# What Drives Occupational Wage Inequality in the U.S.: Productivity or Rent Sharing?*

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**Abstract**

Why do some occupations pay increasingly more than others over time? To answer this question, I combine hand-collected historical labor market data with a theory-guided accounting framework that allows me to decompose occupational wage inequality into two groups of explanations: productivity and rent sharing. In order to implement this decomposition, I use an equilibrium model of search and matching to derive a mapping from unobserved wage markdowns due to search frictions into a set of measurable labor market statistics for each occupation. I find that productivity, as opposed to rent sharing, explains most of the occupational wage inequality, both in the cross section and over time.

**Keywords:** Wage Inequality, Occupations, Job Vacancies, Productivity, Rent Sharing
**JEL Codes:** E24, E25, J31

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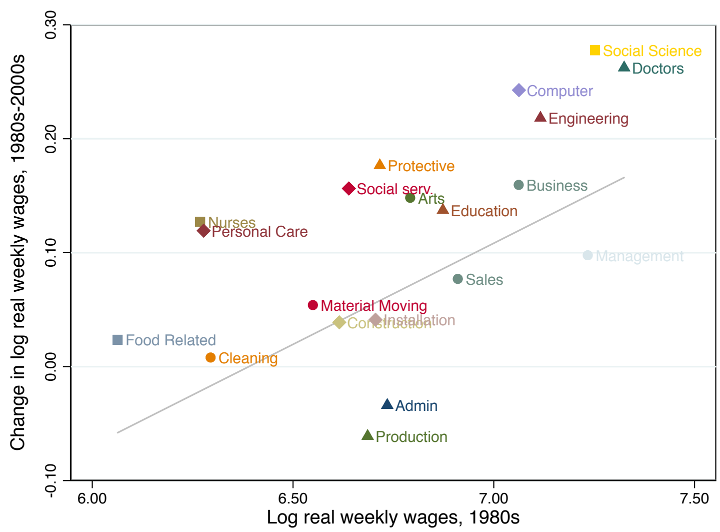
# 1 Introduction

Over the past decades, the U.S. labor market has been characterized by a systematic divergence in wage growth between occupations.[1] To illustrate this point, Figure 1 shows the change in log real weekly wages between the 1980s and the 2000s as a function of initial wages across occupation groups. Two facts stand out from this figure. First, there is significant dispersion in occupational wage growth over time, ranging from −7 percent for production workers to +28 percent for social scientists. Second, occupations that were already higher paying initially saw relatively higher growth in log real weekly wages between the 1980s and the 2000s. For example, the wage gap between production workers and social scientists increased from around 60 log points to almost 100 log points over this period.

**Figure 1.** Wage growth by occupation, 1980s–2000s




*Notes*: Data is based on a sample of men aged 16 to 64 during the year in which they earned income. For each decade, wages are averaged by occupation for ten-year intervals (1980–1989 and 2000–2009). The data include full-time workers who indicated working at least 35 hours per week during the previous year. Wages reflect data from all states. Top-coded wage data are cleaned following Autor et al. (2008) and Katz and Murphy (1992). Wages are winsorized at 1 and 99 percentiles. Nominal wages are deflated using the Personal Consumption Expenditures (PCE) deflator. Best fit line is weighted by occupation shares. The crosswalk between occupations in the Current Population Survey (CPS) and the 20 occupation groupings used in the figure is based on Autor and Dorn (2013). *Source*: March Annual Social and Economic Supplement (ASEC) of the CPS accessed via the Integrated Public Use Microdata Series (IPUMS).

The drivers of occupational wage inequality have been the subject of an extensive literature, which has proposed several explanations for this phenomenon.[2] At the same time,

[1]See, for example, Acemoglu and Autor (2011).

[2]Among the drivers of occupational wage inequality proposed by the literature are changing returns

this literature lacks an overarching framework that allows researchers to quantify the relative importance of broad groups of explanations behind trends in occupational wage inequality. Such a framework is useful because it can guide studies of specific drivers of occupational wage inequality, which is key for the design of economic policies that affect the distribution of income across workers.

The contribution of this paper is to provide a framework to decompose occupational wage inequality. To this end, I combine hand-collected historical labor market data with a theory-guided accounting framework to shed light on the determinants of occupational wages. Specifically, an occupation's wage, $w$, can be written as the product of its marginal revenue product of labor, $MRPL$, and its wage markdown, $\mu$:

$$w = MRPL \times \mu \tag{1}$$

Based on the accounting identity in equation (1), drivers of occupational wages fall into two categories. The first category pertains to the $MRPL$, which captures changes in workers' marginal productivity through changes in technology or product demand-driven prices—henceforth *"productivity."* The second category pertains to the wage markdown, $\mu$, which captures search frictions and rent sharing between workers and firms—henceforth *"rent sharing."* Importantly, the two components of occupational wages, $MRPL$ and $\mu$, may not be orthogonal to each other. For example, the rise of domestic outsourcing might shift workers' productivity as well as their bargaining power. For this reason, understanding the correlation between $MRPL$ and $\mu$ may be important.[3]

In a competitive labor market, workers are paid their full marginal revenue product (i.e., $\mu = 1$). However, labor market concentration or frictions create a wedge between workers' $MRPL$ and their wage $w$, leading to a markdown of less than unity (i.e., $\mu < 1$). Much of the recent literature has been interested in estimating the component of markdowns that arises due to monopsony power. However, in this paper I focus on the portion of the markdown resulting from search frictions and bargaining power in the context of a search model.

I use the accounting identity in equation (1) in order to answer two questions related to the occupational wage structure. First, what share of occupational wage dispersion

to education (Goldin and Katz, 2010), changes in technology, skills, and tasks (Acemoglu and Autor, 2011), rising automation (Acemoglu and Restrepo, 2020), globalization and offshoring (Autor et al., 2014), and the erosion of labor market institutions such as unions and the minimum wage (Lee, 1999; Autor et al., 2016; Fortin et al., 2021).

[3]Even when certain economic mechanisms (e.g., domestic outsourcing) affect both $MRPL$ and markdowns, $\mu$, at the same time, decomposing their total effect into parts due to $MRPL$ versus markdowns, $\mu$, is useful as it helps us quantify the channels through which those mechanisms affect occupational wages.

in the cross section is due to productivity versus rent sharing? Second, how much have changes in productivity and rent sharing, respectively, contributed towards changes in occupational wage inequality over the past decades? A key challenge to implementing the above accounting identity is that, absent occupation-level productivity data, only the wage but neither the $MRPL$ nor the wage markdown, $\mu$, are observed at the occupation level. Consequently, further assumptions are required to disentangle productivity from rent sharing. To overcome this challenge, I present an equilibrium model of search and matching in the tradition of the seminal Diamond-Mortensen-Pissarides (DMP) framework, which I use to derive a mapping from the unobserved wage markdown, $\mu$, into a set of measurable labor market statistics for each occupation. The key insight is that the DMP framework provides an expression for firms' labor demand, which I invert to obtain an equilibrium mapping between the wage markdown, $\mu$, and a set of empirical objects that can be measured separately for each occupation.

A key ingredient of the equilibrium mapping that I derive is the occupation-specific degree of labor market tightness (i.e., the ratio of the number of job vacancies to the number of unemployed). While labor market tightness is well estimated in recently available administrative and survey data, unfortunately there does not exist structured historical data on job vacancies by occupation group reaching several decades back in time. In the absence of such data, I hand-collect close to 12 thousand job vacancy records from historical newspaper advertisements to construct measures of relative labor demand at the occupation level. I combine these historical measures with survey data on job transition (i.e., finding and separation) rates, estimates of recruiting costs, and the real interest rate in order to implement the accounting decomposition of wages into the $MRPL$ and the wage markdown, $\mu$, for each occupation. In line with my model-guided interpretation of these objects, I show that the resulting estimates of the $MRPL$ and wage markdowns, $\mu$, correspond to empirical measures of computer use and unionization rates.I show that wages and tightness move together, and this is consistent with a world in which changes in wages are driven by changes in marginal products and not markdowns, or bargaining power.

My main finding is that productivity, as opposed to rent sharing, is the dominant driver behind occupational wage differences, both in the cross section and over time. In the cross section, variation in productivity accounts for 129 percent of the total variance of log wages during the initial period of the 1980s. In contrast, variation in wage markdowns, $\mu$, accounts for a relatively small share of 9 percent of initial wage dispersion. Furthermore, $MRPL$ and wage markdowns, $\mu$, covary negatively, explaining an additional $-38$ percent of initial wage dispersion. This means that occupational wages are initially compressed due to the fact that higher-paid occupations have a lower labor share.

Over time, my estimates suggest two salient drivers behind increasing occupational wage dispersion between the 1980s and the 2000s. First, between-occupation variation in $MRPL$ increased substantially, accounting for 114 percent of the total increase in the variance of log wages across occupations. Second, dispersion in wage markdowns, $\mu$, declined while the $MRPL$ and wage markdown, $\mu$, covary less negatively over time, each explaining $-7$ percent of the increase in occupational wage dispersion. In other words, occupational wage inequality would have increased even more, had it not been for a relative compression in rent sharing and a concurrent decline in the labor share among higher-paying occupations.

In summary, the results of this exercise suggest that productivity, rather than rent sharing, explains most of the occupational wage inequality in the U.S., both in the cross section and over time.

**Related Literature.** This paper proposes a theory-guided accounting decomposition of occupational wage inequality into two broad groups of explanations: productivity and rent sharing. A benefit of this general approach is that it allows me to bound the relative contributions of each of the two groups of explanations, rather than focusing on any one specific mechanism. Existing work on occupational wage polarization has studied specific mechanisms in either one of these two groups.

On the one hand, a large strand of the literature has proposed productivity-related drivers of occupational wages, including labor supply and demand (Katz and Murphy, 1992; Card and Lemieux, 2001), skill-biased technological change and capital-skill complementarity (Berman et al., 1998; Krusell et al., 2000), and the adoption of new technologies such as robots (Autor et al., 2003; Acemoglu and Restrepo, 2018). Works in this strand of the literature typically fall under the neoclassical paradigm that labor markets are competitive so that workers are paid their marginal revenue product of labor. While this outcome is a special case of the framework that I propose when $\mu = 1$, my approach is more general in that I allow for wage markdowns $\mu < 1$ that may represent labor market concentration or frictions.

On the other hand, a separate strand of the literature has linked wage inequality to labor market institutions such as labor unions (Stansbury and Summers, 2020; Farber et al., 2021) minimum wages (DiNardo et al., 1996; Lee, 1999; Autor et al., 2016; Jardim et al., 2020), and worker strikes (Alder et al., 2017). There are also spillover effects of institutional changes. In an influential study Lee (1999) shows that the decline in the minimum wage can explain half of the increase in the standard deviation of log wages.

As for unions, when spillover effects are included, the contribution of deunionization to growing wage inequality doubles (Taschereau-Dumouchel, 2020; Fortin et al., 2021). My work complements this strand of the literature by focusing on the occupational, rather than the overall, structure of wages since occupations are a natural unit of analysis when thinking about differentiated labor inputs.

Existing work on the demand side of labor markets has been constrained by the availability of historical job vacancy data. For example, Gavazza et al. (2018) and Davis et al. (2013) use microdata from the Job Openings and Labor Turnover Survey (JOLTS) by the U.S. Bureau of Labor Statistics (BLS), which was administered starting in 2004. Hobijn and Perkowski (2016) use data from Job Vacancy Surveys (JVS) for thirteen states starting in 2005, similar to the Help-Wanted Online (HWOL) database published by the Conference Board. Starting in 2007, digital job vacancy data from Burning Glass Technologies are available and have been used by recent work that includes Hershbein and Kahn (2018), Braxton and Taska (2020), Acemoglu et al. (2020), Hazell and Taska (2020), and Hazell et al. (2021). In relation to these papers, my work adds a historical perspective on the distribution of job vacancies in relation to firms' labor demand for different occupations.

This paper adds to recent estimates of markdowns in the U.S. Markdowns, or the wedge between workers' wages and their marginal product, can arise from multiple sources. Specifically, markdowns reflect the combination of both monopsony power as well as wedges due to search frictions. In this paper, I quantify the importance of this second component of the markdown, namely the portion of the markdown that is due to search frictions and bargaining power. Much of the recent literature has aimed to estimate the component of markdowns due to monopsony power. For example, Yeh et al. (2022) find markdowns of around 0.65 in the manufacturing industry, and Kroft et al. (2021) find markdowns of around 0.80 in construction. Azar et al. (2022) estimate markdowns from a large online job board and Lamadon et al. (2022) from the universe of matched employer-employee data from tax records. Both papers find average national markdowns in the $0.80 - 0.85$ range. The findings of my paper do not contradict the existing literature. Rather the difference in magnitude between the markdown estimates I find and these papers reflects the constrasting components of the markdown that are being measured. By ignoring labor market tightness, the existing literature overlooks the markdown arising from search frictions and bargaining power.

Two closely related works also use historical data on job vacancy postings, similar to this paper. First, Wolcott (2021) uses data from a BLS pilot survey of establishments in 1979 to distinguish between three drivers of changes in employment: demand considerations, supply factors, and search frictions. This paper builds on her work in a few dimensions. Rather than explore drivers of changes in employment by skill, this paper seeks to disentangle drivers of changes in wages by occupation. In addition, the new measure of historical labor market tightness I use allows for state-level analysis in addition to national level. Furthermore, I show how one can estimate $MRPL$s and wage markdowns directly from the data without defining a specific wage setting process such as Nash bargaining. Second, Atalay et al. (2020) collect a large number of historical job advertisements from three major metropolitan newspapers, which they classify according to skill and task contents. Neither of those related works study occupational wages or their determinants—productivity and rent sharing—which are the focus of the current paper.

**Outline.** The rest of this paper is structured as follows. Section 2 lays out the model that is used to derive an accounting decomposition of occupational wages into $MRPL$ and wage markdowns. Section 3 discusses the data and measurement issues. Section 4 presents the main results. Section 5 develops two extensions to the baseline model. Finally, Section 6 concludes.

## 2 Model

This section introduces an equilibrium model that allows me to decompose occupational wages into two terms: $MRPL$ and wage markdowns, $\mu$. Although, absent occupation-level productivity data, neither of these terms is directly measurable, the model provides a mapping from the unobserved wage markdown, $\mu$, into a set of measurable objects for each occupation.

**Environment.** There is a frictional labor market as in the seminal DMP framework (Diamond, 1982; Mortensen, 1982; Pissarides, 1985). Time is continuous and a constant interest rate $r$ is used to discount the future. As I consider a stationary economy, I drop the time subscript $t$ for for notational convenience. The economy is populated by workers and firms, each of which permanently belong to an occupation indexed by $j$ and meet with one another in separate, occupation-specific labor markets.

**Workers.** Workers are different across occupations, but identical within occupations. This assumption is because I am interested in understanding inequality within and not across occupations, i.e., why managers earn more than administrators. Workers are immobile across occupations. At any point in time, workers are either employed or unemployed. While employed, workers in occupation $j$ consume their wage $w_j$, which is the outcome of some wage setting process that is left unspecified in the interest of generality but encompasses, for example, Nash bargaining or strategic wage posting. While unemployed, workers receive flow value of leisure $b_j$. Workers find jobs at equilibrium rate $f_j$ and exogenously separate at rate $\lambda_j$.

**Firms.** A firm is a job for one worker. After firms hire a single worker, they then sell the output of the match to a labor aggregator.[4] At any point in time, jobs are either filled or vacant. A filled job for occupation $j$ produces flow output $MRPL_j$ for the duration of the match. When firms post a vacancy, they only take into account the marginal product, which is what they will get paid for producing that relationship.[5] A vacant job attracts workers in occupation $j$ from unemployment at flow cost $\kappa_j w_j$. Jobs are filled at equilibrium rate $q_j$ and exogenously destroyed at rate $\lambda_j$.

**Matching.** Each instant, a mass $u_j$ of unemployed workers meets a mass $v_j$ of vacancies in occupation-specific market $j$, which results in a mass $m_j = m(u_j, v_j)$ of matches according to a constant-returns-to-scale matching function. Given labor market tightness $\theta_j \equiv v_j/u_j$, a worker's job finding rate is $f_j = f(\theta_j) = m(u_j, v_j)/u_j = m(1, \theta_j)$ and a firm's vacancy filling rate is $q_j = q(\theta_j) = m(u_j, v_j)/v_j = m(1/\theta_j, 1)$.

**Value functions.** The flow value of a worker in occupation $j$ being employed equals the wage minus the probability of exogenous separation multiplied by the difference between the value of employment $W_j$ and the value of unemployment $U_j$:

$$rW_j = w_j - \lambda_j \left[W_j - U_j\right]. \tag{2}$$

The flow value of a worker in occupation $j$ being unemployed equals the flow value of leisure minus the probability of job finding multiplied by the difference between the value of unemployment and the value of employment:

$$rU_j = b_j - f\left(\theta_j\right) \left[U_j - W_j\right]. \tag{3}$$

The flow value of a firm with a filled job in occupation $j$ equals flow output net of wage payments, minus the probability of exogenous separation multiplied by the difference

[4]Section 5 presents two extensions to the baseline model featuring multi-worker firms: one with product market concentration and one with labor market concentration.

[5]If firms were posting multiple vacancies, they would take into account the average revenue product of labor rather than the marginal product.

between the value of a vacancy $J_j^V$ and the value of a filled job $J_j^F$:

$$rJ_j^F = MRPL_j - w_j - \lambda_j \left[J_j^V - J_j^F\right]. \tag{4}$$

Finally, the flow value of a firm with a vacancy in occupation $j$ equals the negative of the flow cost of maintaining the vacancy plus the probability of job filling multiplied by the difference between the value of a filled job and the value of a vacancy:

$$rJ_j^V = -\kappa_j w_j + q\left(\theta_j\right)\left[J_j^F - J_j^V\right]. \tag{5}$$

The value of a match here is assumed to be constant, namely equal to the marginal product. However, it is possible to have a value or occupational price that changes depending on the number of people employed. If that were the case, none of the resulting expressions would change.

**Equilibrium.** A stationary equilibrium in the market for occupation $j$ consists of a set of values $\{W_j, U_j, J_j^F, J_j^V\}$, quantities $\{u_j, v_j\}$, and price $w_j$ such that firms take as given $w_j$, values satisfy the Bellman equations (2)–(5), and the free-entry condition holds:

$$J_j^V = 0. \tag{6}$$

**Accounting identity.** I posit the following accounting identity, as stated in equation (1), which separates wages into the marginal product and a wage markdown for each occupation $j$:

$$w_j = MRPL_j \times \mu_j,$$

where the wage markdown $\mu_j \equiv w_j / MRPL_j$ is simply the ratio between the wage and the marginal product. The key insight is that both the wage markdown, $\mu_j$, and the $MRPL_j$ can be expressed in terms of measurable objects. To this end, I combine two equilibrium conditions of the model—see Appendix A for details. This yields the following expressions for the wage markdown, $\mu_j$, and $MRPL_j$:

$$\mu_j = \frac{f\left(\theta_j\right)}{\kappa_j \theta_j\left(r+\lambda_j\right) + f\left(\theta_j\right)}, \tag{7}$$

$$MRPL_j = \frac{w_j\left[\kappa_j \theta_j\left(r+\lambda_j\right) + f\left(\theta_j\right)\right]}{f\left(\theta_j\right)}. \tag{8}$$

Equations (7)–(8) relate the wage markdown, $\mu_j$, and $MRPL_j$ to a set of measurable labor market variables for each occupation: the job finding rate, the job separation rate, labor market tightness, the occupation-specific wage, vacancy posting costs in multiples of the prevailing wage, and the interest rate. All else equal, the wage markdown is decreasing in the interest rate, job separation rate, and vacancy posting cost. If we assume that the matching function is Cobb-Douglas, $m(u_j, v_j) = \chi_j u_j^{\alpha} v_j^{1-\alpha}$, then the job finding rate $f(\theta_j)$ and markdowns $\mu_j$ are also increasing in the matching efficiency $\chi_j$ but decreasing in labor market tightness $\theta_j$.[6] The choice of Cobb-Douglas as a functional form follows Petrongolo and Pissarides (2001) who estimate the matching function and show it to be a good fit.

**Discussion.** The model that forms the basis for the accounting identity is a variant of the seminal DMP framework with two departures. The first departure is that the per-period vacancy cost in the current model scales with the wage rate, $w_j$, whereas the cost is expressed as a constant in the standard DMP framework (e.g., Albrecht, 2011). This modeling choice conveniently allows me to express the wage markdown, $\mu_j$, without reference to the prevailing wage, $w_j$. This choice is also innocuous since I recalibrate the vacancy cost for each occupation and period, so expressing it in terms of multiples of the prevailing wage is without loss of generality.

The second departure is that the current model does not specify a wage setting process, whereas the standard DMP framework assumes that the surplus is divided according to Nash bargaining. This feature can be viewed as a strength of my approach, as it does not tie my hands to any particular wage setting protocol. For example, while Nash bargaining has an appealing axiomatic foundation, several alternative wage setting protocols, such as wage posting, have been studied in the literature. Since firms take the wage as given when making their choices, details of the wage setting protocol are not essential for the derivation of the accounting identity.

Finally, it is worth noting that the current model nests that of a competitive labor market. For this to be the case, it would have to be the case that all workers are paid their marginal product, or $\mu_j = 1$ of all $j$. This is the case if vacancies are costless or $\kappa_j = 0$, so that labor markets are infinitely thick or $\theta_j = 0$. Although theoretically possible, the existence of substantial hiring costs together with the fact that unemployed workers and

[6] This last comparative static may at first seem counterintuitive because it indicates that markdowns, are lower when labor market tightness is higher. Note, however, that for fixed wages the wage markdown is monotonically increasing in unobserved productivity. Hence, a lower markdown reflects the fact that the unobserved productivity must be relatively high if a market is relatively tight. Intuitively, firms want to post more vacancies when the flow payoff from hiring is greater.

unfilled vacancies coexist at any point in time is prima facie evidence that this is not the empirically relevant case.

# 3 Data and Calibration

The key insight from the labor market model is that although *MRPL* and wage markdowns, $\mu$, are not directly observable at the occupation level, in principle the right-hand side variables in equations (7)–(8) can be measured in the data. These include the job finding rate, the job separation rate, labor market tightness, the occupation-specific wage, vacancy posting costs in multiples of the prevailing wage, and the interest rate. An empirical challenge is that there exists no structured historical data on occupation-level labor market tightness (i.e., the ratio of the number of job vacancies to the number of unemployed) in the U.S. going back in time as far as the 1980s.

**Occupation Classifications.** Throughout the analysis, I use 20 occupation classifications following BLS groupings. While it is possible to construct more detailed occupation classifications in each of the periods, a relatively coarse occupation classification allows me to keep occupation groups comparable over time since my study spans several decades between the 1980s and the 2000s.

**Job Vacancy Shares.** To obtain historical job vacancy data, I draw on two different sources for the two periods representing the 1980s and the 2000s. For the 1980s, a challenge is that there exists no structured vacancy data by occupation. To overcome this shortcoming, I hand-collect and digitize close to 12 thousand job advertisements from newspaper archives. I do this for a sample of seven U.S. states, namely Kansas, Minnesota, Nebraska, Oklahoma, Oregon, Rhode Island, and Washington. The choice of states is determined by which states had job vacancy surveys publicly available in the 2000s. In each state, I identify the newspaper with the largest circulation at the time—see Appendix C for details. For each newspaper, I collect around $1,500$ job vacancy postings per state over a random sample of days in the second quarter for years between 1980 and 1989. Importantly, the set of states and timing of these historical newspaper postings are chosen to align with the data source for job vacancies in the 2000s, as described below.

The only other source of historical job vacancy data across states going this far back in time is a pilot survey from 1979 that was conducted by the BLS. In comparison to the BLS pilot survey, the newspaper vacancy data that I collect have several advantages. The first is that my data allow for more disaggregated analyses at the level of states and occupations, complementing previous studies at the national level such as Atalay et al. (2020), and Wolcott (2021). Accounting for heterogeneity in jobs across states, as I do in the analysis below, is important because different parts of the U.S. specialize in different types of economic activity. In addition, there is a considerable amount of business-cycle-frequency fluctuations in job vacancies, which could lead to noisy measures of labor market tightness. By considering a random sample of newspapers editions spanning a whole decade, my measure of job vacancies is more robust to such idiosyncratic variation.

Depending on the source of job vacancies (e.g., newspapers advertisements versus online boards), certain occupations may be more accurately represented than others. If the source of vacancies between the 1980s and 2000s differed in their representativeness for certain occupations, this would bias my estimates of labor market tightness in the cross section and changes therein over time. Theoretically, it is not clear in which direction such a bias would push my results. However, there is no evidence that newspaper job advertisements differed in the set of job applicants they targeted in the 1980s relative to the set of job applicants targeted by the business survey conducted in 2000s.

Figure 2 shows an example of job advertisements from *The Oregonian*, the flagship newspapers from the U.S. state of Oregon. Although anecdotal, this example shows the breadth of advertised job openings, ranging from relatively low-skilled cooks to medium-skilled programmers and high-skilled dentists.

**Figure 2.** Example of newspaper job advertisements from *The Oregonian* on February 4, 1985

Foyt-Unser team wins at Daytona; details in Sports

The Oregonian

Forecast: cold; high, 35; low, 25; report on Page A2

VOL. 135 — No. 44,289 SUNRISE EDITION MONDAY, FEBRUARY 4, 1985 50 PAGES 25 CENTS E

COCKTAIL SERVERS, experienced only. Apply after 5pm. Earthquake Ethels, 2970 SW Cedar Hills Blvd, Beaverton

COMPTROLLER
Portland-based mfg company serving national and international market, seeking individual with strong accounting and computer background. Send resume to Oregonian, Box 1043-M, Ptld, 97201

COMPUTER Peripheral Field Service Technician wanted for rapidly growing peripheral sales & service co. Part time. Need exper w modems, terminals, printers & people. Send resume to Personnel, PO Box 959, Mukilteo, WA 98275. Postmark by Feb 10. Interviews Feb 14-15.

CONCRETE PUMP OPERATOR
Exper only...1-386-1400

CONSTRUCTION SECRETARY
Exciting challenge for the sharp secretary with a well established general contractor. Good working conditions, excellent benefits w/competitive salary.

DENTAL ASST
Position avail for highly motivated & exper dental asst, X-ray certification. Opportunity to contribute to very successful dental practice. Medical & dental bnfts avail. Salary nego. Call for appt, Mon-Fri 8am-5:30pm, 667-0436.

DENTAL laboratory, seeking a ceramist & a crown & bridge technician with 5 years exper. Salary negotiable. Benefits. Equal Opportunity Employer. Dahlin Laboratory, 233-6486.

DENTAL
WE WANT A SPECIAL PERSON
Responsible chairside position with opportunity to grow as a valued member of our team. If you are experienced in dentistry & have excellent creative people skills, & are excited by the potential for expanded duties, call 254-6569.

DENTAL-Ortho Asst: Exper, patient oriented, enthusiastic, X-ray cert. SW Office. Resume: Oregonian Box 1087-M 97201

Equal Opportunity Employer

ENGINEER
ChE Degree and minimum 3 years experience in waste treatment, filtration techniques, fluid dynamics, heat transfer systems, food plant safety and sanitation design engineering are required. Familiarity with computerized analytical techniques and vendor negotiations and selection are desired. Travel is required.
Equal Opportunity Employer M/F/H/V. Send resume and salary history to Division Personnel Manager, J.R. Simplot Co., PO Box 1059, Caldwell, ID 83606-1059. (208)459-0071.

EXPERIENCED MOBILE HOME salesperson, experienced, on Portland lot on 82nd Ave. Only those with experience need apply. Monthly minimum wage draw guaranteed against commission. Call 654-0390 Don, or collect 1-826-2661 Gary.

FABRICATION FOREMAN (male-female), exper, for non-union steel fab, NW firm. Write to Oregonian, Box 1084-M, 97201

*Notes*: This figure shows an example of a newspaper job posting from the classifieds section of *The Oregonian* from the U.S. state of Oregon on February 4, 1985. Each job posting is allocated to an occupation. Newspaper job postings are streamlined in accordance with BLS occupation groupings. In cases where an explicit number of open positions are mentioned in the advertisements, this number is recorded accordingly. When a job posting refers to more than one opening without further specificity, the job is multiplied by two. The results are robust to using other multiples for this adjustment. *Source*: The Oregonian, retrieved from https://www.newsbank.com/ on March 1, 2022.

In the 1980s, local newspapers were the dominant source for job vacancies in the U.S. As technology and information sources changed over time, so did employers' recruiting practices. For the period of the 2000s, my job vacancy data is derived from state-level business surveys. Starting in the 2000s, several U.S. states began conducting job vacancy surveys of establishments for administrative purposes. The job vacancy survey I use is the Quarterly Census of Employment and Wages of the BLS. The survey is a random sample stratified by industry, establishment size, and geographic region designed to be representative of the economies in each of the seven states listed above. To aggregate to the decade level, I take the mean vacancy share by occupation for all available years from 2005 to 2010.

Appendix Figure 12 shows the share of vacancies in the 2000s compared to the 1980s. Overall, occupations' vacancy share is relatively persistent across decades. Occupations that saw the largest decline in vacancies are workers in administration, production, and installation. Occupations that saw the largest increase in vacancies include doctors and workers in education and computing.[7]

[7]Figures 16–20 in Appendix B.2 show a similar pattern when disaggregating the data by state and occupation.

**Unemployment Rates.** I compute unemployment rates by occupation group using the CPS microdata accessed via IPUMS (Flood et al., 2020). For each time period, I construct a crosswalk from the occupation codes reported in the CPS to the twenty occupation classifications based on the BLS groupings. To this end, I build on the aggregation of U.S. Census occupation codes from Dorn (2009), and Autor and Dorn (2013), accounting for the fact that a number of new occupation codes are added every Census decade. Throughout the remainder of the analysis, I focus on men since women's labor market participation had a very different trajectory in the timeframe considered.

**Labor Market Tightness.** Many definitions of labor market tightness refer to the number of vacancies divided by the number of unemployed workers. For the purposes of my calibration, I consider the share of unemployed workers and vacancies for each occupation, rather than their levels, on account of the differing data sources for each cross section. Luckily, the only result of this is a rescaling of the matching efficiency parameter, which is inconsequential for my purposes. To see this, consider a Cobb-Douglas matching function, $m(u, v) = \chi u^{\alpha} v^{1-\alpha}$, and suppose that both the number of unemployed $u$ and the number of vacancies $v$ are in levels. Redefining the matching function in terms of unemployment rates and vacancy shares yields an alternative matching function given by $m(\tilde{u}, \tilde{v}) = \chi \tilde{u}^{\alpha} \tilde{v}^{1-\alpha}$, where $\tilde{u} = u/u^{\text{total}}$ and $\tilde{v} = v/v^{\text{total}}$ are the unemployment and vacancy shares. Here, $u$ is the number of unemployed workers in a particular occupation and $u^{\text{total}}$ is the total number of unemployed, while $v$ is the number of vacancies targeting a particular occupation and $v^{total}$ is the total number of vacancies. Note that the second matching function can be rewritten to match the first, namely $m(u, v) = \tilde{\chi} u^{\alpha} v^{1-\alpha}$, where $\tilde{\chi} = \chi (u^{\text{total}})^{-\alpha} (v^{\text{total}})^{\alpha-1}$.

**Vacancy Posting Cost.** Many costs are involved in hiring workers beyond vacancy posting costs, such as selection and training. The model here focuses solely on costs to attracting applicants, i.e., recruitment. Estimates of hiring costs in the human resources literature are measured in terms of earnings, either the total wage bill or monthly earnings. I use two different sources of recruitment costs in the U.S. to obtain measures of vacancy posting costs for each occupation and cross section.

For the 1980s, I draw on the Employment Opportunity Pilot Project (EOPP), which is a BLS survey from 1980 and 1982 that asks employers detailed questions about recruitment and training, including the cost of the last hire. I follow the approach in Manning (2011). This involves combining hiring costs with the total number of hours spent on recruiting from Barron et al. (1997). Hours are multipled by 1.5, which is an estimate of the relative wage of recruiters to new hires from Silva and Toledo (2009). I then divide this by 40 hours to have a measure of recruiting in terms of monthly earnings. This gives a vacancy posting cost of 0.2 in terms of monthly earnings. I rescale this cost for a coarse set of occupations depending on the median duration of unemployment from Barron et al. (1997).

Meanwhile for the 2000s, I draw on estimates from Dube et al. (2010) who evaluate the California Establishment Survey (CES) from 2003–2009. This is the only readily available source of vacancy costs from the mid-2000s that allows for disaggregating between occupations. The CES asks establishments about worker replacement costs, which include recruitment, selection, screening, and on-the-job training for different occupations. The survey distinguishes between four occupational categories: professionals; clerical workers; sales workers; and manual labor. I allocate the 20 occupations to these four coarse groupings.[8] Replacement costs are $6,800 for professionals, $5,000 for sales workers, $3,000 for clerical workers, and $1,700 for blue collar and manual workers. Muehlemann and Leiser (2018) find that recruitment costs corresponds to one-fourth of total worker replacement costs. As such, I divide the replacement costs from the CES by four to have a measure of the recruitment costs. I then express all values in terms of the numeraire, chosen to be the mean monthly earnings of blue collar workers, as in Wolcott (2021). Appendix C shows the resulting vacancy costs, $\kappa_j$, for each occupation and cross section.

**Wages.** To construct weekly wages, I follow the approach used in Autor et al. (2008), Autor (2019), and Autor et al. (2020). I use the March Current Population Survey for earnings years 1980-1989 for the 1980s cross section and 2000–2009 for the 2000s cross section. The analysis is limited to workers who are male, aged 16 to 64, work full-time (as defined by the Census as having worked usually 35 hours in the previous week), and who worked at least ten weeks in the preceding year. The type of work is limited to the private sector or government employment, i.e., excluding self-employment and other undefined sources. Weekly earnings is the logarithm of annual earnings divided by weeks worked. Top-coded earnings are multiplied by 1.5 following Katz and Murphy (1992), and Autor et al. (2008). Prior to 1988, total wage and salary earnings of the previous year were reported in a single variable. Beginning in 1988, total earnings in the CPS were divided into two variables corresponding to the primary and secondary source of earnings. To construct a total earnings measure as of 1988, I combine these two variables, adjusting for top-coding if needed. All earnings are deflated by a price deflator for personal consumption

[8] Engineers, business, computer specialists, healthcare practitioners, managers, social scientists, education, arts fall into the professional category. Meanwhile admin falls into clerical workers. Meanwhile sales, social services, nurses falls into sales workers. Lastly, production, protective, material moving, installation, cleaning, construction, food related, personal care fall into manual labor.

expenditures (PCE). Individual weights are used in all calculations and for the national analysis, and weights equal to the state's population share in the nation are applied for the state-level analysis.

**Job Finding and Separation Rates.** Estimates of these remaining variables are drawn from the CPS. The state-level analysis includes only data from the seven relevant states while the national analysis reweighs the data using state population weights. I pool all years from 1980–1989 for the first cross section and 2000–2009 for the second cross section. To measure the finding and separation rates by occupation, I take advantage of the rotating panel dimension of the CPS. The monthly finding rate is defined as workers who at month $t$ were unemployed and then found a job the subsequent month $f\left(\theta_j\right) = \mathbb{P}\left(l_{t+1} = E \mid l_t = U\right)$. Conversely the monthly separation rate is workers who were employed at month $t$ and then lost their job $\lambda_j = \mathbb{P}\left(l_{t+1} = U \mid l_t = E\right)$.

Appendix Figure 14 shows that changes in the monthly job finding rates between the 1980s and 2000s are idiosyncratic by occupation. Finding rates declined across most occupations and only increased for cleaning, construction, and education workers. Meanwhile Appendix Figure 15 shows monthly job separation rates to be more constant and also maintain a similar ordering between the two time periods. There has been a decline in the separation rates for occupations that Autor (2019) dubs "low skill" such as manual and services work, and also "middle skill" occupations such as production work. These trends are corroborated by the state-level evidence presented in Appendix Section B.2.

**Interest Rate.** The real interest rate is set to 6.8 percent for the 1980s and to 3.2 percent for the 2000s.

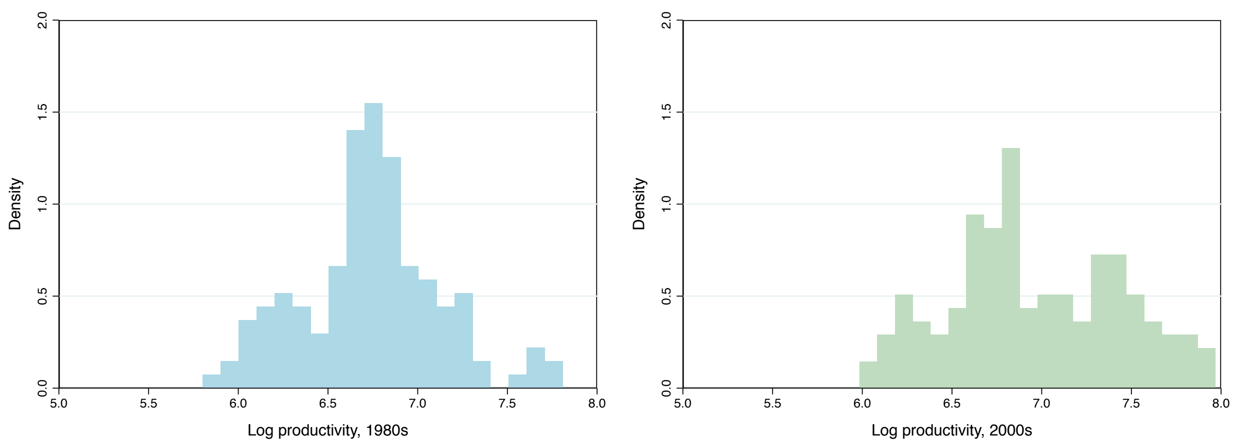
# 4 Results

By combining the equilibrium model of search and matching from Section 2 with the occupation-specific labor market data presented in Section 3, it is possible to use equations (7)–(8) to quantify the relative contributions of productivity versus rent sharing toward occupational wages, both in terms of levels and in changes over time.

**Inspecting the Estimates.** As a first look at the estimated model objects, Figures 3 and 4 show, respectively, the distribution of estimated productivity and estimated markdowns in each decade. Productivity shows significant dispersion in the 1980s and has become more dispersed over time, particularly in the right tail of the distribution. Meanwhile, markdowns are concentrated between 0.80 and close to 1.00 in the 1980s and have become, if anything, more clustered near the top over time.

**Figure 3.** Distribution of log productivity, 1980s and 2000s

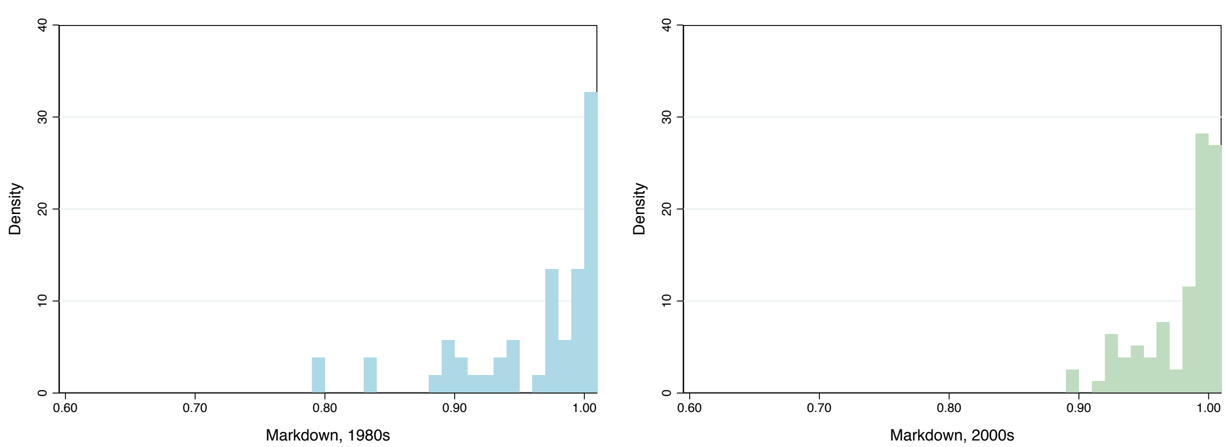
**(a)** 1980s **(b)** 2000s




*Notes*: This graph shows the distribution of log productivity by state and occupation for the 1980s (panel a) and for the 2000s (panel b). *Source*: Data sources and construction described in the main text.

**Figure 4.** Distribution of markdowns, 1980s and 2000s

**(a)** 1980s **(b)** 2000s

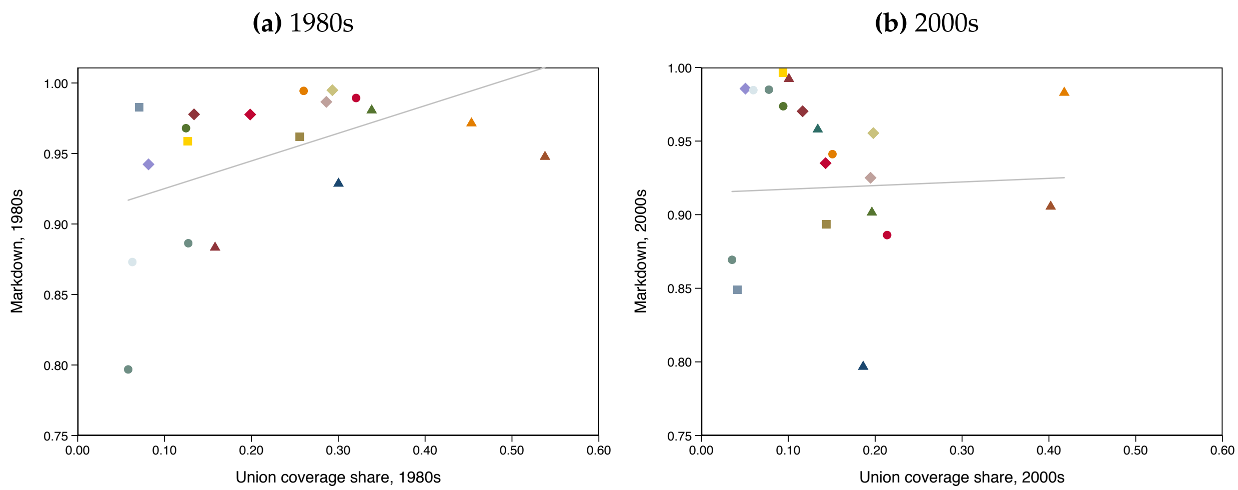



*Notes*: This graph shows the distribution of log productivity by state and occupation for the 1980s (panel a) and for the 2000s (panel b). *Source*: Data sources and construction described in the main text.

To test whether my estimates of productivity and markdowns capture economically meaningful concepts, I plot the estimates against empirical proxies for technology and rent sharing. Figure 5 plots the markdown against unionization rates, where unionization rates reflect the share of workers who are either a member of or covered by a union.

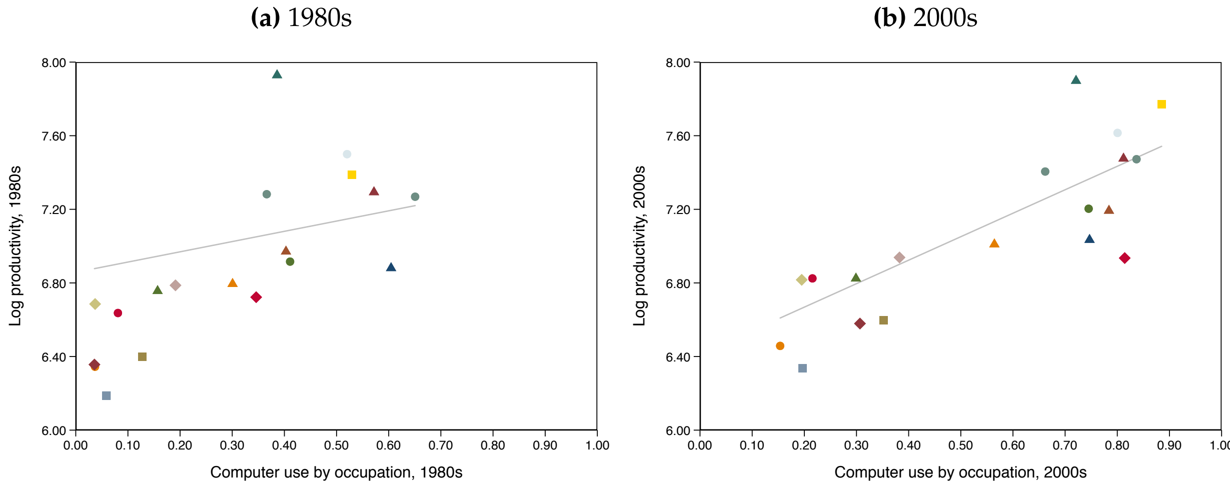
The distinct positive relationship in the 1980s shows that occupations in which workers commanded a larger share of rents were also those that had higher unionization rates. This relationship weakens in the 2000s, in line with literature on the decline of union power (Stansbury and Summers, 2020). As a proxy for productivity, I draw on a question from the CPS asking whether the respondent uses a computer at work. Figure 6 plots a similar set of graphs, showing a positive relationship between productivity and computer use in each cross section. These sets of graphs indicate that the constructed measures of productivity and markdowns hold economic content.

**Figure 5.** Estimated markdowns versus unionization coverage, 1980s and 2000s




*Notes*: This graph plots estimates of the wage markdown against the empirical unionization rates for the 1980s (panel a) and for the 2000s (panel b). *Source*: Estimated markdowns are constructed as described in the main text. Unionization statistics are from the Monthly CPS via IPUMS.

**Figure 6.** Estimated productivities versus computer use, 1980s and 2000s



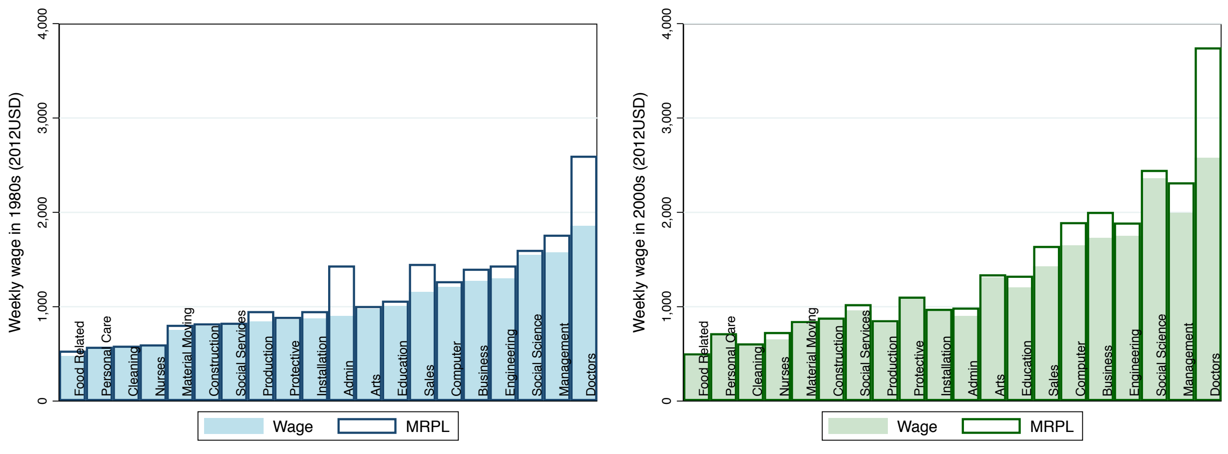

*Notes*: This graph plots the estimates of productivity (MRPL) in logs against empirical rates of computer use by occupation for the 1980s (panel a) and for the 2000s (panel b). *Source*: Estimated productivity is constructed as described in the main text. Computer use statistics are from the Monthly CPS via IPUMS.

**Levels.** The cross-sectional decomposition of wages for the 1980s and the 2000s is plotted in Figure 7. Separately for each period, the figure shows occupation-specific $MRPL$s and also the shares accruing to workers in the form of wages. Two points are worth noting. First, there are large occupational differences in the $MRPL$, which is strongly correlated with a given occupation's wage. Second, higher-paid occupations have significantly higher gaps between $MRPL$ and wages, particularly for the later period.[9]

[9]The finding that higher paying jobs also have a lower markdown, $\mu$, is consistent with theoretical models of equilibrium wage dispersion, such as Burdett and Mortensen (1998) and Gouin-Bonenfant (2022).

**Figure 7.** Wage shares of $MRPL$, 1980s and 2000s

**(a)** 1980s **(b)** 2000s




*Notes*: This graph shows the contribution of the marginal revenue product of labor towards explaining wages for the 1980s (panel a) and for the 2000s (panel b). The difference between the transparent bars with dark frames and the colored bars reflects the contribution of markdowns toward wages. *Source*: Data sources and decomposition described in the main text.

To formalize these insights, Table 1 quantifies the contribution of productivity versus rent sharing toward occupational wage dispersion for each decade. Occupational wage inequality, measured by the variance of mean log wages across occupations, is substantial in the 1980s and increased further between the 1980s and the 2000s. In each period, the contribution of productivity in each cross section is above 100 percent, suggesting that occupational wage dispersion would be greater at any point in time if workers were paid their marginal product. Specifically, the productivity dispersion accounts for 129 percent of occupational wage dispersion in the 1980s and 123 percent in the 2000s. Meanwhile, dispersion in markdowns accounts for a relatively small share of the variance of occupational wages, making up 9 percent of occupational wage dispersion in the 1980s and 3 percent in the 2000s. Finally, the covariance between productivity and markdowns is negative and sizable in magnitude in both periods, explaining $-38$ percent of occupational wage dispersion in the 1980s and $-26$ percent of that in the 2000s.

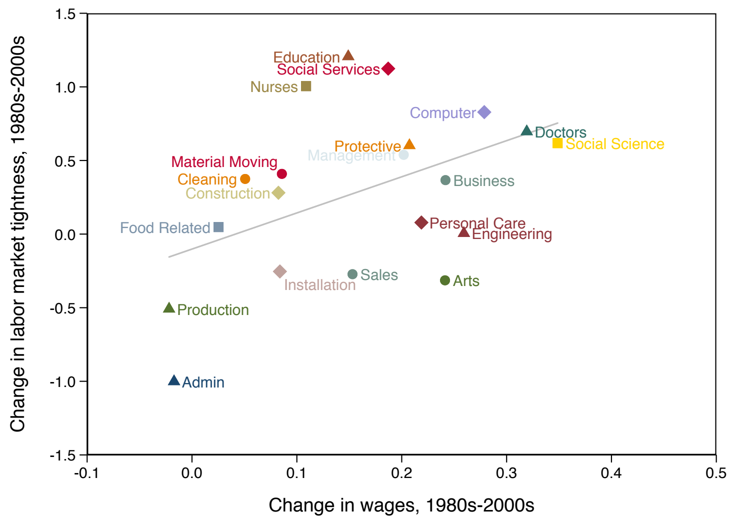
**Table 1.** Variance decomposition of occupational wages, 1980s and 2000s

| | 1980s | 2000s | Change, 1980s–2000s |
|---|---|---|---|
| $Var\left(\ln\left(w\right)\right)$ | 0.138 (100%) | 0.220 (100%) | 0.082 (100%) |
| $Var\left(\ln\left(MRPL\right)\right)$ | 0.178 (129%) | 0.272 (123%) | 0.094 (114%) |
| $Var\left(\ln\left(\mu\right)\right)$ | 0.013 (9%) | 0.007 (3%) | $-0.006$ ($-7\%$) |
| $2 \times Cov\left(\ln\left(MRPL\right), \ln\left(\mu\right)\right)$ | $-0.053$ ($-38\%$) | $-0.059$ ($-26\%$) | $-0.006$ ($-7\%$) |

*Notes:* The table shows the decomposition of wages in terms of levels and change into a productivity, rent-sharing, and covariance term. Each term reflects the following equation: $Var\left(\ln\left(w\right)\right) = Var\left(\ln\left(MRPL\right)\right) + Var\left(\ln\left(\mu\right)\right) + 2 \times Cov\left(\ln\left(MRPL\right), \ln\left(\mu\right)\right)$. *Source*: Data sources described in the paper.

**Changes over time.** To motivate the analysis of changes in occupational wage components over time, it is worth first noting that the empirical comovement between wages and labor market tightness is indicative ofwhether productivity or rent sharing drive changes in occupational wage dispersion over time. On one hand, if the increase in an occupation's wage is driven by an increase in productivity, then employers should post more vacancies and hence increase labor market tightness. On the other hand, if the increase in an occupation's wage is driven by an increase in the markdown, $\mu$, then employers should post fewer vacancies, which in turn reduces labor market tightness. Figure 8 shows a strong positive relationship between the empirical changes in occupational wages and changes in labor market tightness, suggesting that changes in productivity—rather than changes in rent sharing—account for most of the observed wage growth at the occupation level.

**Figure 8.** Change in labor market tightness versus change in wages, 1980s–2000s




*Notes*: The graph shows the change in log wages between the two cross sections plotted against the change in log labor market tightness. *Source:* Labor market tightness is measured using newspaper job classifieds as the source of vacancy data in the 1980s and state-level business surveys in the 2000s. Unemployment is from the monthly CPS. Wage data are from the ASEC CPS.

Harnessing the historical vacancy microdata collected for this project, I estimate the following long-difference regression at the occupation-state level:

$$\Delta^{2007-1979} w_{js} = \Delta^{2007-1979} X + \gamma_j + \eta_s + \varepsilon_{js} : \quad X \in \{MRPL_{js}, \mu_{js}\}$$

The regression results in Table 2 show that changes in productivity are positively and significantly associated with differences in real wages. Meanwhile the relationship between wages and the markdown is negative and statistically insignificant. Productivity changes explain around 60 percent of the variation in wages, while markdown changes only explains 7 percent when state and occupation fixed effects are excluded.

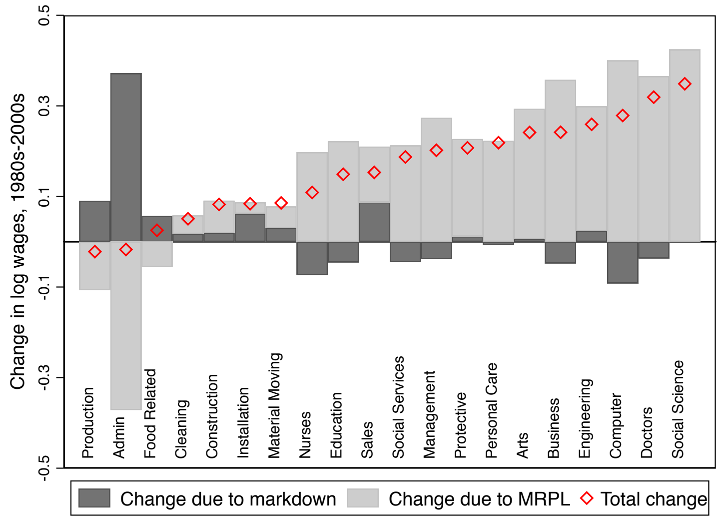
**Table 2.** Explaining changes in real log wages with changes in productivity versus changes in markdowns, 1980s–2000s

| | Dependent variable: change in log real wage | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Change in $\ln(MRPL)$ | 0.446$^{***}$ | 0.390$^{***}$ | | |
| | (0.036) | (0.040) | | |
| Change in $\ln(\mu)$ | | | $-0.124$ | $-0.143$ |
| | | | (0.079) | (0.070) |
| Constant | 0.057$^{***}$ | 0.070$^{***}$ | 0.155$^{***}$ | 0.154$^{***}$ |
| | (0.012) | (0.011) | (0.013) | (0.009) |
| Observations | 135 | 135 | 135 | 135 |
| Adjusted $R^2$ | 0.65 | 0.77 | 0.07 | 0.56 |
| State fixed effects | no | yes | no | yes |
| Occupation fixed effects | no | yes | no | yes |

*Note:* This table shows regressions results from projecting the empirical change in mean log real wages on changes in model estimates of log productivity (i.e., $MRPL$) and log markdown. between the 1980s and the 2000s Robust standard errors are in parentheses. *Source:* CPS via IPUMS and model estimates. $^{*}$ denotes a p-value $< 0.10$, $^{**}$ denotes a p-value $< 0.05$, and $^{***}$ denotes a p-value $< 0.01$.

Figure 9 shows the main results in terms of changes. Occupations that saw the smallest changes in real wages also saw declines in productivity and increases in markdowns. These results are consistent with a decline in the demand for occupations characterized by routine tasks (Autor et al., 2003). At the opposite end, professional occupations saw the largest positive changes in real wages, driven primarily by increases in productivity.

**Figure 9.** Decomposing changes in occupational wages

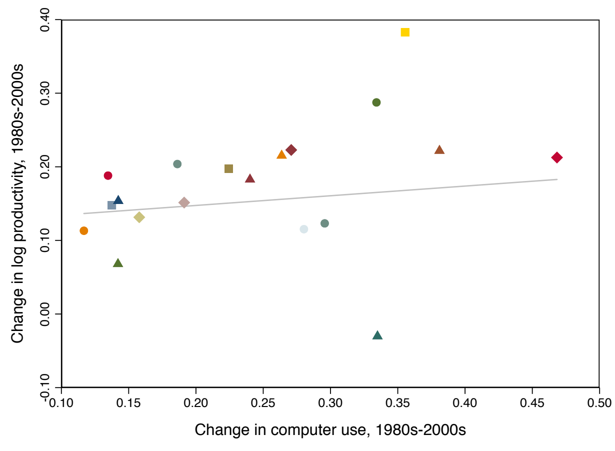



*Notes*: The bar graph plots the total change in log wages for each occupation, showing the contribution due to changes in the marginal revenue product of labor versus markdown. Occupations are ranked by total change in wages, with production workers seeing declines in the real wage and social science workers seeing the largest gains. *Source*: Data sources described in the paper.

These insights are confirmed by the last column of Table 1, which shows that changes in the variance of productivity explain more than the entire change in, or 115 percent of, the variance of wages. This feature of the estimates reflects the fact that high-paid occupations grew faster in productivity than other occupations. In contrast, changes in the variance of markdowns contributed negatively towards changes in the overall variance of wages, or $-7$ percent. This suggests that initially high-paid occupations have lost some of their bargaining power in relative terms. Finally, the covariance term has remained negative and constant in absolute magnitude over time thereby explaining a smaller share of the overall variance of wages over time, or around $-7$ percent.

To see whether these results reflect any economically meaningful phenomena, Figure 10 plots the change in estimated productivity against the change in computer use across occupations. Indeed, this exercise yields a positive correlation, suggesting that my estimates of changes in occupational productivity reflect changes in the technology used in the workplace.

**Figure 10.** Change in estimated productivities versus change in computer use, 1980s–2000s




*Notes*: This graph plots changes in the estimates of productivity (MRPL) in logs against changes in the empirical rates of computer use by occupation between the 1980s and the 2000s. *Source*: Computer use is part of the Computer Internet Supplement of the Monthly CPS for the 1980s (panel a) and for the 2000s (panel b). The variable is binary, capturing whether or not the respondent uses a computer at work (variable "ciwrkcmp"). The Supplement ran for two years in the 1980s (i.e., 1984 and 1989) and two years in the 2000s (i.e., 2001 and 2003). Estimated productivity (MRPL) is constructed as described in the main text.

# 5 Model Extensions

In this section, I present two model extensions that modify the basic accounting framework to incorporate two dimensions of market concentration: one based on product market concentration, or monopoly (Section 5.1), and one based on labor market concentration, or monopsony (Section 5.2).

## 5.1 Extension 1: Monopoly

In the next two sections I consider extensions to the benchmark model presented above to incorporate features of market concentration, first in the product market and second in the labor market. In terms of product market concentration, the main difference relative to the benchmark is that the monopolist hires workers to product output subject to a downward-sloping product demand curve. The economic environment is characterized by a continuum of varieties with each firm being a monopolist over a single variety. An occupation can have multiple monopolists.

The monopolist faces a downward-sloping demand curve for its product defined by $P\left(f\left(L\left(v_j\right)\right)\right)$, which is given by the inverse of demand $D^{-1}$. Hence the monopolist knows that by hiring more workers, it is going to change the price of the product.

Each firm produces a homogeneous good using only labor. The entry of a new monopolist is equivalent to a new product variety being created. Firms have no labor market power and hence compete for workers. The monopolist has a linear production function in which output $Y$ depends on the number of workers $L$, which in turn depends on the number of vacancies $v$: $f\left(L\left(v_j\right)\right) = L\left(v_j\right)$. From the steady-state of the DMP model, the outflow of workers is equal to the inflow: $\lambda_j L_j = v_j \times q\left(\theta_j\right)$. I combine this linear production function with employment flows in the DMP steady-state to obtain the following production function: $f\left(L\left(v_j\right)\right) = L\left(v_j\right) = v_j \times q\left(\theta_j\right)/\lambda_j$.

Since each firm is a monopolist, there are two firm value functions of interest: the value of a new entrant and the value of an incumbent.

$$\begin{aligned} J^M_{\text{new entrant},j} &= \max_{v_j}\left[J^M_{\text{incumbent},j} - \frac{L\left(v_j\right)}{q\left(\theta_j\right)}\kappa_{\text{entry},j}\right] \\ rJ^M_{\text{incumbent},j} &= \max_{v_j}\left[P\left(L\left(v_j\right)\right)L\left(v_j\right) - L\left(v_j\right)\left[w_j + \frac{\lambda_j}{q\left(\theta_j\right)}\kappa_{\text{hire},j}\right]\right] \end{aligned}$$

The cost for a new entrant is simply the hiring cost needed to have enough workers to be in steady state. Hence $\kappa_{\text{entry},j}$ is multiplied by $L\left(v_j\right)$ and scaled by the vacancy-filling rate. Meanwhile the problem for the incumbent has two components: the wage paid for the output of workers $L\left(v_j\right)w_j$, and the flow cost of posting vacancies for workers who separate $L\left(v_j\right)\lambda_j\kappa_{\text{hire},j}/q\left(\theta_j\right)$. After a firm pays the cost to be a new entrant, it jumps to steady state because of the linearity of the cost function. $J^M_{\text{new entrant},j}$ is not a flow value because it is a one-time value. Meanwhile $rJ^M_{\text{incumbent},j}$ is a flow value, and hence is multiplied by $r$.

Substituting the incumbent's problem into the new entrant's problem yields the following multi-worker firm maximization problem:

$$J^M_{\text{new entrant},j} = \max_{v_j}\frac{1}{r}\left[P\left(L\left(v_j\right)\right)L\left(v_j\right) - L\left(v_j\right)\left[w_j + \frac{\lambda_j}{q\left(\theta_j\right)}\kappa_{\text{hire},j}\right] - \frac{L\left(v_j\right)}{q\left(\theta_j\right)}\kappa_{\text{entry},j}\right]$$

This yields the following first order condition:

$$\underbrace{P'\left(L_j\right)L_j + P\left(L_j\right)}_{\text{MRPL}} = w_j + \frac{1}{q\left(\theta_j\right)}\left[\lambda_j\kappa_{\text{entry},j} + \kappa_{\text{hire},j}\right]$$

Together with the free entry condition specified, one can obtain new expressions for the $MRPL_j$ and markdown $\mu_j$.

$$\begin{aligned}\mu_j =& \frac{f\left(\theta_j\right)}{\theta_j\left[\kappa_{\text{entry},j}+\kappa_{\text{hire},j}\left[\lambda_j+1\right]\right]}\\ MRPL_j =& w_j \times \frac{\theta_j}{f\left(\theta_j\right)}\left[\kappa_{\text{entry},j}+\kappa_{\text{hire},j}\left[\lambda_j+1\right]\right]\end{aligned}$$

Compared to the baseline accounting framework, incorporating monopoly features changes the expressions in a few ways. One noteworthy change is that this extension requires us to distinguish between two types of hiring costs, reflecting the differential entry and steady-state hiring costs of the monopolist. This added complexity makes it more challenging to estimate this extension in the data.

## 5.2 Extension 2: Monopsony

The wedge that emerges between workers' wages and their marginal product can arise for numerous reasons. In the baseline model presented in 2, I focus on the markdown that is introduced on account of bargaining and search frictions. In this extension, I incorporate features of labor market power to show the additional wedge that arises from monopsony. The combination of the markdown I find due to search frictions and bargaining power together with the markdown due to monopsony power estimated from the literature ((Lamadon et al., 2022; Yeh et al., 2022; Kroft et al., 2021)) comprises a more accurate total markdown.

Each occupation now consists of a monopsonist hiring multiple workers. The entry of a new monopsonist entails the creation of a new occupation. The monopsonist faces an upward-sloping labor supply curve. Thus firms have labor market power and do not compete for workers. The main difference here is that the monopsonist internalizes that by posting additional vacancies, this will increase tightness and wage in equilibrium. Hence tightness is a function of aggregate vacancies: $\theta\left(v_j\right)$. The technology is the same as above, namely output is linear in labor: $f\left(L\left(v_j\right)\right)=L\left(v_j\right)=v_j\times q\left(\theta\left(v_j\right)\right)/\lambda_j$. This extension calls for defining the functional form of the matching function. The matching function is a constant-returns-to-scale Cobb-Douglas function: $m\left(u_j,v_j\right)=\phi_j u_j^{\alpha}v_j^{1-\alpha}$, where $\phi_j$ is the matching efficiency and $\alpha\in(0,1)$ is the elasticity of substitution. The job finding rate is $f\left(\theta_j\right)=\phi_j\theta_j^{1-\alpha}$ and vacancy filling rate $q\left(\theta_j\right)=\phi_j\theta_j^{-\alpha}$.

In a similar manner to the product market extension in Section 5.1, there are two firm value functions of interest: the value of a new entrant and the value of an incumbent.

$$\begin{aligned}
J^S_{\text{new entrant},j} =& \max_{v_j} \left[ J^S_{\text{incumbent},j}\left(v_j\right) - \frac{L_j}{q\left(\theta\left(v_j\right)\right)} \kappa_{\text{hire},j} \right] \\
rJ^S_{\text{incumbent},j}\left(v_j\right) =& \max_{v_j} \left[ Pf\left(v_j\right) - L_j \left[ w\left(\theta\left(v_j\right)\right) + \frac{\lambda_j}{q\left(\theta\left(v_j\right)\right)} \kappa_{\text{hire},j} \right] \right]
\end{aligned}$$

Substituting the incumbent's problem into the new entrant's problem yields the following multi-worker firm maximization problem:

$$J^S_{\text{new entrant},j} = \max_{v_j} \frac{1}{r} \left[ Pf\left(v_j\right) - L_j \left[ w\left(\theta\left(v_j\right)\right) + \frac{\lambda_j}{q\left(\theta\left(v_j\right)\right)} \kappa_{\text{hire},j} \right] - \frac{L_j}{q\left(\theta\left(v_j\right)\right)} \kappa_{\text{entry},j} \right]$$

This yields the following first order condition:

$$\underbrace{Pq\left(\theta\left(v_j\right)\right) + Pv_j q'\left(\theta\left(v_j\right)\right)\theta'\left(v_j\right)}_{\text{MRPL}} = \phi_j \theta_j^{1-\alpha} \left[ \frac{w_j}{\theta_j} - w_j \alpha + w_v \right] + \left[ \lambda_j \kappa_{\text{hire},j} + \kappa_{\text{entry},j} \right]$$

Together with the free entry condition specified, one can obtain new expressions for the $MRPL_j$ and markdown $\mu_j$.

$$\begin{aligned}
\mu_j =& \frac{w_j}{\phi_j \theta_j^{1-\alpha} \left[ \frac{w_j}{\theta_j} - w_j \alpha + w_v^j \right] + \lambda_j \kappa_{\text{hire},j} + \kappa_{\text{entry},j}} \\
MRPL_j =& \phi_j \theta_j^{1-\alpha} \left[ \frac{w_j}{\theta_j} - w_j \alpha + w_v^j \right] + \lambda_j \kappa_{\text{hire},j} + \kappa_{\text{entry},j}
\end{aligned}$$

In the baseline model presented in Section 2, there are two important objects. These are the marginal product and the wage, with the markdown being the gap between the two. However when features of monopsony are incorporated, the marginal revenue product of labor term changes because firms internalize that by increasing employment, they also have to increase wages. As a result, there is an additional wedge due to monopsony power. Monopsony changes the surplus from a match that goes to a firm. The expressions for productivity and the markdown now include variables that are more challenging to estimate in the data such as the matching efficiency, $\phi_j$, and marginal effect of posting an additional vacancy on the wage, $w_v$.

# 6 Conclusion

Over the past decades, there has been a significant increase in wage dispersion across occupations. In this paper, I use a theory-guided accounting framework combined with hand-collected historical labor market data to decompose the observed trends in occupational wages into two groups of explanations: productivity and rent sharing. To this end, I use an equilibrium model of search and matching to derive a mapping from the unobserved wage markdown into a set of observables for each occupation. I implement this decomposition on historical labor market data, including close to 12 thousand job vacancy records from historical newspaper advertisements.

I present two main results. First, dispersion in workers' productivity accounts for most of the occupational wage dispersion in the 1980s and 2000s. Second, changes in the distribution of productivities across occupations account for most of the increase in occupational wage dispersion over time. These findings shed light on the potential drivers behind occupational wage inequality and suggest that technological factors related to productivity, rather than institutional factors related to rent sharing, play a central role.

These findings have direct implications for the role of policy to address rising occupational wage inequality. On one hand, policies that target worker productivity—including training programs and investments in research and development—affect the main driver of occupational wage inequality. On the other hand, policies that target rent sharing—including unions and minimum wages—are less likely to be responsible for the observed pattern of occupational wage inequality, both in the cross section and over time.

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# Appendix

## A Model Expressions for MRPL and Wage Markdowns

Our starting point is the accounting identity for the wage in occupation $j$ in equation (1):

$$w_j = MRPL_j \times \mu_j$$

To derive model expressions for the $MRPL_j$ and wage markdown, $\mu_j$, I combine two equilibrium expressions from the model presented in Section 2. The first equilibrium expression is the free-entry condition in equation (6):

$$J_j^V = 0$$

Substituting the value of a vacancy from equation (5) and rearranging yields the following expression:

$$\kappa_j w_j = q\left(\theta_j\right) J_j^F \tag{9}$$

The left-hand side of equation (9) is the flow cost of maintaining a vacancy, while the right-hand side is the expected flow benefit of maintaining a vacancy. Equation (9) states the familiar condition that, in equilibrium, the flow cost of a vacancy must equal the flow benefit of a vacancy.

The second condition is the value of a filled job in the steady state equilibrium of the model, which, after rearranging, yields

$$J_j^F = \frac{MRPL_j - w_j}{r + \lambda_j} \tag{10}$$

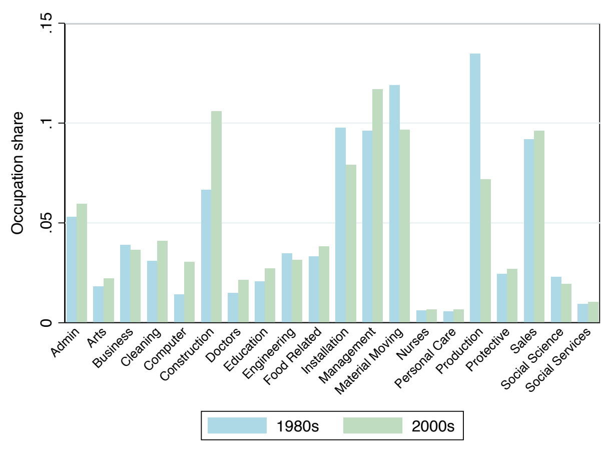
Equation (10) simply states that the equilibrium value of a filled job equals its net present flow value, discounted by the sum of the interest rate and the exogenous job separation rate.

By combining equations (9)–(10) with the accounting identity in equation (1), we arrive at the key expressions in equations (7)–(8) of the main text.

# B Descriptive Statistics

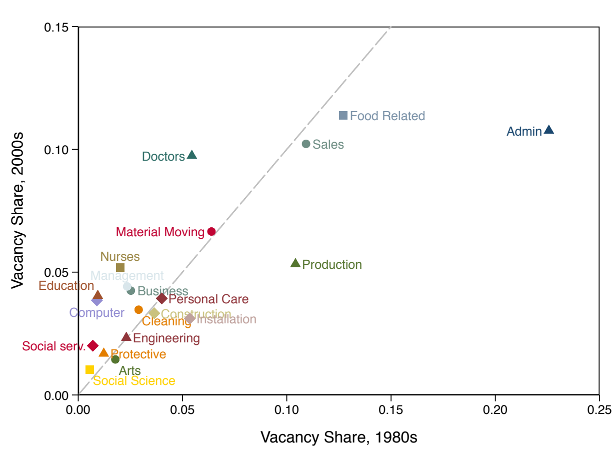
## B.1 National Statistics

**Figure 11.** Distribution of occupations, 1980s and 2000s



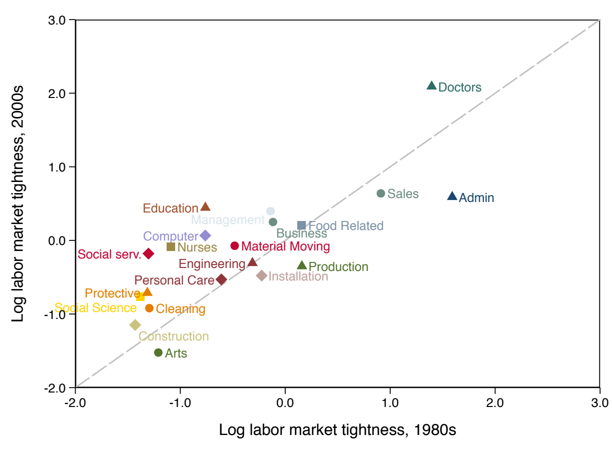

*Notes*: The graph plots the share of each occupation in the 1980s against the 2000s. The shares reflect male workers between ages 16 and 64. Individual CPS weights applied. *Source*: Monthly CPS via IPUMS.

**Figure 12.** Vacancy shares by occupation, 2000s versus 1980s



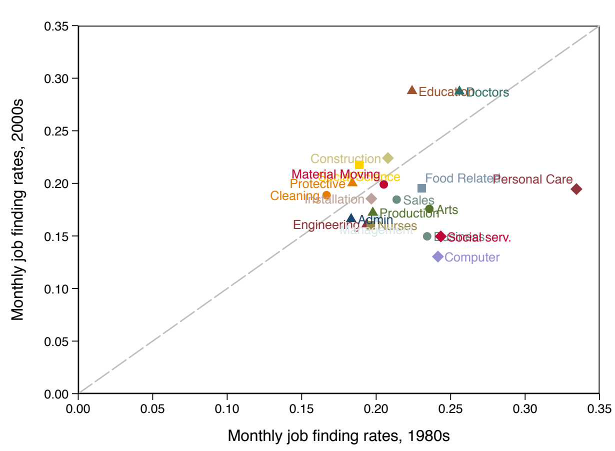

*Notes*: The mean share of vacancies in the 1980s is plotted against that those for the 2000s. The data are from seven states, with weights applied. *Source*: Vacancy shares by occupation for the 1980s are based on job advertisements in newspapers classifieds. Vacancy shares for the 2000s are from business surveys conducted by respective state-level Departments of Labor.

**Figure 13.** Market tightness by occupation, 2000s versus 1980s



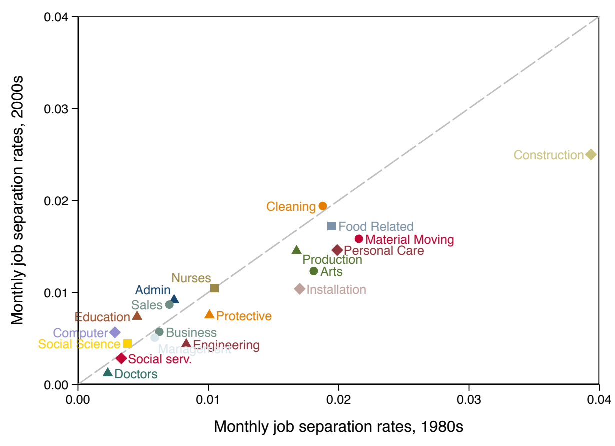

*Notes*: The graph plots the mean of log tightness in the 1980s against the 2000s. Tightness is defined as the share of vacancies divided by the share of unemployed by occupation. *Source*: Vacancy shares by occupation for the 1980s are drawn from newspapers classifieds and for the 2000s from state-level business surveys conducted by respective Departments of Labor. Unemployment statistics are from the monthly CPS via IPUMS.

**Figure 14.** Monthly job finding rates by occupation, 2000s versus 1980s




*Notes*: Monthly job finding rates for men are calculated as workers who were unemployed at month $t$ and employed at month $t+1$. The statistics take advantage of the panel dimension of the CPS. State-level weights applied. Job finding rates are averaged across the 1980s are plotted against those in the 2000s. The 45-degree line is plotted to delineate which occupations saw an increase or decrease in the job finding rate. Computer workers saw the largest decline and education workers the largest increase. *Source*: Monthly CPS via IPUMS.

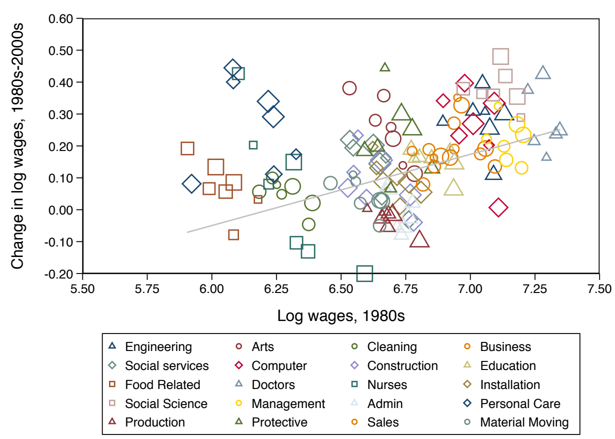
**Figure 15.** Monthly job separation rates by occupation, 2000s versus 1980s




*Notes*: Monthly job separation rates for men are calculated as workers who were employed at month $t$ and unemployed at month $t+1$. Construction workers saw the largest decline in separation rates. State-level weights applied. *Source*: Monthly CPS via IPUMS.

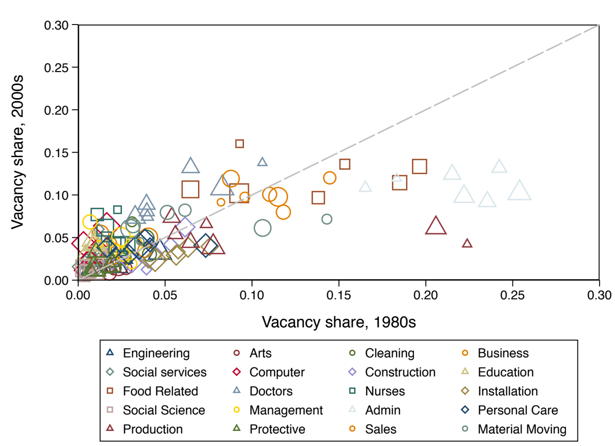
## B.2 State-Level Statistics

**Figure 16.** Wage growth between 1980s and 2000s versus initial wage level, by occupation and state



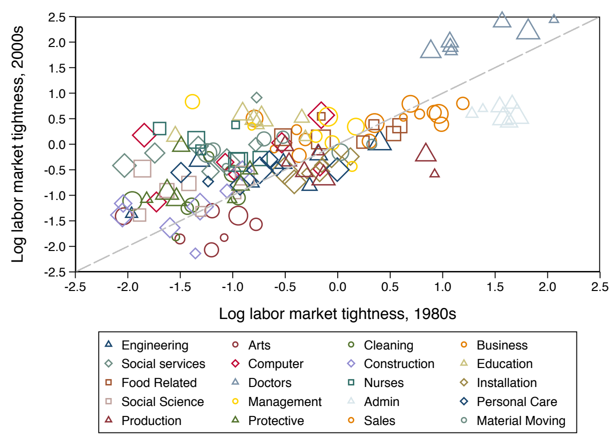

*Notes*: This graph shows average wages at the occupation and state-level. Each color and shape combination reflects an occupation. States are weighted by their population in 2000 and market sizes reflect the relative weights. *Source*: March ASEC of the CPS via IPUMS.

**Figure 17.** Vacancy share by occupation and state, 2000s versus 1980s



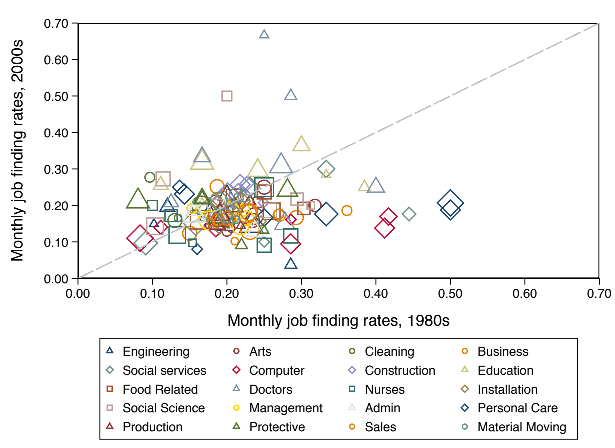

*Notes*: This figure shows the change in vacancies by state and occupation between the 1980s and 2000s. States are weighted by their population in 2000. *Source*: Newspaper job ads for the 1980s and state-level business surveys for the 2000s.

**Figure 18.** Labor market tightness by occupation and state, 2000s versus 1980s



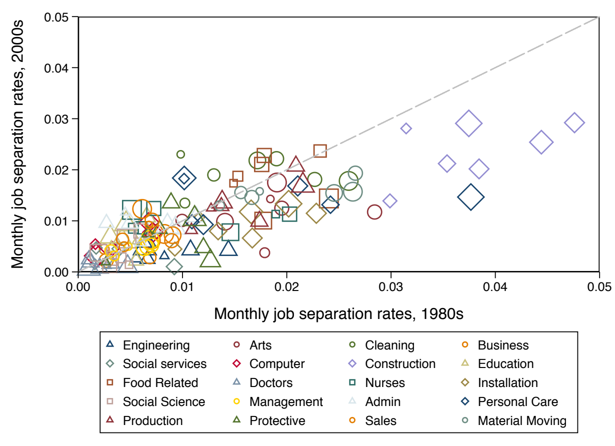

*Notes*: This figure shows the change in log labor market tightness by state and occupation between the 1980s and 2000s. States are weighted by their population in 2000. *Source*: Monthly CPS via IPUMS, newspaper job ads, state-level business surveys.

**Figure 19.** Monthly job finding rates by occupation and state, 2000s versus 1980s




*Notes*: This figure shows the change in job finding rates by state and occupation between the 1980s and 2000s. States are weighted by their population in 2000. *Source*: Monthly CPS via IPUMS.

**Figure 20.** Monthly separation rates by occupation and state, 2000s versus 1980s




*Notes*: This figure shows the change in job separation rates by state and occupation between the 1980s and 2000s. States are weighted by their population in 2000. *Source*: Monthly CPS via IPUMS.

# C Details of the Historical Vacancy Data

**Table 3.** Sources of historical vacancy data for the 1980s

| State | Newspaper | Postings digitized | Source |
|---|---|---|---|
| Kansas | Kansas City Star | 1,713 | https://kclibrary.org/ |
| Minnesota | Star Tribune | 1,791 | https://www.newspapers.com/ |
| Nebraska | Omaha World-Herald | 1,475 | https://www.newsbank.com/ |
| Oklahoma | The Daily Oklahoman | 1,850 | https://www.newspapers.com/ |
| Oregon | The Oregonian | 1,671 | https://www.newsbank.com/ |
| Rhode Island | Providence Journal | 1,345 | https://www.newsbank.com/ |
| Washington | Seattle Times | 1,893 | https://www.newsbank.com/ |
| Total | | 11,738 | |

*Note:* This table shows the sources of vacancy data for the 1980s for the seven states used in the empirical analysis. *Source:* Kansas City Public Library, Newspapers.com, and Newsbank.com.

**Table 4.** Estimated vacancy posting costs by occupation, 1980s and 2000s

| Occupation | 1980s | 2000s | Change, 1980s–2000s |
|---|---|---|---|
| Architecture and Engineering | 0.49 | 0.52 | 0.03 |
| Arts, Design, Entertainment, Sports, and Media | 0.38 | 0.52 | 0.13 |
| Building and Grounds Cleaning and Maintenance | 0.34 | 0.19 | −0.15 |
| Business and Financial Operations | 0.49 | 0.52 | 0.03 |
| Community and Social Services | 0.38 | 0.38 | −0.01 |
| Computer and Mathematical | 0.49 | 0.52 | 0.03 |
| Construction and Extraction | 0.34 | 0.19 | −0.15 |
| Education, Training, and Library | 0.49 | 0.52 | 0.03 |
| Food Preparation and Serving Related | 0.34 | 0.19 | −0.15 |
| Healthcare Practitioners and Technical | 0.49 | 0.52 | 0.03 |
| Healthcare Support | 0.38 | 0.52 | 0.13 |
| Installation, Maintenance, and Repair | 0.34 | 0.19 | −0.15 |
| Life, Physical, and Social Science | 0.49 | 0.52 | 0.03 |
| Management | 0.49 | 0.52 | 0.03 |
| Office and Administrative Support | 0.38 | 0.23 | −0.16 |
| Personal Care and Service | 0.20 | 0.23 | 0.03 |
| Production | 0.34 | 0.19 | −0.15 |
| Protective Service | 0.34 | 0.19 | −0.15 |
| Sales and Related | 0.38 | 0.38 | −0.01 |
| Transportation and Material Moving | 0.34 | 0.19 | −0.15 |

*Note:* This table shows the estimated vacancy posting costs, defined as the fraction of monthly earnings spent on recruiting, for each occupation by period. See text for details. *Source:* Vacancy posting costs for the 1980s are from Barron (1997, Table 7.1). Hours spent on recruiting is multiplied by 1.5 following Manning (2011) and then divided by 40 hours to have a measure of recruiting in terms of monthly earnings (Silva & Toldeo 2009). The cost is rescaled for a coarse set of occupations from Table 7.8 in Barron (1997).