National Wage Setting*

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November 2021

Abstract

How do firms set wages across space? Using vacancy data with detailed job-level information supplemented with a survey of HR managers and self-reported data on workers' wages, we show that, within the firm, 30-40% of posted wages for a given job are identical across space. Compared to differences between firms, nominal posted wages within the firm vary relatively little with local prices, a pattern that is present for realized wages as well. Using the pass-through of local shocks to wages in other locations of the firm, we argue that the limited variation of wages within firms is due to *national wage setting*, meaning that firms choose rigid pay structures in which they set very similar nominal wages for the same job in different regions. Our survey suggests that one reason firms set wages nationally is that nominal, rather than real, wage comparisons matter to workers.

JEL Codes: J24, J45, J33, H56

*We thank Lila Englander, Michael Galperin, Nidhaan Jain, and Isaac Liu for excellent research assistance; Anna Stansbury for sharing code; and Otis Reid for helpful discussions that shaped the development of the project. We also thank Adrien Bilal, Ellora Derenoncourt, Jonathan Dingel, Alex Frankel, Erik Hurst, Anders Humlum and Simon Jager for helpful discussions that shaped this draft. First version: September 2021.

1 Introduction

In the US, big firms have grown in large part by expanding into new regions (Hsieh and Rossi-Hansberg, 2019). The result is that local labor markets are increasingly dominated by a small number of large firms that operate in many regions. Indeed, while the concentration of employment across firms in local labor markets has fallen in the last several decades, the concentration of employment nationally has risen (Autor, Dorn, Katz, Patterson, and Van Reenen, 2020; Rossi-Hansberg, Sarte, and Trachter, 2020). Understanding how large national firms set wages matters for many phenomena, such as wage inequality, the growth of labor market power, and the response of the economy to local shocks.

This paper investigates how firms set wages across space. Standard models of the labor market assume that firms vary wages freely across space, adjusting wages at each establishment to account for local productivity or local differences in labor supply. Unless firms face identical labor market conditions, this will lead to differences in wages across locations within the firm. In this paper, we find that instead, wages within the firm are very compressed, with around 30-40 percent of jobs within the firm having exactly the same posted wage. We argue that this wage compression arises because of *national wage setting*, wherein firms adopt rigid pay structures in which they set the same nominal wage for the same job in different locations, even if labor market conditions are different across the locations.

The primary dataset we use to establish these results has online job vacancies provided by Burning Glass Technologies. The dataset includes 10% of US vacancies, either online or offline, between 2010 and 2019, and provides posted wages for detailed occupations across establishments within a firm.[1,2] Investigating national wage setting with standard administrative datasets is difficult for two reasons. First, without detailed information on job titles, the changing job composition within a firm across regions may mask national wage-setting. For example, even if CVS pays the same wage to cashiers in Cincinnati and San Francisco, average wages will be lower in the Cincinnati store if CVS hires more cashiers there. Second, most administrative datasets measure earnings and not wages. In this example, this could mask national wage-setting if workers in San Francisco work longer hours.

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

[2]The full dataset collected by Burning Glass contains the universe of online vacancies, which is 70% of total vacancies including vacancies that are not posted online. We study only the vacancies in Burning Glass that post wage information.

The Burning Glass data allows us to overcome these challenges. First, the data contains detailed job level information, meaning we can directly control for changes in job composition across regions. Second, vacancies separately post wages and hours, allowing us to distinguish between wages and earnings. The disadvantage of using vacancy postings is that we do not measure realized wages, which could differ from posted wages if workers negotiate or receive bonuses. This biases our conclusions only if the gap between posted and realized wages varies with geography. We show that the Burning Glass wages closely correspond to the other publicly available wage measures for occupations and regions, suggesting posted wages capture much of the variation in pay across locations. Moreover, our analysis is limited to the set of jobs that post wages online, which, while covering a broad swath of the economy, slightly over represents professional occupations.

We complement these data with two additional datasets. First, we conducted an original survey of HR managers and executives. We asked questions about how firms set wages and why they adopt their wage-setting policy. The survey data allows us to test whether realized wages show similar patterns to posted wages, to explore whether our findings are similar for firms outside of our Burning Glass sample, and to explain why firms choose to set wages nationally. Second, we use data on self-reported wages and other forms of compensation from Payscale, and data compensation company, to test whether workers' realized wages are also compressed across space.

We begin the analysis with four descriptive facts about wage setting across space. First, we find a large amount of identical wages across firms' establishments, with 30-40% of postings for the same job in the same firm but in different locations having exactly the same wage. Second, we find that identical wage setting is a choice made by firms for each occupation – for a given occupation, some firms set identical wages across *all* their locations, while the remaining firms set different wages across most of their locations. Third, we show that within firms, nominal wages are relatively insensitive to local prices. Fourth, we show that firms setting identical wages pay a wage premium. These facts are in line with HR professionals' survey responses regarding how they set pay. We additionally use the Payscale data to show that realized wages are also insensitive to local prices.

In the next part of the paper, we argue that firms set identical wages across space in large part because of what we term *national wage setting* – certain firms pay the same wage everywhere regardless of how local labor market conditions vary. To fix ideas, we develop a simple model of firms who employ workers in multiple locations, integrating standard models of imperfect labor market competition (e.g. Card et al., 2018) and spatial equilibrium (i.e. the Rosen-Roback model). There are two types of firms: national wage setters, who due to a rigidity must pay the same nominal wage everywhere; and local wage setters, who can vary nominal pay across locations. Identical wages can arise for two reasons. First, local wage setters might set equal wages across space if they have both the same revenue product of labor everywhere and the same labor supply elasticity in each market. Second, national wage setters set equal wages across space regardless. We derive estimating equations from the model to differentiate between the explanations for identical wages. The model makes two predictions about the wage dynamics of national wage setters. First, wage *changes* in different establishments of national wage setters should "bunch" at the same values. Second, for national wage setters, local shocks to labor productivity in a single establishment should affect wages throughout the firm.

We test these predictions using a shock to the demand for natural resources, which creates a labor demand shock for establishments located in natural resource-intensive regions but not directly operating in the natural resource sector. A large share of firms raise wages in all establishments after the natural resources shock, even those not directly exposed, consistent with national wage setting. More nuanced predictions of national wage setting also hold in the data: firms that we classify as national wage setters change wages by less in regions affected by natural resource shocks; they are more likely to pass any wage changes through to their other unaffected establishments; and wage changes across the firm move by similar amounts in response to the shock. We conclude that a substantial portion of identical wages across space reflect these constraints.

Next, we ask *why* firms choose to set wages nationally. Our combination of job vacancy and survey evidence suggests that firms set wages nationally for two main reasons – firms set national wages to simplify management when the costs to doing so are low, and because workers care about nominal, rather than real, pay comparisons across space. In support of the second explanation, firms report setting national wages because they hire workers on a national labor market, and nationally mobile workers compare nominal wages – instead of real wages – across space. Firms also report that they implement this practice to adhere to fairness norms within the firm that constrain nominal wages across locations.

Lastly, we carry out a simple exercise with our model to measure the profits at stake from setting wages nationally. We estimate what wage dispersion would have been for national wage setters, in a counterfactual where they vary wages across regions. For this estimate we assume that observably similar firms, who do not set wages nationally, provide a reasonable counterfactual for the distribution of wages across locations of national wage setters. We find that in the absence of national wage setting, wages for national wage setters would vary by across establishments by a median of 7 percent and profits would be between 4 and 8 percent higher. Alternatively, firms may choose to set wages nationally because it leads to higher productivity. If so, our estimate captures the increase in profits needed to make national wage setting optimal.

Related literature. The main contribution of our paper is to empirically show that a large share of firms set the same nominal wage for the same job in different regions. This finding relates to several literatures.

First, several papers show that multi-establishment firms do not respond to local conditions in the context of price setting. For example, DellaVigna and Gentzkow (2019) show that most firms in the retail sector set the same price for the same product in different regions of the United States; Cavallo, Neiman, and Rigobon (2014) show that global retailers set the same price for the same product in different countries of the same currency union.[3] We complement these papers by studying wage setting instead of price setting, by studying the entire economy beyond the specific setting of the retail sector, and by combining survey and micro data to understand the reasons why firm behavior responds little to local conditions.

A second literature studies the firm-level determinants of worker pay. An emerging body of evidence shows that different firms often pay similar workers different wages (Card, Heining, and Kline, 2013; Song, Price, Guvenen, Bloom, and Von Wachter, 2019). There are a range of explanations for this phenomenon, including amenities (Sorkin, 2018; Lamadon, Mogstad, and Setzler, 2019), rent sharing of firm productivity (Card, Cardoso, Heining, and Kline, 2018), and variation in firms' wage setting power due to their market share (Berger, Herkenhoff, and Mongey, 2019; Jarosch, Nimczik, and Sorkin, 2019). National wage setting policies are another reason that different firms may pay similar workers in the same location different wages.[4]

Our finding also relates to work on firm wage setting and fairness norms. Various papers show that fairness norms are important for workers' performance either in qualitative survey data (Blinder and Choi, 1990; Campbell III and Kamlani, 1997; Bewley, 1999) or in specific contexts (Card, Mas, Moretti, and Saez, 2012; Breza, Kaur, and Shamdasani, 2018; Dube, Giuliano, and Leonard, 2019). We show with micro data that fairness norms affect wage setting for a large share of firms.[5] Additionally, the previous evidence on fairness

[3] Nakamura (2008), Hitsch, Hortaçsu, and Lin (2020) and Cavallo (2018), amongst others, also document such "uniform price setting" in the retail sector. Clemens and Gottlieb (2017) show that Medicare's uniform pricing impacts the pricing strategies of private insurers.

[4] A distinct literature studies the *worker*-level determinants of rent sharing (e.g. Caldwell and Harmon, 2019; Jäger, Schoefer, Young, and Zweimüller, 2020).

[5] This finding complements Saez, Schoefer, and Seim (2019), who study a payroll tax cut in Sweden. They argue fairness norms can explain rent sharing of a payroll tax cut to workers who are ineligible for the policy, but are in the same firm as beneficiaries of the policy.

norms shows that workers compare nominal pay to others *within* locations of a firm. Our survey finds workers also compare nominal pay *between* locations of the firm, in part because some workers are in national labor markets.[6]

Several recent papers share our focus on how firm pay varies across space. Hjort, Li, and Sarsons (2020) study wage setting in multinationals using granular firm by occupation data. Their results complement ours by showing that firms anchor the real wage paid overseas to wages paid at headquarters. By contrast this paper compares *nominal* wages across space, which is not feasible using international data on wages paid in different currencies. Our different setting leads to sharper results on the nature of firm wage setting. For instance, we are able to show that some firms set identical nominal wages across space, that this wage setting behavior concentrates entirely in a subset of firms, and that nominal pay comparisons by workers are an important reason for why firms compress wages. Another related paper is by Derenoncourt, Noelke, and Weil (2020), who study the consequences for local labor markets of four large firms' national minimum wage policies. Instead, we document that national wage setting is common across firms and across the wage distribution, and then investigate the causes.[7]

Lastly, the findings in this paper relate to a third literature which uses various macroeconomic models that assume firms cannot pay different workers different wages within the firm, and then explores the implications for diverse outcomes such as wage dispersion, unemployment fluctuations, firm dynamics, the spillover effects of minimum wages, or the evolution of the labor share (see, e.g., Burdett and Mortensen, 1998; Manning, 2003; Gertler and Trigari, 2009; Moscarini and Postel-Vinay, 2013; Gouin-Bonenfant, 2018; Fukui, 2020; or Engbom and Moser, 2021). We provide direct evidence justifying this assumption by showing that many firms pay the same wage for all workers hired into a given job.

[6] This finding echoes Simonsohn and Loewenstein (2006), who find homebuyers are affected by nominal comparisons of house prices across locations.

[7] Three more papers on wage setting are Propper and Van Reenen (2010), who study the consequences of national wage setting among nurses in English hospitals on healthcare quality; Alfaro-Urena, Manelici, and Vasquez (2019), who report survey evidence that multinational corporations partly pay high wages overseas to ensure cross-country pay fairness; and Boeri, Ichino, Moretti, and Posch (2019), who study the effect of national wage setting among unions in Italy, compared with flexible wage setting among unions in Germany, on regional outcomes in each country.

2 Data Description

The main dataset we use comes from Burning Glass Technologies, a company that scrapes online job postings. Throughout the paper, we complement these data with information from a survey that we ran with HR managers and executives.

2.1 Job Level Data from Burning Glass

Our main data source is an establishment-level dataset of job vacancies covering 2010-2019. The dataset was developed by Burning Glass Technologies. Burning Glass collects data from roughly 40,000 company websites and online job boards, with no more than 5% of vacancies from any one source. They then apply a deduplication algorithm and convert the vacancies into a form amenable to data analysis. In total, Burning Glass covers around 70% of vacancies in the United States (Carnevale, Jayasundera, and Repnikov, 2014). However, only 17% of vacancies in Burning Glass include wages, meaning that the subset of vacancies that include wages, the main sample that we study in this paper, is roughly 10% of total US vacancies.[8]

For those vacancies that include wage information, we have detailed information on the wage, including the pay frequency of the contract (e.g., whether pay is annual or hourly) and the type of salary (e.g. whether compensation includes a bonus). We define the wage as the annual earnings for that job. Roughly half of the vacancies with wage information post a range of salaries, rather than a single value. For jobs that post a range, we use the midpoint of the range, but we show the robustness of the main findings to either excluding vacancies that post a range or to making alternate assumptions about the distribution of salaries across locations within the posted range. Appendix Table A1 shows that wages are more likely to be posted at smaller firms, in occupations that have lower wages, and for jobs with lower education and experience requirements.[9]

In addition to the posted wage, the vacancies specify several additional features of the job and characteristics of the desired worker that we use throughout our analysis. On the worker side, the vacancy includes information on required years of education or years of experience. On the job side, the language of the job

[8] By matching establishments to 2018 data from the analytics company Dun and Bradstreet, we estimate that these vacancies cover about 8% of private employment.

[9] Appendix Table A2 shows that firms are also slightly less likely to post wages in higher cost of living counties, but the magnitude of this difference is very small. Specifically, we find that, after controlling for the composition of vacancies across locations, firms are 0.07 percentage points less likely to post a wage on a vacancy in one of the superstar cities (i.e. LA, San Francisco, NYC, or Washington DC) than in other locations. Additionally, conditional on posting wages anywhere, 80 percent of occupations in a given firm and year have posted wages in all counties in which there are vacancies. These statistics suggest that the strategic posting of wages across locations is unlikely to meaningfully affect our estimates of national wage setting.

posting reveals an occupation, which Burning Glass codes into a six-digit (SOC) occupation code.[10] On average, firms in a given year post vacancies in 39 occupations. Throughout the analysis, we define a job as the combination of the occupation, salary type, and pay frequency (e.g. pest control workers with hourly base pay).[11] Lastly, in addition to detailed occupations, we explore alternate specifications defining jobs using the 13,436 standardized job titles included in the vacancy data.

Burning Glass also assigns a firm name and county to each vacancy, which allows us to define establishments. We cleaned firm names using a deduplication procedure outlined in Appendix Section A1.2. We define an establishment of a firm as the collection of vacancies assigned to a firm within a county.[12] 72 percent 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.

One important feature of the Burning Glass data is that it provides measures of posted wages, not the realized wages paid to workers. Appendix Figure A1 plots the tight positive relationship between the median posted wage in Burning Glass in each 6-digit occupation within a metro area against the corresponding measure from the Occupational Employment Statistics (OES) data – when Burning Glass wages are 1 percent higher, occupation wages from the OES are also roughly 1 percent higher. We more extensively probe this relationship in Appendix Section A1.1 and show that i) all types of posted wages in Burning Glass closely track realized wages in the OES data and ii) the tight relationship in Figure A1 applies not only to median wages; the 10th and 90th percentiles of the wage distribution within an occupation and MSA are also highly correlated. These patterns suggest that at the detailed occupation and region level, posted wages in Burning Glass are very close to realized occupation wages in the OES.

Lastly, for our main analysis, we make several sample restrictions. Appendix Table A3 reports the sample restrictions, and how they affect the number of observations. Our main sample includes only those vacan-

[10]Six-digit occupation codes are highly granular, including occupations such as pest control worker, college professor in physics, and home health aide. The detailed occupation information is an important advantage of the Burning Glass data, as it is often not reported in administrative datasets (e.g. the ADP payroll data used in Grigsby, Hurst, and Yildirmaz, 2019).

[11]We define the job using salary type and pay frequency since it is challenging to make wage comparisons across those categories. We find that, within an occupation, firms rarely post vacancies with different salary types, and pay frequencies, with only 5 percent of occupation and firm pairs posting multiple salary types across locations within a year and 3 percent posting multiple pay types. This small dispersion suggests that firms do not strategically vary the structure of pay across locations and therefore, looking within jobs defined by the combination of occupation, salary type and pay frequency is unlikely to bias our estimates of wage compression within the firm.

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

cies with non-missing wage, occupation, industry, and location information in the private sector and not in a military occupation. We further exclude jobs that pay on commission, as those posted wages are likely least reflective of realized pay. We collapse to have one observation per year in each establishment, occupation and pay group (e.g. hourly base pay) and take the average salary across vacancies.[13] In Appendix Figures A2 and A3, we document how well the resulting sample represents employment in overall US economy. We over-represent occupations in computing, transportation, and healthcare and under-represent sales and construction occupations. Additionally, the sample over-represents the transportation industry and the West Coast of the country.

2.2 Payscale Data

We use data from Payscale, a compensation data company, to address the fact that we see posted rather than realized wages in the Burning Glass data. Payscale is a compensation data company that aims to provide both employees and employers with accurate information on job market compensation. One way it does so is by having current job-holders fill out their compensation information, including their current salary or wage, the average number of hours they work per week, and information on bonuses and benefits. The dataset we received contains the self-reported information that job-holders enter. Specifically, we have information on the individual's current firm and job title, her wage/salary, bonuses and other forms of compensation the individual receives, hours worked, and other individual-level characteristics such as age and gender. Pooling data from 2011-2018, the dataset covers 3.22 million individuals. We restrict attention to workers between the ages of 20 and 65 with positive reported earnings, leaving 2.55 million workers in the sample, 56% of whom work in salaried occupations. Details on the industry and occupation representation are discussed in Appendix A1.

For our purposes, the key limitation of the Payscale data is that it is sampled at the worker, rather than firm, level. Therefore, the vast majority of workers within the Payscale data are in firms without comparable workers in other establishments of the same firm. Specifically, only 26 percent of the sample works in a job that is present in multiple establishments of the firm. This additional restriction distorts the sample, tilting it heavily towards the finance, insurance, and healthcare sectors.

[13]This averaging potentially causes a downward bias in our measure of wage compression. To see this, consider a firm that sets identical wages across 2 locations but posts in location 1 in Q1 and location 2 in Q4 and changes its wages in all locations in Q3. Our measure would show no wage compression even though, in this example, it exists.

For this reason, we do not use the Payscale data as our main dataset and instead use it to complement the Burning Glass analysis in two ways. First, we explore the extent to which firms use bonuses to adjust for differences across local markets. Second, for the subset of jobs that do appear in multiple locations, we replicate the Burning Glass analysis and demonstrate a substantial amount of wage compression within the firm that is not undone with other forms of compensation.

2.3 Survey

We supplement our data with a survey that we administered to human resource 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. The survey was designed to collect extra evidence on firm wage-setting policies and to understand the motivation behind these choices.

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 (see Appendix Figure B1), and work in a range of industries. We have a particularly large number of respondents from manufacturing, professional and scientific industries, and finance (see 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.[14] The majority of respondents are HR managers or executives and are directly involved in setting pay (Appendix Figure B4).

In the survey, 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. More details on the sample and survey design are provided in Appendix B1.

3 Descriptive Facts on Wages within the Firm Across Space

We begin by presenting four descriptive findings on wage compression within the firm across regions.[15]

[14] Appendix Figure B3 shows the number of states (panel A) and cities (panel B) in which firms operate.

[15] In Appendix Section A3, we also explore trends in remote work through the Covid-19 pandemic. We present evidence from the survey that the majority of firms do not intend to adjust wages for remote workers based on where they live and find suggestive evidence that a rise in the share of workers who are remote will increase the prevalence of national wage setting, even among the non-remote workers.

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

We begin by demonstrating that a large share of wages are set identically within firms across locations. 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 (i.e. postings for administrative assistants at Deloitte in Boston and San Francisco in 2019). For each of these pairs, we construct a corresponding between-firm pair for the same job in the same locations but with the job in the second location being in a randomly selected different firm in the same industry (i.e. postings for administrative assistants at Deloitte in Boston and administrative assistants at Ernst & Young in San Francisco in 2019). Figure 1 shows the distribution of wage differences for the within-firm pairs (blue) and the corresponding between-firm pairs (green). Approximately 35 percent of within-firm pairs post *exactly* the same wage, while only 8 percent of between-firm pairs post exactly the same wage.[16] That number rises to 39% if we consider all within-firm wage pairs rather than just those with a between-firm match. Moreover, 50% of within-firm pairs are within 5% of each other, while only 15% of between-firm pairs are within that same band.

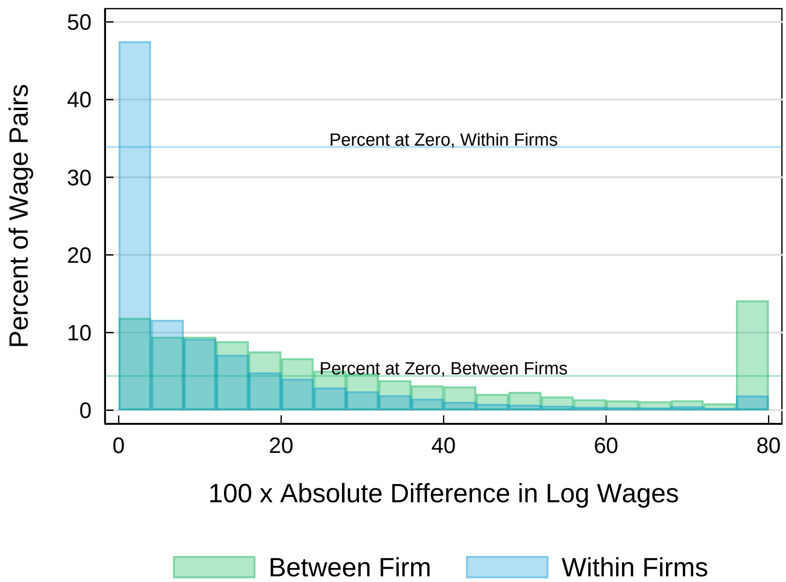
The uniformity in Figure 1 reflects national rather than regional patterns. Appendix Figure A8 divides the pairs into those that are within the same census division and those that are in different census divisions. It then plots the fraction of within-firm pairs at all differences in the wage. We see that within-firm uniformity is only slightly more prevalent for geographically-close pairs (e.g. Boston and New York City) than for pairs that are geographically more dispersed (e.g. Boston and Miami).

Our survey results closely mirror these patterns within job postings. Figure 2 shows responses to the question "Which of the following describes how your firm sets pay bands (wages) across locations for the majority of your workers?"[17] Respondents could choose one of three options: pay bands (wages) are determined separately for each establishment, are set identically so that workers with the same job title face the same pay band (wage), or sometimes separately but not always. Nearly 30% of respondents state that they work at firms that set wages identically across establishments ("Identical"). An additional 45% of firms set pay iden-

[16] Appendix Figure A6 shows that 47 percent of within-firm job pairs post exactly the same wage when we define jobs using detailed job titles rather than occupations. We define jobs using occupations in the baseline analysis to capture wage compression that is not affected by strategic job title inflation across locations (i.e. firms hire junior baristas in Houston but senior baristas in NYC as a way of circumventing national wage setting policies). However, in using occupations, we also pool differences in job composition across locations so as to bias us against finding relevant wage compression. To be conservative, we use occupations to define a job and demonstrate the robustness of the descriptive patterns to using job titles in the appendix.

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

Figure 1: Distribution of Wage Comparisons Between and Within Firms



Notes: This figure shows the distribution of wage differences for within- and between-firm pairs. Differences in the log of the wage are top-coded at 0.8. 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 167,526,615 pairs both between and within firms.

tically for some, but not all, of their jobs ("Mix"). Only around 25% of respondents report working at a firm that sets different wages for workers with the same job title, but who are working in different establishments ("Separate").

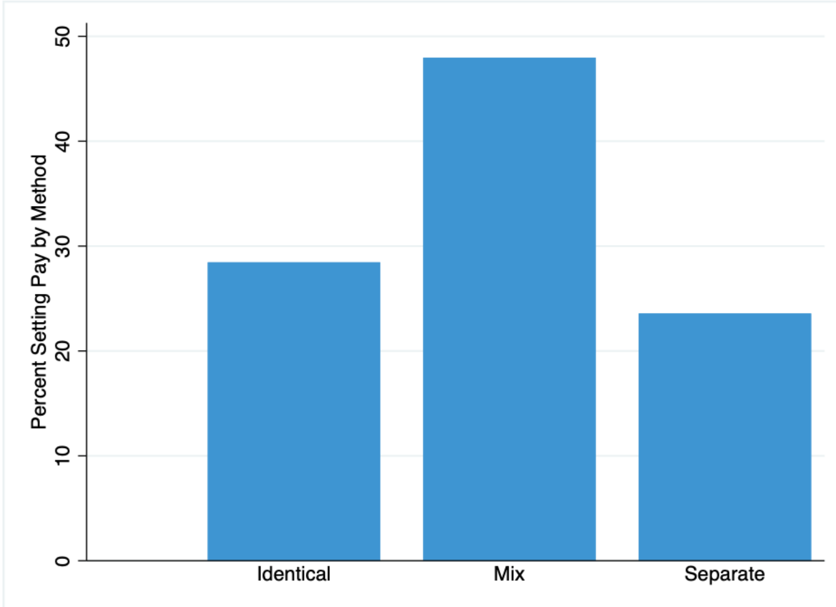
Fact 2: Identical wages are a characteristic of occupations within firms.

The previous figures demonstrate that 30-40 percent of within-firm job wages across counties are exactly the same. This pattern could be the result either of some firms setting identical wages for all of their jobs or a larger set of firms setting identical wages for some of their jobs. We find evidence for the latter, with identical wages being a choice that firms make separately for each occupation within the firm.

First, for a given job within a firm, we find that firms either set wages identically across all locations or the wages vary across most locations.[18] It is rare to see a firm setting identical wages for a given job in some of

[18] Appendix Figure A10 shows the faction of pairs that are identical for each occupation and firm. We find a clear bimodal distribution, with many occupations within firms having less than 10% of pairs being identical, many having all pairs being identical, and very few having between 50 and 95 percent of pairs being identical.

Figure 2: Survey Responses: Method of Setting Wages



Notes: This figure shows survey responses to a question asking how the respondent's firm sets pay bands (or wages) across locations for the majority of its workers. "Identical" means that a respondent stated that pay bands (wages) are set identically across establishments so that workers with the same job title face the same pay band. "Mix" means that a respondent stated that pay bands (wages) are sometimes determined separately but not always. "Separate" means that a respondent stated that pay bands (wages) are determined separately for each establishment/plant/store. The exact question asked is shown on pages 5/6 in Appendix B1.

the locations but then varying the wages across the remaining locations.[19] Indeed, among those jobs where at least 50% of the job pairs were the same, over 60 percent were identical across all locations.[20]

Second, while firms that choose to set identical wages for an occupation tend to do so for all locations, firms do not tend to choose to set identical wages for all of their jobs. Specifically, we find that while roughly 10% of firms set nationally identical wages for all occupations, the majority of firms setting any national wages set nationally identical wages for only a subset of their occupations (See Appendix Figure A10).

Third, not all firms choose to set national wages for the same occupations. Appendix Figure A12 shows that identical wages are widespread across occupations, but moderately more common in high-wage or tradable

[19]Jobs with identical wages are also relatively evenly distributed across the country. Appendix Figure A14 shows the fraction of jobs in each state that set identical wages. No state has fewer than 10 percent and some states, like Maine and Arkansas, have up to 35 percent. On average, states with higher GDP per capita have fewer jobs with identical wages, as do urban areas and in particular, superstar cities like DC, New, York, San Francisco and Los Angeles (see Appendix Table A11).

[20]Appendix Figure A9 shows that within the firm, the probability that posted wages are the same across pairs is decreasing in the geographic distance between the establishments and in the differences in price levels. However, while this slope exists, the magnitude is very small – in establishments that are 4000 miles away from each other, 28 percent of job pairs within the firm are identical, which is only 4 percentage points less than job pairs that are within 20 miles of each other.

occupations, which we define as those that can be done remotely (Dingel and Neiman (2020)).[21]

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

Motivated by these patterns, throughout the rest of the analysis, we define a *firm* as being an identical wage setter if at least 50% of their occupations in that year are nationally identical. We define an *occupation* within a firm as being nationally identical if at least 80 percent of the within-firm wage pairs in a given year are the same. We define a *job* as nationally identical if it is within an occupation and firm that are nationally identical, and the job pays the wage that is set for the majority of jobs in that occupation and firm.[22] Using these relatively strict definitions, we find that among firms with at least 4 establishments in a given year, 19 percent of jobs are nationally identical and 32% of firms are identical wage setters.[23] These estimates from job vacancies are very similar to the almost 30% of HR managers in the survey who reported working in firms setting all wages nationally. Note, however, that there is also a substantial amount of wage compression that occurs in so-called ”mixed” firms, where wages are set identically for a subset of jobs. These firms do not qualify as identical wage setting firms by our strict definition.

We further explore characteristics of jobs with identical wages in Appendix Figure A13. This figure displays the correlation between four job characteristics and the probability that the job is a nationally identical job. Experience requirements are uncorrelated with the probability that a job is nationally wage set, suggesting that identical wage setting is not just for entry-level jobs. We also calculate the HHI of the job postings for the firm across locations for each occupation. A high HHI value means that a firm has one large establishment posting the majority of vacancies, whereas a lower value means that vacancies within a firm are more equally spread across establishments. We see that jobs in firms with a high HHI are more likely to be identical. The

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

[22] Since these definitions require a sufficient number of pairwise comparisons, we only define identical wage setting for the firm by occupation by year cells where there are at least 4 establishments. We summarize this sample in row 6 of Appendix Table A3.

[23] Appendix Table A10 shows the robustness of the main finding about the relative wages of nationally identical jobs (i.e. fact 4) to using alternate definitions of identical wage setting.

same is true for the local concentration of each occupation, which we calculate by aggregating vacancies across all years and all firms in the data.

Lastly, in Appendix Table A7, we use the survey data to explore whether certain types of firms are more likely to set identical wages across establishments. Specifically, we test whether identical wages are more common in large firms (column 1), firms that have mainly salaried employees (column 2), and firms with centrally-determined pay and hiring (columns 3 and 4). We find that firms with centrally-determined pay are more likely to post identical wages, but otherwise do not find any strong relationships concerning these variables.

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

As long as firms setting identical wages operate in regions with different local prices, the patterns in Figure 1 imply that for the same job, firms tend to pay a lower real wage in regions with high prices and higher real wages in areas with low prices. We explore this by estimating the within-firm relationship between wages and local prices as

$$log w_{ijot} = \beta \text{price level}_{jt} + \theta_{oi} + \theta_t + \epsilon_{ijot} \tag{1}$$

where $log(w_{ijot})$ is the posted wage in occupation o in firm i in county j in year t. Price level$_{jt}$ represents a local price index for the county, sourced from the Bureau of Economic Analysis.[24] θ_t are year fixed effects, which control for differences in posted wages over time. The inclusion of job by firm fixed-effects (θ_{oi}) means we estimate the correlation between nominal wages and prices within the firm. To account for measurement error in the local price indices, we instrument the local price index with county-level home price indices from Zillow.[25]

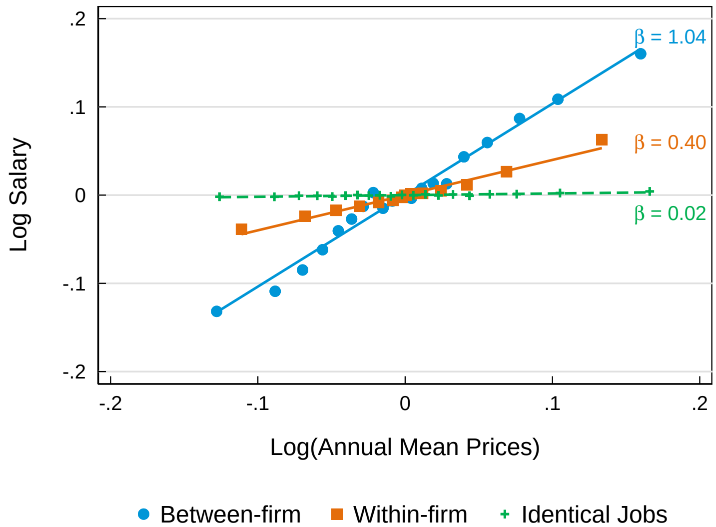
For comparison, we also estimate the correlation of nominal wages and local prices *between* firms and across locations. We follow DellaVigna and Gentzkow (2019) and estimate

$$\log w_{ijot} = \gamma \overline{\text{price level}}_{it} + \theta_o + \theta_t + \epsilon_{ijot} \tag{2}$$

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

[25]In Appendix Table A8, we show similar results using Zillow home price indices directly or using measures of average local nominal incomes. We also report the non-instrumented version of the regressions in Figure 3.

Figure 3: Sensitivity of Nominal Wages to Local Prices



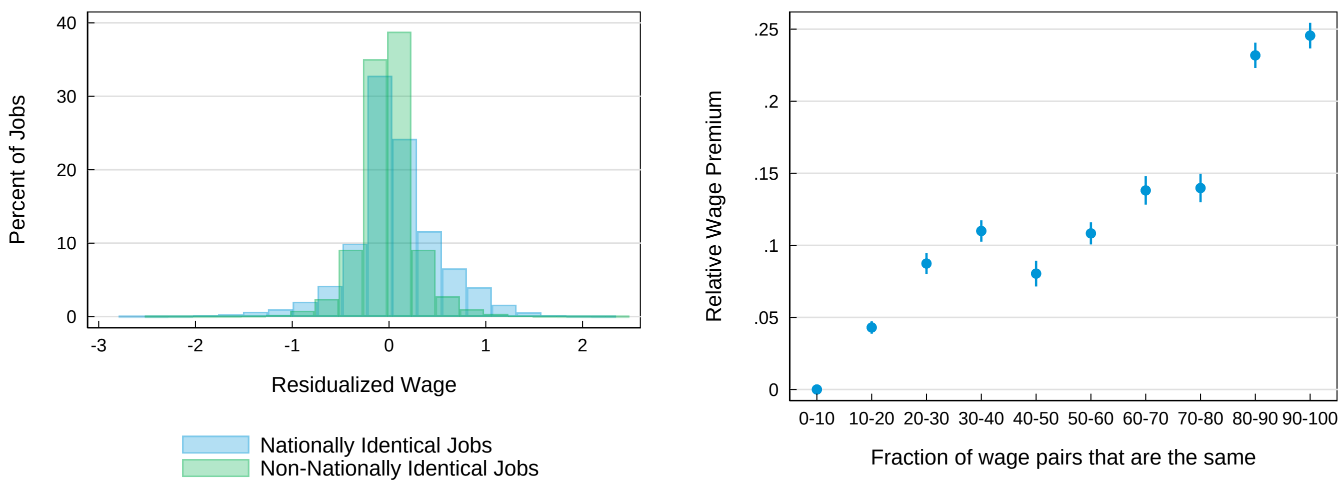
Notes: This binned scatterplot shows the relationship between the local price index, instrumented by county-level home prices, and the log wage. The blue line and circles correspond to Equation 2 and the orange line and squares correspond to Equation 1. The dashed green line and crosses correspond to Equation 1 but we run this regression restricting to national firms. National firms are those firms for which 50% of their jobs are national (80% of job pairs have identical wages). All regressions include job and year fixed effects and the green and orange regressions include firm fixed effects as well. Because of the fixed effects, both the y-axis and x-axis are demeaned.

where $\overline{\text{price level}}_{it}$ is the average value of local prices for all counties in which the firm operates.

Figure 3 plots binned scatter plots, with orange squares corresponding to regression (1) and blue circles corresponding to regression (2). The within-firm coefficient is low, both in absolute terms and when compared to the between-firm coefficient. The slope of the orange line, representing α_1, is positive, implying that within the firm, nominal wages are higher in counties with higher prices. However the coefficient is less than 0.5 – within the firm, a job in a county with 1% higher prices tends to pay a real wage that is 0.5% lower. The estimate of β_1 is close to 1: a 1% higher price level is associated with a 1% higher nominal wage, meaning that real wages are roughly constant.

These patterns imply that national wage setting affects the distribution of real wages. If areas with high prices pay lower real wages on average, then national wage setters could increase real wage inequality since they contribute to larger differences in real wages across space. Conversely, if high-price areas pay higher real wages on average, national wage setting could lead to a drop in real wage inequality. Either way, national wage setting has consequences for the distribution of real wages.

Figure 4: Relative Wages of National Wage Setters



Notes: The left panel shows the distribution of residuals of a regression of log posted wages on soc*year*county*industry fixed effects, and a quadratic in establishment size and firm size. 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 right panel shows the relationship between the relative wage premium (y-axis) and the fraction of jobs within a firm×occupation that have the same wage. All coefficients are plotted relative to the 0-10 bin. The regression includes soc*year*county*industry fixed effects, and a quadratic in establishment size and firm size. The sample in both panels includes all firm-job pairs present in at least 4 establishments in that year.

Of course, it is possible that identical wage setters operate in counties with less dispersion in prices, allowing them to set identical wages without significant costs. To test this possibility, we estimate equation 1 on the sample of identical wage-setting firms. The relationship between prices and wages for this subset of firms is shown by the dashed line in Figure 3. The slope is close to zero by construction. Importantly, though, the range of prices that identical wage setting firms face is similar to that which other firms face, as seen from the range of the x-axis for this subset.

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

The left panel of Figure 4 plots the wages of jobs with nationally identical wages, in comparison to the wages of jobs without nationally identical wages in the same labor market. Specifically, we plot the distribution of residual wages, residualized from a regression of log posted wages on occupation by year by county by industry fixed effects. These fixed effects control for differences in wages that stem from the different distribution of nationally identical jobs across labor markets. Additionally, since large firms tend to pay higher wages on average, we also include in the regression a quadratic in establishment size and a quadratic in firm size, both measured by vacancies. The blue bars show the distribution of residual wages for nationally identical jobs while the green bars show the same for all other jobs. The distribution of wages for nationally identical jobs is shifted to the right, demonstrating that nationally identical jobs tend to pay relatively high wages conditional on controls. The right panel of Figure 4 shows that this link between wage compression and relative wages is not just a feature of firms that set all wages identically, but rather, the relative wage premium of the jobs within the firm is increasing in the fraction of the establishments in that occupation within the firm that have the same wage.

Table 1 summarizes these patterns with regressions, showing in column 1 that, on average, nationally identical jobs pay 15 percent more than other comparable jobs within their markets. Column 2 shows that this wage premium is smaller in higher-wage occupations, and column 3 shows that the premium is lower in urban areas. Columns 4 and 5 explore the extent to which firms accompany this posted wage premium with higher requirements for education and experience. We find that there are no differences in experience requirements for jobs with nationally identical wages and that the required years of education actually is lower than the typical job in the market. Moreover, Appendix Figure A15 shows that separately for both high-cost and lower-cost of living areas, national jobs do not have greater education or experience requirements – the premium for nationally identical jobs is lower in counties with higher prices, but there is no offsetting change in required education or experience to attract workers in those areas.

3.1 Discussion of Descriptive Facts

In this section, we discuss the robustness of the descriptive facts above.

Posted Wages vs. Realized Wages: One key feature of the job vacancy data is that we have information on the posted, rather than the realized, wage. While we find that the posted wages track the geographic distribution of realized wages in each occupation very closely, it is possible that the relationships between posted and realized wages differ in a way that could bias our result. For example, since we take the midpoint of a posted salary range, we would overstate the amount of identical wages for firms that post the same range across locations but adjust wages within the range depending on location.

One compelling piece of evidence suggesting that our use of posted wages is not driving the estimates is that we find a similar, if not higher, share of firms that do not vary nominal pay across space in our survey data

Table 1: Relative Wages, Education Requirements and Experience Requirements of National Firms

	Outcome:				
	Log Salary			Experience	Education
	(1)	(2)	(3)	(4)	(5)
Nationally Identical Job	0.15	0.49	0.19	0.02	-0.82
	(0.00)	(0.08)	(0.01)	(0.02)	(0.03)
Nationally Identical Job * Avg. SOC wage		-0.04			
		(0.01)			
Nationally Identical Job * Urban			-0.04		
			(0.01)		
Observations	3,580,139	3,549,979	3,555,707	1,557,918	2,767,496

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 4 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.

(Figure 2). Our estimates of identical wage setting are also strikingly similar to what large compensation consulting companies have found in their surveys. For example, Empsight, a salary survey company that works with Fortune 500 firms, found in their 2018 survey that 30% of firms do not adopt geographically differentiated compensation policies (Empsight International LLC (2018)).

In terms of salary ranges, we show within the vacancy data that the degree of identical wage setting is slightly higher in those postings with a single wage than for those that post a range (see Appendix Figure A16). Moreover, we can bound the potential contribution of posted wage ranges by looking at the degree of identical wage setting within firms when we take the extreme points of the range for within-firm pairs, rather then the mean of the ranges. This would give the amount of identical wages if the realized wages for all wage pairs with posted ranges fell at opposite ends of the ranges, an unlikely extreme outcome, but a useful lower bound. Appendix Figure A7 shows that the implied degree of identical wage setting drops with this extreme assumption, but even so, just below 20 percent of these wage pairs are still exactly the same.

We additionally use the Payscale data to show that the wage compression that we document in the Burning Glass data is not undone by bonuses and bargaining during the hiring process. Specifically, we replicate Figure 3 and show that wages within the firm co-vary with local prices substantially less than wages between firms. We follow the analysis in Section 3 and estimate Equation 1 and 2 using base pay reported in Payscale. For this analysis, we define a unique job as the combination of pay frequency (salaried or hourly), occupation, education, and worker age.[26]

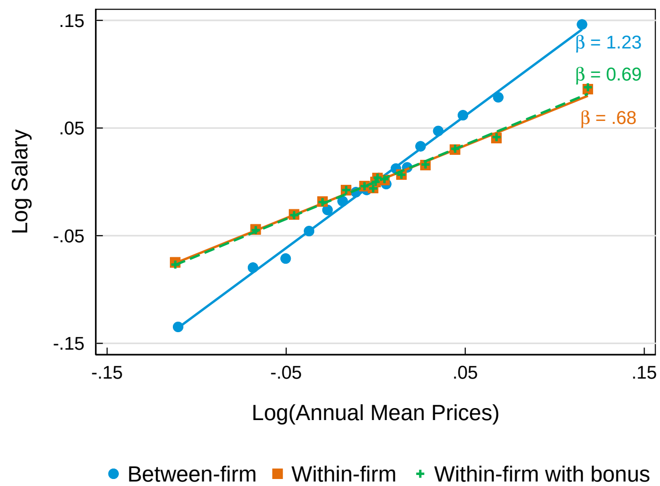
Figure 5 visualizes the results. We see in the blue circles that between firms, there is a strong positive relationship between earnings and prices. However, within firms, that slope is substantially attenuated and is around half of the between-firm slope, roughly the same pattern as that we saw in Burning Glass for posted wages. Moreover, the green line shows the estimated relationship when we include reported bonuses in annual compensation. The within-firm slope is nearly indistinguishable, suggesting that bonuses do not moderate the wage compression that we observe in the Burning Glass data. Appendix Table A9 reports the regressions underlying Figure 5 and presents additional results. We find that the within-firm slope is around half of the between-firm slope when using OLS (i.e not instrumenting local price indices with house house prices) and when restricting to either just hourly or just salaried workers. In Appendix Table A16, we additionally explore the extent to which, within a job, bonuses are more or less likely in high-cost of living areas and find that bonuses are uncorrelated with the cost of living. Details of this analysis are provided in Appendix A1.

Worker Composition Across Locations: While using posted wages has several limitations, one key advantage of posted wages relative to realized wages is that they do not explicitly include differences in earnings across workers that are driven by individual characteristics such as performance, experience or education. Our goal is to measure the differences in the wage setting rule, capturing how firms would change the wages of the same workers in the same jobs across locations. Posted wages more closely capture the wage setting rules, while realized wages capture the outcomes of those rules. For example, if accountants in NYC tend to have masters degrees while accountants in Cleveland do not and firms adjust pay based on education, we would see that accountants in NYC earn more than those in Cleveland, although that is not driven by their location but rather is driven by their education.

We can also use the information within the job posting to directly look for differences in education and experience requirements across locations. Among within-firm wage pairs where the wage is identical, over 90% of the jobs also have identical experience and education requirements, suggesting that firms displaying

[26]We include worker age in order to crudely account for differences in worker experience at the firm (e.g. differences in pay between an assistant professor and a tenured professor) and we include education to control for well-known differences in pay for similar jobs with different terminal degrees. Since we are interested in isolating differences in wages paid across locations for workers performing the same job, it is important to include controls for worker observables that would create wage dispersion even within establishment and that may be differentially distributed across locations.

Figure 5: Nominal Wages and Local Prices in Payscale Database



Notes: Data is from Payscale and the unit of observation is the individual. The blue circles show a binscatter with 20 bins for Equation 2. The orange squares show the binscatter with 20 bins for Equation 1. The green circles includes reported bonuses in total compensation. In each regression, we instrumented local price indices with county-level home prices. We define a job as the combination of pay frequency, salary type, age, and education level. Each regression includes year fixed effects. All three regressions are restricted to include the same sample of 109,085 observations. See Table A9 for additional details.

national wage setting are not aiming to attract observably different workers across locations.

Scope of Burning Glass Data: One concern with the Burning Glass data is that firms setting nationally identical wages may be more likely to post wages than other firms. Appendix Figure A17 uses the survey data to show the prevalence of nationally identical wages separately for firms that report posting wages in their job vacancies and those that report not posting wages. As in the Burning Glass data, 10 percent of survey respondents state that they work for a firm that posts wages. However, we find that if anything, firms with nationally identical wages are *less* likely to post wages for their job vacancies. This suggests that the estimates within the job vacancy data are informative for the broader set of firms, and that selection into posting wages is not a meaningful source of bias for our estimates.

4 Evidence for National Wage Setting

Our descriptive facts show that within an occupation, a substantial fraction of firms set exactly the same nominal wage in almost all establishments. In this section, we argue identical wages are in large part due to *national* *wage setting* – some firms adopt a rigid pay structure, and pay the same nominal wage everywhere even if labor market conditions vary across the locations.

We begin by developing a simple framework of wage setting by multi-establishment firms. Specifically, we combine a standard model of imperfect labor market competition, as in Card et al. (2018), with a standard Rosen-Roback model of spatial equilibrium. We show that firms might set identical wages across space either because they set wages nationally or because they set wages flexibly but the marginal revenue product of labor is the same across their establishments.

Our framework predicts different wage dynamics for the two types of firms. For firms setting wages nationally: (i) nominal wage changes in different establishments of the same firm and occupation should bunch together; and (ii) an exogenous shock to the marginal revenue product of a single establishment should increase wages in the firm's other establishments. For local wage setters, these predictions would hold only in special knife-edge cases. With estimating equations derived from the model, we find evidence for both predictions, and conclude that the identical wages that we documented in Section 3 are in large part due to national wage setting.

4.1 A Simple Framework for National Wage Setting

There are $j = 1, ..., N$ regions and a unit measure of workers. There are two sectors, producing either tradable or non-tradable goods. In each sector $S \in \{N, T\}$ there are $i = 1, ..., M_S$ firms who hire workers in all regions. Specifically, in each region, firm i operates an establishment that posts wages and employs workers. In either sector there are two types of firms. A fraction $\mathcal{N}$ of firms are national wage setters – they pay the same nominal wage across all establishments. The remaining fraction $1-\mathcal{N}$ are local wage setters, who can vary wages across establishments. The fraction $\mathcal{N}$ is the same in both sectors.

Establishments in sector S have heterogeneous productivity $A^S_{ij} = A^S_i \times A^S_j$, where A^S_i and A^S_j are drawn from distributions that can vary by sector. The establishment posts a wage W^S_{ij}, which it then pays to all its workers. Given employment L^S_{ij}, the establishment operates a decreasing returns to scale production function $F\left(L^S_{ij}\right) = (L^S_{ij})^{1-\alpha}$ and produces output $Y^S_{ij} = A^S_{ij} F\left(L^S_{ij}\right)$ sold in a competitive market. Goods in the tradable sector are sold at a price that does not vary by region and which, without loss of generality, we normalize to 1. Goods in the non-tradable sector are sold at a price P^N_j that varies by region.

There is a unit continuum of ex-ante identical agents consuming goods and supplying labor, which we index by $k \in [0,1]$. Each agent has idiosyncratic, nested logit preferences for working at each establishment ij, that depends on both the identity i of the firm and on the region j. We denote the value of agent k's idiosyncratic taste for establishment ij by ε_{ijk}, and their indirect utility from working in this establishment by V_{ijk}. If agent k works in establishment ij, they consume C^N_{ijk} of the non-tradable good and C^T_{ijk} of the tradable good. Agents derive utility from a homothetic aggregator across consumption $C_{ijk} = C\left(C^N_{ijk}, C^T_{ijk}\right)$, and have logarithmic utility in C_{ijk}.

The agent's problem is to choose the establishment with the highest utility. They solve $\max_{ij} V_{ijk}$, where indirect utility is defined by $V_{ijk} = \max_{C_{ijk}} [\log C_{ijk} + \varepsilon_{ijk}]$, subject to a budget constraint $C^T_{ijk} + P^N_j C_{ijk} \leq W_{ijk}$. We assume that the distribution of idiosyncratic preferences is nested logit, i.e.

$$F\left(\{\varepsilon_{ij}\}_{i \in M, j \in N}\right) = e^{-\sum_{j \in N}\left(\sum_{i \in M} e^{-\rho_j \varepsilon_{ij}}\right)^{\frac{\eta}{\rho_j}}} \quad \rho_j \geq \eta, \tag{3}$$

where M is the set of firms in the economy, across both sectors. In our model, workers supply labor across markets in order to maximize their utility, as in the canonical Rosen-Roback model. Mobility across markets depends on η. This parameter is the dispersion of idiosyncratic tastes for different markets by each worker k, and it governs how substitutable different regions are from the worker's perspective.[27]

Workers also supply labor within markets to different establishments. Mobility within markets across establishments depends on ρ_j. This parameter is the dispersion of idiosyncratic tastes for different establishments within region j, and it governs how substitutable establishments in region j are from the worker's perspective. We can interpret ρ_j as the ability of workers to reallocate between establishments, and we allow ρ_j to exogenously vary across regions. Appendix Section C1 shows that the labor supply curve facing each establishment is

$$L_{ij} = W_{ij}^{\rho_j} \tilde{P}_j^{-\eta} \left(\sum_{k \in M} W_{kj}^{\rho_j}\right)^{\frac{\eta - \rho_j}{\rho_j}} \kappa, \tag{4}$$

where $\tilde{P}_j$ is the local consumer price index, the ideal price index associated with the homothetic consumption aggregate C_{ij}; and κ is an aggregate constant. Therefore ρ_j is also the labor supply elasticity to the establishment.[28]

[27] Equivalently, η stands in for the extent of mobility costs across regions.

[28] For simplicity, we do not allow multiple occupations in the model. We can think of an establishment in this model as corresponding

A local wage setter i in sector S solves a separate problem in each labor market j, aiming to maximize each establishment's profits

$$\max_{W_{ij}^S, L_{ij}^S} P_j^S A_{ij}^S F(L_{ij}^S) - W_{ij}^S L_{ij}^S \tag{5}$$

given the establishment labor supply curve (equation 4). In contrast, national wage setting firms in sector S pay the same wage W_i in all establishments, meaning that they sum across establishments to maximize firm profits

$$\max_{W_i^S, L_{ij}^S} \sum_{j \in N} \left[P_j^S A_{ij}^S F(L_{ij}^S) - W_i^S L_{ij}^S \right] \tag{6}$$

again given each establishment's labor supply curve. The rigidity affects only a subset of firms, but affects all locations within these firms. This feature matches our second descriptive fact that national wage setting concentrates in certain firms, but varies little across the firm's establishments.

In the equilibrium of the model, each agent maximizes utility by choosing a region, establishment, and consumption bundle according to equation (3). Each establishment maximizes profits according to equations (5) or (6). Goods markets clear in the tradable and non-tradable sector of each region.

4.2 Reasons for Identical Wages: National vs. Local Wage Setters

The framework shows that either type of firm – those subject to a rigidity and those able to set wages flexibly across regions – can set identical wages across locations. First, local wage setters will set identical wages across locations if both markdowns and the marginal revenue product of labor is the same across regions. The first order condition of the local wage setter's problem (5) implies

$$W_{ij}^S = \underbrace{\frac{\rho_j}{1+\rho_j}}_{\text{markdown}} \overbrace{P_j^S A_{ij}^S F'\left(L_{ij}^S\right)}^{\substack{\text{marginal revenue} \\ \text{product}}} \tag{7}$$

for each establishment j of the firm. The result is standard: establishments set nominal wages as a markdown of nominal revenue product, where the markdown depends on the labor supply elasticity to the establishment. Firms pay the same nominal wage in two establishments if the establishments have the same marginal revenue

to an establishment by occupation observation in the data. Alternatively, we could add another "nest" to the labor supply function, to let the representative worker reallocate across occupations within a region.

product and the same markdown. Otherwise, these firms pay different nominal wages across locations.

Nominal revenue product can vary due to workers' productivity A_{ij}, producer prices P_j, and the optimal scale of the firm given by its productivity, L_{ij}^S. Separate from producer prices, higher local consumer prices also raise wages by causing workers to migrate out of the region, reducing labor supply to the region, lowering L_{ij}^S, and raising marginal revenue product.[29] In our model, the markdown $\rho_j/(1+\rho_j)$ varies exogenously across regions, though richer models endogenize markdowns as a function of establishments' market share (Berger et al., 2019).

Second, national wage setters must set the same nominal wage across locations. The first order condition for the problem specified in equation (6) implies

$$W_i^S = \sum_{j \in N} \omega_{ij} \frac{\rho_j}{1+\rho_j} P_j^S A_{ij}^S F'(L_{ij}^S), \tag{8}$$

where $\omega_{ij} = (1+\rho_j)\, L_{ij}^S / \sum_{k \in N} \left[(1+\rho_k)\, L_{ik}^S\right]$ is a weight for each location. These firms set wages as a *weighted average* of marked-down revenue product in each location, with weights that depend on labor supply elasticities and employment in each region.

Importantly, in the model, firms that set wages nationally can have higher productivity and pay higher wages on average. This feature of the model can match our fifth fact, that firms with identical wages pay a premium. This framework therefore allows for the possibility that rigid pay structures raise a firm's productivity and offset the cost of setting suboptimal wages in some regions.[30]

This framework clarifies that identical wages may be due to either limited dispersion of labor market conditions within firms across space or national wage setting. Existing evidence suggests a great deal of dispersion in both productivity and local competition, suggesting that national wage setting is important reason for identical wages. For example, Kehrig and Vincent (2019) find that most of the dispersion of productivity within US manufacturing occurs within firms across their establishments; Hershbein et al. (2018) estimate a great deal

[29]In Appendix Section C1, we formally show that in partial equilibrium, higher consumer prices raise the wages paid by an establishment, unless the establishment's labor demand curve is infinitely elastic. Existing evidence suggests establishments' labor demand is far from infinitely elastic (see, e.g., Lamadon et al., 2019).

[30]Indeed, in equilibrium, profit maximizing firms might prefer to adopt regionally rigid wages. In Appendix Section C1.3, we extend our model to formalize this argument and endogenize the share $\mathcal{N}$ of rigid wage setters. We study a two stage game. The second stage of the game is the same as the model of the main text. In the first stage, firms choose whether to adopt nominally rigid pay structures. Rigid wage setters have higher productivity, but cannot vary wages across regions to optimally respond to local market conditions. If the productivity gains from these constraints are intermediate, there will be a mix of rigid and non-rigid wage setters in the subgame perfect equilibrium.

of variation in labor markdowns, even within narrowly defined industries; and there is much dispersion of local consumer prices across space (e.g. Diamond and Moretti, 2021). Moreover, various realistic features that are not included in our model – such as regional amenities, use of land in production, or differing worker composition across regions – would further increase dispersion in the labor market conditions that matter for wage setting.

4.3 Wage Dynamics for National Wage Setters

While both local and national wage setters may set the same nominal wages across space, the wage dynamics for these firms should be different. Specifically, we derive from our framework two empirical tests that differentiate between national wage setters and local wage setters:

1. Bunching of wage changes. For national wage setters, wages in different establishments should grow at the same rate, meaning that wage changes should *bunch* at the same value. We would not expect bunching for local wage setters – wages in their establishments grow at the same rate as revenue, and each location is unlikely to receive exactly the same shocks to revenue.[31] The degree of bunching of wage changes is informative about the extent of national wage setting. Of course, it is possible that a local wage setter operating in many locations could experience common shocks to all establishments, but exact bunching should be rare.

2. Pass-through of local shocks to wages in the rest of the firm. Our simple framework suggests an estimating equation that we can bring to the data. To arrive at a regression equation, we allow labor supply elasticities and labor productivity to vary, difference equations (7) and (8) and take conditional expectations. Then, we show in Appendix section C1 that for any two establishments j and j' of a firm i we have

$$E\left[\Delta \log W_{ij} | \Delta \log W_{ij'}\right] = \mathcal{N} \Delta \log W_{ij'} + (1 - \mathcal{N})\, \mu_j E\left[\Delta \log A_{ij} | \Delta \log W_{ij'}\right] + \gamma_j, \tag{9}$$

This equation relates wage growth across two establishments of the firm, $\Delta \log W_{ij}$ and $\Delta \log W_{ij'}$. The first term on the right hand side reflects that for a fraction $\mathcal{N}$ of firms, the national wage setters, wage growth must be equal across the two establishments. The second term on the right hand side reflects that for the remaining fraction of firms $1 - \mathcal{N}$ that set wages locally, wage growth depends on productivity growth $\Delta \log A_{ij}$ in the establishment as well as a pass through parameter μ_j from productivity to wages. Finally γ_j is a variable that

[31] See Cengiz et al. (2019) and Derenoncourt et al. (2020) for recent applications of bunching to wage data.

depends on the region and not the establishment. This market level fixed effect subsumes the forces affecting wages from outside market j, including shocks to productivity in other markets, migration by workers across markets, and changing composition of product demand.[32]

In principle, we can estimate this equation with a linear regression of wage growth in an establishment j on the wage growth of any other establishment in the firm. The coefficient of interest on $\Delta \log W_{ij'}$ is $\mathcal{N}$, the share of firms setting wages nationally – firms setting wages nationally must increase wages at establishment j one-for-one with a shock to wages in j' while other firms should not changes wages at establishment j at all, meaning that the average change in the population is $\mathcal{N}$.

Omitted variable bias affects least squares estimates of $\mathcal{N}$ if productivity growth in establishment j is correlated with wage growth in the rest of the firm (i.e. $E\left[\Delta \log A_{ij} | \Delta \log W_{ij'}\right] \neq 0$). Firm-wide demand or productivity shocks lead to this kind of bias and mean that $\Delta \log W_{ij}$ and $\Delta \log W_{ij'}$ will co-move even without a rigidity. We can recover an unbiased estimate of $\mathcal{N}$ using an instrument for $\Delta \log W_{ij'}$ that is uncorrelated with establishment j's productivity. Importantly, with a valid instrument in hand, we can estimate $\mathcal{N}$ *without* parameterising any other features of the model, which will be "differenced out" by the market level fixed effect γ_j.

4.4 Empirical Evidence for National Wage Setting

This section tests the two predictions of our framework to gauge whether national wage setting drives the patterns in Section 3.

4.4.1 Bunching of Wage Changes

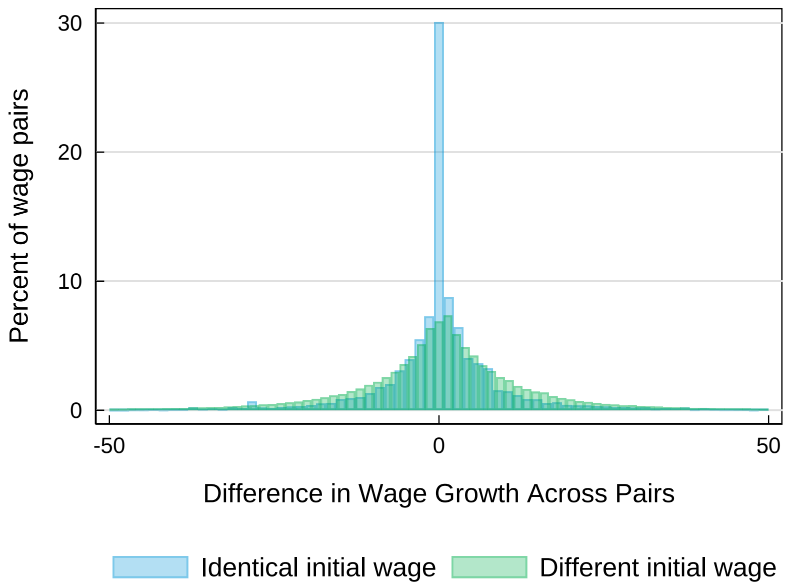
We calculate annual wage growth within each establishment and occupation and take the difference in annual wage growth for each pair of establishments in the same occupation and firm.[33] We exclude all changes where the first establishment in the pair has no change in the posted wage.[34] Figure 6 plots the distribution of the difference in wage changes across establishments of the firm, plotted separately for job pairs that pay exactly

[32] This derivation ignores transitional dynamics given that the model is purely static.

[33] Due to the sparseness of job posting over time within a job, we construct changes over the shortest interval for which we observe the job posting in both locations and normalize by the number of years between postings to get an implied average annual change.

[34] We exclude the zero changes since they may reflect inaction on the part of the employer. We find a larger degree of bunching if we include these observations. We also find similar patterns when we restrict our attention to 4-year changes and consider only those job pairs that are observed 4 years apart.

Figure 6: Bunching of Wage Growth Across Establishments Within the Firm



Notes: Sample includes 6,078,224 pairs of jobs in different establishments of the same firm and year, that initially set the same wage; and 34,780,714 pairs of jobs in different establishments of the same firm and year, that initially set different wages. For pairs that initially set the same wage, 22% of wage changes are identical across the pairs; for pairs that initially set different wages, less than 1% of wage changes are identical across the pairs

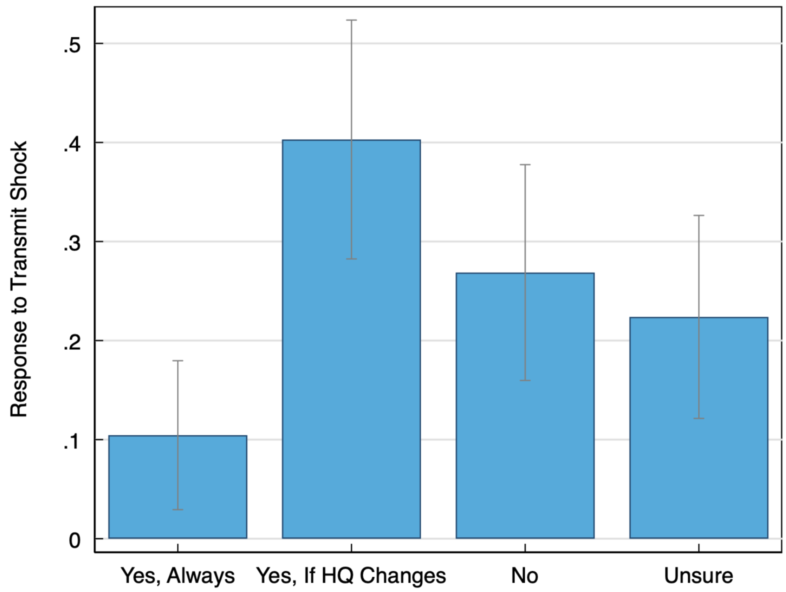
the same wage in the initial period and those that pay different initial wages. Establishment pairs that pay identical wages in the initial period display considerable bunching, with 22 percent of pairs having exactly the same change in wages. Bunching is far less common for job pairs that did not have the same level of wages in the initial period, with no visible discontinuity at zero, less than 1 percent of establishment pairs having exactly the same change. This pattern demonstrates that identical wage levels also predict identical wage changes over time.

4.4.2 Pass Through of Local Shocks to Wages in the Rest of the Firm

Our second test explores the degree to which identical wage setters raise wages in all locations after a shock raises wages in a single location. We begin by exploring this question using survey evidence and then in the job vacancy data using an instrument based on natural resource booms.

In the survey, we posed a hypothetical scenario to respondents working at firms that set identical wages for some or all of their jobs. We asked whether their firm would change its wages or pay bands in response

Figure 7: Impact of Wage Change in A Single Establishment on Other Establishments



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

to a shock that forced the firm to change its wages or pay bands in a single establishment.[35] In our simple framework, firms that raise wages elsewhere after a shock to a single location are national wage setters.

The responses are summarized in Figure 7. Half of respondents state that a wage change in one establishment would impact the wages that they pay in other establishments (combining the first two bars). However, of those respondents, 80% stated that this would only be the case if the headquarter was the establishment that had its wages change. Fewer than 30% of respondents state that a change to wages in one location would not impact wages in other locations.

We next turn to the Burning Glass data. Adapting the estimating equation (9) derived from the model, our main equation of interest is

$$\Delta \log w^{s}_{oijt} = \gamma_{ojt} + \beta \Delta \log w^{p}_{ojt} + \varepsilon_{oijt} \tag{10}$$

[35]In the hypothetical scenario, the shock that we ask respondents to consider is a scenario in which a single establishment must raise wages in order to compete with other establishments in the surrounding area.

where $\Delta \log w^s_{oijt}$ is the change in the log wage that firm i pays to workers in occupation o in its secondary establishments located in county j from year $t-1$ to year t. The independent variable of interest, $\Delta \log w^p_{ojt}$, is the same measure for the firm's primary establishment. The primary establishment is defined as the largest establishment in the firm, measured using the total number of vacancies over 2010-2019. All other establishments of multi-establishment firms are secondary. We use the primary establishment since we found in Figure 7 that wages throughout the firm are most sensitive to changes in wages at the firm's headquarters. Consistent with the model, we include job by county by year fixed effects to capture any market-level factors affecting wages in a given year. In this sense, we are comparing to job postings for a given job located in the same county in a given year, but that are attached to different firms with (potentially) different primary establishment locations.

To avoid omitted variable bias, we instrument for wages in the primary establishment with a shock to natural resources demand in the county to which the primary establishment belongs. This shock is appealing because i) natural resource employment is highly localized and therefore likely to directly affect only some establishments within the firm and ii) the sector experienced large shocks over this period stemming from international movements in oil prices (See Appendix Figure A18 and Hazell and Taska (2020) for an extended discussion). Specifically, we construct a shift-share instrument that measures a county's exposure to natural resource shocks as:

$$B_{j,t} = 100 \times \frac{\text{Natural resources employment}_{j,2009}}{\text{Total employment}_{j,2009}} \times \log(\text{Natural resources employment}_{-j,t}) \tag{11}$$

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 and the growth in all other counties' employment in natural resource industries.[36] We take the difference of the instrument over time, in line with equation (10).

For this instrument to be valid, a natural resource shock to the primary location must affect wages in unexposed secondary establishments *only* through the impact on wages in the exposed primary establishment. We take four steps to strengthen this is the case. First, we exclude firms that directly operate in the natural resource sector, since all establishments are likely affected by resource booms regardless of where they are located. Second, we exclude secondary establishments in counties exposed to natural resources, since they are

[36]Natural resources industries are NAICS sectors 11 and 21, and we measure employment in each county using the Quarterly Census of Employment and Wages.

naturally affected by shocks.[37] Since natural resource employment is highly concentrated in a few counties, this restriction is modest (See Appendix Figure A20). Third, to avoid geographic spillovers, we only study secondary establishments located in a different census division than the exposed primary establishment. Fourth, the job by county by year fixed effects in our estimating equation account for market-level effects of the natural resources shock such as migration across regions.

Panel B of Table 2 reports the first stage estimates of the impact of increased exposure to natural resources in the primary location on the wage in the primary establishment. The first column has only year by county fixed effects. In the second to fourth columns, we progressively add year by occupation, year by county by occupation, and year by industry fixed effects. The shift-share instrument has a strong first stage: a one percent increase in exposure leads to a 0.2 percent increase in posted wages (with a first-stage robust F statistic of 18-49 across the specifications).

Panel A of Table 2 shows our main result. The estimates of equation (10) using OLS are shown in column 1 of Table 2. A one percent increase in the posted wage for a specific job in a firm's primary establishment is associated with 0.26 percent higher posted wages for the same job in the firm's secondary establishments.

In columns 2-4 of Table 2, we present the results using the shift-share shock to instrument for primary establishment wages. The results suggest that a 1% increase in a primary establishment's wage for a given job increases the wage in the firm's secondary establishments by 0.65% to 0.81%.[38] The IV estimate is likely larger than the OLS estimate due to measurement error induced by our averaging across postings within the year, and averaging across different job titles in the same occupation.

In principle, wage shocks to primary establishments could pass through to wages in secondary establishments through other channels, such as internal financial networks or product demand spillovers within the firm. We now provide two additional tests motivated by our model of national wage setting. They suggest our instrument is, at least in part, isolating the effect of national wage setting.

First, we detect heterogeneous effects of the instrument consistent with national wage setting. Our model predicts that national wage setting firms should (i) change wages in the primary establishment by less than

[37] We define exposed counties as having more than 5% of employment in natural resources.

[38] In Appendix Table A12, we show that these results are robust to using constant weights, different levels of trimming, using only the first lag of the instrument, and clustering by primary establishment location by firm (rather than by secondary establishment county by firm). In Appendix Table **??** we also show that worker composition – proxied by education and experience requirements in the text of the vacancy – respond little to the wage change. In Appendix Table **??**, we test whether the estimate could be biased by differential selection of national wage setters into vacancy posting, and find no evidence for such effects.

Table 2: Pass Through of Natural Resources Shock to Wages in the Rest of the Firm

	(1)	(2)	(3)	(4)	(5)
Panel A (Structural Equation)			Outcome: Δ Log Secondary Establishment Wage		
Δ Primary Estab. Wage	0.27	0.81	0.66	0.65	0.64
	(0.02)	(0.28)	(0.25)	(0.20)	(0.19)
Δ Primary Estab. Wage x T2 Wage Gap					0.02
					(0.12)
Δ Primary Estab. Wage x T3 Wage Gap					-0.54
					(0.20)
Observations	263,259	259,859	184,581	181,905	184,581
Specification:	OLS	IV	IV	IV	IV
Panel B (First Stage)			Outcome: Δ Log Primary Establishment Wage		
Instrument	0.20	0.21	0.29	0.18	
	(0.03)	(0.04)	(0.03)	(0.04)	
Instrument x T2 Wage Gap				0.06	
				(0.04)	
Instrument x T3 Wage Gap				0.17	
				(0.08)	
Observations	272,079	193,339	190,593	187,937	
Panel C (Bunching)			Outcome: Primary and Secondary Wage Equal		
Instrument	-0.001	-0.0002	-0.002		
	(0.001)	(0.0005)	(0.001)		
Observations	259,859	184,581	181,905		
Fixed Effects:					
Year by county	✓	✓			
Year by occupation	✓	✓			
Year by occupation by county			✓	✓	✓
Year by industry				✓	

Notes: The primary establishment is the firm's largest establishment, by vacancies, over 2010-2019. All other establishments of the firm are secondary. The sample excludes public sector firms, firms in natural resources (NAICS industry 21), secondary establishments in a county with an employment share in natural resources greater than 5%, and secondary establishments in the same census division as their primary establishment. The observation counts exclude singletons. The standard errors are clustered by the county of the secondary establishment and the firm. Wages are trimmed at the 2.5% and 97.5% level, within each occupation, pay frequency, salary type and year. In panel A, the outcome variable, from Burning Glass, is 100 x the change in the log of the secondary establishment wage. In panel A, the outcome variable is 100 x the change in the log of the secondary establishment wage. The regressor is 100 x the change log of the primary establishment wage, also from Burning Glass. Column (1) is an OLS regression of the outcome variable on the regressor. Columns (2)-(5) are IV regressions, instrumented with the natural resources shift share instrument from the primary establishment's county, constructed from the County Business Patterns. In panel B, the outcome variable is 100 x the change log of the primary establishment wage. The regressor is the natural resources instrument from the primary establishment's county. In Panel C, the outcome variable is the change in an indicator for whether primary and secondary wages are equal. The regressor is the natural resources instrument from the primary establishment's county. All regressions are weighted by the number of vacancies in the job.

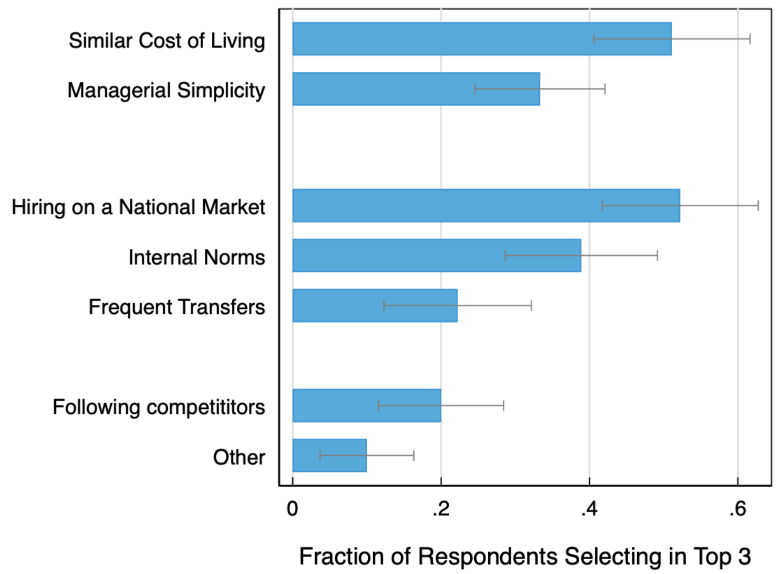
local wage setters, in response to the natural resources shock; and (ii) pass through any wage changes that occurs in the primary establishment to the secondary establishments. We test these predictions. In column 5, we interact the natural resources instrument with the lagged difference between the primary and secondary establishments' wages. Specifically, we first calculate the absolute value of the difference in the posted wage for a given job in a firm's primary and secondary establishments, and then split this variable into terciles. The first tercile includes firms that set similar wages for their jobs across locations, who are more likely to be national wage setters; while the third tercile includes firms that set different wages across space, who are less likely to be national wage setters.

The results are consistent with national wage setting. The first stage in column 5 of Panel B in Table 2 shows that a 1 percent increase in natural resources demand leads to a 0.18 percent increase in the primary establishment wages for firms setting wages similarly across establishments (including national wage setters). Jobs in firms in the second and third terciles have larger first stages, with firm-jobs in the third tercile, where wages are most flexible, seeing the largest effect of a natural resources shock. However, we see the opposite pattern in the IV regression (column 5 of Panel A). Here, the impact of an increase in the primary establishment wages, induced by a natural resource shock, leads to the largest increase in secondary establishment wages for firms that set wages similarly across space. Firms that set wages flexibly across space, those in the third tercile, see an impact that is roughly 1/5 the size and statistically indistinguishable from zero.

Our second test exploits that for national wage setters, wages should move by *exactly* the same amount in the primary and secondary establishments. We show evidence for this prediction in panel C of Table 2. We regress an indicator for whether the primary and secondary establishment pay exactly the same wage, on the natural resource shock to the primary establishment. If firms change wages in primary and secondary establishments by exactly the same amount in response to the shock, there should be no change in the probability that the wages in the two locations are the same – national wage-setters will change wages in both establishments by the same amount, local wage setters will have different wages in both periods. As predicted by national wage setting, the coefficient on the instrument is close to 0 in all columns.[39]

[39] In Appendix Figure A18, we estimate for each year the effects of exposure to the natural response shock in the primary location, separately for primary establishments (i.e. the first stage) and for secondary establishments (i.e. the reduced form). In each year, the secondary wage responds by less to the instrument than the primary wage – as expected, since only the primary establishment is directly exposed and many firms do not set wages nationally. More importantly, the dynamic effects track movement in global oil prices over this period – both the global oil price and the effect of the instrument increase in 2011, fall through to 2015, and increase afterward. The dynamics support the identifying assumption that changes in natural resource employment in the primary location are driven by shocks to natural resources demand.

Figure 8: Reasons Why Firms Do Not Vary Nominal Wages Across Space



Notes: Sample is restricted to the set of respondents working at firms that set identical pay for some or all of their jobs. The bars are grouped into three broad categories: managerial costs (top two bars), nominal illusion (middle bars), and other (bottom bars). Nominal illusion refers to the fact that workers tend to consider on nominal rather than real wages when making job decisions. *Similar Cost of Living* is the selection "All of our employees work in areas with similar costs of living". *Managerial Simplicity* is the selection "It is administratively costly to tailor wages to each location." *Internal Norms* is the selection "We want workers performing the same job to be paid the same wage." *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". Additional details on this question are shown in Appendix B1.

5 Reasons for National Wage Setting

This section asks why firms choose to set wages nationally. In order to understand the factors that might lead to national wage setting, we included a free-form question in the survey pilot, asking managers who report working at firms setting the same nominal wages across locations why their company adopted this practice. We grouped the free-form answers into seven reasons and in the full survey, we asked respondents whose firms do not vary nominal the wages of some or all jobs to rank those reasons in order of importance.[40] Figure 8 shows what HR managers report as one of the top three reasons for setting national wages.

We see these responses as broadly supporting two main explanations for national wage setting. The first explanation for national wage setting is that firms are aiming to simplify their wage-setting processes and reduce costs, as in DellaVigna and Gentzkow (2019). Around 35 percent of respondents report that they set

[40]The full responses can be seen in Appendix Section B1. We presented options to the full sample in a randomized order.

national wages because it is administratively costly to tailor the wages to each location and almost half of all respondents cite that their workers are in areas with similar costs of living. We interpret this second response as indicating cost reduction as an explanation since markets are unlikely to be completely identical and factors other than cost of living affect the wages, as shown in the framework in Section 4.2. Operating in areas with a similar cost of living would lead to pay compression within a job, but it is unlikely to lead to identical wages.[41] Reporting that a firm sets identical wages due to a similar cost of living across space likely captures the notion that when the optimal wages across locations are sufficiently close, it is more cost effective to set identical wages than it is to adopt a more sophisticated pay structure that depends on location.[42]

Setting wages nationally to simplify management makes the most sense when the costs to doing so are somewhat small, as we find it unlikely that the gains from simplicity are large for several reasons. First, as we discussed in Section 3, many firms set wages nationally in some occupations, but set wages locally in others. Firms that are able to set wages locally for some occupations can presumably set wages locally for the other occupations with little additional difficulty. Second, compensation consulting firms – such as Payscale, Empsight, or Aon McLagan – can provide companies with information on local wages, meaning that firms can easily acquire the relevant information to set wages locally. Third, while DellaVigna and Gentzkow (2019) find support for the importance of managerial simplicity in explaining uniformity of prices, wages are generally reset less frequently than prices, suggesting that the managerial costs associated with geographically differentiated wages is lower. Additionally, with modern IT and payroll management systems, managing a wide variety of pay levels is unlikely to be very difficult, if it is otherwise profit-maximizing.

The second explanation is that national wage setting arises because workers care about nominal, rather than real, pay comparisons. We find evidence for this in the importance of three explanations. First, just over half of respondents cite doing national wage setting because they are hiring on a national labor market, meaning that they employ mobile workers who could move throughout the country for a job. This would cause firms to equalize nominal, rather than real, wages if firms thought workers compared nominal offers when considering locations within the firm. Second, almost 40 percent cited internal norms that constrain nominal wages to be

[41] Additionally, only 5% of respondents cite that a similar cost of living is the *only* reason for setting national wages, further suggesting that most respondents considered the national pay policy to be an active choice of the firm rather than simply being the optimal flexible wages.

[42] Of course, it is possible that firms operate in areas with a similar cost of living *because* they adopt rigid pay structures. For example, if a firm cannot or chooses not to vary nominal pay across establishments, the firm may decide not to open up establishments in high cost of living areas. However, we found limited evidence for this (see Appendix Figure A21).

similar across locations.[43] An additional 20 percent said that they set national wages because workers transfer across locations and they don't want to adjust their nominal pay if they do, again suggesting that nominal pay differences are what matter to workers. Overall, nearly 80 percent of respondents choose one of these three explanations as an explanation for setting wages nationally.

The Burning Glass data also suggests that national labor markets, fairness norms, and frequent transfers are important factors determining national pay setting. First, supporting the importance of national labor markets, we find that national wage setting is more common for higher-wage occupations, where the workers are more geographically mobile and recruiting is more national (Ganong and Shoag, 2017). Second, supporting the importance of internal transfers and national job markets, in Appendix Figure A20, we show that jobs are more likely to have exactly the same wage when workers move between the two locations more.[44] Third, supporting the importance of internal fairness norms, we show in Appendix Figure A22 that firms with nationally set wages have less cross-occupation wage dispersion within the firm – these firms are not only paying exactly the same wage to workers within the same job in different locations, but they are paying more similar wages across jobs as well.[45]

Lastly, the responses from firms that do *not* set wages nationally also suggest nominal pay comparisons matter for this decision. Respondents who work at firms that set pay for some or all jobs differently across locations report that hiring on a local market is a major reason why their firm differentiates nominal pay across regions (See Appendix Figure A23). This finding is the complement of our result in Figure 8.

[43]Previous survey evidence finds that nominal pay comparisons within establishments matters to workers, due to internal norms about fairness (Blinder and Choi, 1990; Campbell III and Kamlani, 1997; Bewley, 1999). Our survey evidence suggests that nominal pay comparisons between establishments also matters to workers, potentially because many workers are from a national labor market and learn about what others are paid across the firm. This norm could therefore reflect workers' aversion to nominal pay differences.

[44]Specifically, we use the Census J2J Origin Destination statistics and measure worker mobility between MSA A and B as the total number of employment to employment transitions from A to B and from B to A, divided by the population in A. A high number here demonstrates that workers often move between these two areas. Consistent with the survey evidence, we find that, within the firm, wages are more likely to be the same for job pairs in areas with more mobility.

[45]Specifically, we calculate the average wage within an occupation by establishment by year for firm i and use this to calculate the ratio of the 90th wage percentile to the 10th wage percentile within each establishment by year. Appendix Figure A22 plots the distribution of the 90/10 ratio in each establishments separately for those establishments at nationally wage setting firms and those at other firms. We clearly find that wages across occupations are more compressed in national firms than in other firms: the average ratio of the 90th and 10th percentile of wages in a national firms is 1.71, compared to 2.02 for non-national firms. In order to account for the fact that national wage setting firms may hire in different occupations, we also create a "benchmark" measure of compression by doing the same calculation using the wages of other firms in a given county, leaving out firm i. This benchmark captures the 90/10 ratio that would be predicted by the set of occupations employed by the establishment. Appendix Table A14 shows that nationally wage setting firms not only have lower levels of inequality (90/10 ratios and 75/25 ratios), they also have lower benchmark ratios (i.e. they choose an occupational mix that is less dispersed on average) and have even less cross-occupation wage dispersion than would be predicted by their occupational mix.

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

We return to our simple model from Section 4.1 to measure whether national wage setting has large effects on profits. In particular, we calculate how firms would have set wages in the absence of national wage setting and then, using a simplified version of our model, provide a back of the envelope estimate of the profits foregone by firms due to national wage setting. It is possible that setting wages nationally increases worker productivity and maximizes profits – recall from Section 3 that firms setting national wages pay a premium. If so, our calculation measures the increase in firm profits due to national wage setting.

We assume that jobs paying identical wages everywhere, as measured in Section 3, are setting wages nationally. We start with simple estimates of what wage dispersion would have been for these jobs, if they had not chosen to set wages nationally. We calculate two benchmarks intended to be a lower and an upper bound for this counterfactual wage dispersion. First, as in Figure 1, for each location in which the national job operates, we calculate the average wage in that location and occupation for other establishments in the same industry that are not national jobs. In order to account for the wage premia of large firms, we also restrict to the set of firms that post similar numbers of vacancies both overall and at the given establishment. This "between-firm" match captures the market-level average wage paid by similar establishments for exactly the same occupation. In our simple model, this benchmark is the counterfactual wage dispersion of national wage setters as long as the local elasticity of labor supply and the local component of productivity is the same for the various establishments. We consider this an upper bound, since, despite our matching procedure, there are likely unobserved differences across establishments that will contribute to between-firm differences in wages.

We construct an alternative benchmark wage difference using within-firm differences across locations for the set of jobs that do *not* set wages nationally. Specifically, for each location pair in which a national wage setter is hiring, we calculate the average percent difference in the wage across those two locations *within firms that are not setting wages nationally*.[46] Through the lens of the simple model, this is the correct counterfactual if productivity differences across space are the same for these two firms (i.e. $A_{ij}/A_{ij'} = A_{kj}/A_{kj'}$) and all firms within a market face the same labor supply elasticity. 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.

[46] I.e. if for local wage setters that operate in both Boston and Austin, the average wage difference is 7%, we apply that to the national wage setters that operate across those two locations.

Table 3: Estimated Magnitudes for National Wage Setting

	25th	Median	75th
Panel A: Percent Difference in Wages			
Between-Firm Benchmark			
	6.1	20.3	48.3
Within-Firm Benchmark			
	2.9	6.6	15.3
Panel B: Percent Difference in Profits			
Between-Firm Benchmark			
$\rho = 2$	1.1	12.5	39.4
$\rho = 4$	3.8	37.8	197.2
$\rho = 6$	7.8	66.2	631.3
Within-Firm Benchmark			
$\rho = 2$	0.1	1.3	6.8
$\rho = 4$	0.4	4.2	21.6
$\rho = 6$	0.8	8.7	42.1

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%.

Panel A of Table 3 shows the results. The median differences between the actual wage and the wage that the between-firm and within-firm benchmarks suggest the national wage setter should have paid are 20 percent and 7 percent respectively. Even according to the more conservative within-firm benchmark, 25% of the nationally wage set jobs differ by over 15 percent. This demonstrates that firms engage in national wage setting even across markets that have meaningful dispersion in wages.

Lastly, we combine these empirical benchmarks with the structure of the simple model in 4.1 to provide an estimate for the share of profits affected by national wage setting. For this simple back of the envelope, we make an additional simplifying assumption: the labor supply elasticity is the same in all markets for all firms (i.e. $\rho_j = \rho$ for all j). Then the model will attribute all differences in wages across locations to differences in productivity rather than differences in markdowns.[47] Then we can derive a simple formula for the reduction in profits from national wage setting. Specifically, we have

[47] This assumption is innocuous, because differences in local productivity and local markdowns are not separately identified by our model.

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

where $\overline{W}_i$ and $\overline{\Pi}_i$ are the actual wages and profits of national wage setters, whereas W_{ij}^* and Π_{ij}^* are the wages and profits in the counterfactual. Under the assumption that the matched pair provides an estimate for W_{ij}^*, we can calculate the profit loss from national wage setting, given a value of ρ.

Panel B of Table 3 presents the estimated change in profits from national wage setting. The numbers reported in this table are the average percent increase in profits that a national job would receive from setting wages locally, holding constant other factors. Of course, there may be important productivity effects or changes in market-level outcomes that would result from this change, all of which we abstract from for this simple benchmark. This simple benchmark, however, implies that the effect of national wage setting on profits is substantial. We focus on estimates for a labor supply elasticity of 4, which is in the range of estimates found in the recent literature (see for example Dube et al., 2018, Lamadon et al., 2019), but report results for higher and lower values. Using our more conservative within-firm benchmark, we find that with national wage setting, the median job is 4 percent less profitable than it would be with flexible wage setting. This number rises to 37 percent using the between-firm benchmark. These simple calculations suggest that for the median firm, there are substantial profits at stake from national wage setting.

7 Conclusion

This paper demonstrates the prevalence of national wage setting using data from online job postings and a survey of HR professionals, finding that 35% of multi-establishment firms set wages nationally. We first demonstrated, descriptively, that firms often set exactly the same nominal wage for the same job in different locations. This practice concentrates in certain firms, is widespread across states, industries and occupations, and is more common in higher-wage occupations and tradable occupations or industries. Second, using information on 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 adopt rigid pay structures that compel them to set the same nominal wage in all of the regions in which they operate. Third, we found that firms adopt these national wage setting practices because it simplifies management when the costs to doing so are low and because workers care about nominal, rather than real, wage comparisons.

These findings affect our understanding of labor markets in several ways. First, national wage setting has implications for whether monopsony power in labor markets has increased over time. According to our evidence, a large share of firms set wages nationally because they are competing for workers on a national labor market. For these firms, national measures of labor market power may matter more than local measures of labor market power for wage setting. National employment concentration has been rising while local concentration – a common measure of labor market power – has been falling (Rossi-Hansberg et al., 2018; Rinz, 2018; Berger et al., 2019; Autor et al., 2020). Second, national wage setting may have implications for the aggregate effect of nominal wage rigidity. Midrigan (2011) and Alvarez and Lippi (2014) argue that when firms synchronize price changes across products, the aggregate amount of nominal price rigidity increases. We find that firms synchronize wage changes across establishments, which may increase the aggregate amount of nominal wage rigidity through similar mechanisms.

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A1 Data Appendix

A1.1 Posted Versus Realized Wages

One important feature of the Burning Glass data is that it provides measures of posted wages, not the realized wages paid to workers. Posted and realized wages may differ if, for example, there is bargaining by workers after they are hired.

We extensively explore the extent of this deviation by comparing the posted wages in Burning Glass to realized wages from other datasets. In particular, we compare the median wage within each 6 digit occupation within an MSA in Burning Glass, averaged over 2010-2019, to the median annual wage for each 6 digit occupation and MSA in the Occupational Employment Statistics (OES) data, again averaged over 2010-2019. We construct the Burning Glass wages separately for each type of salary and pay frequency of the salary type. We then regress log occupation by MSA wages from the OES on log occupation by MSA wages from Burning Glass, weighting either occupation by its employment in the OES.

Figure A1 plots the relationship for all jobs posting an hourly base pay, demonstrating that the Burning Glass and OES measures of detailed occupation and regional wages are highly correlated – when Burning Glass wages change by one percent, occupation wages from the OES also change by roughly 1 percent. Table A4 reports the regression results for hourly base pay, annual total pay, and hourly total pay. In all cases, the regression coefficient is close to but slightly below 1. Additionally, Table A5 shows that Burning Glass wage measures not only capture the median wages, but they match the other moments of the distribution of wages as well – when the 10th and 90th percentile of posted wages in a given occupation and MSA in burning Burning Glass go up by 1 percent, the 10th percentile and 90the percentile of wages in OES go up by 0.8 and 0.87 percent, respectively. These high correlations suggest that at the detailed occupation and region level, posted wages in Burning Glass are very close to realized occupation wages in the OES.

A1.2 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. (2020) 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 percent of each group of names sharing the first two letters. Within each cluster of names generated by dedupe, we set all names to that of the most common employer to form a list of 933,718 unique cleaned employer names.

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

Table: Examples of Precleaning and Dedupe Clusters

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

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

A1.3 Payscale Data

The Payscale data contains data on individuals’ self-reported salaries/wages, bonus and other non-salary benefits, other personal characteristics such as age and gender, and current firm/job title. Payscale harmonizes jobs across firms by mapping job titles to O*NET “Detailed Occupation” categories, which are roughly similar to SOC-6 codes.[48] Throughout our analysis, we use the O*NET Detailed Occupation codes.

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

Figure A4 shows the industry and broad occupation representation in the overall data. Table A6 shows how well the data tracks the distribution of wages reported in the Occupation Employment Data (OES) at the occupation by MSA level. Overall, the data is less nationally representative than the Burning Glass data (Appendix Figure A4) but tracks OES wages moderately well, especially towards the top of the wage distribution.

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

In terms of bonuses, we find that within the database, 27 percent of the workers report bonuses, the average size of which is 2.5 percent of base earnings, very similar to the magnitudes found in Grigsby et al. (2019) using the ADP payroll data. Like in Grigsby et al. (2019), we find that bonuses are a larger part of compensation for workers at the top of the income distribution (See Figure A5).

We use the Payscale data to explore the relationship between bonuses and cost of living. Specifically, we estimate a variation on the following regression

$$B_{ijot} = \alpha_1 \text{local price}_{jt} + \alpha_2 \log(w_{ijt}) + \theta_{fot} + \epsilon_{ijot} \tag{12}$$

and present the results in Appendix Table A16. In equation 1, local price_{jt} is a measure of local prices (either the local price index from the BEA of local house prices from Zillow), $\log(w_{ijt})$ is the base salary of the worker, and θ_{fot} is a fixed effect for the firm and 6-digit occupation. B_{ijot} is either an indicator for whether the worker received a bonus (column 1 and 2), the log of the reported bonus (columns 3 and 4) or the log of all additional compensation, defined as total compensation minus base pay (columns 5 and 6). The coefficient of interest is α_1, which captures the extent to which firms are more likely to compensate workers in high-cost areas with bonuses. Panel A shows the relationship for all workers and panel B restricts to salaried workers, who are most likely to have bonuses constitute a substantial fraction of their compensation (Grigsby et al. (2019)). In all cases, we find that the probability of receiving a bonus is slightly negatively correlated with the cost of living, although the differences are not always statistically significant. Importantly, there is no evidence that firms are using bonuses to circumvent national wage setting constraints and compensate workers in high-cost areas.

A2 Appendix For Section 3

A2.1 Comparing National and Franchised Firms

Since the Burning Glass data does not include information on whether a firm is franchised, we manually coded the 135 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 excluded the set of firms that we determined followed an agent model and looked at the prevalence of national wage setting for the firms we were able to identify as either franchised or not-franchised. Table A13 reports the results. While the results are relatively imprecise, we find evidence that firms following a franchising model have less uniform wages. This is true overall (columns 1 and 4) and when looking within specification industries and occupations (columns 3 and 6). The estimate in column 1 suggests that franchised firms are 6.5 percentage points less likely to have occupations paying a national wage.

A3 National Wage Setting and Remote Work

This appendix presents descriptive evidence relating national wage setting to remote work. We first explore the rise in remote work and present suggestive evidence that the majority of firms plan to pay remote workers a national wage. Second, we explore whether increases in the amount of remote work will encourage firms to adopt national wage setting even for non-remote workers. Our results tentatively suggest that a rise in remote work will cause a rise in national wage setting even for non-remote workers.

A3.1 Wages for Remote Work

We begin by exploring trends in remote work through the Covid-19 pandemic. Within the Burning Glass data, we measure remote work using a vacancy-level "work from home" flag that is derived from the text of vacancy postings. The flag is provided to us by Burning Glass Technologies. Jobs that are flagged as "work from home" are not assigned to an establishment of the firm. We find that both the number of remote and non-remote vacancies have grown over time in our sample period. Remote vacancies peak in 2020, when there are roughly 220,000 remote postings in our data. However, the share of all vacancies represented by remote postings is small in all years and an order of magnitude lower than survey-based estimates of the economy-wide remote work share during the COVID-19 pandemic.[49] In 2020, when this share is highest, remote vacancies make up 2.53% of all vacancy postings. We suspect that there are many vacancies that allow remote work but are not coded as such in our data.[50] We therefore interpret our remote work variable as a noisy measure of the true number of new vacancy postings that allow remote work and interpret our regression results with caution.

In our survey, we also asked employers whether the share of employees who work remotely increased during the pandemic, whether they expect that share to be higher after the pandemic relative to before, and whether the firm adjusted pay for employees who transitioned to remote work. 68 percent of firms expect that the fraction of employees working remotely will be higher even after the pandemic subsides. This is true for all firms, regardless of whether they set wages nationally or not. Moreover, the majority of firms in our sample do not intend to adjust pay based on location for remote workers: Figure A24 shows that only 10% of firms currently setting wages identically across establishments have already or have plans to adjust the wages for remote workers. Perhaps more surprisingly, a slightly *smaller* fraction of firms with local wage setting anticipate adjusting pay for remote workers based on location. For these firms, a rise in remote work will lead to more uniformity in wages across workers within the firm, even if there is no change in the wage setting policy for non-remote workers.

A3.2 Remote Work and National Wage Setting

We now using the Burning Glass data to explore whether more remote work is likely to affect the overall wage setting policies of the firm. The results in Figure A24 suggest that the large majority of firms do not plan to index wages for remote workers to their physical locations. This suggests that as the share of workers in fully remote jobs rises, firms may decide to reconsider the degree to which they index all jobs based on geography. We use the Burning Glass data to show some evidence that this is the case.

As in the main text, we define a job as a (SOC $\times$ Pay Frequency $\times$ Pay Type) and an establishment as the combination of the firm and county. For the results presented in this section, we say that a wage is nationally set if at least 50% of the establishments in the firm-job-year have at least one vacancy that posts a that wage.

[49]See, e.g., https://www.pewresearch.org/social-trends/2020/12/09/how-the-coronavirus-outbreak-has-and-hasnt-changed-the-way-americans-work/.

[50]We expect this measurement error to be particularly strong during the COVID-19 pandemic.

For each firm-job-year, we set $\text{NWS}_{fjt} = 1$ if there is at least one nationally set wage.[51] We restrict our analysis to firm-job-years with at least five establishments, and construct the sample using vacancies posted from 2010 through 2020. Note that the definition of a national job does not include the remote work, but rather captures the extent of national wage setting for non-national jobs.[52]

We estimate the relationship between remote work and national wage setting using regressions of the form:

$$\text{NWS}_{fjt} = \eta_{fj} + \xi_t + \gamma \text{RW}_{fjt} + \varepsilon_{fjt} \tag{13}$$

where NWS_{fjt} is a measure of national wage setting for firm f in job j and year t, and RW_{fjt} is a measure of remote work at the firm-job-year level. Our specifications include firm-by-job fixed effects η_{fj} and year fixed effects ξ_t. The coefficient of interest, γ, is identified based on year-to-year variation within a firm-job cell, after purging the data of yearly fluctuations in remote work and national wage setting that are common to all firm-jobs.

Estimates of γ from Equation 13 may be biased if there are unobserved factors that affect both the degree of national wage setting and the propensity of the firm to allow remote work. To address this concern, we construct a Bartik-style instrument for RW_{fjt} based on each firm's exposure to remote work based on the counties in which they operate. Our instrument is:

$$\text{RW}^{\text{Bartik}}_{fjt} = \sum_c \left(s_{fjct} \times \overline{\text{RW}}_{-f,jct} \right) \tag{14}$$

where s_{fjct} is the share of firm f's employment in job j that is located in county c in year t, and $\overline{\text{RW}}_{-f,jct}$ is the average remote work share among all other firms in job–county–year (ojc, t). This instrument captures the change in remote work that is predicted by the locations in which the firm is operating. The exclusion restriction assumes that increases in other firms' remote work share only affects a given firm's decision to set wages nationally for non-remote workers through an increase in that firm's share of remote jobs.

We find that our Bartik measure is predictive of remote work at the firm-job-year level. Panel A of Table $A15$ reports first-stage coefficients from two-stage least squares estimation of Equation 13. The dependent variable

[51] Note that this definition differs slightly from the definition of national wage setting used in the main text, which we do to allow for many vacancies within each firm-job-year cell.

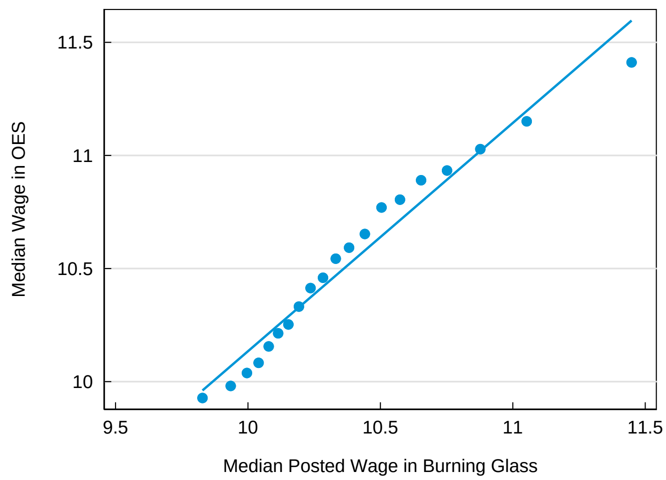
[52] We find that remote jobs in firms with national wage setting are highly likely to pay the national wage.

in Columns (1) and (2) is the share of vacancies that are remote in each firm-job-year cell, and the dependent variable in Columns (3) and (4) is an indicator for whether the firm-job-year has any remote work. In our preferred specification (Column 2), an increase in the Bartik remote shock from 0 to 1 increases the remote work share by 24.6%. This means that if other firms in your areas are increasing their amount of remote work, you are likely to as well.

Our main results from 2SLS estimation of Equation 13 are presented in Panel B of Table $A15$. We find that remote work is positively associated with national wage setting: In our preferred specification, which includes employer-by-job and time fixed effects, an increase in the remote work share of 10 percentage points is associated with a 4.39% increase in the propensity of the firm to set wages nationally for non-remote jobs in the same job. These results suggest that the large rise in remote work through the Covid-19 pandemic may encourage employers to adopt national wage setting.

Appendix Tables and Figures

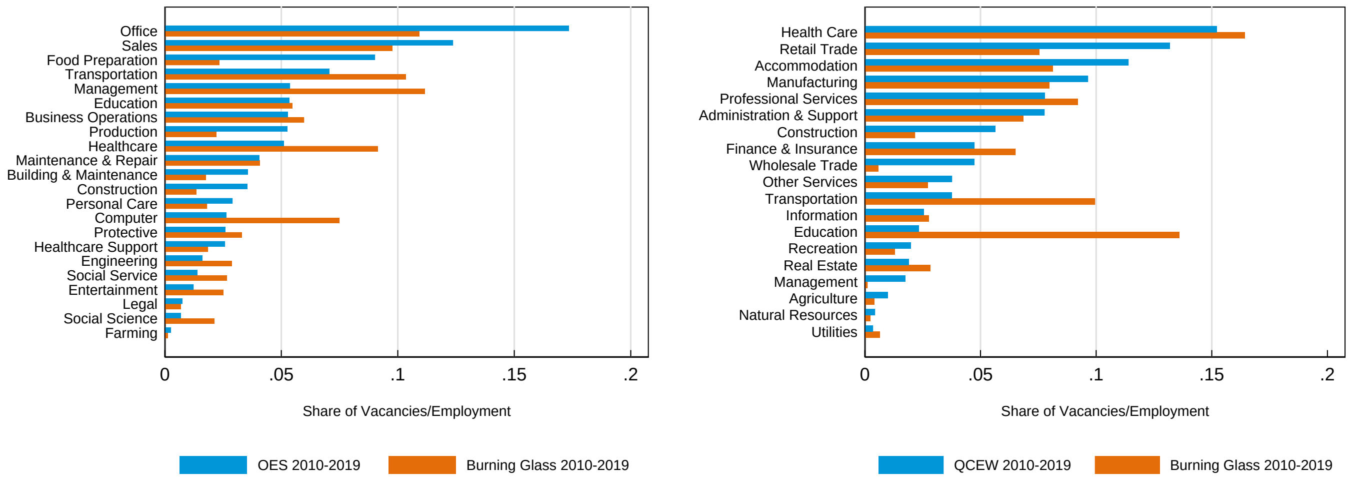
Figure A1: Distribution of Median Wages in Burning Glass and Occupational Employment Statistics



Notes: The OES wage on the y-axis is the log of the occupation by MSA median hourly wages from the Occupational Employment Statistics. The x-axis is the log median wages from Burning Glass for all jobs posting hourly basepay. In both cases, we study the wage averaged over 2010-2019. In both datasets, occupations are at the 6 digit level. MSA by Occupation cells are weighted by average occupation employment over 2010-2019. This is a binscatter plot and each dot represents 5% of the data. The slope of the line of best fit is 0.998. See Table A4 for the corresponding regression.

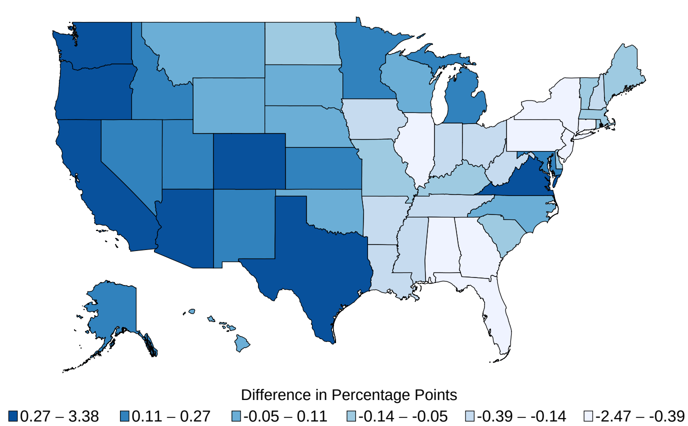
Figure A2: Occupation and Industry Shares in Burning Glass and Public Administrative Data

(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 wage.

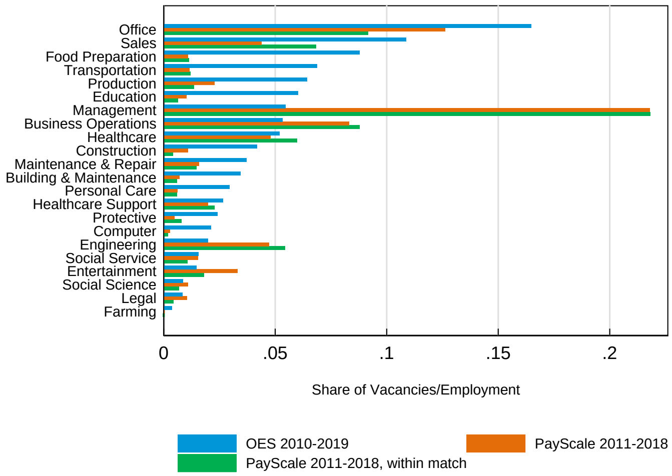
Figure A3: Geographic Representation of Burning Glass



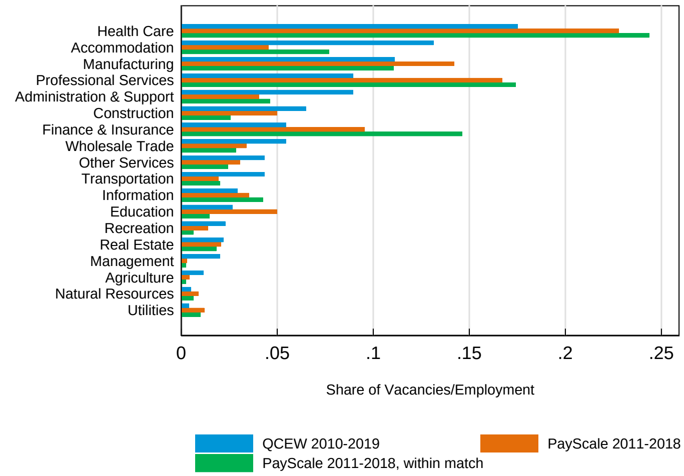
Notes: The values plotted are the difference between the vacancy share in Burning Glass and the employment share in the Occupational Employment Statistics (OES), multiplied by 100. Shares are calculated using the total number of vacancies/employment summed across 2010-2019. Sample includes the set of vacancies including a posted wage.

Figure A4: Occupation and Industry Distribution of Payscale Data

(a) Occupation

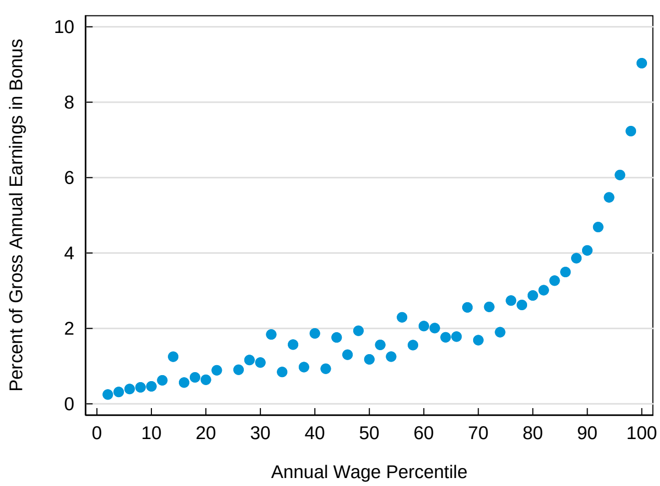


(b) Industry



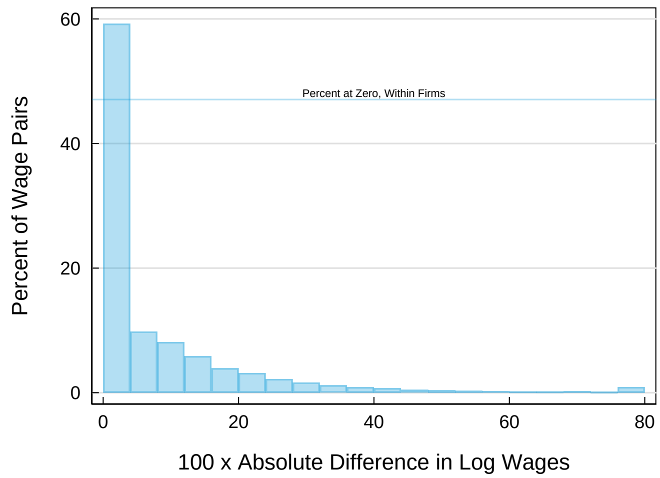
Notes: Shares are calculated using the total number of workers summed across 2010-2019. In the left panel, benchmark employment is from the 2010-2019 Occupational Employment Statistics, by broad occupation. In the right panel, benchmark employment is by broad industry from the Quarterly Census of Wages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

Figure A5: Bonuses as a fraction of total pay in Payscale data



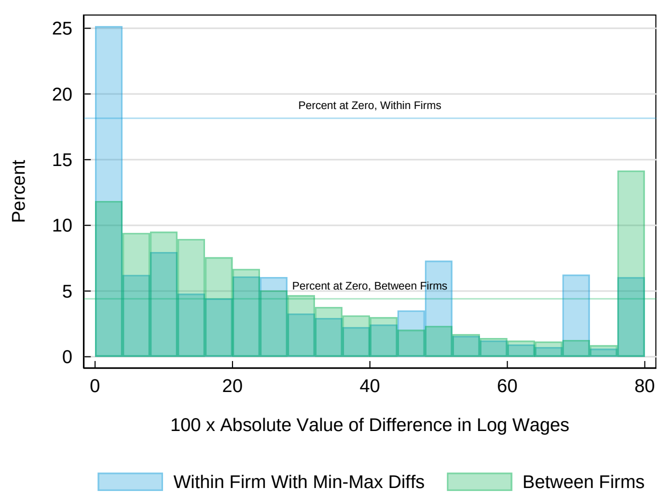
Notes: This figure shows reported bonuses as a percentile of reported base pay for each part of the wage distribution. The y-axis is the fraction of total compensation that comes from bonuses. Each dot represents 2 percent of the data. The x-axis shows the wage percentile, calculated over the entire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

Figure A6: Identical Wages using Job Titles



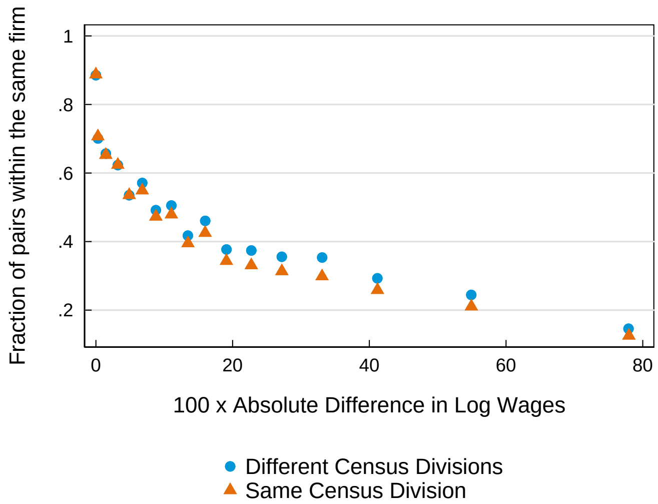
Notes: We plot the difference in the posted wage for all pairs of job titles within the firm for the same job title in different locations in a given year. Differences in the log of the wage are top-coded at 0.8. The figure includes 244,413,998 job pairs.

Figure A7: Bounding Exercise for Salary Ranges



Notes: Wage differences within the firm are defined using using the top of the range for one posting and the bottom of the wage for the other posting for all pairs with salary ranges for both vacancies in the pair and using the top of the range for one posting for all pairs with salary ranges for only 1 posting in the pair. Differences in the log of the wage are top-coded at 0.8.

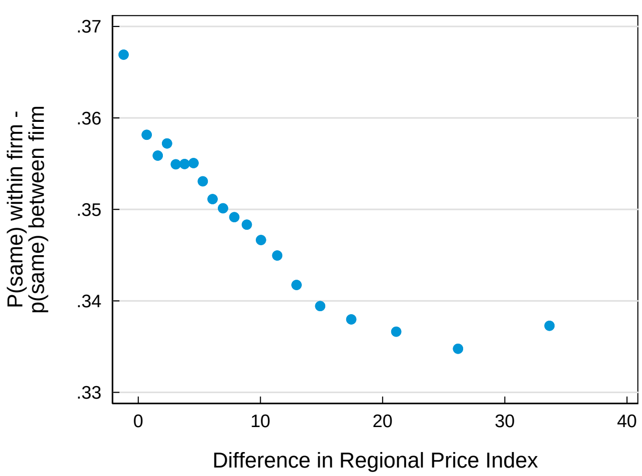
Figure A8: Identical Wages Within and Across Census Divisions



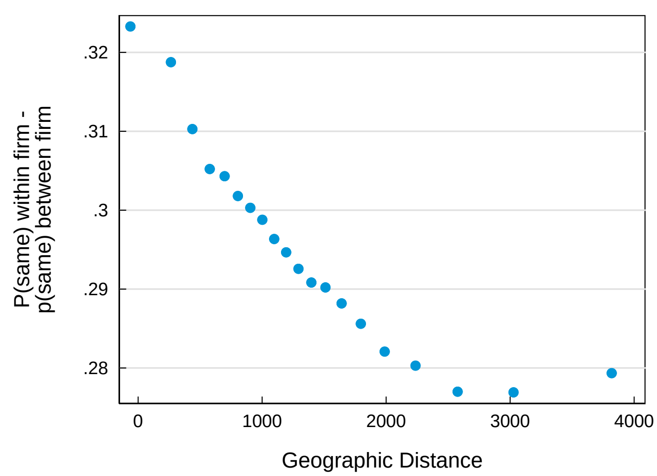
Notes: This figure is a binscatter with 20 bins. Orange triangles show the fraction of pairs that are within-firm for all pairs that are within the same census division while blue circles show the same metric for all pairs that are not in the same census division. 18,762,056 pairs are within the same census division and 99,293,010 pairs are between census divisions. There are 9 census divisions.

Figure A9: Likelihood of Identical Wages and Differences Between Markets

(a) Regional Price Index



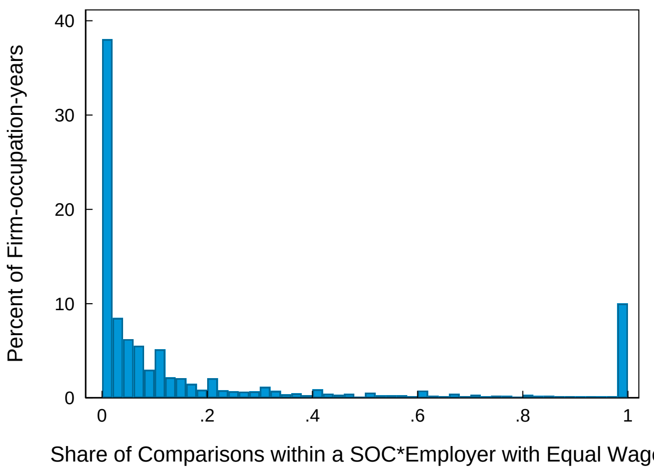
(b) Geographic Distance



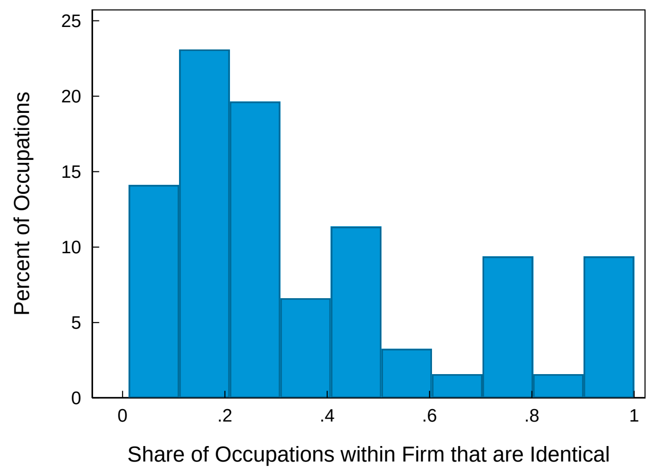
Notes: Each plot shows a binscatter with 20 bins. Binscatters include job*firm fixed effects. The y-axis is the difference between the probability that the wage is identical within the firm and the probability that the wage is identical in the matched between-firm pair.

Figure A10: Prevalence of Identical Wages Within the Firm

(a) Within job, across locations



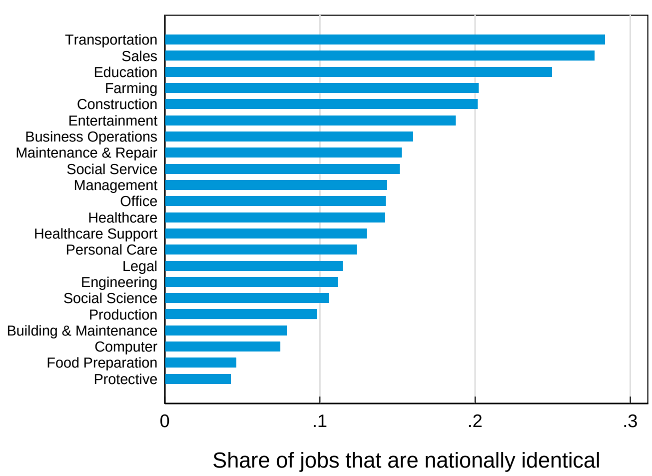
(b) Within firm, across occupations



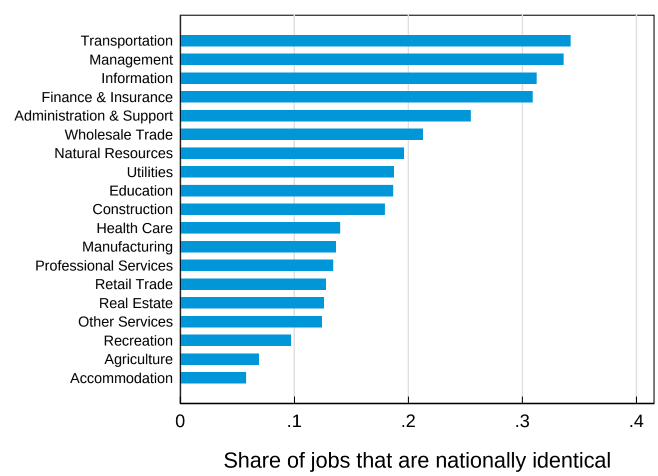
Notes: In the left panel, the sample excludes job cells where there are fewer than 5 within-firm pairs. This results in 25,377 firms. In the right panel, we further condition the sample to include the set of firms with at least 1 national occupation and at least 3 occupations. National occupations are defined as those where at least 80% of wage pairs are the same.

Figure A11: Identical Wages by 2-digit Industries and Occupations

(a) 2-Digit Occupations



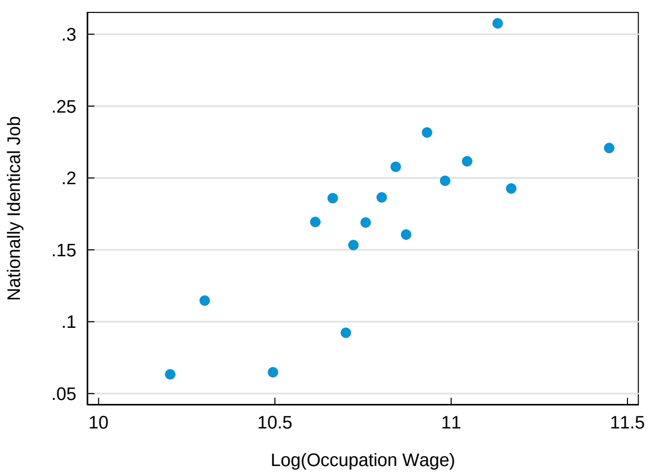
(b) 2-Digit Industries



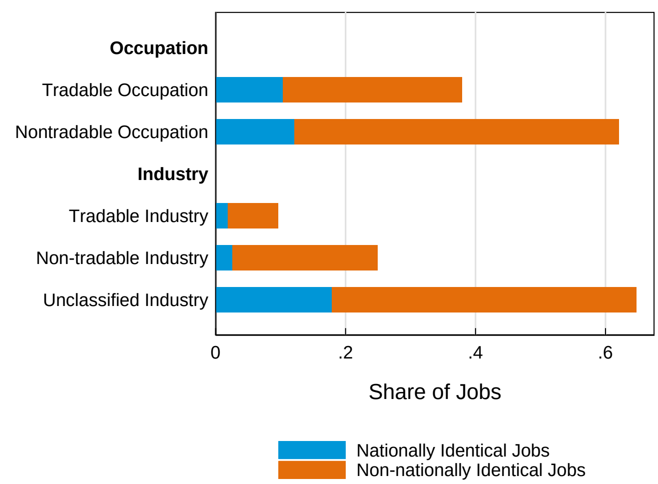
Notes: Nationally identical jobs are defined as those jobs paying the modal wage in occupation*firm*year cells in which at least 80% of wage pairs are the same. Sample includes all firm-job pairs present in at least 4 establishments in that year. Industries are defined using 2-digit NAICS codes for the firm.

Figure A12: Uniform Wage Setting By Job Characteristics

(a) Occupation Wages

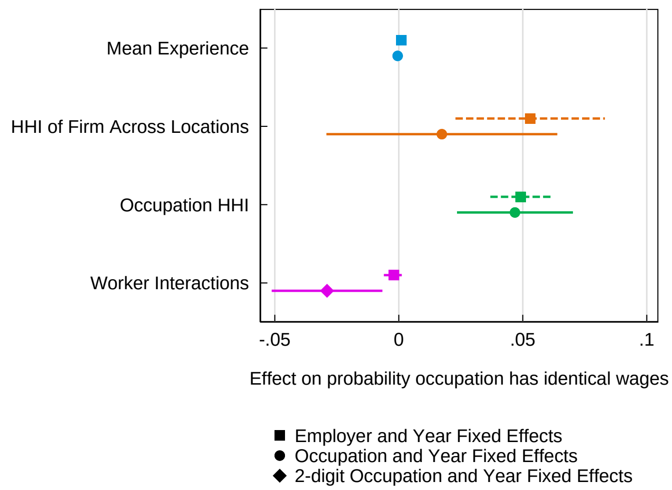


(b) Tradability



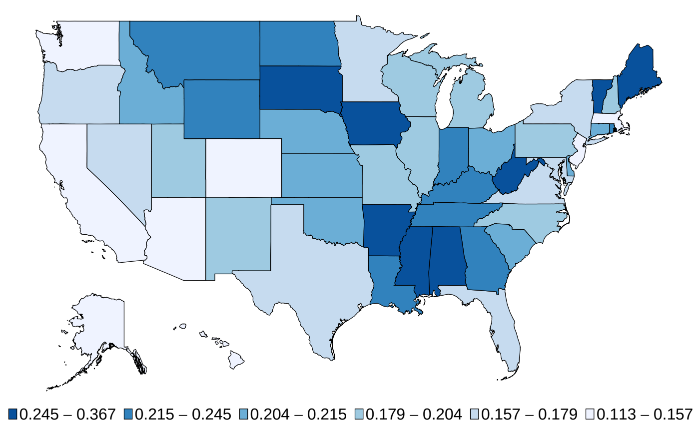
Notes: The left panel shows a binscatter of the probability that a job has nationally identical wages. The occupation wage is defined using 2018 wages for employed workers from the Occupational Employment Statistics from the Bureau of Labor Statistics. The regression includes 2-digit occupation fixed effects. The right panel defines a tradable occupation as one that can be done remotely following Dingel and Neiman (2020) and tradable and non-tradable industries following Mian and Sufi (2014). 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.

Figure A13: Characteristics of Nationally Identical Jobs



Notes: Nationally identical jobs are defined as those jobs paying the modal wage in occupation*firm*year cells in which at least 80% of wage pairs are the same. Sample includes all firm-job pairs present in at least 4 establishments in that year. The HHI of the firm across locations is calculated separately for each occupation within the firm but aggregates across all years (i.e. the share of vacancies in job j in location k is total number of vacancies posted in that job and location over the entire sample period, divided by the number of vacancies in job j across all locations over the entire sample period). Similarly, the local HHI of the occupation is calculated for each occupation and county (i.e. the share of firm i in occupation j in county k is the number of postings by that firm over the entire sample period, divided by the total number of postings for occupation j in county k by all firms in the sample). The degree of worker interactions are measured using O*NET and captures the answer to the question "How important is it to work with others in a group or team in this job?".

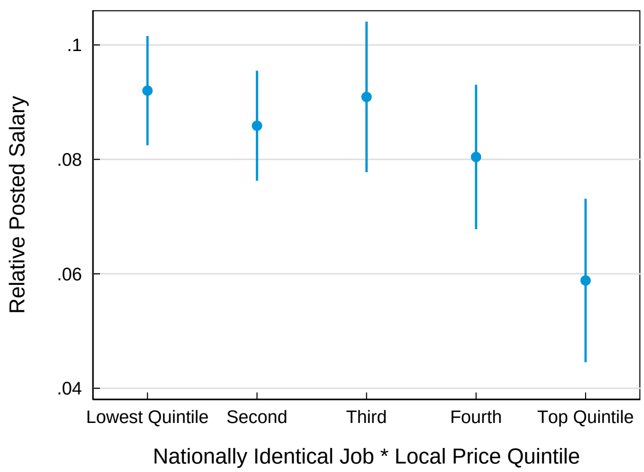
Figure A14: Fraction of Job Postings with Nationally Identical Wages



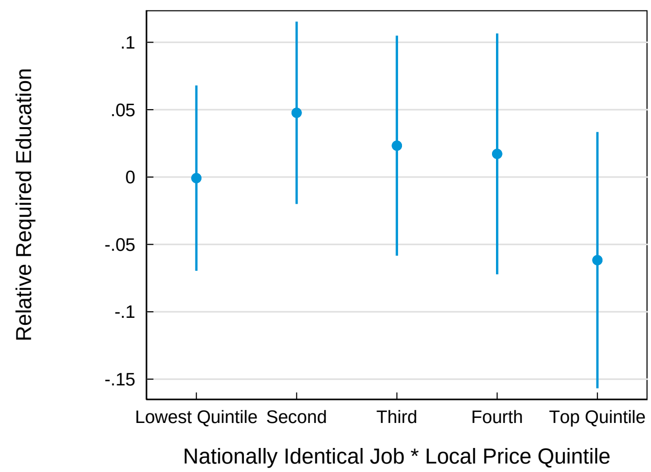
Notes: Nationally identical jobs are defined as those jobs paying the modal wage in occupation*firm*year cells in which at least 80% of wage pairs are the same. Sample includes all firm-job pairs present in at least 4 establishments in that year.

Figure A15: Relative Wages, Education and Experience by Local Price Level

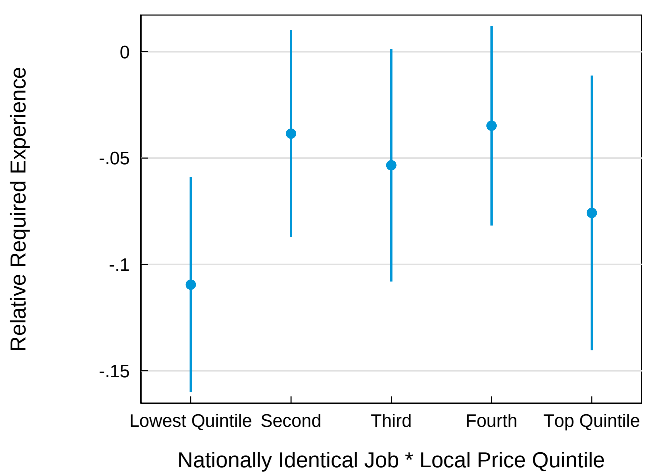
(a) Posted Wage



(b) Required Education

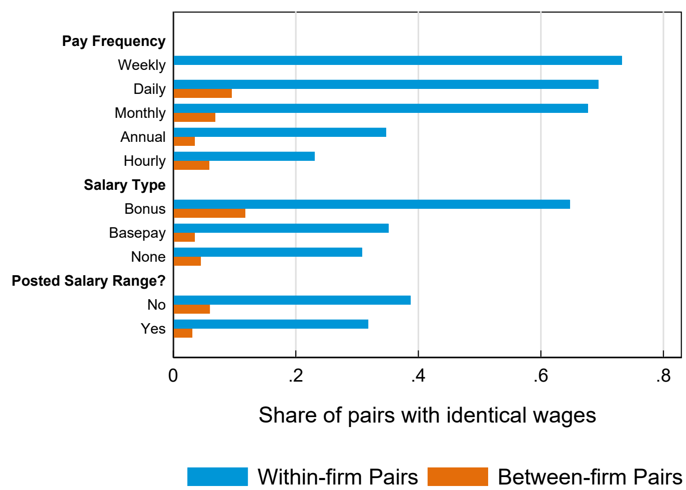


(c) Required Experience



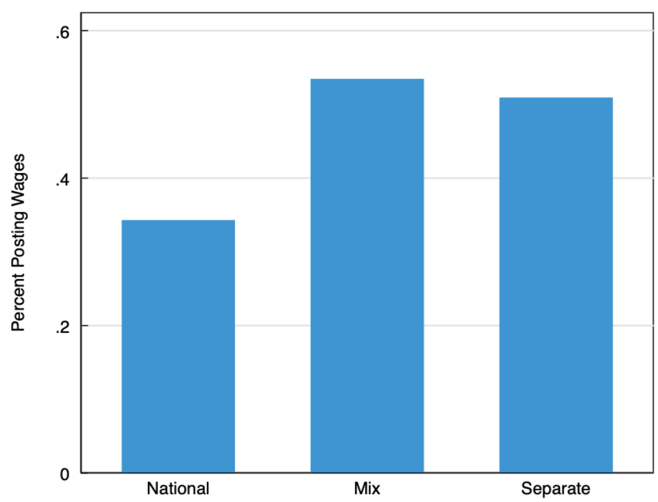
Notes: Each regression includes a quadratic in establishment size, a quadratic in firm size, and fixed effects for job*county*industry*year. Nationally identical jobs are defined as those jobs paying the modal wage in occupation*firm*year cells in which at least 80% of wage pairs are the same. Sample includes all firm-job pairs present in at least 4 establishments in that year.

Figure A16: Identical Wages by Type of Job Posting



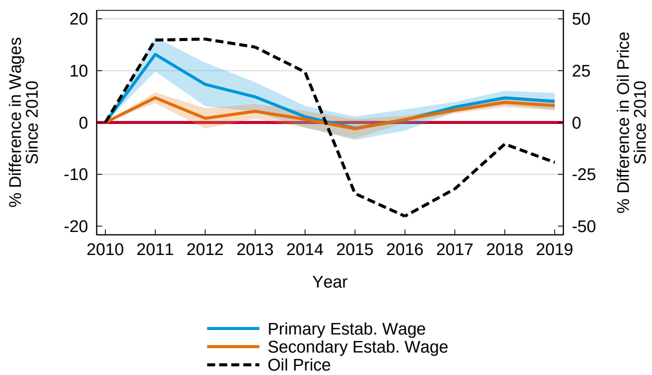
Notes: Pay frequency refers to the frequency of pay posted on the job posting. All wages are annualized by Burning Glass to reflect annual salaries of standard work schedules. Salary type refers to the stated form of compensation on the job posting. Posted salary range means that the job posting includes a range of wages rather than a single dollar value. For jobs with ranges, we take the midpoint throughout the analysis.

Figure A17: Fraction of Firms Posting Wages



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 Appendix B1.

Figure A18: Dynamic Effects of Natural Resources Instrument



Notes: The dashed black line is the annual average of the Brent Crude oil price. We estimate the first stage regression

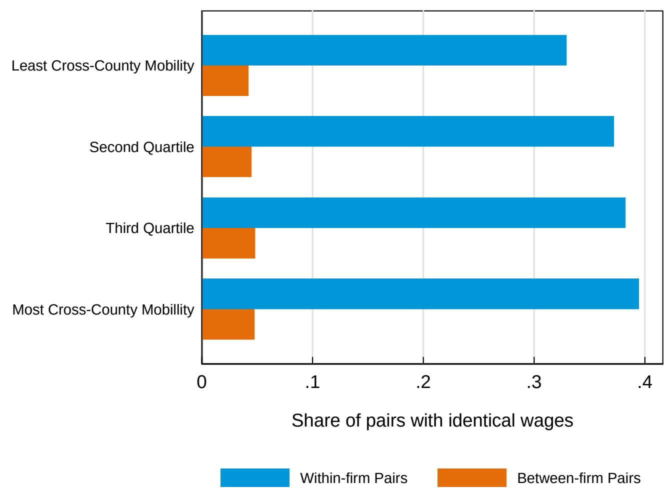
$$\log w^p_{jfct} = \alpha_{jfc} + \gamma_{jct} + \sum_{y=2011}^{2019} \beta_y \times \text{primary county natural resources share}_{jfc,2009} + \varepsilon_{jfct} \tag{15}$$

and the reduced form regression

$$\log w^s_{jfct} = \alpha_{jfc} + \gamma_{jct} + \sum_{y=2011}^{2019} \delta_y \times \text{primary county natural resources share}_{jfc,2009} + \varepsilon_{jfct} \tag{16}$$

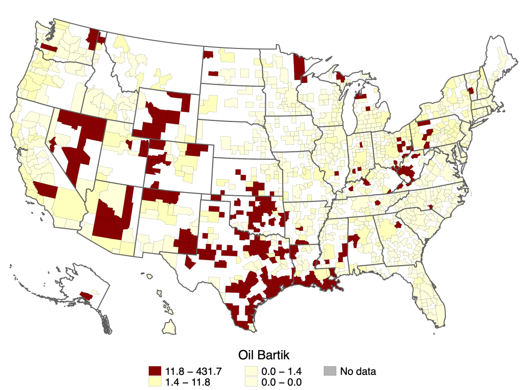
where $\log w^p_{jfct}$ is 100 x the log of the wage in the primary establishment, $\log w^s_{jfct}$ is 100 x the log of the wage in the secondary establishment, primary county natural resources share is the percent share of employment in natural resources industries in the primary establishment's county, α_{jfc} is a fixed effect for the job (i.e. occupation by pay frequency by salary type) and establishment, and γ_{jct} denotes occupation by time and county by time fixed effects. The blue line plots the values of β_y from the first stage regression and the orange line plots the values of δ_y from the reduced form regression, the shaded areas denote 95% confidence intervals of standard errors clustered by firm and secondary establishment county. All other details of the regression are identical to Table 2, column (3).

Figure A19: Identical Wages by Geographic Mobility



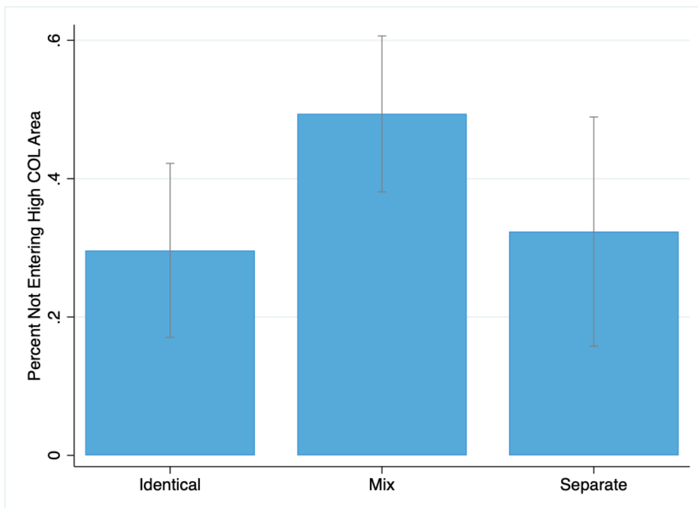
Notes: The mobility measure is computed for counties within US metropolitan areas. The level of mobility between two counties A and B is measured as the sum of employment-to-employment flows from A to B and employment-to-employment flows from B to A, divided by the population. These measures are then averaged from 2010-2019. The 4 groupings represent quartiles for these flows. Data on employment-to-employment inflows and outflows come from the Census J2J Origin-Destination statistics.

Figure A20: Regional Exposure to Natural Resources Instrument



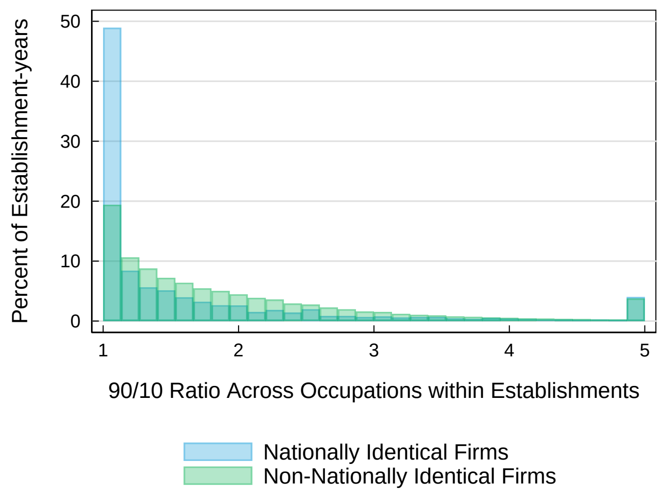
Notes: This figure presents a heat map showing the geographic distribution of natural resource shocks in the U.S., measured in 2012, by county. The map is constructed by grouping counties into ten deciles and shading such that lighter colors correspond to lower rates of natural resource demand. The natural resource instrument is defined as in Section 11.

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



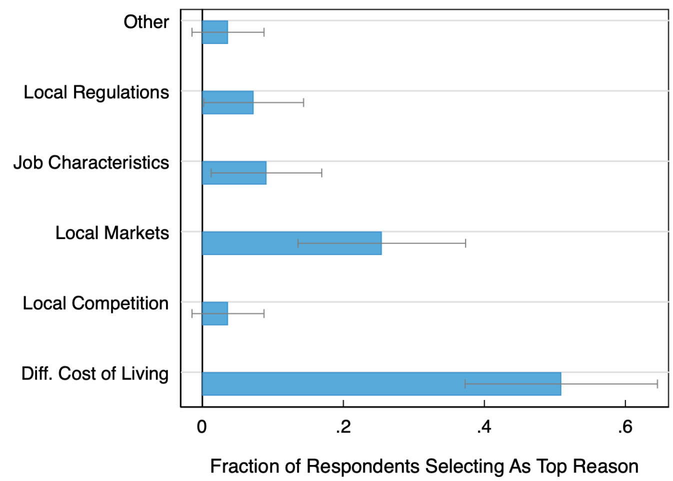
Notes: This figure shows the fraction of respondents who state that their firm would not enter a high cost of living area due to their decision to adopt a rigid pay structure.

Figure A22: Cross-Occupation Wage Dispersion within Firms: 90-10 Ratio



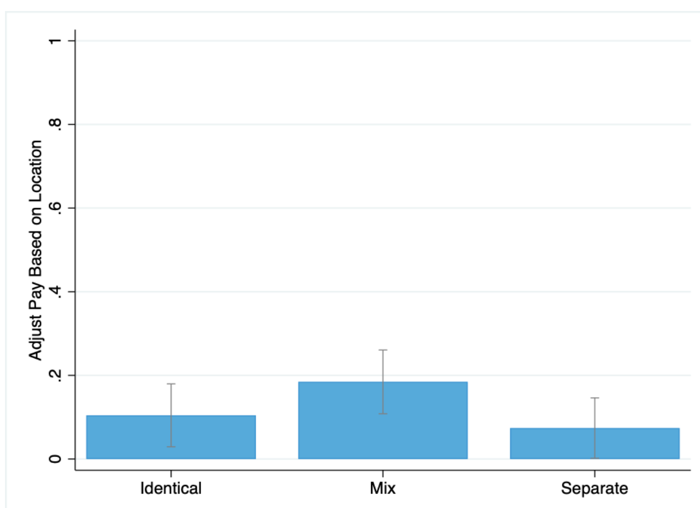
Notes: The sample includes all firm-years with at lease 4 establishments. The unit of observation is the establishment by year. We define a nationally identical firm as one where at least 50% of their occupations in which they post in at least 4 counties have at least 80% of their wage pairs being identical.

Figure A23: 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 A24: Fraction of Firms Adjusting Pay for Remote Workers



Notes: This figure shows the fraction of respondents who state that their firm will or has plans to adjust pay for their remote workers.

Table A1: The Likelihood of Posting a Wage

	Outcome: Percentage Chance of Posting a Wage			
	(1)	(2)	(3)	(4)
Median Hourly OES Occupation Wage	-0.170			
	(0.0002)			
Posted Education		-1.207		
		(0.001)		
Posted Experience			-0.932	
			(0.001)	
Firm Number of Establishments				-0.444
				(0.0004)
Observations	146,347,774	106,302,307	77,155,440	153,624,336

Notes: All sample restrictions in row 4 of Table A3 except for the removal of missing wages remain in place. The dependent variable is the percentage chance of posting a wage (0 to 100). The units for the independent variables are dollars (row 1), years (row 2 and 3), and the hundreds of establishments (row 4).

Table A2: Geographic Dispersion in Wage Posting

	Outcome: Percentage Chance of Posting a Wage					
	(1)	(2)	(3)	(4)	(5)	(6)
County Price Index	-0.067	-0.016				
	(0.0004)	(0.004)				
County Home Price Index			0.005	0.001		
			(0.00002)	(0.0003)		
Superstar Cities					-0.393	0.071
					(0.017)	(0.171)
Observations	65,119,128	65,119,128	65,119,128	65,119,128	87,730,616	87,730,616
Fixed Effects:						
Firm by Year by SOC		✓		✓		✓

Notes: The dependent variable is the percentage chance of posting a wage (0 to 100). Standard errors are clustered at the county by year level. Sample includes all Burning Glass vacancies from 2010-2019.

Table A3: Summary Statistics on Sample Formation

	Vacancies	Firms	Establishments	Counties
Full 2010-2019 Data	239,029,970	2,742,555	9,117,553	3,224
Drops Missing Wages	40,625,295	1,267,503	3,529,713	3,221
Drops Missing Firm, County, Sector, Occupation or Military	21,192,965	934,684	3,088,056	3,213
Collapses to year-establishment-occ-pay group	12,116,117	934,684	3,088,056	3,213
Restrict to 4 establishments in year	3,504,867	43,129	1,168,656	3,200

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. The third row drops observations with missing firm, region, industry sector or occupation information and excludes military occupations. The fourth row collapses the data to the year by occupation by pay group by establishment level and excludes public administration. A pay group is the pay frequency and type of the salary (e.g. hourly base pay). The fourth row is the main sample for our analysis. The fifth row restricts to firm by occupation by pay groups by year cells where there are postings in at least 4 establishments. It is on this sample that we will define national firms.

Table A4: Comparing Median Wages in OES and Burning Glass

	Annual Basepay	Hourly Basepay	Annual Total	Hourly Total
	(1)	(2)	(3)	(4)
Posted Wages	0.911	0.998	0.732	0.906
	(0.0155)	(0.00610)	(0.0112)	(0.00842)
Observations	90,155	100,503	88,044	85,586

Notes: We regress occupation by MSA log median hourly wages from the Occupational Employment Statistics, on occupation by MSA log median wages from Burning Glass. In both cases, we study the wage averaged over 2010-2019. In both datasets, occupations are at the 6 digit level. In the first column, the Burning Glass wage is annual base pay. In the second column the wage is hourly base pay; in the third, annual total pay; and in the fourth column, hourly total pay. The observations are weighted by occupation by MSA employment over 2010-2019. Robust standard errors are reported in parentheses.

Table A5: Comparing OES and Burning Glass Wages Across the Distribution

	10th	25th	Median	75th	90th
	(1)	(2)	(3)	(4)	(5)
Posted Wages	0.792	0.924	0.998	0.975	0.867
	(0.00571)	(0.00569)	(0.00610)	0.00687)	(0.00625)
Observations	100,789	100,741	100,503	100,021	99,359

Notes: In each column, the dependent variable is the specified moment of the occupation by MSA hourly wages from the Occupational Employment Statistics. The independent variable is the same moment of the posted wage distribution in the Burning Glass data. In both cases, we take logs and study the wage averaged over 2010-2019. In both datasets, occupations are at the 6 digit level. In all columns, the Burning Glass wage is annual base pay. The observations are weighted by occupation by MSA employment over 2010-2019. Robust standard errors are reported in parentheses.

Table A6: Comparing OES and Payscale Wages Across the Distribution

	10th	25th	Median	75th	90th
	(1)	(2)	(3)	(4)	(5)
Payscale Wage	0.451	0.616	0.774	0.806	0.701
	(0.00680)	(0.00906)	(0.0101)	(0.0100)	(0.00904)
Observations	67,642	67,642	67,617	67,469	67,064
R^2	0.419	0.499	0.554	0.533	0.457

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

Table A7: Correlates of National Wage Setting

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

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

Table A8: Sensitivity of Posted Wages to Local Conditions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Average Local Price for Firm	0.890						1.027	
	(0.019)						(0.023)	
Local Price		0.353						0.400
		(0.011)						(0.012)
Average Local House Price for Firm			0.159					
			(0.003)					
Local House Price				0.064				
				(0.002)				
Local Income for Firm					0.437			
					(0.010)			
Local Income						0.162		
						(0.004)		
No. Obs.	5,988,556	3,691,004	9,917,827	6,685,708	9,924,636	6,726,835	5,986,992	3,680,407
No. Firms	452,958	119,671	743,782	218,441	744,939	218,955	452,660	119,520
Specification								
	OLS	OLS	OLS	OLS	OLS	OLS	IV	IV
Fixed-effects								
Year	✓	✓	✓	✓	✓	✓	✓	✓
Occupation	✓	✓	✓	✓	✓	✓	✓	✓
Firm by Occupation		✓		✓		✓		✓

Notes: Standard errors are clustered at the firm level. All coefficients are estimated using OLS. Local prices come from the Bureau of Labor Statistics. Local House Price indices come from Zillow. Average local incomes are computed from Occupational Employment Statistics (OES).

Table A9: Sensitivity of Nominal Wages in Payscale to Local Conditions

	OLS		IV		Hourly Workers		Salaried Workers		Including Bonuses	
Local Average	0.5923		0.6763		0.6671		0.6858		0.6912	
	(0.0276)		(0.0256)		(0.0377)		(0.0266)		(0.0270)	
Log Avg. Prices		1.0941		1.2317		1.2726		1.2155		1.2735
		(0.0453)		(0.0502)		(0.1101)		(0.0504)		(0.0543)
Year Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Job Fixed Effects		✓		✓		✓		✓		✓
Job*Firm Fixed Effects	✓		✓		✓		✓		✓	
No. Obs	109,085	109,085	108,910	108,910	47,763	47,763	61,147	61,147	108,910	108,910

Notes: Data is from Payscale and the unit of observation is the individual. In each regression, we define a job as the combination of pay frequency, salary type, age, and education level. Each regression includes year fixed effects.

Table A10: Relative Wages of National Firms: Robustness to Identical Firm Definition

	Outcome: Log Posted Salary			
	(1)	(2)	(3)	(4)
Nationally Identical Job (80%)	0.15			
	(0.00)			
Nationally Identical Job (4)		0.15		
		(0.00)		
Nationally Identical Job (50%)			0.15	
			(0.00)	
Nationally Identical Job (90%)				0.14
				(0.00)
Observations	3,580,139	3,580,139	3,580,139	3,580,139

Notes: The dependent variable in all columns is the log of the posted salary. Each column differs in the definition of a nationally identical occupation within a firm. In column 1, we define a nationally identical occupation as one where at least 80% of within-firm pairs are the same. In column 2, we define a nationally identical occupation as one where at least 4 of within-firm pairs are the same. In column 3 and 4, we define a nationally identical occupation as one where at least 50% or 90% of within-firm pairs are the same, respectively. In all cases, a nationally identical job is the one that is in an occupation classified as identical for that firm and that pays the modal wage for that job within the firm. All panels include firm fixed effects. The unit of observation in all panels is the establishment*job*year and the sample includes only those firm-job-years with postings in at least 4 locations. Regressions in all columns include a quadratic in establishment size, a quadratic in firm size, and fixed effects for job*county*industry*year. Size is measured using vacancies. The sample includes all firm-job pairs present in at least 4 establishments in that year. Standard errors are clustered at the county level and reported in parentheses.

Table A11: Geographic Determinants of National Wage Setting

	Outcome: National Wage			
	(1)	(2)	(3)	(4)
Urban	-0.0773	-0.0741	-0.0604	-0.0582
	(-101.21)	(-96.86)	(-5.01)	(-4.88)
Superstar City	-0.0381	-0.00562	-0.0273	-0.00353
	(-37.42)	(-4.99)	(-3.23)	(-0.48)
State GDP Per Capita		-1.776		-1.317
		(-66.70)		(-10.11)
Observations	3,555,707	3,554,673	3,555,707	3,554,673
Fixed Effects:				
Occupation			✓	✓

Notes: The dependent variable is an indicator for whether the job pays a nationally identical wage. Columns 1 and 2 have robust standard errors while columns 3 and 4 cluster the standard errors by occupation. T-statistics are in parenthesis

Table A12: Robustness – Pass Through of Natural Resources Shock to Wages in the Rest of the Firm

	(1)	(2)	(3)	(4)
Panel A	Outcome: Log Secondary Establishment Wage			
Log Primary Wage	0.76	0.55	0.77	0.75
	(0.29)	(0.10)	(0.30)	(0.27)
Observations	578,228	165,140	430,153	458,233
Specification:	Estab. by 3 digit	Control group	Occ. weighted	Constant weight
Panel B	Outcome: Log Secondary Establishment Wage			
Log Primary Wage	0.82	0.89	0.88	0.67
	(0.27)	(0.30)	(0.28)	(0.19)
Observations	243,204	260,229	272,405	238,390
Specification:	Pay type control	No trim	10% trim	Exposed region
Panel C	Outcome: Log Secondary Establishment Wage			
Log Primary Wage	0.88	0.88	0.89	1.50
	(0.38)	(0.39)	(0.39)	(0.49)
Observations	458,233	458,233	427,430	127,265
Specification:	First lag instrument	Primary cluster	No bonus	No range

Notes: The primary establishment is the firm's largest establishment, by vacancies, over 2010-2019. All other establishments of the firm are secondary. The observation counts exclude singletons. In all panels, the outcome variable from Burning Glass is 100 x the log of the secondary establishment wage. The regressor is 100 x the log of the primary establishment wage, also from Burning Glass, instrumented with the natural resources shift share instrument from the primary establishment's county, constructed from the County Business Patterns. All columns control for job (i.e. occupation by salary type by pay frequency by establishment) fixed effects, county-by-year fixed effects and 6 digit occupation-by-year fixed effects. Unless otherwise noted, the regression is weighted by the number of vacancies in the job; the standard errors are clustered by the county of the secondary establishment and the firm; wages are trimmed at the 2.5% and 97.5% level, within each occupation, pay frequency, salary type and year; the primary and secondary wages are means within pay frequency, salary type, 6 digit occupation, year and establishment cells; and the sample excludes public sector firms, firms in natural resources (NAICS industry 21), secondary establishments in a county with an employment share in natural resources greater than 5%, and secondary establishments in the same census division as their primary establishment.

In Panel A column (1) we use fixed effects at the 3 digit occupation level instead of the 6 digit level. In column (2) we let the control group be firms whose establishments are all located in counties with zero mining employment share. In column (3) we reweight to target the 6 digit occupation distribution of employment from the 2010 Occupational Employment Statistics. In Column (4) we use constant weights. In Panel B column (1) we control for pay frequency and salary types interacted with year fixed effects. In Column (2) we do not trim the outcome variable. In Column (3) we trim the top and bottom 5%. In Column (4) we define natural resource exposed counties as having employment shares in natural resources above 10%. In Panel C column (1) we use the first lag of the instrument. In Column (2) we cluster by the county of the primary location and the firm. In column (3) we drop wages with bonuses, and in column 4 we drop wages with ranges.

Table A13: Identical Wage Setting at Franchised Firms

	Outcome:					
	Nationally Identical Job			Fraction of Identical Wage Pairs		
	(1)	(2)	(3)	(4)	(5)	(6)
Franchise Model	-0.065	-0.055	-0.078	-0.064	-0.037	-0.066
	(0.037)	(0.061)	(0.069)	(0.044)	(0.070)	(0.081)
Observations	630,599	630,585	630,580	630,599	630,585	630,580
Fixed Effects:						
Industry		✓			✓	
Occupation by Industry			✓			✓

Notes: The unit of observation is the job by year by establishment. The dependent variable in columns 1-3 is an indicator for whether the occupation within the firm is nationally identical and in columns 4-6 is the fraction of within-firm job pairs that are the same. Regression includes only jobs within the firms with postings for at least 4 establishments. Regression includes 131 firms, 55 of which are coded as franchised. Regression includes a control for the number of vacancies in each occupation*firm*year cell. Standard errors are clustered at the firm level. See text for details on how firms were classified as franchises.

Table A14: Fairness Norms: Wage Compression and Nationally Identical Wages

	Outcome: 90-10 Ratio			Outcome: 75-25 Ratio		
	Actual	Benchmark	Difference	Actual	Benchmark	Difference
	(1)	(2)	(3)	(4)	(5)	(6)
Nationally Identical Firm	-0.13	-0.26	-0.13	-0.07	-0.11	-0.04
	(0.02)	(0.03)	(0.03)	(0.01)	(0.03)	(0.03)
Observations	642,486	688,111	642,486	642,486	688,111	642,486
Dep. Var mean	1.745	1.989	.2678	1.522	1.656	.143

Notes: The sample includes all firm-years with at least 4 establishments. Standard errors are clustered at the firm level. The unit of observation is the establishment by year. All regressions include industry fixed effects and a control for the number of occupations within the establishment. The dependent variable in column 1 is the ratio of the 90th-10th percentile of posted wages in the establishment. The dependent variable in column 2 is the 90/10 ratio replacing the actual posted wage with the average wage for that occupation within the county in which the firm operates. We exclude from this variable all occupations where there are fewer than 4 firms hiring in that county in a given year. Column 3 is the difference between the actual and the benchmark, with lower values indicating that the 90/10 ratio is lower than what would have been predicted by the occupational mix of the establishment. Columns 4 through 6 replicate the analysis in columns 1-3 but using the 75/25 ratio.

Table A15: Effect of Remote Work on National Wage Setting

	(1)	(2)	(3)	(4)
Panel A: First Stage		Outcome:		
	Share Work from home		Any work from home	
Bartik WFH Shock	0.2149	0.2457	0.3791	0.3949
	(0.0734)	(0.1104)	(0.0741)	(0.1089)
Observations	366,354	366,354	366,354	366,354
R^2	0.49241	0.83934	0.33056	0.67431
Panel B: Structural Equation		Outcome: Identical Wage Setter		
Share WFH	0.4622	0.4398		
	(0.1319)	(0.1971)		
Any WFH (Binary)			0.2620	0.2736
			(0.0786)	(0.1228)
Observations	366,354	366,354	366,354	366,354
R^2	0.55847	0.83935	0.54868	0.83450
Fixed-effects				
Year	✓	✓	✓	✓
Employer	✓		✓	
Occupation	✓		✓	
Employer by Occupation		✓		✓

Notes: The dependent variable in columns 1 and 2 of Panel A is the fraction of vacancies within a firm-job-year that are fully remote. The dependent variable in columns 3 and 4 is an indicator for whether any of the vacancies in that firm-job-year are fully remote. The dependent variable in all columns in Panel B is an indicator for whether the job-firm-year has at least 50% establishments pay the same wage in one of their job postings. The sample includes firm-occupation-years with at least 5 establishments and include data from 2010-2020. Standard-errors are clustered by employer.

Table A16: Local Prices and Bonus Payments in Payscale's Compensation Database

	Any Bonus		Log Bonus		Additional Comp.	
Panel A: Full Sample						
County Price Index	-0.0008		-0.0019		-0.0009	
	(0.0001)		(0.0003)		(0.0003)	
Log Zillow Rent Prices		-0.0092		-0.0199		-0.0061
		(0.0013)		(0.0054)		(0.0054)
Observations	522,785	563,139	134,926	141,301	122,594	127,674
Panel B: Salaried Employees						
County Price Index	-0.0007		-0.0013		-0.0009	
	(0.0001)		(0.0003)		(0.0003)	
Log Zillow Rent Prices		-0.0062		-0.0128		-0.0061
		(0.0018)		(0.0054)		(0.0054)
Observations	308,918	324,876	115,822	120,456	122,594	127,674

Notes: Data is from Payscale and the unit of observation is the individual. Regression includes fixed effects for year*occupation*firm and industry. Local price indices come from the BLS and local house prices come from Zillow. Panel A includes the full sample of hourly and salaried workers. Panel B restricts to salaried workers.

B1 Survey Appendix

B1.1 Survey Description

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.

B1.1.1 Sample

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 Figure B3 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 B4 displays the job titles of respondents.[53] The majority of respondents work as HR managers or executives. In column 1 of 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.

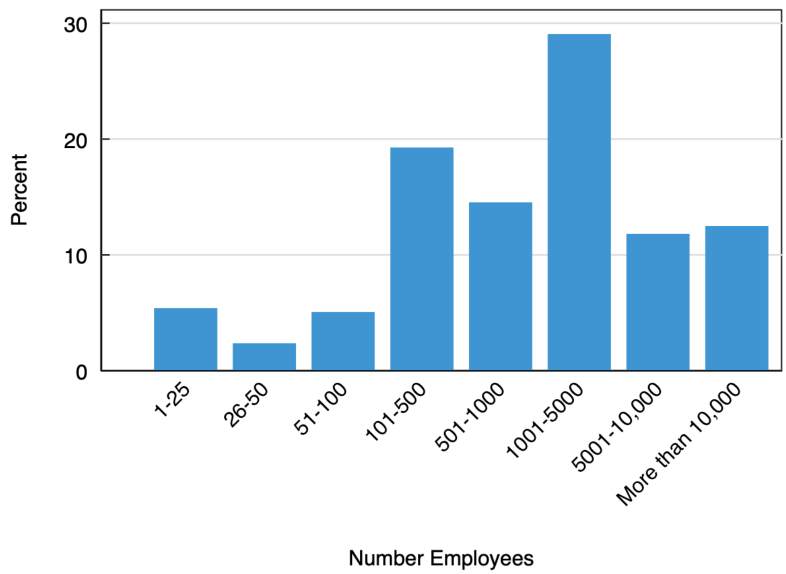
[53] We allowed respondents to write in their title and then aggregated them.

Table B1: Survey Summary Statistics

	(1) Full Sample	(2) Flexible Pay	(3) Some or All Identical Pay
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]
N	282	58	224

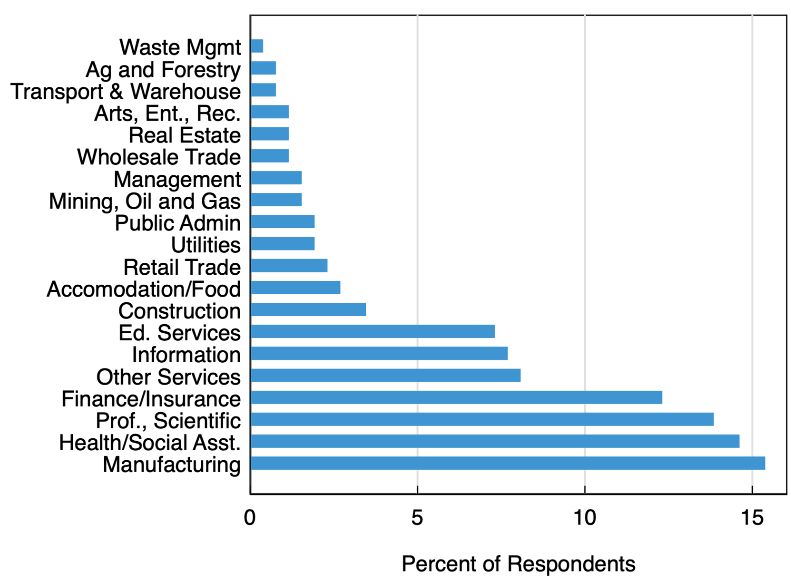
Notes: This table presents summary statistics for the set of survey respondents working at firms that operate in more than one city. Column 2 restricts to the sample of respondents who state that they work at a firm that does not set identical wages for jobs across locations. Column 3 restricts to the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

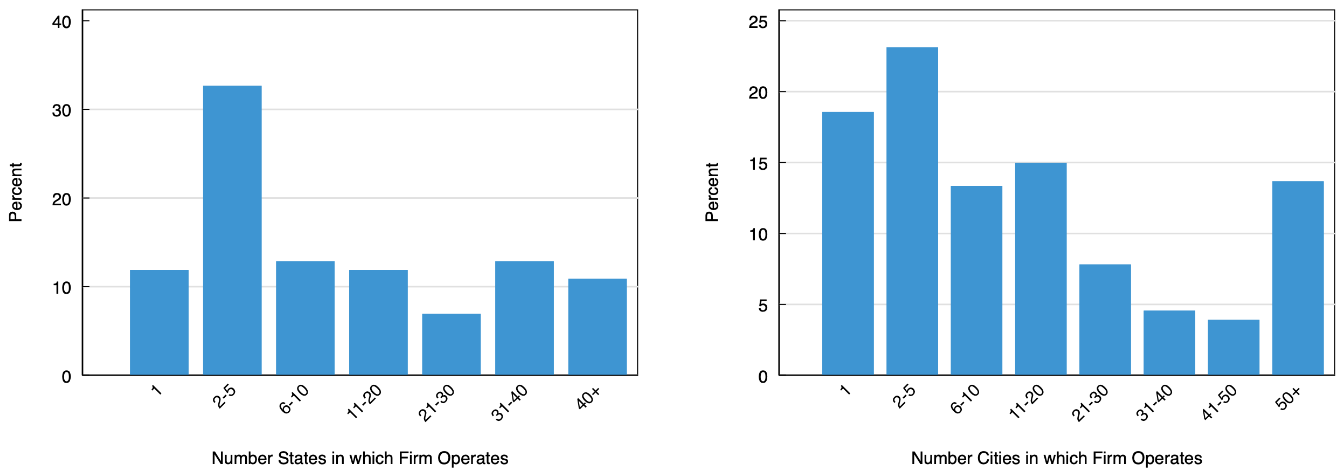
Figure B2: Sector Representation of Survey Respondents



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

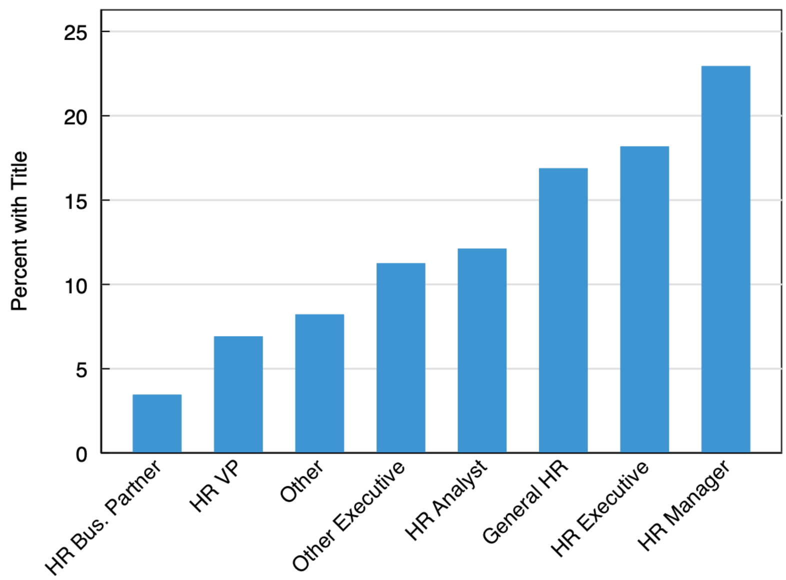
Figure B3: Number of Cities and States in which Firms Operate

A. States A. Cities



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)

Figure B4: 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.

B1.2 Survey Questionnaire

Survey Block 1

1. We'd like to ask you a few questions about your position and your firm. No questions about potentially identifying information will be asked.

   Approximately how many employees does your company currently employ?
   - 1-25
   - 26-50
   - 51-100
   - 101-500
   - 501-1000
   - 1001-5000
   - 5001-10,000
   - More than 10,000
2. Do you currently work in Human Resources?
   - Yes
   - No
3. What is your current position at the firm where you currently work? If you are not currently working, please leave blank. [fill in]
4. For how many years have you worked in your current position at this firm? Please round to the nearest number. [fill in]
5. Are you involved in setting employee pay?
   - Yes
   - No
6. At what level are hiring decisions made?
   - HR managers or personnel in the location where workers are employed
   - HR managers or personnel in the headquarter or another centralized location
   - Other (please specify)
7. What is the main sector in which your firm or company operates?
   - Agriculture, Forestry, Fishing and Hunting
   - Mining, Quarrying, and Oil and Gas Extraction
   - Utilities
   - Construction
   - Manufacturing
   - Wholesale Trade
   - Retail Trade
   - Transportation and Warehousing
   - Information
   - Finance and Insurance

- Real Estate and Rental/Leasing
- Professional, Scientific, and Technical Services
- Management of Companies and Enterprises
- Waste Management and Remediation Services
- Educational Services
- Health Care and Social Assistance
- Arts, Entertainment, and Recreation
- Accommodation and Food Services
- Public Administrative
- Other Services
- Other (please specify)

8. What proportion of your employees are salaried vs. hourly employees? Please list a number between 0 to 100% [fill in]
9. Does your firm post salaries/wages and/or pay bands on your job vacancy ads? That is, do you list a specific dollar value for the expected wage/salary (or a minimum and maximum salary)?
   - Yes
   - No
   - For some jobs but not all
   - I'm not sure
10. In how many cities in the United States does your company currently operate?
    - 1
    - 2-5
    - 5-10
    - 11-20
    - 21-30
    - 31-40
    - 41-50
    - More than 50
11. In how many states does your company currently operate?
    - 1
    - 2-5
    - 6-10
    - 11-20
    - 21-30
    - 31-40
    - More than 40
12. Does your firm or company have any establishments (i.e. offices/plants/stores) in any of the following high cost-of-living metro areas: San Francisco, New York, Washington D.C., Seattle, Los Angeles, or Boston
    - Yes

- No

13. What considerations do you take into account when you set wages? Please choose up to three of the most important from the following list. If a consideration is not on the list, please choose other and write in your answer.
    - The wages our competitors are paying (including the use of salary surveys)
    - Local cost of living
    - Employee characteristics (e.g. experience or credentials)
    - Keeping workers motivated
    - Being able to recruit or retain workers
    - Other (please specify)
14. Does your firm primarily use pay bands to set wages/salaries? By a pay band, we mean a pre-specified minimum and maximum salary or wage for a given job.
    - Yes
    - No

Survey Block 2: This block is only shown to respondents who respond "Yes" to question 14 in Block 1.

1. Which of the following best describes how your firm sets pay bands across locations for the majority of your workers?
    - Pay bands are determined separately for each establishment/plant/store.
    - Pay bands are sometimes determined separately but not always. For example, workers in some jobs may face the same band regardless of where they work, but others face pay bands that differ by location. Or, pay bands might be determined separately for each state/region, but workers with the same job title within a state/region face the same pay band.
    - Pay bands are set nationally so that most workers with the same job title face the same pay band.
2. Which of the following best describes who determines pay bands within your firm?
    - Pay bands are primarily left to the discretion of management at each establishment/plant/store.
    - Pay bands are primarily decided by state or regional managers.
    - Pay bands are primarily decided centrally by national management.
3. Do local managers have any discretion in setting wages/salaries at their plant/store/location? Select all that apply. This question is only shown to respondents who do not select "Pay bands are primarily left to the discretion of management at each establishment/plant/store" in question 3.
    - Yes, they can adjust pay based on performance
    - Yes, they can adjust pay based on education or experience
    - Yes, they can adjust pay to match an employee's prior salary
    - Yes, they can adjust pay to match the pay at other competing firms in their region
    - Yes, they can adjust pay to match the cost of living in their area
    - No, local managers do not have discretion to adjust pay
4. How is an employee's wage or salary determined within a pay band? Select all that apply.
    - Education/experience
    - Competition from other firms

- Performance
- Local cost of living
- His/her prior salary

5. Are any of the following approaches used to compensate employees for differences in cost of living across locations? Select all that apply.
   - Bonus pay (including signing bonuses)
   - Housing or relocation allowances
   - Other benefits or perks (such as commuting subsidies or childcare provisions)
   - Other (please specify):
   - None
6. Say you are hiring two salaried employees who have the same job title but who work in two different cities. Would you use the same pay band to determine the two employees' salaries or would you use different pay bands?
   - The pay band would be different in each location.
   - The pay band would be the same across locations.
   - The pay band would be the same but locations determine each person's salary within the pay band.
7. Say you are hiring two hourly employees who have the same job title but who work in two different cities. Would you use the same pay band to determine their hourly pay or would you use different pay bands?
   - The pay band would be different in each location.
   - The pay band would be the same across locations.
   - The pay band would be the same but locations determine each person's salary within the pay band.

Survey Block 3: This block is only shown to respondents who respond "No" to question 14 in Block 1.

1. Which of the following best describes how your firm sets wages/salaries across locations for the majority of your workers?
   - Wages are determined separately for each establishment/plant/store.
   - Wages are sometimes determined separately but not always. For example, workers in some jobs may have the same wage regardless of where they work, but others have wages that differ by location. Or, wages might be determined separately for each state/region, but workers with the same job title within a state/region face the same wage.
   - Wages are set nationally so that most workers with the same job title are paid the same.
2. Which of the following best describes who determines wages/salaries within your firm?
   - Wages are primarily left to the discretion of management at each individual store.
   - Wages are primarily decided by state or regional managers.
   - Wages are primarily decided centrally by national management.
3. Do local managers have any discretion in setting wages/salaries at their plant/store/location? Select all that apply. This question is only shown to respondents who did not select "Wages are primarily left to the discretion of management at each individual store" in question 2.
   - Yes, they can adjust pay based on performance
   - Yes, they can adjust pay based on education or experience

- Yes, they can adjust pay to match an employee's prior salary
- Yes, they can adjust pay to match the pay at other competing firms in their region
- Yes, they can adjust pay to match the cost of living in their area
- No, local managers do not have discretion to adjust pay

4. Are any of the following approaches used to compensate employees for differences in cost of living across locations? Select all that apply.
   - Bonus pay (including signing bonuses)
   - Housing or relocation allowances
   - Other benefits or perks (such as commuting subsidies or childcare provisions)
   - Other (please specify):
   - None
5. Say you are hiring two salaried employees who have the same job title but work in two different cities. Would you set the same salary for each employee or would you set different salaries?
   - We would likely pay different salaries
   - We would likely pay the same salary
   - We would offer the same salary but negotiations might result in different final salaries
6. Say you are hiring two hourly employees who have the same job title but work in two different cities. Would you set the same hourly pay for each employee or would you set different hourly pay?
   - We would likely set different hourly pay
   - We would likely set the same hourly pay
   - We would offer the same hourly pay but negotiations might result in different final pay

Survey Block 4: This block is only shown to respondents who respond "Pay bands are set nationally so that most workers with the same job title face the same pay band" to question 1 in Block 2 and respondents who respond "Wages are set nationally so that most workers with the same job title are paid the same" to question 1 in Block 3.

1. Why are salaries or pay bands set nationally? Please choose up to three of the reasons provided below. If a reason is not on the list, please choose "other" and write in your answer.
   - For simplicity: It is administratively costly to tailor wages to each location
   - All of our employees work in the same geographic region or in areas with similar costs of living
   - We want workers performing the same job to be paid the same wage, regardless of where they are located
   - This is how our competitors set wages
   - We are hiring on a national market (i.e. we are recruiting from across the country rather than locally)
   - Workers in these jobs sometimes transfer across locations and we do not want to adjust their pay if they do
   - Other (please specify)
2. Say an establishment in your company located in City A had to change its wage or pay bands to keep up with local competition. Would other establishments/plants/stores in your firm located in cities B and C also then change their wage or pay bands?
   - Yes

- No
- Only if it is the headquarter that is changing its wages/pay bands
- I'm not sure

Survey Block 5: This block is only shown to respondents who respond "Pay bands are sometimes determined separately but not always" to question 1 in Block 2 and respondents who respond "Wages are sometimes determined separately but not always" to question 1 in Block 3.

1. Do you set the same wage (or pay band) for workers with the same job title across location for any of the following groups of workers? You may choose more than one.
   - Workers who frequently travel to or work in multiple locations
   - Workers who work in a single location
   - Salaried employees
   - Hourly employees
   - Workers we recruit on a national market
   - Other (please specify)
2. Do you set the same wage (or pay band) for workers with the same job title within any of the following geographic locations?
   - Establishments located in the same state
   - Establishments located in the same city
   - All establishments except for those located in the most expensive cities (e.g. San Francisco or NYC)
   - All establishments except for those located in the least expensive cities
   - All establishments across the country
   - Other (please specify):
3. You have mentioned that you set the same wages or pay bands across locations for some jobs in your firm. Why does your company choose to set those wages uniformly across establishments?
   - We want workers performing the same job to be paid the same wage, regardless of where they are located
   - Workers in these jobs sometimes transfer across locations and we do not want to adjust their pay if they do
   - Other (please specify)
   - For simplicity: It is administratively costly to tailor wages to each location
   - We are hiring on a national market for these jobs (i.e. we are recruiting from across the country rather than locally)
   - This is how our competitors set wages for these jobs
   - The jobs for which we set wages nationally are located in the same geographic region or in areas with similar costs of living
4. 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? Please choose up to three answers and rank.
   - The jobs for which we set pay separately are located in areas with different costs of living
   - We are hiring on a local market for these jobs

- This is how our competitors set pay for these jobs
- There are different local regulations affecting the wages for these jobs
- The jobs for which we set pay locally are niche jobs
- Other (please specify)

5. Say an establishment in your company located in City A had to change its wage or pay bands to keep up with local competition. Would other establishments/plants/stores in your firm located in cities B and C also then change their wage or pay bands?
   - Yes
   - No
   - Only if it is the headquarter that is changing its wage/pay bands
   - I'm not sure

Survey Block 6: This block is only shown to respondents who respond "Pay bands are determined separately for each establishment/plant/store" to question 1 in Block 2 and respondents who respond "Wages are determined separately for each establishment/plant/store" to question 1 in Block 3.

1. Which, if any, of the following approaches are used to compensate employees for differences across locations? You may select more than one.
   - Separate base salary structures for various locations
   - Individual adjustments to the base salaries of certain workers in a region (including bonus pay and the outcome of individual negotiations)
   - Housing or relocation allowances
   - Other benefits or perks (such as commuting subsidies or childcare provisions)
   - None of the above
   - Other (please specify):
2. What considerations do you take into account when you decide geographic differences in wages for workers with the same job title? Please choose up to three answers and list them in order of importance. You can choose and rank answers by dragging them from the left side to the right side and reordering them.
   - Competition for workers in the local area
   - Local cost of living
   - State or municipal minimum wages
   - How niche the position is
   - Other (please specify)
   - We follow salary surveys to benchmark wages in each geographic region
   - Wages stipulations determined by a workers' union

Survey Block 7

1. Is it easier or more difficult to recruit/retain workers in your establishments/plants/stores that are located in cities with a low cost of living?
   - Easier
   - More difficult

- It does not make a difference
- We do not have any establishments located in such cities

2. Is it easier or more difficult to recruit/retain workers in your establishments/plants/stores that are located in cities with a high cost of living? (e.g. NYC or San Francisco)
   - Easier
   - More difficult
   - It does not make a difference
   - We do not have any establishments located in such cities
3. Has a high cost of living ever prevented your company from entering or setting up in a certain location?
   - Yes
   - No
   - I'm not sure

Survey Block 8

1. Before the Covid-19 pandemic, was remote work common in your company?
   - No, fewer than 5% of employees worked remotely
   - It was not too common. Between 5% and 25% of employees worked remotely.
   - It was quite common. More than 25% of employees worked remotely.
   - Nearly all (¿95%) of employees worked remotely
2. Do you expect the share of your workforce that works entirely remotely to be higher after the Covid-19 pandemic relative to before?
   - Yes
   - No
3. Do you expect the share of your workforce that is able to work remotely at least two days a week to be higher after the Covid-19 pandemic relative to before?
   - Yes
   - No
4. Did you adjust employee pay if they transitioned to remote work during the pandemic?
   - Yes, we increased pay for all workers that work remotely
   - Yes, we reduced pay for all workers that work remotely
   - Yes, we adjusted pay based on the location from which the employee decided to work
   - Yes, we adjusted pay for employees hired after the start of the pandemic, but not for those who were hired before
   - We did not change pay and do not plan to in the future
   - We have not adjusted pay yet but plan to if employees continue to work remotely

C1 Model Appendix

C1.1 Deriving Equations in the Main Text

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

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

subject to

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

This implies that

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

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

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

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

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

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

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

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

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

as in equation (4) in the main text.

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

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

which has first order condition

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

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

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

which is equation (7) from the main text.

National wage setters solve

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

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

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

which has first order condition

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

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

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

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

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

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

where $\omega_{ij} = (1+\rho_j) L_{ij}^S / \sum_{k \in N} \left[(1+\rho_k) L_{ik}^S \right]$. We have derived equation (8) from the main text.

To derive regression equation (9), note that

$$
\begin{aligned}
E\left[\Delta \log W_{ij} | \Delta \log W_{ij'}\right] &= P\left(i \in \mathcal{N}\right) E\left[\Delta \log W_{ij} | \Delta \log W_{ij'}, i \in \mathcal{N}\right] + P\left(i \notin \mathcal{N}\right) E\left[\Delta \log W_{ij} | \Delta \log W_{ij'}, i \notin \mathcal{N}\right] \\
&= \mathcal{N} E\left[\Delta \log W_{ij} | \Delta \log W_{ij'}, i \in \mathcal{N}\right] + \left(1-\mathcal{N}\right) E\left[\Delta \log W_{ij} | \Delta \log W_{ij'}, i \notin \mathcal{N}\right] \\
&= \mathcal{N} \Delta \log W_{ij'} + \left(1-\mathcal{N}\right) E\left[\Delta \log \left[\frac{\rho_j}{1+\rho_j} P_j^S A_i^S A_j^S \left(1-\alpha\right) \left(L_{ij}^S\right)^{-\alpha}\right] | \Delta \log W_{ij'}\right] \\
&= \mathcal{N} \Delta \log W_{ij'} + \left(1-\mathcal{N}\right) E\left[\Delta \log \left[\frac{\rho_j}{1+\rho_j} P_j^S A_j^S\right] - \alpha \Delta \log \left[L_{ij}^S\right] + \Delta \log \left[A_i^S\right] | \Delta \log W_{ij'}\right]
\end{aligned}
\tag{17}
$$

where to obtain the final term of the third line, we drop the conditioning on $\mathcal{N}$ for simplicity of notation, we use the fact that $\Delta \log W_{ij} = \Delta \log W_{ij'}$ for all firms in $\mathcal{N}$, and we use $F'(L) = (1-\alpha)L^{-\alpha}$. We then solve out for L_{ij}^S. We have the establishment's markdown of marginal revenue product

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

and the labor supply curve to the establishment

$$
L_{ij}^S = \left(W_{ij}^S\right)^{\rho_j} \kappa_j
$$

$$
\implies W_{ij}^S = \left(\frac{L_{ij}^S}{\kappa_j}\right)^{\frac{1}{\rho_j}}
$$

Putting these equations together implies

$$
\frac{\rho_j}{1+\rho_j} P_j^S A_{ij}^S \left(1-\alpha\right) \left(L_{ij}^S\right)^{-\alpha} = \left(\frac{L_{ij}^S}{\kappa_j}\right)^{\frac{1}{\rho_j}}
$$

$$
\implies \frac{\rho_j}{1+\rho_j} P_j^S A_{ij}^S \left(1-\alpha\right) = \left(L_{ij}^S\right)^{\frac{1}{\rho_j}} \left(\kappa_j\right)^{-\frac{1}{\rho_j}} \left(L_{ij}^S\right)^{\alpha}
$$

$$
\implies \frac{\rho_j}{1+\rho_j} P_j^S A_{ij}^S \left(1-\alpha\right) \left(\kappa_j\right)^{\frac{1}{\rho_j}} = \left(L_{ij}^S\right)^{\frac{1}{\rho_j}+\alpha}
$$

$$\implies L_{ij}^S = \left[\frac{\rho_j}{1+\rho_j} P_j^S A_{ij}^S (1-\alpha)(\kappa_j)^{\frac{1}{\rho_j}}\right]^{\frac{1}{\frac{1}{\rho_j}+\alpha}}$$

$$\begin{aligned}
\implies \log L_{ij}^S &= \frac{1}{\frac{1}{\rho_j}+\alpha} \log\left[\frac{\rho_j}{1+\rho_j} P_j^S A_{ij}^S (1-\alpha)(\kappa_j)^{\frac{1}{\rho_j}}\right] \\
&= \frac{1}{\frac{1}{\rho_j}+\alpha} \left(\log\left[\frac{\rho_j}{1+\rho_j} P_j^S A_i^S A_j^S (1-\alpha)(\kappa_j)^{\frac{1}{\rho_j}}\right]\right) \\
&= \frac{1}{\frac{1}{\rho_j}+\alpha} \log\left[\frac{\rho_j}{1+\rho_j} P_j^S A_j^S (1-\alpha)(\kappa_j)^{\frac{1}{\rho_j}}\right] + \frac{1}{\frac{1}{\rho_j}+\alpha} \log\left[A_i^S\right]. \qquad (18)
\end{aligned}$$

Substituting equation (18) into (17) implies

$$\begin{aligned}
E\left[\Delta \log W_{ij} | \Delta \log W_{ij'}\right] &= \mathcal{N} \Delta \log W_{ij'} + (1-\mathcal{N}) E\left[\Delta \log\left[\frac{\rho_j}{1+\rho_j} P_j^S A_j^S\right] - \alpha \Delta \log\left[L_{ij}^S\right] + \Delta \log\left[A_i^S\right] | \Delta \log W_{ij'}\right] \\
&= \mathcal{N} \Delta \log W_{ij'} + \gamma_j + (1-\mathcal{N}) \mu_j E\left[\Delta \log A_i^S | \Delta \log W_{ij'}\right]
\end{aligned}$$

where $\gamma_j \equiv (1-\mathcal{N}) \left(\frac{1}{1+\rho_j\alpha}\right) \Delta \log\left[\frac{\rho_j}{1+\rho_j} P_j^S A_j^S\right] - \frac{\alpha}{1+\rho_j\alpha} \Delta \log[\kappa_j]$ and $\mu_j \equiv \frac{1}{1+\rho_j\alpha}$. This is equation (9) from the main text.

C1.2 Higher Local Consumer Prices Raise Establishment Wages

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

We study the partial equilibrium problem of a single local wage setting establishment, and ask what happens to establishment wages when local consumer prices rise. From the wage setting equation (7), we have

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

and from the labor supply equation (4) we have

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

Substituting equation (4) into (7) implies

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

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

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

We now consider a partial equilibrium exercise, in which we study the response of establishment wages W_{ij} to a change in local consumer prices $\tilde{P}_j$, holding other variables fixed. We have

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

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

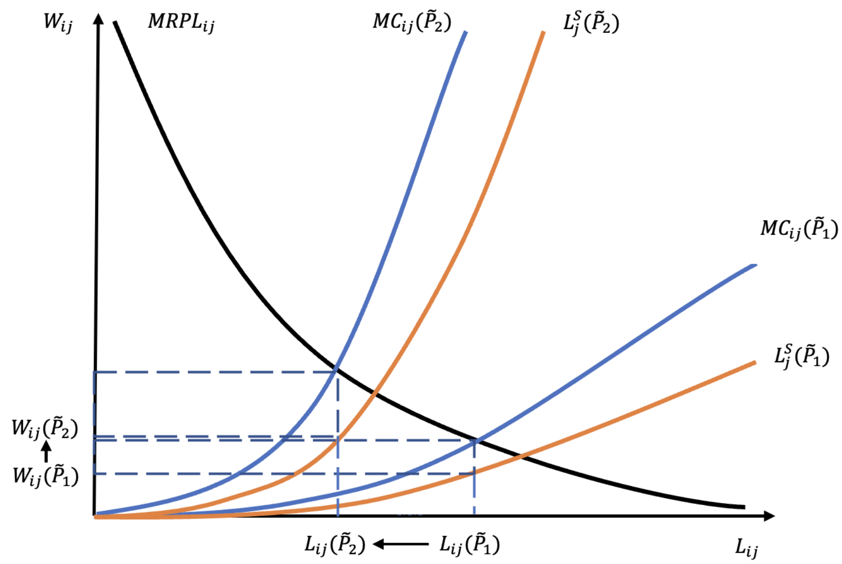
Therefore in partial equilibrium, increases in local consumer prices strictly increase establishment wages, except in the knife-edge case where $\alpha = 0$, which corresponds to an infinitely elastic labor demand curve, or constant returns to labor in production, or $\eta = 0$, meaning there is no mobility across locations. Note that the labor supply function depends on local prices because workers will move to areas with lower prices, all else equal, and increase the supply of labor. The wage depends on labor supply when there are decreasing returns to scale in production. Existing evidence suggests that $\alpha > 0$ for most establishments, that is, there is decreasing returns to labor (see, e.g., Lamadon et al., 2019).

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 below.

C1.3 Endogenizing the Share of National Wage Setters

This subsection considers a two stage game that endogenizes $\mathcal{N}$, the share of wage setters subject to rigidity. We allow firms to choose whether to set rigid wages, i.e. whether to be a national wage setter. If firms choose to set rigid wages, they receive a productivity benefit, which they balance against the cost of paying the same

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 $\tilde{P}_2$.

nominal wage across all their labor markets. We show that when the productivity benefits of national wage setting are at an moderate level, some firms will find national wage setting optimal and others will prefer local wage setting. In equilibrium, there can be a mix of national and local wage setters as is the case in the data.

C1.3.1 Model Setup

Consider the following stage game that extends our baseline model.

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

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

C1.3.2 Discussion

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

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

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

- **Fact 2: Identical wages concentrate within certain firms.** National wage setters pay the same nominal wage across all establishments, local wage setters can vary nominal wages across establishments.
- **Fact 5: National wage setters pay a wage premium**. If $\mu_F > 1$ (on average there is a productivity gain from national wage setting), then national wage setters will pay a premium.

C1.3.3 Proposition and Discussion

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

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

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

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

Proof available on request.