section 6, we explore a benchmark in which national wage setters vary pay similarly to local wage setters, using Burning Glass. Specifically, we set the variance of wages within firms for national wage setters 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 6 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 6, 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.[50]

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 exercise is illustrative and ignores several important issues. For instance, we do not study real wages, given measurement error in local prices. Moreover our counterfactual ignores general equilibrium responses to national wage setting.

8 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, accords with firms' sense of fairness, and 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.

[50] 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).

References

ADLER, L. (2023): "What'sa Job Candidate Worth? Explaining Variation in Pay-Setting Practices," .

ALFARO-URENA, A., I. MANELICI, AND J. P. VASQUEZ (2021): "The Effects of Multinationals on Workers: Evidence from Costa Rica," Working Papers 285, Princeton University, Center for Economic Policy Studies.

ANGRIST, J. D. AND A. B. KRUEGER (1995): "Split-sample instrumental variables estimates of the return to schooling," Journal of Business & Economic Statistics, 13, 225–235.

AUTOR, D., D. DORN, L. F. KATZ, C. PATTERSON, AND J. VAN REENEN (2020): "The Fall of the Labor Share and the Rise of Superstar Firms*," The Quarterly Journal of Economics, 135, 645–709.

BATRA, H., A. MICHAUD, AND S. MONGEY (2023): "Online Job Posts Contain Very Little Wage Information," NBER Working Paper 31984.

BERGER, D. W., K. F. HERKENHOFF, AND S. MONGEY (2022): "Labor Market Power," The American Economic Review, 112, 1147–1193.

BOERI, T., A. ICHINO, E. MORETTI, AND J. POSCH (2021): "Wage Equalization and Regional Misallocation: Evidence from Italian and German Provinces," Journal of the European Economic Association, 19, 3249–3292.

BORUSYAK, K., X. JARAVEL, AND J. SPIESS (2022): "Revisiting Event Study Designs: Robust and Efficient Estimation," Working paper.

BOUND, J. AND A. B. KRUEGER (1991): "The extent of measurement error in longitudinal earnings data: Do two wrongs make a right?" Journal of labor economics, 9, 1–24.

BROOKINGS INSTITUTION (2018): "Countering the geography of discontent: Strategies for left-behind places," Brookings, November.

CAPPELLI, P. AND K. CHAUVIN (1991): "An interplant test of the efficiency wage hypothesis," The Quarterly Journal of Economics, 106, 769–787.

CARD, D., A. R. CARDOSO, J. HEINING, AND P. KLINE (2018): "Firms and labor market inequality: Evidence and some theory," Journal of Labor Economics, 36, S13–S70.

CARD, D., J. HEINING, AND P. KLINE (2013): "Workplace heterogeneity and the rise of West German wage inequality," The Quarterly Journal of Economics, 128, 967–1015.

CARNEVALE, A. P., T. JAYASUNDERA, AND D. REPNIKOV (2014): "Understanding online job ads data," Georgetown University, Center on Education and the Workforce, Technical Report (April).

CAVALLO, A. (2018): "Scraped data and sticky prices," Review of Economics and Statistics, 100, 105–119.

CAVALLO, A., B. NEIMAN, AND R. RIGOBON (2014): "Currency unions, product introductions, and the real exchange rate," The Quarterly Journal of Economics, 129, 529–595.

CENGIZ, D., A. DUBE, A. LINDNER, AND B. ZIPPERER (2019): "The effect of minimum wages on low-wage jobs," The Quarterly Journal of Economics, 134, 1405–1454.

Chodorow-Reich, G., P. T. Nenov, and A. Simsek (2021): "Stock market wealth and the real economy: A local labor market approach," American Economic Review, 111, 1613–1657.

Clemens, J. and J. Gottlieb (2017): "In the Shadow of a Giant: Medicare's Influence on Private Payment Systems," Journal of Political Economy, 125, 1139–1180.

Cullen, Z., S. Li, and R. Perez-Truglia (2022): "What's My Employee Worth? The Effects of Salary Benchmarking," Working paper.

DellaVigna, S. and M. Gentzkow (2019): "Uniform pricing in US retail chains," The Quarterly Journal of Economics, 134, 2011–2084.

Derenoncourt, E., C. Noelke, D. Weil, and B. Taska (2021): "Spillover Effects from Voluntary Employer Minimum Wages," Working Paper 29425, National Bureau of Economic Research.

Diamond, R. and E. Moretti (2021): "Where is Standard of Living the Highest? Local Prices and the Geography of Consumption," Working Paper 29533, National Bureau of Economic Research.

Dingel, J. I. and B. Neiman (2020): "How many jobs can be done at home?" Journal of Public Economics, 189, 104235.

Dube, A., A. Manning, and S. Naidu (2020): "Monopsony and Employer Mis-optimization Explain Why Wages Bunch at Round Numbers," Working Paper 24991, National Bureau of Economic Research.

Empsight International LLC (2018): "2018 Policies, Practices & Merit Survey Results," Tech. rep., Empsight International LLC, New York, NY.

Grigsby, J., E. Hurst, and A. Yildirmaz (2021): "Aggregate nominal wage adjustments: New evidence from administrative payroll data," American Economic Review, 111, 428–471.

Hirsch, B. T. and D. A. MacPherson (2003): "Union Membership and Coverage Database from the Current Population Survey: Note," Industrial Labor Relations Review, 56, 349–354.

Hitsch, G. J., A. Hortaçsu, and X. Lin (2019): Working Paper 26306, National Bureau of Economic Research.

Hjort, J., X. Li, and H. Sarsons (2020): "Across-Country Wage Compression in Multinationals," Working Paper 26788, National Bureau of Economic Research.

Hoffmann, F., D. S. Lee, and T. Lemieux (2020): "Growing income inequality in the United States and other advanced economies," Journal of Economic Perspectives, 34, 52–78.

Hsieh, C.-T. and E. Rossi-Hansberg (2021): "The Industrial Revolution in Services," Working paper.

Jarosch, G., J. S. Nimczik, and I. Sorkin (2019): "Granular search, market structure, and wages," Working Paper 26239, National Bureau of Economic Research.

Kambourov, G. and I. Manovskii (2013): "A cautionary note on using (March) Current Population Survey and Panel Study of Income Dynamics data to study worker mobility," Macroeconomic Dynamics, 17, 172–194.

Kehrig, M. and N. Vincent (2019): "Good Dispersion, Bad Dispersion," Working Paper 25923, National Bureau of Economic Research.

LAMADON, T., M. MOGSTAD, AND B. SETZLER (2022): "Imperfect Competition, Compensating Differentials, and Rent Sharing in the US Labor Market," American Economic Review, 112, 169–212.

MACALUSO, C., B. HERSHBEIN, AND C. YEH (2019): "Concentration in U.S. local labor markets: evidence from vacancy and employment data," 2019 Meeting Papers 1336, Society for Economic Dynamics.

NAKAMURA, E. (2008): "Pass-Through in Retail and Wholesale," American Economic Review, 98, 430–37.

PROPPER, C. AND J. VAN REENEN (2010): "Can pay regulation kill? Panel data evidence on the effect of labor markets on hospital performance," Journal of Political Economy, 118, 222–273.

ROSSI-HANSBERG, E., P.-D. SARTE, AND N. TRACHTER (2021): "Diverging Trends in National and Local Concentration," NBER Macroeconomics Annual, 35, 115–150.

SCHOEFER, B. AND O. ZIV (forthcoming): "Productivity, Place, and Plants," Review of Economics and Statistics.

SCHUBERT, G., A. STANSBURY, AND B. TASKA (2021): "Employer concentration and outside options," Working paper.

SONG, J., D. J. PRICE, F. GUVENEN, N. BLOOM, AND T. VON WACHTER (2019): "Firming up inequality," The Quarterly Journal of Economics, 134, 1–50.

SORKIN, I. (2018): "Ranking firms using revealed preference," The Quarterly Journal of Economics, 133, 1331–1393.

VERBOVEN, F. (1996): "The nested logit model and representative consumer theory," Economics Letters, 50, 57–63.

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.

A2 Additional Empirical Results

A2.1 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 A16 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.

A2.2 Robustness: Comovement of Wages and Prices with Job Title Relabelling

If firms wish to vary workers' wages across locations while keeping wages for the same job identical, they could use different job titles across locations (e.g. Starbucks might hire "junior baristas" in Houston but "senior baristas" in NYC as a way of circumventing national wage setting policies). We define jobs using occupations, rather than job titles, in the baseline Burning Glass analysis to account in part for this margin of adjustment; we always study occupations in the LEHD-ACS. However, we also present two pieces of evidence that demonstrate that this margin is not quantitatively meaningful, in Burning Glass data. First, Appendix Figure A22 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 A23, we explicitly test for this by estimating Equation (5) replacing the posted wage with the average wage in the 6-digit SOC for the OES and replacing the 6-digit SOC fixed effects with increasingly aggregated SOC fixed effects (5-digit, 3-digit, 2-digit, or no SOC codes). If firms were strategically shifting to higher-wage 6-digit occupations in high-price areas (e.g. calling baristas managers in New York City), we would see a strong positive slope. Instead, we find very small slopes.

A2.3 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 (A9) 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 A12 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.

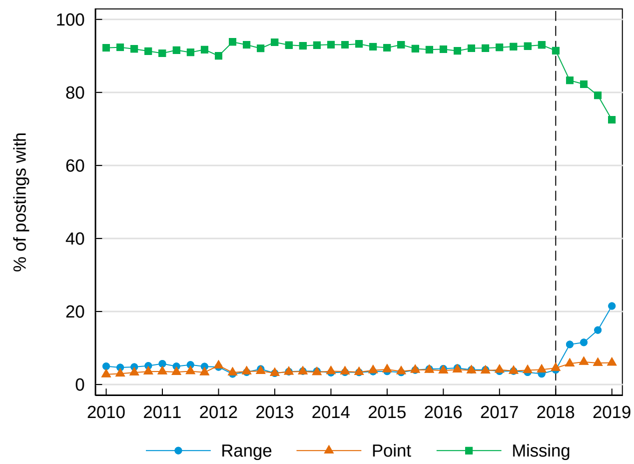
To facilitate a comparison between treatments and clean controls, we first calculate the absolute value of the natural resources shock that each firm faces across all years. We then define a set of untreated units (where a unit is an occupation-county-year) as those whose maximum natural resource shock 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 (A9) by IV without selecting a clean control group. If we simply used the full dataset to estimate the fixed effects, we would erroneously be using some exposed firms are controls. To see this, return to the example above and consider the case where the exposed firm has a third establishment in Boston. The full dataset would include an observation for the Chicago/Boston pair of the exposed firm (i.e. the firm that operates in Houston, Chicago and Boston) which the regression would erroneously assign to the control group. Our procedure prevents us from assigning exposed firms to the control group.

Appendix Tables and Figures

Figures

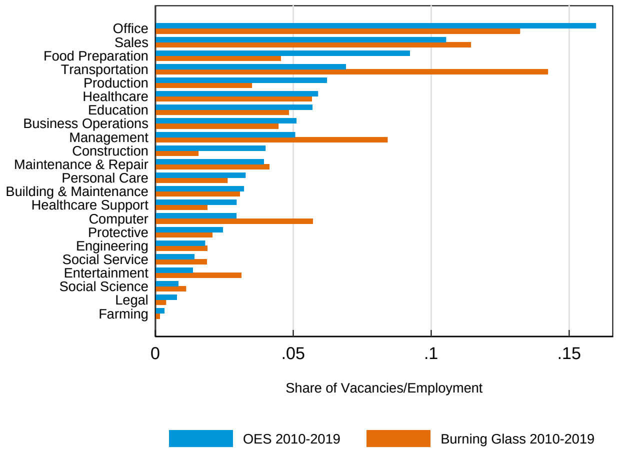
Figure A1: Percentage of Vacancies with Missing Wage Information in Burning Glass



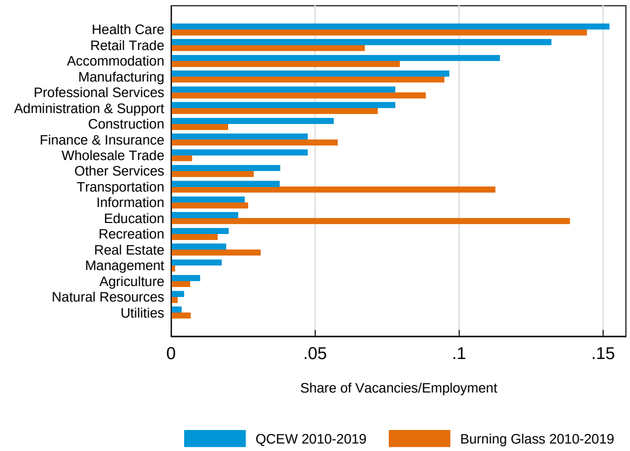
Notes: This timeline depicts the percentage distribution of salaries posted on Burning Glass. The green line, with square markers, indicates the proportion of vacancies with missing wage information. Meanwhile, the blue line with circle markers and the orange line with triangle markers represent the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

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

(a) Occupation

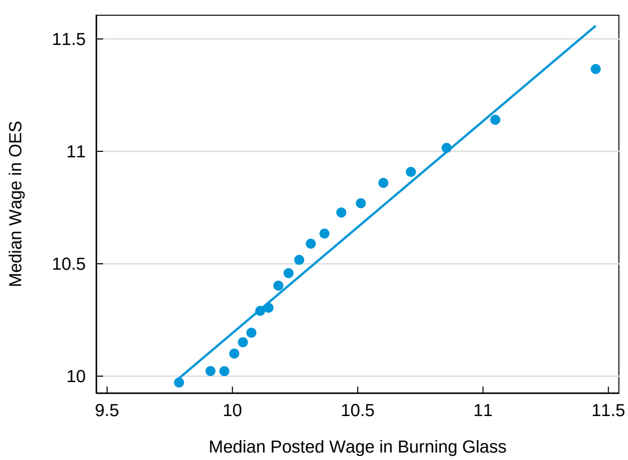


(b) Industry



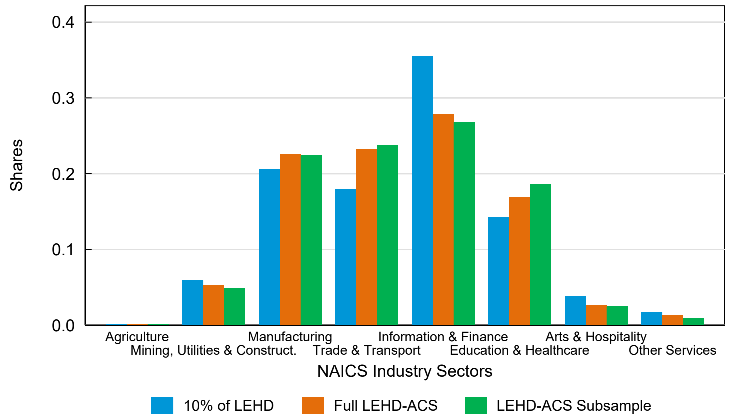
Notes: Shares are calculated using the total number of vacancies or employment summed across 2010-2019. In the left panel, employment is from the 2010-2019 Occupational Employment Statistics, by broad occupation. In the right panel, employment is by broad industry from the Quarterly Census of Wages and Employment from 2010-2019. Sample includes the set of vacancies including a posted point wage (See Table 1, row 5).

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



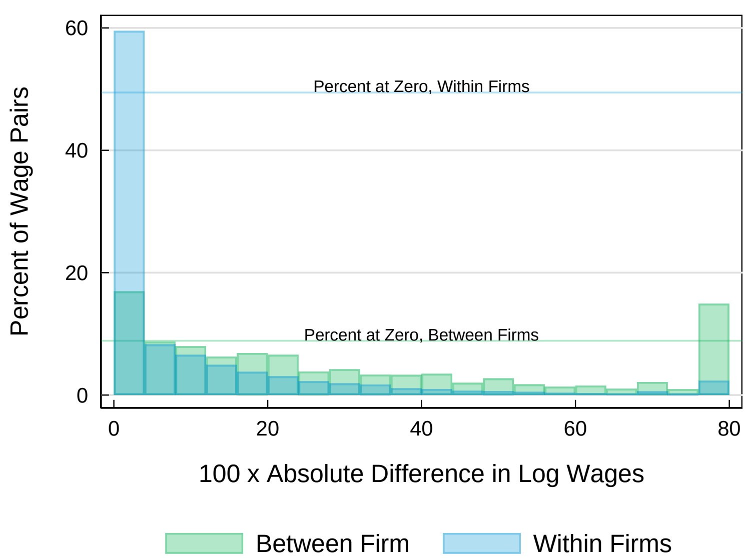
Notes: The OES wage on the y-axis is the log of the occupation by MSA median hourly wages from the Occupational Employment Statistics. The x-axis is the log median wages from Burning Glass for all jobs posting hourly basepay. In both cases, we study the wage averaged over 2010-2019. In both datasets, 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 A1, Column 2.

Figure A4: LEHD-ACS Industry Distribution



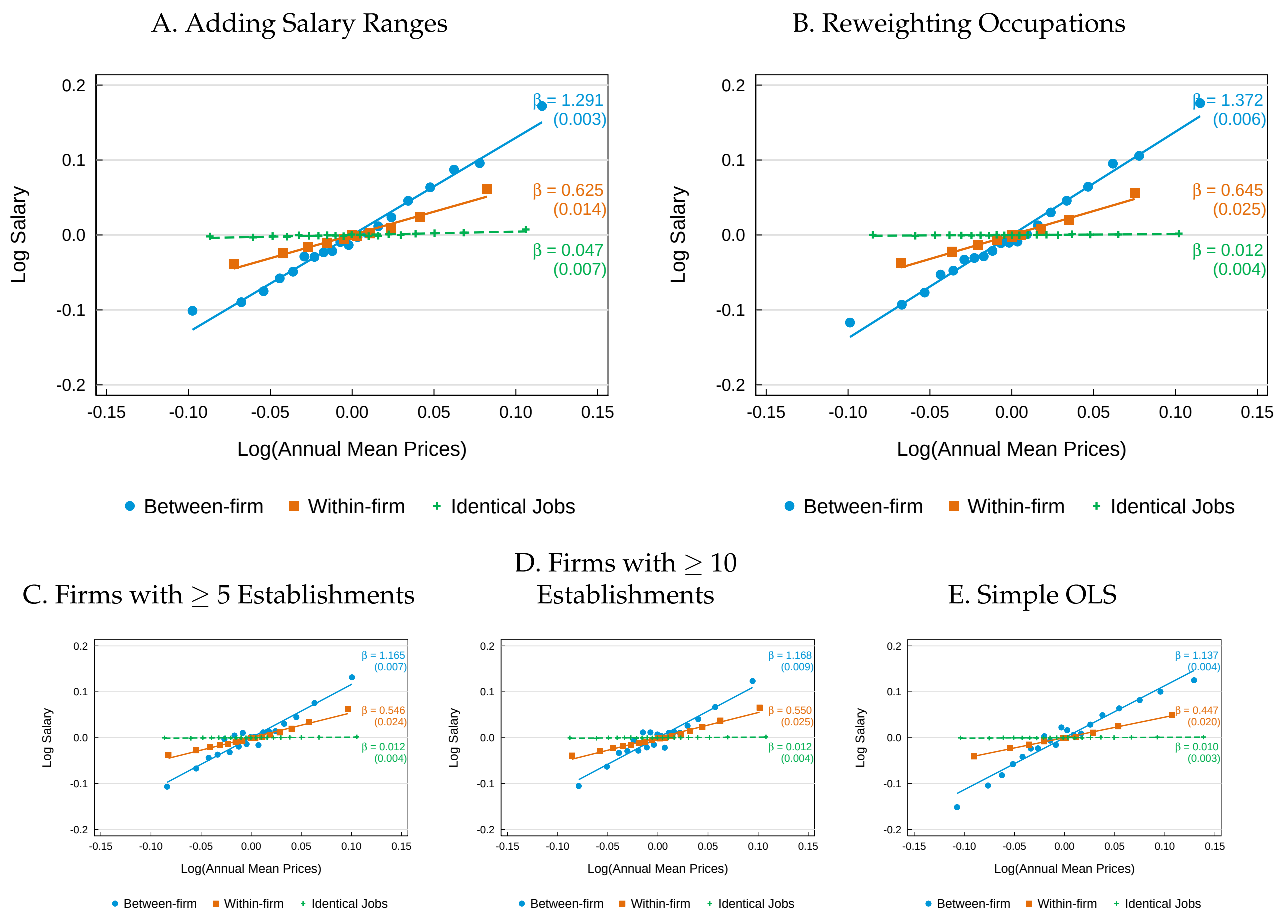
Notes: The figure illustrates the economic sector distributions within each LEDH-ACS sample, utilizing the nine primary industry sectors from the North American Industry Classification System (NAICS). The figure's labels describe each broad economic sector. "Agriculture" also encompasses farming, hunting,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

Figure A5: Identical Wage Setting: Firms with At Least 10 Establishments



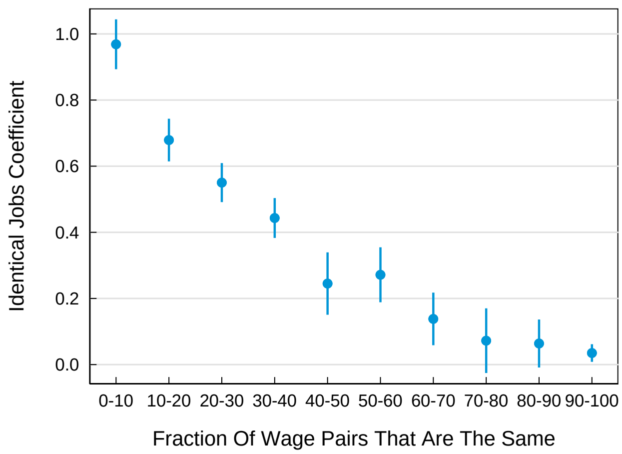
Notes: This figure uses Burning Glass data to replicate Figure 2. We limit to firms that have at least ten establishments. The blue and green lines indicate the fraction of job-pairs for which there is no difference in the absolute wage when looking at job-pairs within firm (blue line) and between-firms (green line).

Figure A6: Posted Wages and Local Prices—Robustness to Wage Ranges and Occupation Weighting



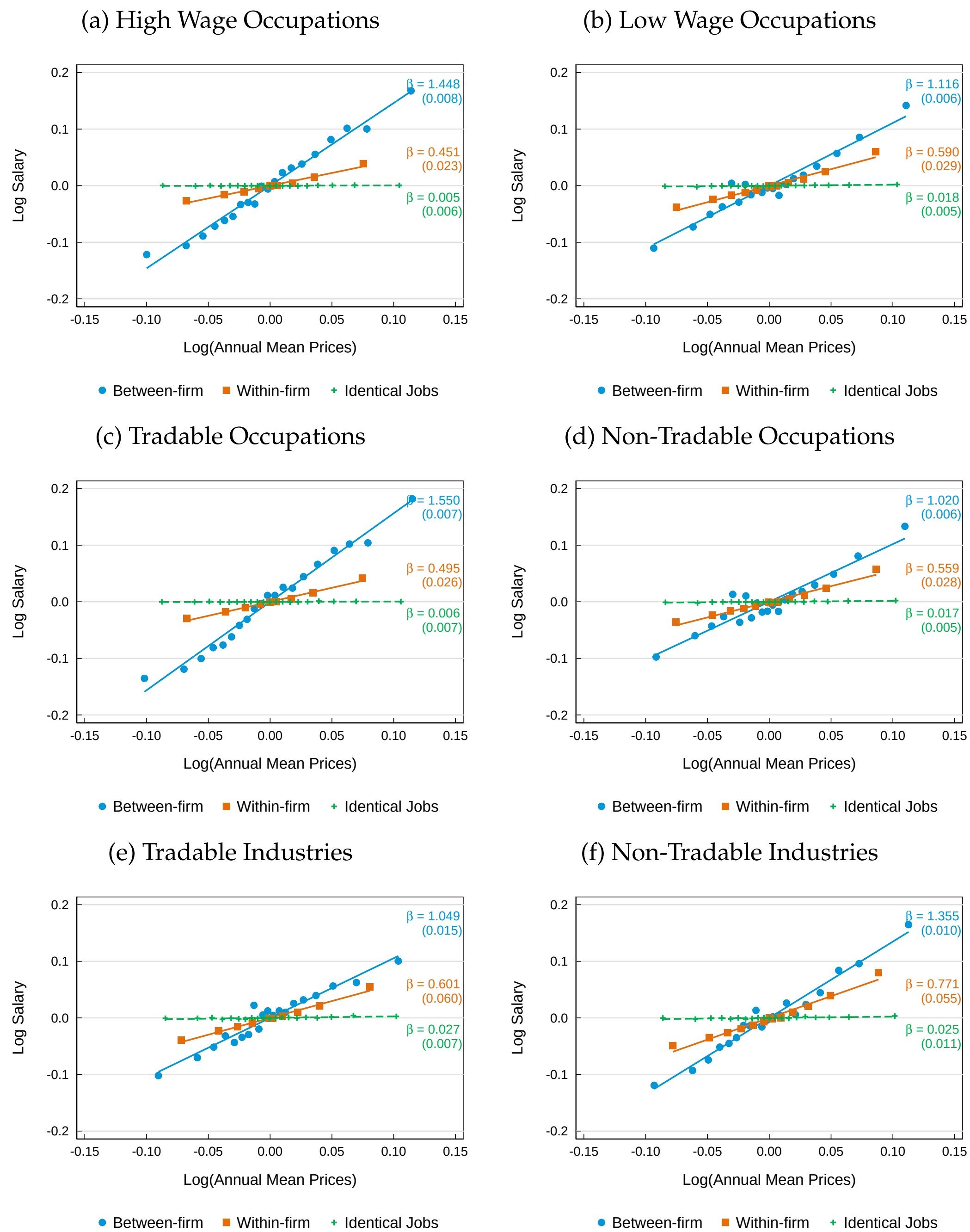
Notes: In all panels, the binned scatterplot shows the relationship between the local price index and the log wage using the same procedure as the main text. The local price index is instrumented by county-level home prices in all panels except in Panel E. In panel A, the sample includes all jobs with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

Figure A7: Identical Jobs Coefficient



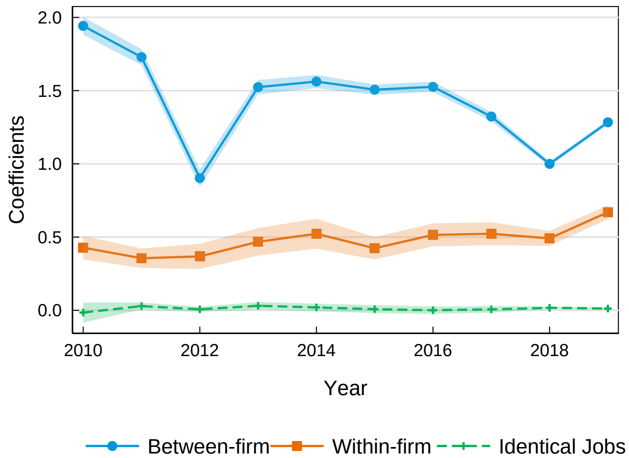
Notes: The figure shows the relationship between the within firm regression coefficients in equation 5 (y-axis) and the fraction of jobs within a firm by occupation that have the same wage.

Figure A8: Wages and Local Prices: Heterogeneity



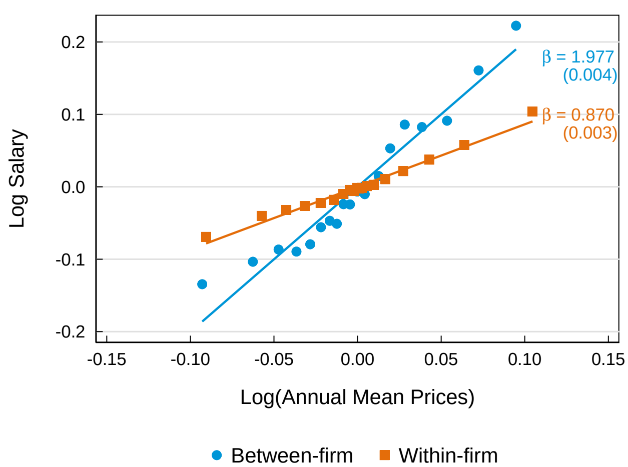
Notes: High-wage occupations are defined as those with an OES wage that is above the median in the sample. We define a tradable occupation as one that can be done remotely following Dingel and Neiman (2020). We define tradable and non-tradable industries following Chodorow-Reich et al. (2021). In all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

Figure A9: Wage compression from 2010 to 2019



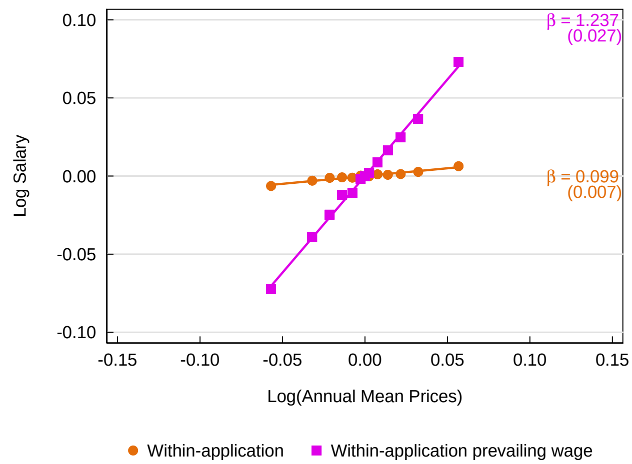
Notes: we estimate the regression coefficients separately for each year of the data. The blue line and circles correspond to Equation (6) and the orange line and squares correspond to Equation (5). The dashed green line and crosses correspond to Equation 5 but we run this regression restricting to national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

Figure A10: Nominal Wages and Local Prices Using LCA Data



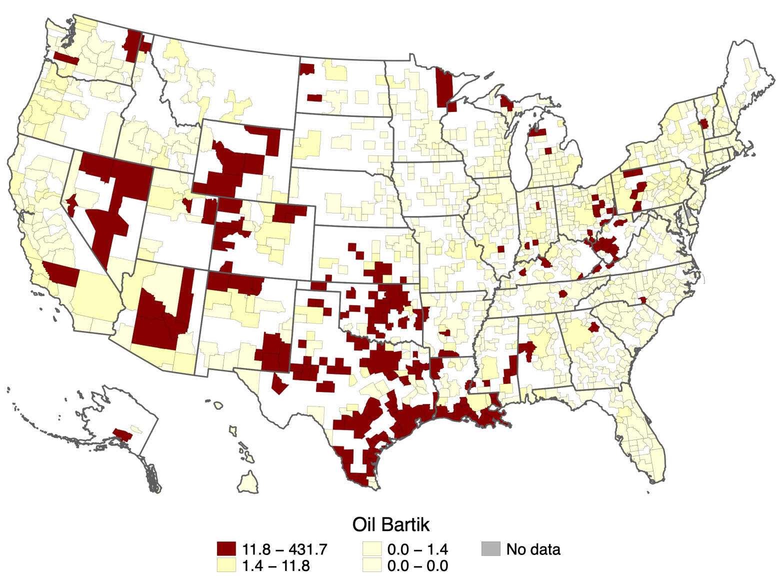
Notes: Data is from all years (2010-2019) in the LCA data. Non-certified and withdrawn visa applications are included. Wages/salaries are annualized. In each regression, we instrumented local price indices with county-level home prices. Controls are included for the year and whether the wage is annual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

Figure A11: Within-Worker Sensitivity of Reported Wages to Local Prices



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

Figure A12: Regional Exposure to Natural Resources Instrument

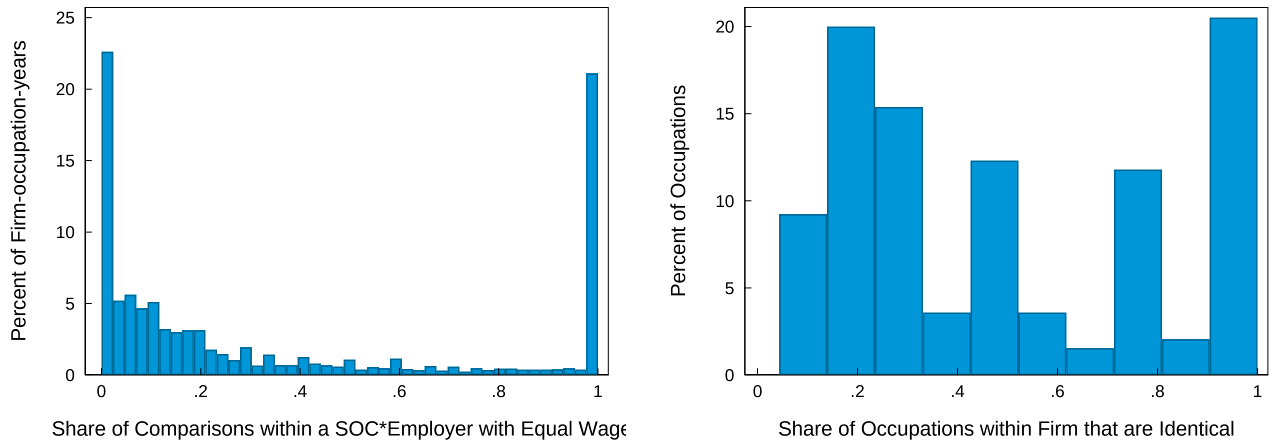


Notes: This figure presents a heat map showing the geographic distribution of natural resource shocks in the U.S., measured in 2012, by county. The map is constructed by grouping counties into ten deciles and shading such that lighter colors correspond to lower rates of natural resource demand. The natural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

Figure A13: Prevalence of Identical Wages Within the Firm

(a) Within job, across locations

(b) Within firm, across occupations

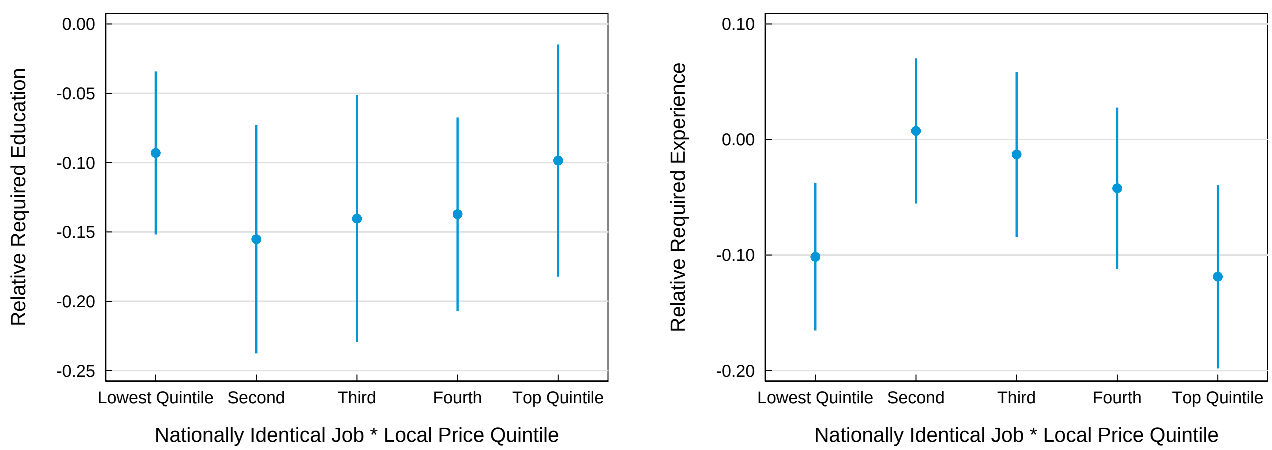


Notes: In the left panel, the sample excludes job cells where there are fewer than 5 within-firm pairs. This results in 7,880 firms. In the right panel, we further condition the sample to include the set of firms with at least 1 national occupation and at least 3 occupations. National occupations are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

Figure A14: Relative Education and Experience by Local Price Level

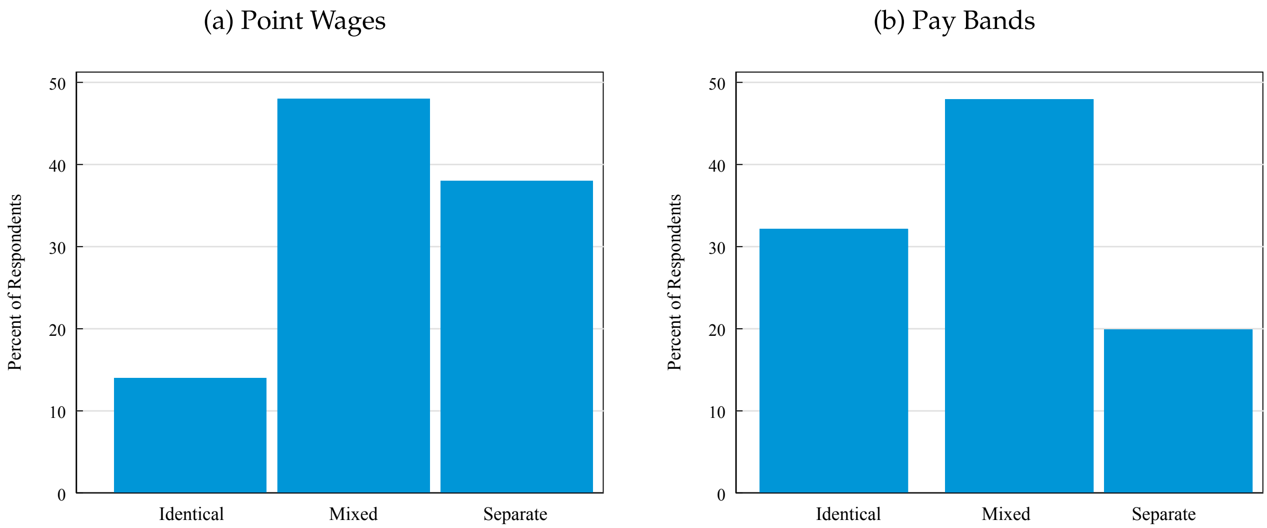
(a) Required Education

(b) Required Experience



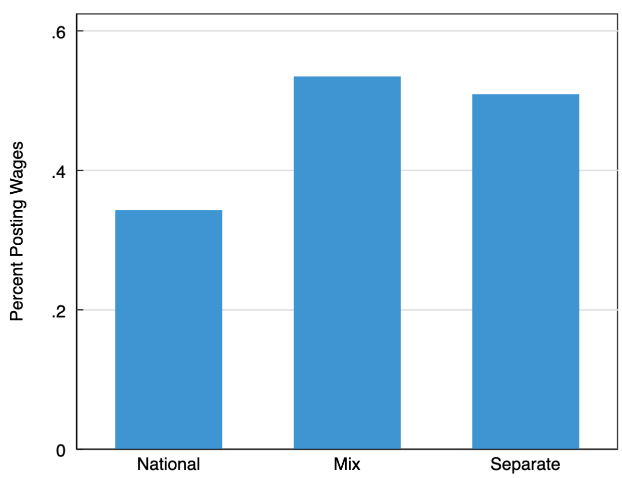
Notes: Each regression includes a quadratic in establishment size, a firm fixed effect, and fixed effects for job by county by industry by year. Nationally identical jobs are defined as those jobs paying the modal wage in occupation by firm by year cells in which at least 80% of wage pairs are the same.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

Figure A15: Method of Setting Wages among Survey Respondents



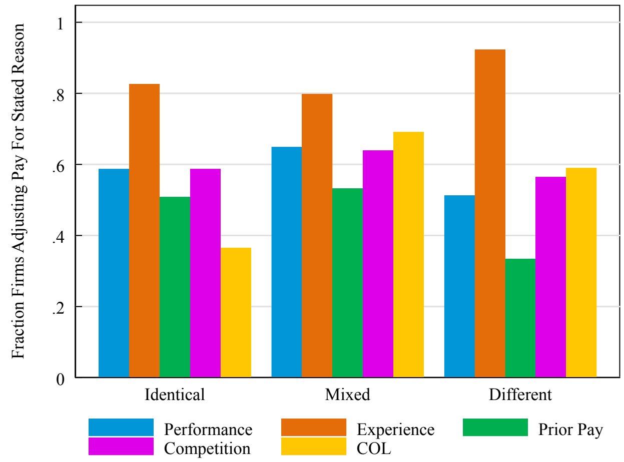
Notes: This figure shows survey responses to a question asking how the respondent's firm sets wages (panel A) or pay bands (Panel B) across locations for the majority of its workers. 20% of respondents (N=60) report setting point wages for the majority of their occupations. 80% (N=244) set pay bands. "Identical" means that a respondent stated that pay bands (wages) are set identically across establishments so that workers with the same job title face the same pay band. "Mix" means that a respondent stated that pay bands (wages) are sometimes determined separately but not always. "Separate" means that a respondent stated that pay bands (wages) are determined separately for each establishment/plant/store. The exact question asked is shown in the survey appendix.

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



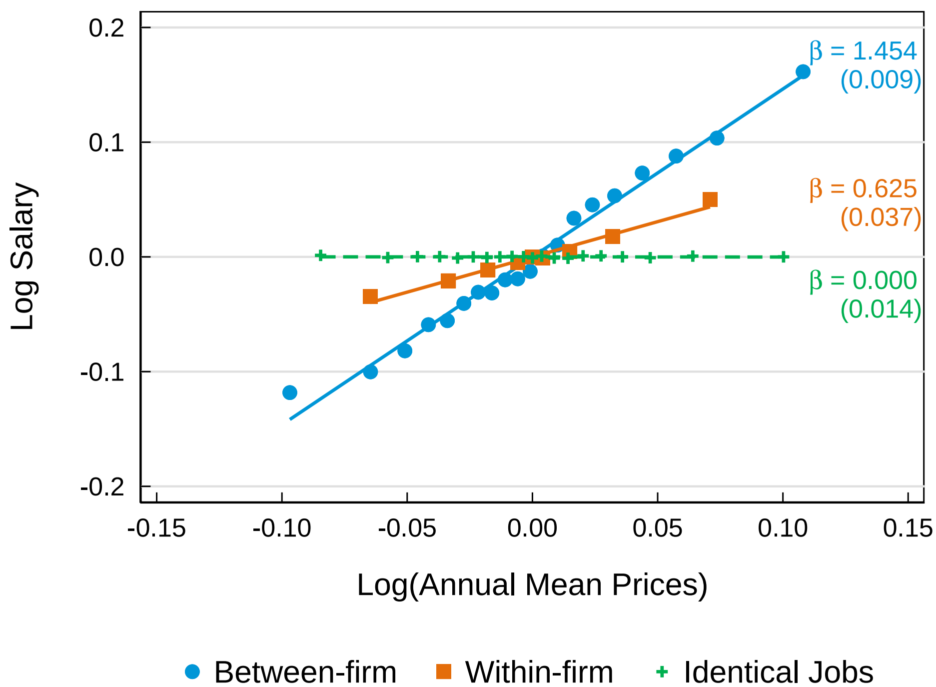
Notes: This figure shows the fraction of survey respondents who state that their firm posts wages or salary bands on the majority of their job vacancies. "National" means that a respondent stated that pay bands (wages) are set identically across establishments so that workers with the same job title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

Figure A17: Reasons for Adjusting Pay within Bands



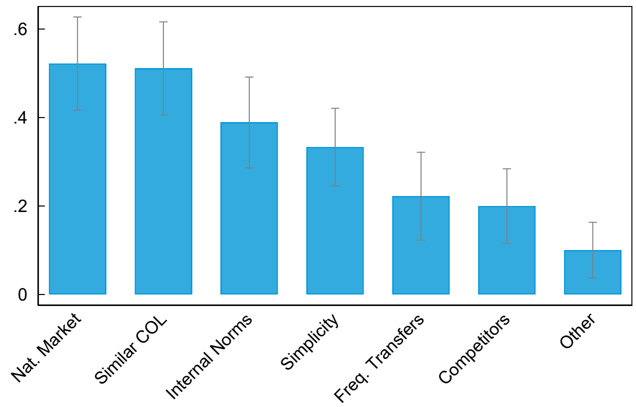
Notes: This figure shows the fraction of firms who state that they adjust pay within bands for the five provided reasons. "Identical" refers to firms who set identical pay bands in all of their establishments, "Mixed" are firms that use identical pay bands for some jobs across establishments but not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

Figure A18: Robustness to Controlling for Experience and Education



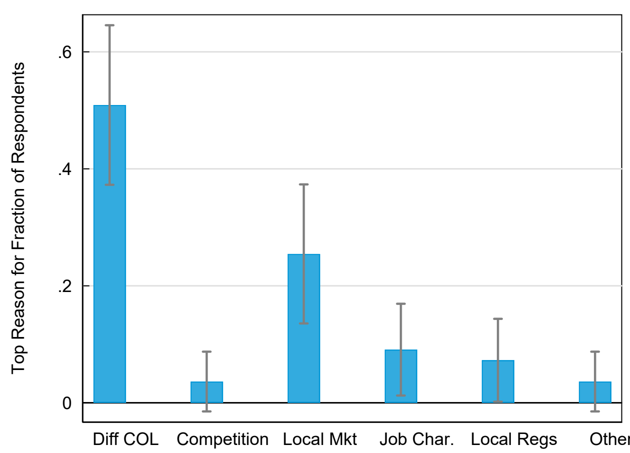
Notes: This figure shows the results from estimating equations 5 and 6 in the paper while including experience and education controls. The figure is produced using the Burning Glass data.

Figure A19: Reasons firms do not vary nominal wages across space—survey evidence



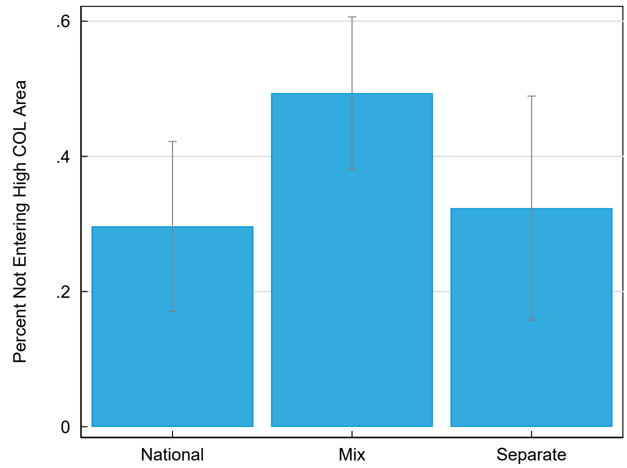
Notes: Sample is restricted to the set of respondents working at firms that set identical pay for some or all of their jobs. *Nat. Market* means that the firm hires on a national market. *Internal Norms* is the selection "We want workers performing the same job to be paid the same wage." *Similar COL*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

Figure A20: 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.

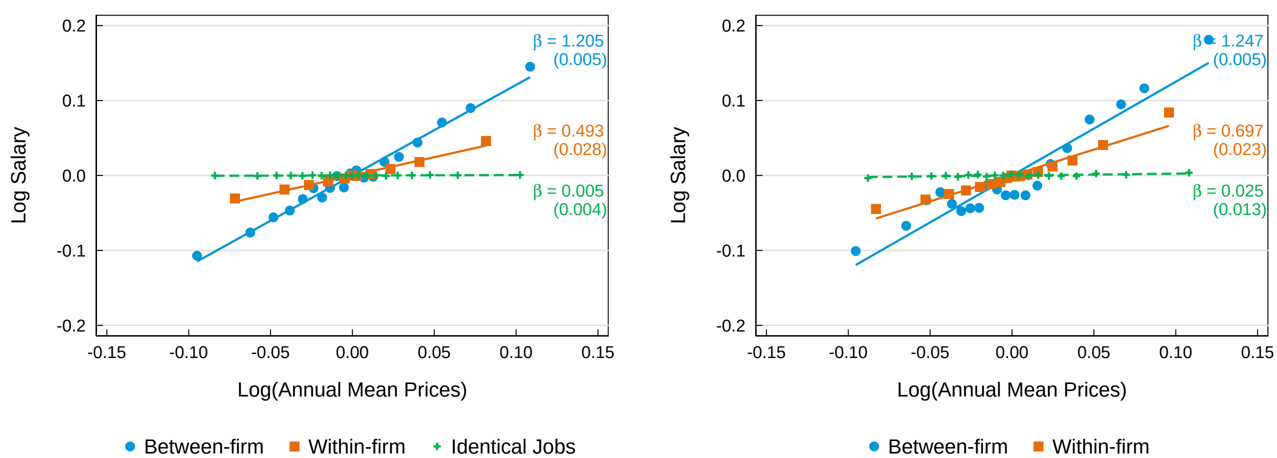
Figure A21: National Wage Setting and Entering High Cost of Living Regions



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.

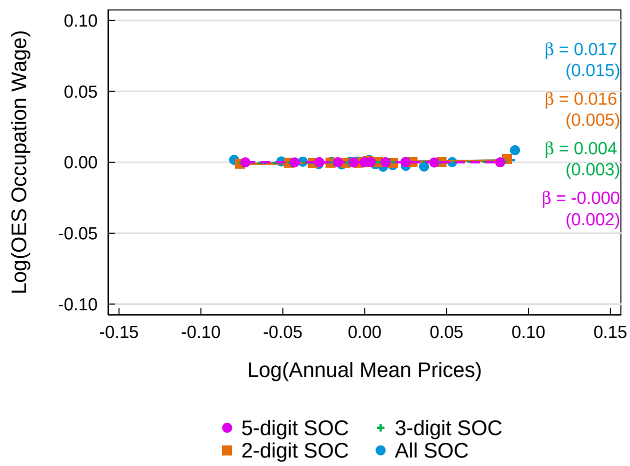
Figure A22: Posted Wages and Local Prices: Different Levels of Aggregation

(a) Within Job Titles (b) Across all occupations



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

Figure A23: Occupation Selection and Prices



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

Tables

Table A1: Comparing Median Wages in OES and Burning Glass

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

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

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

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

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

Table A3: Determinants of Wage Posting

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

Notes: The sample contains the same restriction as in row 4 of Table 1 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 A4: Sensitivity of Posted Wages to Local Conditions

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

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

Table A5: Robustness to Different Price Measures (LEHD-ACS)

	Panel A						
Price Variable:	IV			Local prices		House prices	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Average Local Price for Firm	1.567		1.583	1.433		0.180	
	(0.044)		(0.061)	(0.038)		(0.007)	
Local Price		0.818			0.759		0.091
		(0.041)			(0.037)		(0.006)
Specification	Between	Within	Between (Within Sample)	Between	Within	Between	Within
Observations	36,560,000	27,710,000	27,710,000	36,560,000	27,710,000	36,560,000	27,710,000

	Panel B					
Price Variable:	Post-2008 Reg. prices		2008 Reg. prices		Avg. annual earnings	
	(8)	(9)	(10)	(11)	(12)	(13)
Average Local Price for Firm	1.493		1.386		0.537	
	(0.041)		(0.037)		(0.012)	
Local Price		0.818		0.718		0.255
		(0.045)		(0.036)		(0.015)
Specification	Between	Within	Between	Within	Between	Within
Observations	22,790,000	17,060,000	36,560,000	27,710,000	36,560,000	27,710,000

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

Table A6: Robustness to Different Earnings and Wage Measures (LEHD-ACS)

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

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

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

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

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

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

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

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

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

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

Table A9: Robustness of Pass Through of Natural Resources Shock

	Alternate Clusters		Primary Estab. Sample		Strict Unexposed		Nontradable Occ.		Excluding Tradable Ind.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
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	458,228	2,110,997	196,458	883,500	305,199	1,439,505	265,353	1,930,300	408,332	1,542,219
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 () 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. Columns 7 and 8 restrict to non-tradeable occupations, which cannot be done from home according to Dingel and Neiman (2020). Columns 9 and 10 restrict to non-tradeable industries as defined by Chodorow-Reich et al. (2021). 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 A2.3.

Table A10: Dyadic Regressions - Location Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Within Ind.	0.486	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	0.006						
	(0.000)						
Δ Price x Within	-0.027						
	(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	0.269	0.271	0.271	0.271	0.271	0.271	0.271
Observations	123,058,376	228,952,020	228,973,712	113,323,000	176,821,048	228,973,712	228,914,744

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 4 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 A11: 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	174,681,756	227,318,776	174,686,096

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 4 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 A12: Dyadic Regressions - Firm Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
Within Ind.	0.495	0.495	0.508	0.495	0.495	0.495
	(0.043)	(0.043)	(0.046)	(0.045)	(0.046)	(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					-0.005	
					(0.014)	
Variance of Prices x Within					-0.046	
					(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	0.271	0.271
Observations	228,973,712	228,973,712	228,973,712	228,973,712	228,783,800	228,973,712

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 4 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 Chodorow-Reich et al. (2021). 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.

Table A13: 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 A14: Characteristics of National Wages Setters in Linked Compustat Subsample

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

Notes: Fixed effects are five industry groups (NAICS first digit 1 ,2, 3, 4 and 5-8). For firms with industrial and financial service data in Compustat, we keep industrial observations. For each Compustat firm that merges to Burning Glass, we take the mean across all years. Each row is from a separate regression, considering a different measure of national wage setting. In all rows, nationally identical occupations are defined as those 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.

Table A15: 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	0.46	3.6	17
$\rho = 2$, CRS	3.1	16	73	0.14	1.1	5.2
$\rho = 6$, CRS	20	75	744	0.96	7.4	33
$\rho = 4$, DRS	6.8	32	133	0.31	2.4	11
$\rho = 4$, Rationing	6.8	24	59	0.31	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.

Table A16: Franchise Analysis

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

Notes: The unit of observation on Panel A is a job pair within the firm (i.e. the same job in different locations within the firm). The dependent variable is 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 A4. Column (1) is between-firm relationship for all firms the baseline sample (i.e. Equation 6), column (2) is within-firm relationship for all firms in the baseline sample (i.e. Equation 5), 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.

B1 Survey Appendix

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

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

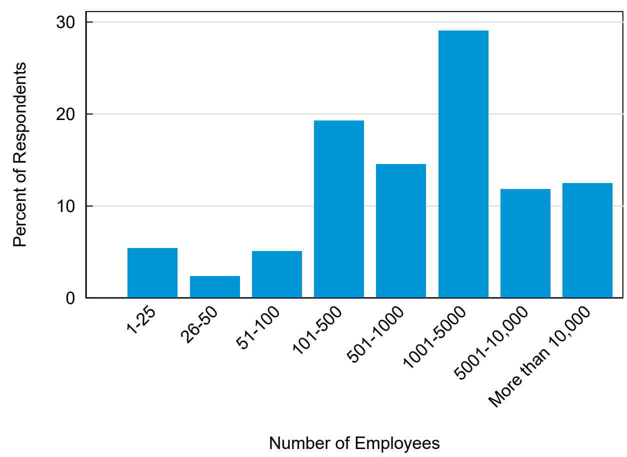
Figure B3 displays the job titles of respondents. To standardize titles, we allowed respondents to write in their title and then aggregated them. The majority of respondents work as HR managers or executives. In column 1 of Appendix Table B1, we provide additional information on the respondents and the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

Table B1: Survey Summary Statistics

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

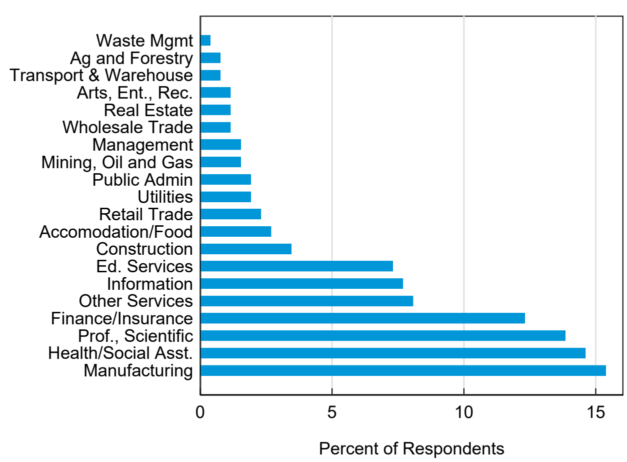
Notes: This table presents summary statistics for the set of survey respondents working at firms that operate in more than one city. Column 2 restricts to the sample of respondents who state that they work at a firm that does not set identical wages for jobs across locations. Column 3 restricts to the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

Figure B1: Number of Employees



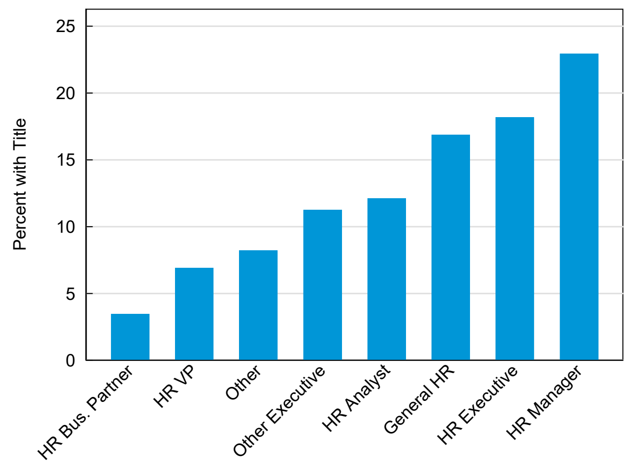
Notes: This figure shows the distribution of firm size (in terms of number of employees) among survey respondents.

Figure B2: Sector Representation of Survey Respondents



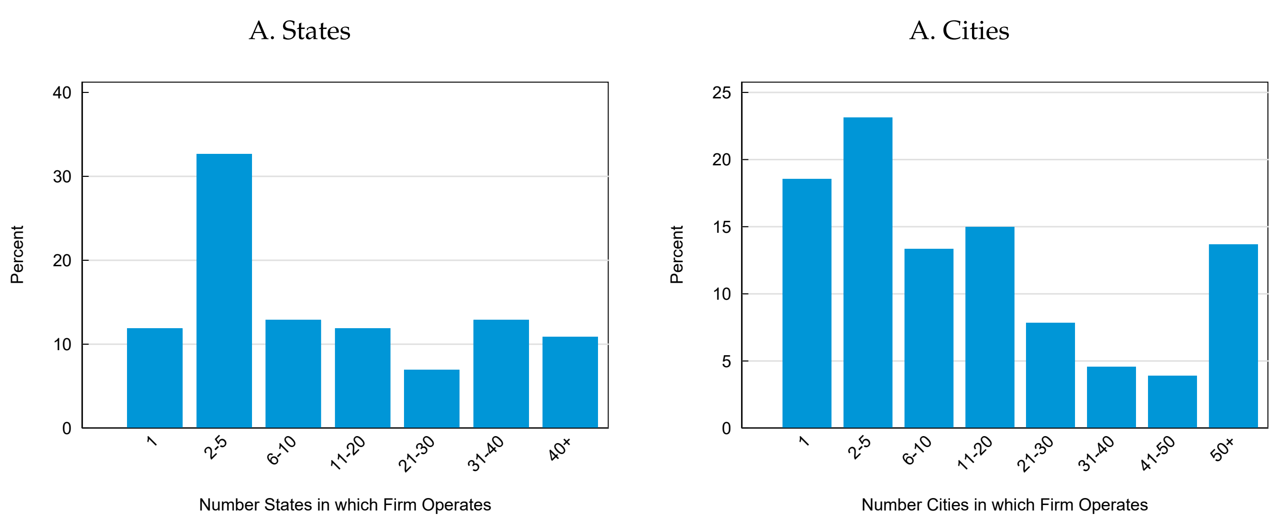
Notes: This figure shows the percent of survey respondents who work at a firm in each of the industries represented on the y-axis.

Figure B3: Respondent Job Titles



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

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



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

C1 Model Appendix

C1.1 Model Setup

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

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

Establishments have heterogeneous productivity $A_{rf} = A_f \times A_r$. The establishment has a wage W_{rf}, which it then pays to all its workers. Given employment L_{rf}, the establishment operates a decreasing returns to scale production function $F(L_{rf}) = (L_{rf})^{1-\alpha}$ and produces output $Y_{rf} = A_{rf}F(L_{rf})$ sold in a competitive market. Goods are sold at a price P_r that varies by region.

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

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

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

$$L_{rf} = W_{rf}^{\rho_r} P_r^{-\eta} \left(\sum_{k\in F} W_{rk}^{\rho_r}\right)^{\frac{\eta-\rho_r}{\rho_r}} \kappa, \tag{12}$$

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

C1.2 Deriving Equations in the Main Text

The household's budget constraint implies that consumption satisfies

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

Therefore the consumer problem simplifies to

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

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

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

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

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

as in equation (2) in the main text.

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

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

which has first order condition

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

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

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

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

which is equation (3) from the main text.

C1.3 Higher Local Consumer Prices Raise Establishment Wages

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

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

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

and from the labor supply equation (2) we have

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

Substituting equation (2) into (3) implies

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

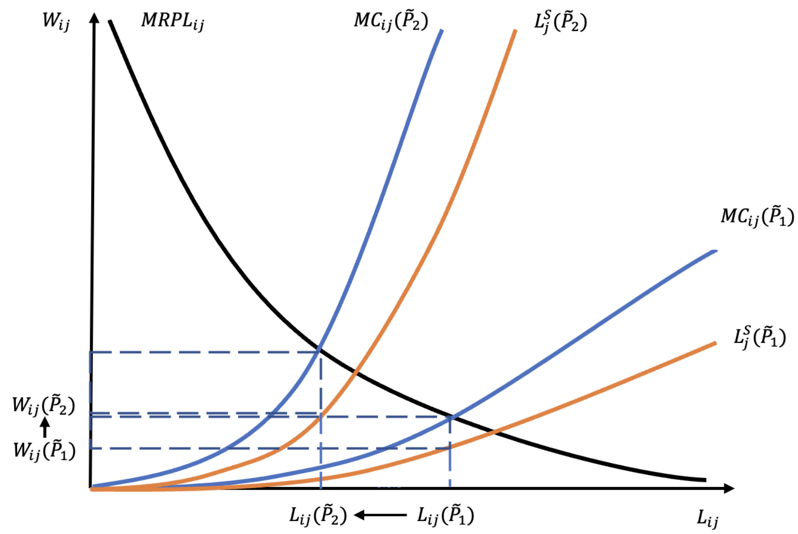
$$\implies W_{rf}^{1+\alpha\rho_r} = \frac{\rho_r}{1+\rho_r} P_r A_{rf} \left(1-\alpha\right) P_r^{\alpha\eta} \tilde{\kappa}_r^{-\alpha}$$

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

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

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

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



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

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

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

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

C1.4 Extending the Model to Tradeable Production

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

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

With these modifications, the firm level profit function is

$$\Pi_f = PF\left(\sum_{r\in R} L_{rf}\right) - \sum_{r\in R} W_{rf} L_{rf}. \tag{13}$$

As before, worker level labor supply to the establishment is

$$L_{rf} = \kappa_r W_{rf}^{\rho_r}, \tag{14}$$

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

Now, we solve the model in order to show that tradeable firms set the same frictionless wage in all establishments. To do so, we assume that the firm maximizes profits (13) subject to labor supply (14).

The first order condition is

$$\begin{aligned}
\frac{\partial \Pi_f}{\partial W_{rf}} &= 0 \\
\implies PF'\left(\sum_{r\in R} L_{rf}\right)\frac{\partial L_{rf}}{\partial W_{rf}} - \frac{\partial}{\partial W_{rf}}\left[\kappa_r W_{rf}^{1+\rho_r}\right] &= 0 \\
\implies PF'\left(\sum_{r\in R} L_{rf}\right)\kappa_r \rho_r W_{rf}^{\rho_r - 1} - \kappa_r\left(1+\rho_r\right) W_{rf}^{\rho_r} &= 0 \\
\implies PF'\left(\sum_{r\in R} L_{rf}\right)\rho_r W_{rf}^{-1} - \left(1+\rho_r\right) &= 0 \\
\implies W_{rf} = \frac{\rho_r}{1+\rho_r} PF'\left(\sum_{r\in R} L_{rf}\right). & \qquad (15)
\end{aligned}$$

Therefore, in the tradeable model, firms set wages as a markdown of marginal revenue product $PF'\left(\sum_{r\in R} L_{rf}\right)$, which varies at the firm level but not at the regional level. $\rho_r/\left(1+\rho_r\right)$ is a measure of regional labor market power. Suppose that labor market power does not vary, that is, $\rho_r/\left(1+\rho_r\right) = \rho/\left(1+\rho\right)$ where ρ is a national variable. Then, equation (15) shows that the frictionless wage does not vary across establishments for tradeable firms.

C1.5 Pass-through of Wage Shocks in the Model

This section derives the regression specification, equation (A9) from the main text. We use this derivation to formalize the exclusion restriction and show how to map the regression coefficients from the main text to the structural parameters of the model.

To start, we assume that (i) labor market power does not vary across space (ii) that establishment productivity has constant returns to scale and (iii) normalize non-tradeable prices $P_r = 1$. Under these assumptions, by equation (3), the wage for local wage setters is simply

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

whereas the wage for national wage setters is $\bar{W}_f$.

For the regression equation, we study the conditional mean of wage growth W_{rf}, conditioning on regional and firm level productivity, and whether the firm sets identical wages in regions r and r'. Some simple algebra implies that this conditional expectation equals

$$\begin{aligned}
&E\left[\Delta \log W_{rf} | A_r, A_f, W_{rf} = W_{r'f}\right] \\
&= I\left(W_{rf} = W_{r'f}\right) P\left(\text{national wage setter} | W_{rf} = W_{r'f}\right) \Delta \log \bar{W}_f \\
&+ I\left(W_{rf} \neq W_{r'f}\right) P\left(\text{national wage setter} | W_{rf} \neq W_{r'f}\right) \Delta \log \bar{W}_f \\
&+ \left[I\left(W_{rf} = W_{r'f}\right) P\left(\text{local wage setter} | W_{rf} = W_{r'f}\right) + I\left(W_{rf} \neq W_{r'f}\right) P\left(\text{local wage setter} | W_{rf} \neq W_{r'f}\right)\right] \Delta \log A_r \\
&+ \left[I\left(W_{rf} = W_{r'f}\right) P\left(\text{local wage setter} | W_{rf} = W_{r'f}\right) + I\left(W_{rf} \neq W_{r'f}\right) P\left(\text{local wage setter} | W_{rf} \neq W_{r'f}\right)\right] \Delta \log A_f.
\end{aligned} \tag{16}$$

To derive this equation we have substituted in wages for national and local wage setters into the conditional expectation, and then rearranged. Here, $I\left(W_{rf} = W_{r'f}\right)$ is an indicator variable equalling 1 if wages are equal across two establishments of the firm, $P\left(\text{national wage setter} | W_{rf} = W_{r'f}\right)$ is the probability that a firm is a national wage setter conditional on setting identical wages.

In equation (16), the first and second terms are how wage growth varies for national wage setters, conditional on national wage setters either setting identical or non-identical wages. The third and fourth terms are how regional productivity affects wages for local wage setters, setting either identical or non-identical wages. The fifth and sixth terms are how firm level productivity affects wages for local wages setters, setting either identical or non-identical wages.

Equation (16), derived here, corresponds to regression equation (A9) from the main text. In this equation, the first term after the equality corresponds to the first term after the equality of regression equation (A9). The second term corresponds to the second term after the equality of regression equation (A9). The third term in this equation is well approximated by a region fixed effect, and therefore corresponds to the penultimate term of regression equation (A9). The final term of this equation is the regression residual of regression equation (A9).

The comparison between equation (16) here, and equation (A9) of the main text makes clear what the identification assumption for our instrument is. We require a shock to firm wages $\bar{W}_f$ that is orthogonal to firm level productivity shocks $\Delta \log A_f$, conditional on the firm setting identical wages between the two locations. We provide an argument in the main text for why local natural resource booms may satisfy this identification assumption.

Finally, again comparing equation (16) here, and regression equation (A9) of the main text, we can see how to interpret the regression coefficients of the main text in terms of structural parameters. Specifically, β_1 from the regression equation of the main text (i.e. the interaction of wage growth with an indicator for equation wages), equals $P\left(\text{national wage setter}|W_{rf} = W_{r'f}\right)$, the share of jobs with identical wages that set wages nationally. In the main text we estimate $\beta_1 = 0.83$ with a standard error of 0.12. Combining the model with the estimates, we cannot reject that $P\left(\text{national wage setter}|W_{rf} = W_{r'f}\right) = 1$, i.e. all jobs with identical wages set wages nationally.

C1.6 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.

C1.6.1 Change in Profits with Constant Returns to Scale

To simplify the algebra, define the labor supply curve, equation (2), as $L_{rf} = \tilde{\kappa}_r W_{rf}^{\rho}$, where $\tilde{\kappa} \equiv P_r^{-\eta}\left(\sum_{k \in F} W_{rk}^{\rho_r}\right)^{\frac{\eta-\rho_r}{\rho_r}} \kappa$; normalize prices $P_r = 1$; assume constant returns to scale in production, so that we have $Y_{rf} = A_f A_r L_{rf}$; and assume that labor market power does not vary across regions, so $\rho_r = \rho$.

Then establishment profits are

$$\Pi_{rf} = Y_{rf} - W_{rf} L_{rf} = \left(A_f A_r - W_{rf}\right) \kappa_r W_{rf}^{\rho},$$

where the second equality substitutes in the labor supply curve and the production function. Therefore profits under local wage setting are

$$\Pi_{rf}^{*} = \left(A_f A_r - W_{rf}^{*}\right) \kappa_r W_{rf}^{*\rho}$$

and profits under national wage setting are

$$\Pi_{rf}^{c} = \left(A_f A_r - \bar{W}_f\right) \kappa_r \bar{W}_f^{\rho},$$

where $\bar{W}_f^\rho$ is the national wage setter's wage. With some simple algebra, the change in profits is

$$\frac{\Pi_{rf}^* - \Pi_{rf}^c}{\Pi_{rf}^*} = 1 - \frac{\left(A_f A_r \bar{W}_f^\rho - \bar{W}_f^{\rho+1}\right)}{\left(A_f A_r W_{rf}^{*\rho} - W_{rf}^{*\rho+1}\right)}. \tag{17}$$

Next, observe by equation (3) that the establishment wage is

$$W_{rf}^* = \frac{\rho}{1+\rho} A_f A_r \implies A_f A_r = W_{rf}^* \frac{1+\rho}{\rho}, \tag{18}$$

where the implication rewrites establishment TFP in terms of wages. We can substitute equation (18) into equation (17) to get

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

which is equation (1) from the main text.

C1.6.2 Change in Profits with Decreasing Returns to Scale

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

$$Y_{rf} = A_f A_r \bar{K}^\alpha L_{rf}^{1-\alpha}$$

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

$$\begin{aligned}
&\max_{W_{rf}, L_{rf}} A_f A_r \bar{K}^\alpha L_{rf}^{1-\alpha} - W_{rf} L_{rf} \\
&= \max_{W_{rf}} A_f A_r \bar{K}^\alpha \left(\kappa_r W_{rf}^\rho\right)^{1-\alpha} - \kappa_r W_{rf}^{1+\rho},
\end{aligned}$$

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

$$A_f A_r \bar{K}^\alpha (1-\alpha)\left(\kappa_r W_{rf}^\rho\right)^{-\alpha} \kappa_r \rho W_{rf}^{\rho-1} - (1+\rho)\kappa_r W_{rf}^\rho = 0$$

$$\implies W_{rf}^{*1+\alpha\rho} \frac{1+\rho}{\rho} \frac{1}{1-\alpha} \kappa_r^\alpha = A_f A_r \bar{K}^\alpha. \tag{19}$$

Profits under optimality for the local wage setter are then

$$\Pi_{rf}^* = A_f A_r \bar{K}^\alpha \left(\kappa_r W_{rf}^{*\rho}\right)^{1-\alpha} - \kappa_r W_{rf}^{*1+\rho}$$

$$
\begin{aligned}
\implies \Pi^*_{rf} &= W^{*1+\alpha\rho}_{rf} \frac{1+\rho}{\rho} \frac{1}{1-\alpha} \kappa_r^{\alpha} \left(\kappa_r W^{*\rho}_{rf}\right)^{1-\alpha} - \kappa_r W^{*1+\rho}_{rf} \\
&= \left[W^{*1+\alpha\rho}_{rf} \frac{1+\rho}{\rho} \frac{1}{1-\alpha} W^{*\rho(1-\alpha)}_{rf} - W^{*1+\rho}_{rf} \right] \kappa_r,
\end{aligned}
$$

where we have used equation (19) in the second line. Profits under national wage setting are

$$
\Pi^c_{rf} = A_f A_r \bar{K}^{\alpha} L^{1-\alpha}_{rf} - \bar{W}_f L_{rf}
$$

$$
\begin{aligned}
\implies \Pi^c_{rf} &= A_f A_r \bar{K}^{\alpha} \left(\kappa_r \bar{W}^{\rho}_{f}\right)^{1-\alpha} - \kappa_r \bar{W}^{1+\rho}_{f} \\
&= \left[W^{*1+\alpha\rho}_{rf} \frac{1+\rho}{\rho} \frac{1}{1-\alpha} \bar{W}^{\rho(1-\alpha)}_{f} - \bar{W}^{1+\rho}_{f} \right] \kappa_r,
\end{aligned}
$$

where again we have used equation (19) in the second line. Then the difference in profits due to national wage setting are

$$
\begin{aligned}
\frac{\Pi^*_{rf} - \Pi^c_{rf}}{\Pi^*_{rf}} &= 1 - \frac{\Pi^c_{rf}}{\Pi^*_{rf}} \\
&= 1 - \frac{W^{*1+\alpha\rho}_{rf} \frac{1+\rho}{\rho} \frac{1}{1-\alpha} \bar{W}^{\rho(1-\alpha)}_{f} - \bar{W}^{1+\rho}_{f}}{W^{*1+\alpha\rho}_{rf} \frac{1+\rho}{\rho} \frac{1}{1-\alpha} W^{*\rho(1-\alpha)}_{rf} - W^{*1+\rho}_{rf}},
\end{aligned}
\tag{20}
$$

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.

C1.6.3 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

$$
\Pi^*_{rf} = A_f A_r L^{*1-\alpha}_{rf} - W^*_{rf} L^*_{rf}
$$

which implies

$$
MRPL\left(L_{rf}\right) = A_f A_r \left(1-\alpha\right) L^{*-\alpha}_{rf},
$$

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

$$
\begin{aligned}
W^*_{rf} &= \frac{\rho}{1+\rho} MRPL\left(L^*_{rf}\right) \\
&= \frac{\rho}{1+\rho} A_f A_r \left(1-\alpha\right) L^{*-\alpha}_{rf}
\end{aligned}
$$

$$\implies \left(\frac{1+\rho}{\rho}W^*_{rf}\frac{1}{A_f A_r(1-\alpha)}\right) = L^{*-\alpha}_{rf}$$

$$\implies L^*_{rf} = \left(\frac{1+\rho}{\rho}W^*_{rf}\frac{1}{A_f A_r(1-\alpha)}\right)^{-\frac{1}{\alpha}}.$$

Therefore profits for local wage setters are

$$\begin{aligned}\Pi^*_{rf} &= A_f A_r L^{*1-\alpha}_{rf} - W^*_{rf}L^*_{rf} \\ &= (A_f A_r)^{\frac{1}{\alpha}}\left[\left(\frac{1+\rho}{\rho}W^*_{rf}\frac{1}{(1-\alpha)}\right)^{-\frac{1-\alpha}{\alpha}} - W^*_{rf}\left(\frac{1+\rho}{\rho}W^*_{rf}\frac{1}{(1-\alpha)}\right)^{-\frac{1}{\alpha}}\right].\end{aligned}$$

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

$$\bar{W}_f = MRPL(L_{rf})$$

$$\implies \bar{W}_f = A_f A_r(1-\alpha)L^{-\alpha}_{rf}$$

$$\implies L_{rf} = \left(\frac{\bar{W}_f}{(1-\alpha)A_f A_r}\right)^{-\frac{1}{\alpha}},$$

which implies profits under rationing are

$$\begin{aligned}\Pi^R_{rf} &= A_f A_r L^{1-\alpha}_{rf} - \bar{W}_{rf}L_{rf} \\ &= (A_f A_r)^{\frac{1}{\alpha}}\left[\left(\frac{\bar{W}_f}{(1-\alpha)}\right)^{-\frac{1-\alpha}{\alpha}} - \bar{W}_{rf}\left(\frac{\bar{W}_f}{(1-\alpha)}\right)^{-\frac{1}{\alpha}}\right].\end{aligned}$$

Then the percentage difference between Π^R_{rf} and Π^*_{rf} is

$$\begin{aligned}\frac{\Pi^R_{rf}}{\Pi^*_{rf}} &= \frac{(A_f A_r)^{\frac{1}{\alpha}}\left[\left(\frac{\bar{W}_f}{(1-\alpha)}\right)^{-\frac{1-\alpha}{\alpha}} - \bar{W}_{rf}\left(\frac{\bar{W}_f}{(1-\alpha)}\right)^{-\frac{1}{\alpha}}\right]}{(A_f A_r)^{\frac{1}{\alpha}}\left[\left(\frac{1+\rho}{\rho}W^*_{rf}\frac{1}{(1-\alpha)}\right)^{-\frac{1-\alpha}{\alpha}} - W^*_{rf}\left(\frac{1+\rho}{\rho}W^*_{rf}\frac{1}{(1-\alpha)}\right)^{-\frac{1}{\alpha}}\right]} \\ &= \frac{\bar{W}_f^{-\frac{1-\alpha}{\alpha}}\left(\frac{1}{(1-\alpha)}\right)^{-\frac{1}{\alpha}}\left[\left(\frac{1}{(1-\alpha)}\right)^{1-\alpha} - 1\right]}{W^{*-\frac{1-\alpha}{\alpha}}_{rf}\left(\frac{1+\rho}{\rho}\frac{1}{(1-\alpha)}\right)^{-\frac{1}{\alpha}}\left[\left(\frac{1+\rho}{\rho}\frac{1}{(1-\alpha)}\right)^{1-\alpha} - 1\right]}.\end{aligned}$$

Define the wage at which the establishment's labor demand and labor supply intersect by $\tilde{W}_f$. The establishment will ration labor if $\bar{W}_f > \tilde{W}_f$, i.e. labor supply exceeds labor demand at the nationally set wage. Hence the establishment will have a profit change $\frac{\Pi^R_{rf}}{\Pi^*_{rf}}$ in this region, and otherwise will have a profit change $\frac{\Pi^c_{rf}}{\Pi^*_{rf}}$ as defined in equation (20).

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

C1.6.4 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

$$Y_{it} = A_f A_r K^{\alpha}_{rf} L^{1-\alpha}_{rf}$$

and labor supply curve

$$L_{rf} = \kappa_r W^{\rho}_{rf},$$

where K_{rf} is rented at cost r and κ_j is defined by equation (2). Then the local wage setter solves

$$\max_{W_{rf}, L_{rf}, K_{rf}} A_f A_r K^{\alpha}_{rf} L^{1-\alpha}_{rf} - W_{rf} L_{rf} - r K_{rf}$$

The first order condition with respect to capital is

$$A_f A_r \alpha K^{\alpha-1}_{rf} L^{1-\alpha}_{rf} - r = 0$$

$$\implies K^*_{rf} = \left(\frac{\alpha A_f A_r}{r}\right)^{\frac{1}{1-\alpha}} L_{rf}.$$

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

$$\max_{W_{rf}, L_{rf}} A_f A_r K^{*\alpha}_{rf} L^{1-\alpha}_{rf} - W_{rf} L_{rf} - r K^*_{rf}$$

$$= \max_{W_{rf}, L_{rf}} \left((A_f A_r)^{\frac{1}{1-\alpha}} \left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha}} - \left[W_{rf} + r^{-\frac{\alpha}{1-\alpha}} (\alpha A_f A_r)^{\frac{1}{1-\alpha}} \right] \right) L_{rf}$$

so profits under optimality are

$$\left((A_f A_r)^{\frac{1}{1-\alpha}} \left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha}} - \left[W^*_{rf} + r^{-\frac{\alpha}{1-\alpha}} (\alpha A_f A_r)^{\frac{1}{1-\alpha}} \right] \right) \kappa_r W^{*\rho}_{rf}.$$

Then note that the optimal wage is

$$\frac{d}{dW^*_{rf}} \left((A_f A_r)^{\frac{1}{1-\alpha}} \left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha}} - \left[W^*_{rf} + r^{-\frac{\alpha}{1-\alpha}} (\alpha A_f A_r)^{\frac{1}{1-\alpha}} \right] \right) \kappa_r W^{*\rho}_{rf} = 0$$

$$\implies \frac{1+\rho}{\rho} W^*_{rf} = \left((A_f A_r)^{\frac{1}{1-\alpha}} \left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha}} - r^{-\frac{\alpha}{1-\alpha}} (\alpha A_f A_r)^{\frac{1}{1-\alpha}} \right).$$

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

$$\max_{L_{rf}, K_{rf}} A_f A_r K^{\alpha}_{rf} L^{1-\alpha}_{rf} - \bar{W}_{rf} L_{rf} - r K_{rf}.$$

The first order condition for the national wage setter is

$$A_f A_r \alpha K^{\alpha-1}_{rf} L^{1-\alpha}_{rf} - r = 0$$

$$\implies K^*_{rf} = \left(\frac{\alpha A_f A_r}{r}\right)^{\frac{1}{1-\alpha}} L_{rf}$$

which simplifies the problem to

$$\max_{L_{rf}, K_{rf}} A_f A_r K^{\alpha}_{rf} L^{1-\alpha}_{rf} - \bar{W}_{rf} L_{rf} - r K_{rf}$$

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

Therefore profits with national wage setting are

$$\left((A_f A_r)^{\frac{1}{1-\alpha}} \left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha}} - \left[\bar{W}_{rf} + r^{-\frac{\alpha}{1-\alpha}} (\alpha A_f A_r)^{\frac{1}{1-\alpha}}\right] \right) \kappa_r \bar{W}^{\rho}_{rf}.$$

The profit loss is then

$$\begin{aligned} \frac{\Pi^*_{rf} - \Pi^c_{rf}}{\Pi^*_{rf}} &= 1 - \frac{\Pi^c_{rf}}{\Pi^*_{rf}} \\ &= 1 - \frac{\left(\frac{1+\rho}{\rho} W^*_{rf} - \bar{W}_{rf}\right) \bar{W}^{\rho}_{rf}}{\left(\frac{1+\rho}{\rho} W^*_{rf} - W^*_{rf}\right) W^{*\rho}_{rf}}, \end{aligned}$$

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

C1.7 Model of National Wage Setting

In the main text, we assume that national wage setters wet a wage W_f that does not vary across establishments. We now specify the national wage setters' problem. Specifically, we assume that national wage setters maximize firm wide profits, subject to labor supply in each region and the constraint that they pay the same wage everywhere. We will show that as a result, national wage setters set their wage as a weighted average of the frictionless wage that they would have set in each region, absent national wage setting. This model of national wage setting will be useful for deriving subsequent results in the Model Appendix, but is not directly used in the main text or in the preceding parts of the Model Appendix.

Therefore national wage setters solve

$$\max_{W_f, L_{rf}} \sum_{r\in R} \left[P_r A_{rf} F(L_{rf}) - W_f L_{rf}\right] \quad \text{subject to } L_{rf} = (W_f)^{\rho_r} \kappa_r$$

$$\implies \max_{W_f} \sum_{r\in R} \left[P_r A_{rf} F((W_f)^{\rho_r} \kappa_r) - W_f (W_f)^{\rho_r} \kappa_r\right]$$

$$\implies \max_{W_f} \sum_{r\in R} \left[P_r A_{rf} F((W_f)^{\rho_r} \kappa_r) - (W_f)^{1+\rho_r} \kappa_r\right]$$

which has first order condition

$$\sum_{r\in R} \left[P_r A_{rf} F'(L_{rf})\rho_r (W_f)^{\rho_r - 1} \kappa_r - (1+\rho_r)(W_f)^{\rho_r} \kappa_r\right] = 0$$

$$\implies \sum_{r\in R} \left[P_r A_{rf} F'(L_{rf})\rho_r (W_f)^{\rho_r} (W_f)^{-1} \kappa_r - (1+\rho_r)(W_f)^{\rho_r} \kappa_r\right] = 0.$$

Substituting in $L_{rf} = (W_{rf})^{\rho_r} \kappa_r$, this becomes

$$\implies \sum_{r\in R} \left[P_r A_{rf} F'(L_{rf})\rho_r (W_f)^{-1} L_{rf} - (1+\rho_r) L_{rf}\right] = 0$$

$$\implies \sum_{r\in R} \left[P_r A_{rf} F'(L_{rf})\rho_r (W_f)^{-1} L_{rf}\right] = \sum_{r\in R} \left[(1+\rho_r) L_{rf}\right]$$

$$\begin{aligned}\implies W_f &= \sum_{r\in R} \frac{\rho_r L_{rf}}{\sum_{k\in N}\left[(1+\rho_k) L_{ik}\right]} P_r A_{rf} F'(L_{rf}) \\ &= \sum_{r\in R} \frac{(1+\rho_r) L_{rf}}{\sum_{k\in N}\left[(1+\rho_k) L_{ik}\right]} \frac{\rho_r}{1+\rho_r} P_r A_{rf} F'(L_{rf})\end{aligned}$$

$$\implies W_f = \sum_{r\in R} \omega_{rf} \frac{\rho_r}{1+\rho_r} P_r A_{rf} F'(L_{rf}), \tag{21}$$

where $\omega_{rf} = (1+\rho_r) L_{rf} / \sum_{k\in N}\left[(1+\rho_k) L_{ik}\right]$. Therefore national wage setters set their wage W_f as a weighted average of $\frac{\rho_r}{1+\rho_r} P_r A_{rf} F'(L_{rf})$, which is the frictionless wage that they would have set in each region absent national wage setting (see equation (3) from the main text).

In the remaining sections of the Model Appendix, we will assume that national wage setters follow this behavior, in order to derive further results. However this model is not used in previous parts of the Model Appendix, nor in the main text.

C1.8 Calculating Magnitudes Using Model

In the main text we asserted that under certain assumptions, the ratio of between-firm versus within-firm coefficients, in Figure 3, identifies the share of local wage setters in the economy. Now, we explain the assumptions under which this result holds, and then derive the result.

First, we state the assumptions:

1. On average, high productivity firms with high A_f do not sort into high productivity areas with high A_r
2. There is constant returns to scale and constant labor market power across space.
3. Different from the main text, firm f operates establishments in only a subset of the regions, but the share of national and local wage setters in each region is $\mathcal{N}$ as in the main text.

As we discuss in the main text, we view the first of these assumptions as the most substantive. This assumption is likely not correct—nevertheless, by making it, we are able to arrive at a useful way to compare the magnitudes of estimates in the two datasets. An additional implicit assumption is that the distribution of productivity within firms, across space, is the same as the distribution of productivity between firms, across space. This assumption is guaranteed by assuming that establishment labor productivity takes the form $A_{rf} = A_r \times A_f$.

In what follows, we will use lower case variables to denote the logarithm of upper case variables. We also note that the result only holds to a first order.

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

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

$$\implies w_{rf}^L = \log\left(\frac{\rho}{1+\rho}\right) + p_r + a_r + a_f$$
$$= \mu_f + p_r + a_r \quad \mu_f \equiv \log\left(\frac{\rho}{1+\rho}\right) + a_f. \tag{22}$$

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

$$a_r = \bar{a} + a'(\bar{p})(p_r - \bar{p}), \tag{23}$$

which implies from equation (22) that the local wage setter's log wage is

$$w_{rf}^L = \mu_f + p_r + \bar{a} + a'(\bar{p})(p_r - \bar{p}).$$

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

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

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

$$
\frac{\partial E\left[w_{rf}|\mu_f, p_r, a_r\right]}{\partial p_r} = (1-\mathcal{N})\left(1 + a'(\bar{p})\right), \tag{24}
$$

since the regression coefficient is simply the derivative of the conditional expectation.

The mean wage for local wage setters, averaging across their establishments, is

$$
\begin{aligned}
W_f^L &= \frac{\sum_{r\in R_f} \frac{\rho}{1+\rho} P_r A_r A_f}{R_f} \\
&= \frac{\rho}{1+\rho} A_f \frac{\sum_{r\in R_f} P_r A_r}{R_f} \\
&\approx \frac{\rho}{1+\rho} A_f \frac{\sum_{r\in R_f} P_r}{R_f} \frac{\sum_{r\in R_f} A_r}{R_f}
\end{aligned}
$$

where the third line is a first order approximation as $P_r \to \bar{P}$ and $A_r \to \bar{A}$. Therefore we have

$$
\begin{aligned}
\implies w_f^L &= \mu_f + \log\left(\frac{\sum_{r\in R_f} P_r}{R_f}\right) + \log\left(\frac{\sum_{r\in R_f} A_r}{R_f}\right) \\
&= \mu_f + \bar{p}_f + \bar{a}_f
\end{aligned}
$$

The mean wage for national wage setters is, by the assumptions of this section and the model of national wage setting in subsection C1.7, given by

$$
W_f^N = \frac{\rho}{1+\rho} A_f \frac{\sum_{r\in R_f} P_r A_r}{R_f}
$$

$$
\begin{aligned}
\implies w_f^N &= \mu_f + \log\left(\frac{\sum_{r\in R_f} P_r A_r}{R_f}\right) \\
&\approx \mu_f + \bar{p}_f + \bar{a}_f
\end{aligned}
$$

Therefore the conditional mean firm wage, averaging across national and local wage setters, and given productivity and prices, is

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

where the second line substitutes equation (23). Therefore the regression coefficient from regressing mean firm wages on the mean price of the firm is

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

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

$$\frac{\partial E\left[w_f|\mu_f,\bar{p}_r,\bar{a}_r\right]}{\partial\bar{p}_f}=1+a'\left(\bar{p}\right). \tag{25}$$

Equation (24) defines the within firm coefficient from a regression of wages on prices. Equation (25) defines the between firm regression coefficient. The ratio of these two regression coefficients is $(1-\mathcal{N})$, the share of local wage setters.

C1.9 Wage Premia for National Wage Setters

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

We now derive an expression for the wage premium of national wage setters. To do so, we make several simplifying assumptions within the baseline model. We assume that establishment production has constant returns to scale, that labor supply elasticities to the establishment are constant across space, and that establishment productivity has a firm and region component so that $A_{rf}=A_rA_f$. Under these assumptions, the wage paid by a national wage setter simplifies from equation (21) of the main text to yield

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

where the first equality is equation (21) of the main text; the second equality substitutes in the definitions of the weights ω_{rf}; the third equality substitutes in labor supply to the establishment (2), and the optimal wage of a local wage setter (3); and the final equality simplifies. Recall from Appendix Section C1.1 that

$\kappa_r \equiv P_r^{-\eta} \left(\sum_{k \in M} W_{rk}^{\rho}\right)^{\frac{\eta-\rho}{\rho}}$ is a composite parameter capturing labor supply to the region.

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

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

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

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

$$\begin{aligned}
W_f^* - \bar{W}_f &= \frac{\rho}{1+\rho} A_f \sum_{r \in R} \frac{\kappa_r}{\sum_{k \in R} \kappa_k} A_r - \frac{\rho}{1+\rho} \tilde{A}_f \frac{1}{R} \sum_{r \in R} A_r \\
&= \frac{\rho}{1+\rho} \left(A_f \sum_{r \in R} \frac{\kappa_r}{\sum_{k \in R} \kappa_k} A_r - \tilde{A}_f \frac{1}{R} \sum_{r \in R} A_r \right). \qquad (26)
\end{aligned}$$

Equation (26) suggests two reasons for a premium. First, national wage setters could be more productive. Clearly, if the productivity of the national wage setter (A_f) is much greater than the productivity of the local wage setter ($\tilde{A}_f$) then there is a premium.

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

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

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

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

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