Labor Market Power and Worker Turnover

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Abstract

The last two decades have seen a significant decrease in labor market turnover and an increase in labor market concentration. We investigate whether labor market power, as manifested by employer concentration and outside options, affect turnover rates. Utilizing online vacancy posting data, we find that moving from the 25th percentile to 75th percentile of employer concentration reduces the turnover rate by 5%, driven by high-school workers in low-skill industries. The same exercise for outside options implies a 39% increase in the turnover rate, driven by workers in high-skill industries.
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1 Introduction

Over the last two decades, the labor market has experienced a sustained decline in turnover rates, as documented by numerous studies (e.g., Hyatt and Spletzer, 2013; Molloy et al., 2016; Pries and Rogerson, 2022). Simultaneously, a noticeable rise in employer concentration has emerged, underscoring an augmentation of labor market power (e.g., Bahn, 2018; Shambaugn et al., 2018; Azar et al., 2020, 2022).

Our study delves into the potential contribution of labor market power to the observed downturn in labor market turnover. Drawing inspiration from the work of Lise and Postel-Vinay (2020) and Jarosch et al. (2021), we introduce a theoretical framework that uncovers a negative correlation between labor market power, quantified by employer concentration, and turnover rates. Meanwhile, we show that outside options, measured by the offer arrival rate of other labor markets, act as catalysts for increasing turnover rates.

We measure labor market turnover using the Quarterly Workforce Indicators (QWI) data, which aggregates hires, separations, and employment at the industry and commuting zone level. The turnover rate is defined as the sum of hires and separations divided by employment (Pries and Rogerson, 2022). We define local labor markets at the three-digit-NAICS-industry-by-commuting-zone level. In alignment with our theoretical framework, we focus on empirically measuring two key aspects: employer concentration and outside options. Employer concentration is assessed using the Herfindahl-Hirschman Index (HHI) of vacancy postings (Hershbein et al., 2022), while outside options are quantified by vacancy postings in "nearby" local labor markets, accounting for worker flows between industries. We leverage online vacancy postings data from the Burning Glass Technologies (BGT), which spans the years 2010 to 2019.[1]

To address potential endogeneity issues stemming from common shocks affecting local labor markets, we adopt an instrumental variable approach, following the methodology outlined by Schubert et al. (2021). Specifically, we instrument employer concentration by interacting the nationwide leave-one-out vacancy growth rate of an employer with its predetermined share of vacancies in the local labor market. This instrumental variable predicts local vacancy postings and, consequently, employer concentration, while importantly remaining uncorrelated with local labor market shocks, under the assumption that employers' leave-one-out nationwide vacancy postings are not influenced by local labor market turnover shocks. We instrument outside options using a shift-share instrumental variable, which interacts predetermined shares of vacancy postings with leave-one-out

[1]The BGT data is available for 2007 and from 2010 onward. Two factors lead to the choice of sample period: 1) Our instrumental variables require consecutive data; 2) We avoid the pandemic period.

vacancy postings by industry.

Our baseline results affirm our theoretical predictions: Employer concentration reduces turnover rates, while outside options increase them. Shifting from the 25th to the 75th percentile of employer concentration (outside options) decreases (increases) the turnover rate by 5% (39%).

We further explore the data to uncover three results: First, employer concentration has a more significant impact on reducing the turnover rate among high-school-educated workers, where the decline is a substantial 9%. Second, employer concentration decreases the turnover rate in low-skill industries, whereas outside options increase turnover rates in high-skill industries more, with industry skill requirements gauged using data from O*NET (Guvenen et al., 2020; Lise and Postel-Vinay, 2020). Third, we observe no significant change in posted salaries.

These findings align with the explanation that large employers in low-skill industries can exert greater labor market power, rather than a higher employer concentration leading to higher wages. As a result, we argue that increasing employer concentration could place high-school-educated workers in low-skill industries at a disadvantage.

Our study contributes to the understanding of the causal effects of employer concentration and outside options on turnover rates. While recent theoretical studies suggest a negative relationship between employer concentration and turnover rates (e.g., Bagga, 2023; Berger et al., 2022, in addition to the citations above), empirical estimates quantifying the extent of this relationship have been scarce.[2] Our empirical results offer valuable insights for theoretical studies aiming to comprehend the aggregate impact of labor market power.

Moreover, this study contributes to the broader literature dedicated to understanding the decline in labor market dynamics (e.g., Decker et al., 2017; Pugsley and Şahin, 2019, in addition to the citations above). The empirical results of our study point to employer concentration as a key factor, while also highlighting the varied impacts that span across different levels of worker skills and industry-specific skill requirements. These findings hold particular relevance for policymakers responsible for labor market regulation and oversight, suggesting that efforts to foster competition and curb excessive employer concentration in low-skill industries are vital for safeguarding the well-being of low-skill workers. By doing so, policymakers can mitigate the potential adverse consequences of concentrated labor market power and ensure fairer labor market outcomes for this vulnerable segment of the workforce.

[2] Marinescu et al. (2021) conducted an analysis on the impact of employer concentration on hiring rates using data from France. To our knowledge, there are no other empirical investigations into the effects of labor market power on turnover rates within the U.S. context.

By establishing a connection between employer concentration, turnover rates, and wages, this research aligns with a growing body of literature examining the impact of labor market power on wages (e.g., Lipsius, 2018; Marinescu et al., 2021; Lamadon et al., 2022; Rinz, 2022; Benmelech et al., 2022; Dodini et al., 2023, in addition to the citations above). We demonstrate that the decrease in turnover rates holds significance in understanding how labor market power influences wages, operating through the redistribution of match surplus rather than diminishing employment.

The organization of the rest of the paper is as follows: Section 2 shows the theoretical framework. Section 3 describes the data and our empirical approach. Section 4 presents the results. Section 5 discuss the effects on wages as well as the implication of minimum wages in the calibrated model. Section 6 concludes. Robustness analysis and model details are relegated to the Appendix.

2 Theoretical Framework

To illustrate the link between labor market power, worker turnover, and wages, we propose a stylized theoretical framework. Our model is based on the framework by Lise and Postel-Vinay (2020), employing a granular search approach in which each sector features a finite number of firms. Time is continuous, and the model has a continuum of ex ante homogeneous workers. We initiate our analysis with a single sector with finite number of firms denoted by $j = 1, ..., M$, where firm boundaries are defined by their respective productivity levels, denoted as z_j. Both firms and workers are assumed to be risk-neutral, with a subjective discount rate denoted by ρ.

Unemployed workers receive unemployment benefits b, and they encounter firm j with a probability of λ_j. Upon receiving an offer from a firm, the worker and the firm engage in sequential negotiations to determine the wage contract.

A distinctive feature of our model is that workers can renegotiate when presented with an outside offer. In this scenario, the current firm and the poaching firm engage in Bertrand competition to retain the worker. The arrival rate of offers from each firm is governed by $\{\lambda_j\}_{j=1,...,M}$. Notably, we assume that workers do not receive offers from their current employer, thus ensuring that a firm's vacancy share exerts a non-trivial influence on the offer arrival rate, especially in the presence of a finite number of firms.

In addition to endogenous worker turnover through poaching and job-finding activities, the model incorporates exogenous turnover stemming from separations at a rate of δ.

The match surplus at a firm with productivity z is denoted as $S(z)$. Bertrand competition dictates the allocation of surplus between the worker and the firm, with renegotiations occurring if the worker receives an outside offer. For instance, let's assume the initial wage contract is W. If the worker is poached by another employer with productivity z', the worker will remain with the current employer if $S(z) \geqslant S(z')$ and move to the poaching firm otherwise. In both cases, the worker receives a new wage contract denoted as $W' = \min\{S(z), \max\{S(z'), W\}\}$. Namely, the worker's new wage contract assumes a value equal to the joint surplus at the poaching firm if the worker chooses to stay or the joint surplus at the previous employer if the worker opts to leave.

We denote the worker's share of surplus as η, given by:

$$\eta = \frac{S(z') - U}{S(z) - U} \tag{1}$$

Here, $U = b/\rho$ represents the value of unemployment. Our model, in line with Lise and Postel-Vinay (2020), assumes that this share remains constant when the worker does not receive outside offers.

When a single sector is considered, the joint surplus satisfies the equation:

$$(\rho + \delta)S(z) = y(z) + \delta U \tag{2}$$

The surplus is discounted by the discount factor ρ and the probability of separation δ, when the left-over value becomes δU. The joint surplus is increasing in the flow output $y(z)$, which, in turn, is increasing in firm-specific productivity z. This implies that worker turnover occurs only when the productivity of a potential employer surpasses that of the current one.[3]

Employer Concentration We illustrate how employer concentration affects worker turnovers and wages in the model. To simplify analysis, we assume there are two firms with $z_1 < z_2$.

Let g_1 and g_2 denote the measure of employed workers at firms 1 and 2, respectively, where $g_1 + g_2 = 1 - u$ and u represents the measure of unemployed workers. The offer arrival rates for firm 1 and firm 2 are denoted as λ_1 and λ_2, respectively, with $\sigma_2 \equiv \lambda_2/(\lambda_1 + \lambda_2)$ representing the vacancy share of firm 2. We define the overall offer-arrival rate as $\lambda \equiv \lambda_1 + \lambda_2$, which we assume to be fixed. The measure of labor market power is quantified

[3]In practice, workers might switch from, e.g., larger or higher-paying firms to smaller or lower-paying firms. We extend the model in the Appendix Section B to show how bilateral switching is possible when we add firm-specific human capital and learning on the job. Importantly, the extension does not change the relation between the turnover rate, employer concentration, and wages.

through the Herfindahl-Hirschman Index (HHI) of offer arrival rates, as given by:

$$EC = \sigma_1^2 + \sigma_2^2 = (1 - \sigma_2)^2 + \sigma_2^2 \tag{3}$$

We refer to Equation (3) as employer concentration, which measures the dispersion of offers while keeping the total offer arrival rate fixed. In this simple example, employer concentration is minimized when $\sigma_2 = 0.5$, indicating an equal probability of workers encountering each firm and resulting in an employer concentration of 0.5.

The turnover rate in the model is:

$$\overline{m} = \lambda u + \delta(1 - u) + \lambda \sigma_2 g_1 \tag{4}$$

This equation accounts for job-finding among unemployed workers, exogenous separations among employed workers, and on-the-job switching from firm 1 to firm 2. In the steady state, the first two terms on the right-hand add to a constant because we assume the job-finding rate λ is constant. Therefore, we concentrate on the third term and rewrite the turnover rate as:

$$\overline{m} = \lambda \sigma_2 g_1$$

This simplified expression underscores the dependence of the turnover rate on the vacancy share of firm 2 and the measure of workers in firm 1. While a higher vacancy share of firm 2 tends to increase the turnover rate by allowing workers in firm 1 to switch to firm 2, it's essential to recognize that this effect may be counteracted by a reduction in the measure of workers in firm 1. The rationale is that when a substantial portion of workers is employed in firm 2, and they do not receive offers from their current firm, the turnover rate can decline due to the lack of on-the-job switching.

Appendix Section B provides the full expression for the turnover rate as:

$$\overline{m} = \frac{(\sigma_2 - \sigma_2^2)\delta}{(1 + \delta/\lambda)(\sigma_2 + \delta/\lambda)} \tag{5}$$

We set $\delta = 0.028$ and $\lambda = 0.4$ to align with the separation rate and job-finding rate in the data. We then vary σ_2 from 0.5 to 1, tracing out the turnover rate and employer concentration. This exercise aims to elucidate the relationship between employer concentration and the turnover rate, commencing from a uniformly distributed labor market.

Figure 1 (a) demonstrates a negative correlation between turnover rates and employer concentration. An increase in the proportion of vacancies from firm 2 raises the offer arrival rate, but this is balanced by a decrease in firm 1's workforce. As a result, a rise in employer concentration is associated with a reduction in turnover rates. In the extreme case where firm 2 provides all job offers, there is a complete absence of on-the-job search, leading to minimal turnover.

Concerning average wages, the relationship is less straightforward. Figure 1 (b) indicates a non-linear relationship between employer concentration and average wages.[4] This suggests that a rise in employment at more productive firms does not uniformly translate to increased wages. With higher employer concentration, more workers are employed by the more productive firm 2, allowing more room for possible wage increases. However, this is offset by a decline in competing job offers from firm 1, which limits workers' ability to negotiate higher wages. In the extreme, when firm 2 is the sole job provider, workers are confined to unemployment benefits, as firm 2 has no willingness to share the match surplus with them.

This analysis highlights a complex interplay between employer concentration and wages. Although larger firms typically offer higher wages (e.g., Song et al., 2019), studies show that in contexts of high employer concentration, wages are often lower (e.g., Schubert et al., 2021; Azar et al., 2020). In such markets, large firms, akin to the high-productivity firm 2, pay more on average when concentration is moderate. Yet, extremely high concentration can lead to reduced wages due to larger surplus extraction by firms.

The influence of employer concentration is also dependent on the model parameters, namely the job-finding and separation rates. Lower rates in either reduce the impact of employer concentration. This is because workers with fewer job offers or lower separation rates are more likely to remain with their current employer, diminishing the relevance of the distribution of external job offers.[5]

Outside Option We extend the example to have two sectors to study the impact of outside options on the turnover rate. For simplicity, we assume that the new sector has one firm, and workers in sector 1 accepts offers from the new sector (sector 2) with probability π. The offer arrival rate from sector 2 is γ, which we interpret as an outside option.

In this setup, the turnover rate in sector 1 is expressed as:

$$\overline{m} = (\lambda + \pi\gamma)u + \delta(1-u) + (\lambda + \pi\gamma)\sigma_2 g_1 + \pi\gamma g_2 \tag{6}$$

Equation (6) reveals an unambiguous relationship between the outside option and the turnover rate. Specifically, an increase in the offer arrival rate implies that more workers in sector 1 would opt to switch to sector 2, all else being equal. In our empirical analysis,

[4]The analytic expression of the average wage does not offer many insights, so we leave it to Appendix Section B.

[5]We demonstrate the intuition numerically in Appendix Section B.1.

we normalize the turnover rate by employment, thereby taking into account potential employment declines resulting from reallocations across sectors.

It's important to note that the distinction between employer concentration and outside options hinges on the definition of a "local" labor market. In our model, a local labor market corresponds to a sector, and employer concentration measures the dispersion of job offers within sectors. Conversely, outside options pertain to turnover across local markets. Our choice of a local labor market is elaborated upon in Section 3.

3 Data and Empirical Methods

Motivated by the theoretical framework, we examine the effects of employer concentration and outside options on the turnover rate. We elaborate on our measurement and empirical methodologies in this section.

3.1 Local Labor Markets

Our first task is to define the empirical counterpart of a local labor market. We choose a local labor market to be a three-digit-NAICS-industry-by-commuting-zone cell, which reflects several considerations.

The discussion of labor market power often explicitly or implicit separates labor market at the industry or occupation level (e.g., Hershbein et al., 2022; Rossi-Hansberg et al., 2020). Our choice to focus on the industry level arises primarily from data constraints, as our dataset exclusively records turnover across industries. At this juncture, we focus on three-digit NAICS industries, striking a balance between capturing the effects of employer concentration and the relevance of outside options. Broader categorizations, such as two-digit NAICS industries, encompass many firms within a local labor market, potentially diminishing the impact of outside options, because turnover rates across such broad categories tend to be lower.

On the other hand, adopting a more granular level, such as four-digit NAICS industries, could artificially amplify the influence of outside options while constraining the effects of employer concentration. This limitation stems from the fact that there are fewer firms at this level, resulting in reduced variation in employer concentration within these narrowly defined industries. Moreover, certain four-digit NAICS industries may exhibit substantial overlap in the pool of desired workers, challenging the notion of distinct "local" labor markets (e.g., 3362 Motor vehicle body and trailer manufacturing and 3363 Motor vehicle parts manufacturing). Therefore, we use three-digit-NAICS industry as the baseline definition of local labor markets, while also conducting robustness checks with different aggregation levels.[6]

Geographically, commuting-zone-level analysis integrates the concept that job seekers primarily explore employment opportunities within reasonable commuting distances. This notion aligns with empirical observations suggesting that individuals tend to search for job openings within approximately 10 miles of their residences (e.g., Manning and Petrongolo, 2017; Marinescu and Rathelot, 2018). We include robustness analysis with county and Metropolitan Statistical Area (MSA) level results in Section 4.3.

The definition of local labor markets, as described, implies that employer concentration pertains to the distribution of job offers within each three-digit-NAICS-industry-by-commuting-zone cell, while outside would correspond to job offers in other local markets, namely another industry in the same commuting zone, the same industry in another commuting zone, or both. This definition effectively captures the idea that workers primarily focus their job searches within their local markets, e.g., a three-digit-NAICS-industry-by-commuting-zone cell, with transitions across these markets incurring substantial costs. Throughout the subsequent sections, we will use terms such as "industry-by-CZ local markets" or simply "local markets" interchangeably to denote these units, unless confusion arises.

3.2 Labor Market Turnover

We construct the turnover rate using Quarterly Workforce Indicators (QWI) sourced from the Longitudinal Employer-Household Dynamics (LEHD) database. The LEHD uses quarterly state unemployment insurance (UI) records to identify worker-firm employment spells, which implies that our measure applies only to formal employment.

Our dataset encompasses all US states and spans from 2010 to 2019, aligning with the timeframe of our vacancy postings data and covering workers aged 19 to 54.[7]

The QWI is quarterly data which identifies new hires as worker-firm pairs that show earnings to state UI agencies in one quarter, but do not show such earnings in the preceding quarter. Similarly, separations are worker-firm pairs that show earnings in one quarter, but show no such earnings in the next quarter. Therefore, new hires include job seekers who leave unemployment, as well as reallocation across firms. Similarly, separations could mean that workers join another firm, or enter unemployment.

We define the turnover rate as the sum of new hires H_t and separations S_t over total

[6]Our data only allows analyzing turnover rates at two- and three-digit-NAICS industry levels.

[7]The age bins in QWI are as follows: 14-18, 19-21, 22-24, 25-34, 35-44, 45-54, 55-64, 65-99.

employment E_t:

$$m_t = \frac{H_t + S_t}{E_t} \tag{7}$$

This definition is the empirical counterpart of the turnover rate in Section 2, which has also been used in other studies on the turnover rate, e.g., Engbom (2018) and Pries and Rogerson (2022). We calculate annual averages of the turnover rate to ensure consistency with our measure of employer concentration.

The turnover rate for a given local labor market is denoted as $m_{i,c,t}$, with i and c indexing industry and commuting zone, respectively. As in our theoretical framework, this turnover rate encapsulates worker flows both within local labor markets and across them.

3.3 Employer Concentration

We follow a strand of literature and use online vacancy postings data to measure employer concentration (Hershbein and Kahn, 2018; Azar et al., 2022). Our theoretical framework establishes the link between vacancy concentration and the turnover rate, because the former indicates the extent to which job opportunities come from the same employers.

Specifically, we use the Burning Glass Technologies (BGT) data which contains the near-universe of online vacancy postings in the US. Let $v_{j,i,c,t}$ be the total number of vacancy postings for employer j in industry i and commuting zone c at time t. For each three-digit-NAICS-industry-by-commuting-zone local market, we construct a HHI of vacancy concentration following the theoretical exercise (Equation 3):

$$HHI_{i,c,t} = \sum_j \sigma^2_{j,i,c,t} \tag{8}$$

where the share of vacancy postings by employer j, $\sigma_{j,i,c,t}$, is defined as

$$\sigma_{j,i,c,t} = \frac{v_{j,i,c,t}}{\sum_j v_{j,i,c,t}} \tag{9}$$

We set the frequency of data to be annual for reasons that we explain in detail later in the section.

3.4 Outside Options

Our calculation of workers' outside options involves vacancy postings from other local labor markets, akin to the offer arrival rate within our theoretical framework. We represent this outside option as the weighted sum of vacancy postings in other local markets, with the weights determined by the rate of worker flows between industries:

$$OO_{i,c,t} = \sum_{k \neq i} \pi_{ik} v_{k,c,t} \tag{10}$$

where π_{ik} is the rate of worker flows between industry i and k. The worker flows embed the notion of "distance" between local markets, which is the empirical equivalence of the switching probability in our theoretical framework (Equation 6).

We constructed worker flows between industries using data from the Current Population Survey (CPS) covering the years 2010 to 2019. The CPS categorizes industries using four-digit Census industry codes. We employed a crosswalk provided by the US Census Bureau to convert these codes into corresponding three-digit NAICS industries, achieving a match for 86% (84/98) of these industries.[8] A switch from industry i to k is identified when a worker changes from one three-digit NAICS industry to another between two consecutive months. Worker flows were aggregated using the CPS final weight, and the outflows from each industry were normalized to sum to one, yielding a set of switching probabilities $\{\pi_{ik}\}$.[9]

Table 1 shows that defining local markets by industry or occupation gives similar HHIs, which is consistent with the evidence in Dodini et al. (2023). Approximately half of the markets exhibit HHIs exceeding 2500, a threshold designating "highly concentrated" markets according to the DOJ/FTC guidelines. However, outside options demonstrate significant variation among local markets, with the median market possessing 84 weighted vacancies from other local markets annually, and the 99th percentile reaching 8722. This pronounced skewness underscores the inequality in switching opportunities across local labor markets.

[8]The remaining NAICS industries that have not been matched are primarily concentrated in the finance and public administration sectors, representing 10 of the 14 unmatched industries. This outcome indicates that the matching process has covered a broad spectrum of industries, encompassing both high- and low-skill sectors. The criteria for defining the skill index are elaborated in Section 4.

[9]Appendix Section A.2 uses the Occupation Flow Public Dataset by Schubert et al. (2021) to construct industry flows using

$$\pi_{ik} = \sum_{o \in i} \sum_{p \in k} \delta_o^i \delta_p^k \lambda_{op}$$

where λ_{op} is the worker flow between two occupations at 6-digit SOC level and δ_o^i is the share of occupation o vacancy postings in industry i. While this method enables the construction of flows for all three-digit NAICS industries, it relies on resume data, which may disproportionately represent workers in higher-skill occupations or industries. The results are broadly consistent with the primary method, although notable variances are primarily observed in high-skill industries.

3.5 Empirical Methods

Following Equation (6), our empirical framework is

$$y_{i,c,t} = \alpha + \beta_1 \log\left(HHI_{i,c,t}\right) + \beta_2 \log\left(OO_{i,c,t}\right) + \gamma_{it} + \eta_{ct} + \lambda_{ic} + \Omega X_{i,c,t} + \epsilon_{i,c,t} \tag{11}$$

where γ_{it} are industry-by-year fixed effects, η_{kt} are commuting-zone-by-year fixed effects, λ_{ic} are industry-by-commuting-zone fixed effects, and $X_{i,c,t}$ are time-varying controls at the industry-by-CZ level, to be discussed below.

The presence of common shocks to both the turnover rate and employer concentration could introduce bias to the estimates. For example, if a new restaurant enters a local labor market, there will be an increase in hiring, and, therefore, turnovers, but a decrease in employer concentration.

The outside option index is also subject to the bias of common shocks. Suppose there is a negative shock to industry i, which leads to worker outflows to other industries. If such outflows induce firms in nearby industries to post more vacancies, the negative shock would be correlated with both the turnover rate and outside option index.

To mitigate potential biases originating from common shocks, we employ instrumental variables. These instruments utilize leave-one-out nationwide changes in firms' vacancy postings. Additionally, we adopt shift-share instrumental variables to account for the influence of common shocks on outside options.

3.6 The Employer Concentration Instrumental Variable

Our instrumental variable for employer concentration follows Schubert et al. (2021). Specifically, we write changes in the HHI as:

$$\begin{aligned} \Delta HHI_{i,c,t} &= \sum_j \sigma^2_{j,i,c,t} - \sum_j \sigma^2_{j,i,c,t-1} \\ &= \sum_j \sigma^2_{j,i,c,t-1} \left(\frac{(1+g_{j,i,c,t})^2}{(1+g_{i,c,t})^2} - 1 \right) \end{aligned} \tag{12}$$

Namely, the increase in local employer concentration depends on the initial vacancy share $\sigma_{j,i,c,t-1}$ and the growth rate of vacancies of one employer $g_{j,i,c,t}$ relative to the average vacancy growth rate of the local labor market $g_{i,c,t}$.

We create an instrument for $g_{j,i,c,t}$ by leveraging nationwide changes in vacancies while excluding vacancies in the local market of origin. Specifically, we utilize the growth rate of leave-one-out nationwide vacancies, denoted as $\tilde{g}_{j,i,c,t}$, to predict the employer's vacancy postings in the local labor market when the employer operates in multiple markets.[10] For example, if Walmart has a large share of vacancies in Retail Trade industry in a commuting zone in Arkansas, and if it increases vacancy postings in Retail Trade industry in other parts of the US, it is likely that Walmart's vacancies in Retail Trade industry in the Arkansas commuting zone would also increase, leading to an increase in employer concentration. The instrumental variable $\tilde{g}_{j,i,c,t}$ satisfies the exclusion restriction, assuming that firms' decisions regarding vacancy postings in other markets are not influenced by shocks specific to the originating labor market. In other words, we would like a nationwide shock to Walmart to trigger changes in employer concentration in Retail Trade industry in a commuting zone in Arkansas, instead of a shock to the local market to affect the nationwide operation of Walmart.

Concretely, the instrumental variable for employer concentration is

$$HHI^{IV}_{i,c,t} = \sum_j \sigma^2_{j,i,c,t-1} \left(\frac{(1+\tilde{g}_{j,i,c,t})^2}{(1+\tilde{g}_{i,c,t})^2} - 1 \right) \tag{13}$$

where $\tilde{g}_{i,c,t} = \sum_j \sigma_{j,i,c,t-1} \tilde{g}_{j,i,c,t}$ is the predicted local vacancy growth rate. Equation (13) uses plausibly exogenous "shocks" to local vacancy growth and endogenous "shares" of previous-period local labor market vacancies of each employer. As Borusyak et al. (2022) suggests, we account for potential bias in cases where exposure "shares" do not sum to one by using $\sum_j \sigma^2_{j,i,c,t} \mathbb{I}\left[\tilde{g}_{j,i,c,t} \neq 0\right]$.

In adherence to our theoretical framework, which assumes a constant job-finding rate, we control for the predicted growth rate of total vacancy postings, denoted as $\tilde{g}_{i,c,t}$, in each local labor market in our empirical analysis. This measure additionally accounts for labor demand shocks in local markets. Consequently, our coefficient β_1 is designed to isolate the effects of employer concentration, rather than conflating these with the impact of total vacancy postings.[11] We note that time-varying labor demand shocks at the commuting zone or industry level are effectively absorbed by the fixed effects.

A potential concern relates to the influence of time-varying worker "quality" in each local market, which could bias our estimates. For instance, college-educated workers typically exhibit lower turnover rates, as shown in Table A.10. If the increase in vacancies aligns with a growing demand for college-educated workers, our estimates might reflect

[10] For example, suppose an employer post 10 vacancies in local market A and 5 vacancies in local market B in year $t-1$. The postings are 10 and 6 for these two local markets in year t, respectively. $\tilde{g}_{j,t}$ would be equal to $(6-5)/5 = 0.2$ for local market A and $(10-10)/10 = 0$ for local market B.

[11] To avoid the inclusion of controls correlated with local shocks, we utilize predicted rather than actual vacancy growth rates. Employing actual vacancy growth rates, which are available upon request, yields results that are largely consistent with our primary findings.

these workers' lower turnover rates rather than the direct impact of employer concentration.

To address possible omitted variable bias, we employ two sets of variables: local market time trends and local controls, which include lagged proportions of college-educated workers and vacancies requiring a college degree. The two sets of variables are sequentially incorporated in our robustness analysis.[12]

The choice of the length of a period becomes relevant because we need two periods of data to construct the instrumental variable. The decision to use annual data frequency is justified for two reasons: firstly, the substantial quarterly volatility in vacancies for most employers, often due to seasonal hiring patterns, may not accurately reflect changes in employer concentration; secondly, our instrumental variable approach focuses on vacancy growth rates for large employers. Annual data helps to exclude smaller employers with inconsistent vacancy posting patterns, thus concentrating on firms with more stable hiring activities.[13]

Furthermore, the annual data frequency aligns more closely with our theoretical framework, which is set in a steady-state context. It is plausible that initial vacancy increases at large firms might temporarily boost worker turnover before eventually displacing smaller firms' vacancies.[14] Annual frequency allows for a longer adjustment period in local markets compared to quarterly data.

3.7 The Outside Option Instrumental Variable

We instrument for the outside option index by utilizing the interaction between predetermined vacancy shares and leave-one-out nationwide vacancies at the industry level. The instrumental variable is represented as:

$$OO^{IV}_{i,c,t} = \sum_{k \neq i} \pi_{ik} \frac{v_{k,c,2007}}{v_{k,2007}} v_{k,\not{c},t} \tag{14}$$

where $v_{k,c,2007}/v_{k,2007}$ is the vacancy share for commuting zone c in 2007, which is the first year with available BGT data. $v_{k,\not{c},t}$ is the total vacancy postings in industry k at time t, leaving out commuting zone c.

[12]Appendix Section A.3 demonstrates that vacancy growth at the local market level does not correlate with local controls, suggesting a negligible link between worker quality and vacancy growth in the BGT dataset. This finding alleviates the aforementioned concern. Additionally, our instrumental variables show no correlation with local controls.

[13]Should an employer that initially operates exclusively in one local labor market extend its operations to another, the vacancies it creates in the new market would not influence the instrumental variable during the initial year of expansion. For an employer's vacancies to impact the instrumental variable, it is necessary to maintain a consistent presence of vacancy postings in a given local market for at least two consecutive years.

[14]Bagga (2023) provides quantitative evidence supporting this argument.

Equation (14) is a standard shift-share instrumental variable. For example, Beaudry et al. (2012) employ an instrumental variable similar to ours. The instrumental variable satisfies the exclusion restriction if initial vacancy shares and leave-one-out industry averages of the outcome variable are not subject to shocks to the origination market. This only needs to hold after controlling for fixed effects. For example, industry-by-year fixed effects would capture nationwide shocks to the turnover rate in industry i, and, therefore, the instrumental variable remains valid if it is not correlated with shocks specific to the origination market. We employ the initial vacancy shares from 2007, as the validity of shift-share instruments hinges on the exogeneity of these shares (Goldsmith-Pinkham et al., 2020). We evaluate the extent to which the instrumental variable for outside options is exogenous in Appendix Section A.1.

3.8 Validating the Instrumental Variables

3.8.1 Summary Statistics

Table 2 shows the summary statistics of the instrumental variables, which normalize the employer concentration IV to be from 0 to 10000.[15] Notably, the instrumental variable for employer concentration exhibits a distribution that is less skewed compared to employer concentration itself. Conversely, the instrumental variable for the outside option index displays a distribution similar to its original counterpart.

We also compare geographic distributions of the HHI and its IV, which sheds light on whether employer concentration display some patterns geographically, because such patterns imply that employer concentration could be correlated with area-specific confounds. Figure 2 shows that the Midwest and Southwest regions tend to have high employer concentrations. On the other hand, the HHI IV is more evenly distributed, except for a few markets with very high values. This implies that the variation relies on the changes in the HHI IV, rather than its differences across space, which lends strength to our empirical strategy.

3.8.2 Measurement and Endogeneity

The literature that tries to identify the causal effects of employer concentration either uses firm mergers to study special cases (Arnold, 2020; Prager and Schmitt, 2019), or adopts instrumental variable strategies which we base our analysis on.

[15]We do not normalize the instrumental variables when we implement the regressions.

We prefer the latter approach for two reasons: First, it is more suitable for the purpose of the current study, which tries to understand the heterogeneous effects of employer concentration and outside options on the turnover rate. Restricting the attention to specific mergers would not allow us to compare the effects on, e.g., high-skill versus low-skill industries. Second, we argue that our instrumental variables are less subject to the main drawback of using online vacancy postings, namely that it is not representative of small firms' labor demand, because it mainly uses variations from large employers.

Appendix Section A.1 discusses the identification assumptions in more detail, which suggests that the main concern is the potential link between firms' nationwide vacancy growth and local shocks. If a local shock drives firms' leave-one-out nationwide vacancy postings, the instrumental variable for employer concentration would not satisfy the exclusion restriction. This is particularly likely for moderately sized employers. For example, an employer who operates in only two commuting zones is very likely to increase its leave-one-out vacancy postings if either commuting zone receives a positive demand shock. In this case, a local shock to one commuting zone would spill over to affect the vacancy postings in another one, which would invalidate the instrumental variable.

On the other hand, the concern is alleviated if local shocks are unlikely to drive firms' leave-one-out nationwide vacancy growth. In other words, our instrumental variable would be valid if a shock to, e.g., Walmart drives local employer concentration, but would be otherwise invalid if a local shock drives the leave-one-out nationwide vacancy postings of Walmart. The former scenario is arguably the case for large employers who operate in multiple markets. And then, the instrumental variable for employer concentration resembles a standard shift-share instrumental variable of, e.g., state-level endogenous variables. A shock to one state is arguably unlikely to spill over to all other states. Similarly, a local shock to, e.g., General Merchandise Stores industry in a commuting zone in Arkansas is arguably unlikely to affect vacancy postings in all other local markets of Walmart, which post over 40,000 vacancies annually.

We show in Appendix Section A.6 that the variation in the instrumental variables relies heavily on firms whose total vacancy postings are above the 99th percentile, and we argue that this is ideal for our purpose because: 1) these large employers are more likely to use online platforms for recruiting extensively; and 2) large employer's nationwide vacancies are less likely to be affected by shocks to a single three-digit-NAICS-industry-by-commuting-zone market.

We follow Borusyak et al. (2022) to show further evidence that the instrumental variable for employer concentration might not be correlated with local shocks by examining the correlation between the instrumental variable and various local economic variables, which include the lag of employment-to-population ratio, lag of log posted salary, and lag of fraction of college workers. Appendix Section A.1 shows little evidence of significant correlation.[16] In addition, we note that local shocks at the commuting zone level are absorbed by commuting-zone-by-time fixed effects, such as log GDP, income taxes, minimum wages, etc. Therefore, our instrumental variable for employer concentration could arguably satisfy the exclusion restriction in our context.

Section 4.1 provides three alternative instrument variables. First, we focus only on large employers who operate in at least three local markets and use online vacancy postings extensively. Second, for each employer, we exclude its local market with the most vacancy postings. Third, we split the sample of local markets evenly into two sub-samples and define two instrument variables for the HHI, which allows us to conduct tests of over-identifying restrictions. A unifying aspect of these alternative instrumental variables is establishing robustness when firms' nation-wide vacancy postings are less likely to be affected by single markets.

On the other hand, this means that our identification strategy is unlikely to capture the effects of small changes in employer concentration in unconcentrated markets. However, to the extent that the instrumental variables allow us to estimate the heterogeneous effects of employer concentration, we argue that the analysis offers new insight to the literature.

4 Empirical Results

We discuss the effects on the turnover rate. And then, we show how the effects change with education and the skill content of industries. We leave details of the robustness analysis to Appendix Section A.

4.1 The Effects on the Turnover Rate

Table 3 Column (1) shows the results from the OLS regression. It suggests a negative correlation between employer concentration and the turnover rate. Column (1) also demonstrates a positive cross-sectional correlation between outside options and the turnover rate. However, the estimates may capture the effects of common shocks.

Column (2) presents the results of the two-stage-least-square (2SLS) regression utilizing instrumental variables. It indicates that the effect of employer concentration is larger in

[16] See Appendix Section A.1 for details. Because of data constraints, we do not have many variables at the three-digit-NAICS-industry-by-commuting-zone level, e.g., log GDP. We rely on the available variables in the QWI and BGT data.

magnitude than that in the OLS regression. Moving from the 25th percentile (corresponding to an unconcentrated local market) to the 75th percentile of employer concentration (corresponding to a highly concentrated local market) results in a 5% decrease in the turnover rate.[17] The point estimate for outside options is larger and positive, aligning with our theoretical expectations. A transition from the 25th to the 75th percentile of outside options corresponds to a substantial 39% increase in the turnover rate.[18]

The negative response of the turnover rate to employer concentration could be linked to reduced job-switching opportunities. Specifically, increased employer concentration might restrict workers to remain with their employers, leading to lower wages since job-switchers typically experience wage gains (e.g., Bartel and Borjas, 1981; Altonji and Williams, 1992; Topel and Ward, 1992; Kambourov and Manovskii, 2009).

The magnitude of the positive effect of outside options is notably larger, signifying that workers respond to opportunities outside their local labor markets despite potential switching costs. This heightened effect could be because an increase in vacancy postings in nearby local markets impacts the job-switching prospects of all workers in the focal market. Conversely, the effects of employer concentration are more nuanced, contingent on whether the local market is already concentrated.

Incorporating local market time trends or local controls does not significantly alter the estimates, as evidenced by the similarity in results between Columns (3) and (4) compared to those in Column (2). Consequently, it is unlikely that changes in worker composition are driving the results.

Alternative Instrumental Variables As discussed in Section 3.8.2, the validity of the instrumental variable for employer concentration is predicated on the assumption that nationwide vacancy growths of firms drive local vacancy postings, rather than the reverse. To bolster the credibility of our findings, we explore three alternative methods for constructing the instrumental variable for the HHI.

First, we narrow our focus to employers operating in at least three local markets and posting a minimum of 100 vacancies from 2010 to 2019. This criterion serves to exclude smaller employers who may not extensively use online platforms for recruitment, thereby aligning with the premise that large employers are less influenced by individual local markets. We then utilize these larger employers to construct our instrumental variable (Equation 13).

Secondly, we build on the first condition by excluding the most important local market for each employer when constructing the instrumental variable. This is achieved by

[17] This is calculated using $\log(4664/1013) * 0.0069/0.227$.

[18] This is calculated using $\log(326/24) * 0.0335/0.227$.

aggregating vacancy postings at the employer-industry-commuting-zone level over our entire sample period and identifying each employer's core local market—defined as the market with the highest number of postings.[19] In calculating the nationwide vacancy growth for firms, we disregard postings from these core markets and exclude each firm's data in its core market when constructing the instrumental variable.[20] This approach, while not completely eliminating "spillover" from core markets, ensures that the instrumental variable is less influenced by firms' most pivotal local markets. Essentially, it leverages firms' smaller markets, which are less likely to impact their postings in other markets.

Third, we divide the local markets into two equal sub-samples and create two separate instrumental variables for the HHI, each based on one half of the markets. We then employ the Hansen J statistic for over-identifying restrictions to test if the instrumental variables are appropriately independent of the error process, indicative of large employers not being overly influenced by individual localities.

Specifically, our instrumental variables for employer concentration are:

$$HHI^{IV,1}_{i,c,t} = \sum_j \sigma^2_{j,i,c,t-1}\left(\frac{(1+\tilde{g}^1_{j,i,c,t})^2}{(1+\tilde{g}^1_{i,c,t})^2} - 1\right), \quad ,HHI^{IV,2}_{i,c,t} = \sum_j \sigma^2_{j,i,c,t-1}\left(\frac{(1+\tilde{g}^2_{j,i,c,t})^2}{(1+\tilde{g}^2_{i,c,t})^2} - 1\right) \tag{15}$$

where $\tilde{g}^1_{j,i,c,t}$ is the leave-one-out sub-sample-wide vacancy growth for firm j in the first half of the local markets.[21] The calculation for $\tilde{g}^2_{j,i,c,t}$ follows a similar process.[22] We incorporate both intrumental variables in our 2SLS regression and repeat the analysis 100 times with randomly divided samples, and we present the distribution of the Hansen J statistics.

Table 4 shows these results, with Column (3) showing the median estimates for the HHI and outside options when the sample is split. These alternative instrumental variables yield coefficients similar to those in the baseline results (Table 3 Column 2). Figure 3 illustrates the distribution of Hansen J statistics, with 93% of the instances not rejecting

[19]For example, if a firm has the highest number of postings in market A compared to market B, market A is considered its core market. In cases where there is a tie in postings across multiple markets, all such markets are designated as core.

[20]For example, suppose a firm posts 4, 3, 2 vacancies in market A, B, and C, respectively, at time t, with its core market being market A. The firm's nation-wide leave-one-and-core-out vacancies would be 2 for market B and 3 for market C. We excluded the firm when calculating the instrumental variable for market A, so that the firm's vacancy postings in its core market do not drive any variation.

[21]As an example, consider a scenario with four local markets divided into two sub-samples: A and B, C and D. If a firm posts vacancies in these markets as 1, 2, 3, and 4 respectively, its leave-one-out sub-sample-wide vacancy would be $(1+2)-1=2$, $3-2=1$, $3-3=0$, $3-4=-1$ for $HHI^{IV,1}_{i,c,t}$, and $(3+4)-1=6$, $7-2=5$, $7-3=4$, $7-4=3$ for $HHI^{IV,2}_{i,c,t}$. We omit any observations with negative leave-one-out sub-sample-wide vacancies.

[22]Accordingly, $\tilde{g}^s_{i,c,t} = \sum_j \sigma_{j,i,c,t-1}\tilde{g}^s_{j,i,c,t}$, $s = 1, 2$.

the hypothesis that the instrumental variables are independent of the error process. This robustness analysis lends further credibility to our identification strategy.

Heterogeneity We estimate the effects separately for college-educated and high-school-educated workers. The regression include workers of all ages because the QWI does not aggregate by age and education. Therefore, the estimates are not comparable to that in Table 3 Column (2) which applies to younger workers whose turnover rates are more sensitive (e.g., Liu, 2022a).

We separately calculate the HHI and outside options for college-educated and high-school-educated workers.[23] Table A.10 shows the distribution of HHI, outside options, and turnover rates segmented by educational level. We observe that the HHIs for both high-school and college-educated workers are comparably similar. The summary statistics indicate a decrease in the turnover rate with the inclusion of older workers in the sample.

Columns (5) and (6) show the results for high-school workers and college workers, respectively, which suggests that the effects of employer concentration are approximately 98% stronger for high-school-educated workers than for college-educated workers. These estimates imply that transitioning from the 25th to the 75th percentile of employer concentration decreases the turnover rate of high-school-educated workers by 9%.[24] This suggests that heterogeneous responses by workers' educational attainment could be important for understanding the negative effects on the turnover rate.

Next, we compare the effects based on the skill content of industries, shedding further light on which sectors see the most negative effects of employer concentration on the turnover rate. We construct a skill index for each industry using O*NET data (e.g., Guvenen et al., 2020), where we calculate the skill requirements of each occupation along three dimensions: cognitive, manual, and inter-personal skills. We aggregate the skill requirements of each occupation to the industry level by calculating the occupation vacancy shares of each industry and then weighting each skill by its productivity in Lise and Postel-Vinay (2020).[25]

[23]Vacancy postings, as well as worker flows are separately calculated by workers' education. Detailed methodologies and data pertaining to these calculations are provided in Appendix Section A.7. The BGT data has education requirement for a job posting. Note that the HHI for college workers remains the same as that in the baseline, as college workers could in principal apply to jobs requiring a high-school degree.

[24]This is calculated using $\log(4634/1007) * 0.0119/0.198$. The relevant HHI and turnover rate are in Table A.10.

[25]For example, suppose the vacancy postings in Finance and Insurance industry is 40% in management occupation and 60% in financial operations occupation. Further suppose the management occupation's skill intensity is 0.5 in cognitive skills, 0.1 in manual skills, and 0.6 in inter-personal skills. The numbers for financial operations occupation are 0.6, 0.1, 0.4. This implies that the skill index for the finance and insurance industry is

$$40\% * (0.5 * p_{cognitive} + 0.1 * p_{manual} + 0.6 * p_{inter-personal}) + 60\% * (0.6 * p_{cognitive} + 0.1 * p_{manual} + 0.4 * p_{inter-personal})$$

Industries with the highest skill indices include Space Research, Lessors of Nonfinancial Intangible Assets, and Computer and Electronic Product Manufacturing, while those with the lowest skill indices comprise Personal and Laundry Services, Couriers and Messengers, and Accommodation.[26]

We divide industries evenly into three groups based on their skill index: high-skill, medium-skill, and low-skill industries. For each group, we estimate the effects of employer concentration and outside options on the turnover rate of workers aged 19 to 54. We use the HHI, outside options, and turnover rate by industry skills in Table A.11 when interpreting the coefficients.

Columns (7) to (9) of Table 3 present the results, revealing two key patterns. First, the negative effect of employer concentration is more pronounced in low-skill industries, indicating that transitioning from the 25th to the 75th percentile of employer concentration leads to a 7% reduction in the turnover rate.[27] On the other hand, the turnover rate in high-skill industries does not respond to changes in employer concentration, as the point estimate is small and statistically insignificant. The comparison is consistent with the employers exercising greater labor market power in low-skill industries by reducing competing vacancies and turnover opportunities. However, large employers in low-skill industries may retain workers by offering higher wages, which we examine in Section 4.2.

Second, the effect of outside options is more substantial in high-skill industries. The large point estimate in Column (7) suggests that a transition from the 25th to the 75th percentile of outside options results in a 69% increase in the turnover rate in high-skill industries.[28] This could be attributed to the fact that firms in high-skill industries share similar skill requirements, as evidenced by the data. For example, the top three high-skill industries have similar skill intensity in cognitive skills. Moreover, the occupational composition of high-skill industries may overlap. For example, a software engineer who switches from Google (tech service) to Amazon (retail trade) would contribute to an increase in turnover induced by outside options.

In contrast, the response of the turnover rate to increased outside options is notably smaller in low-skill industries. Specifically, a shift from the 25th to the 75th percentile of outside options results in only a 27% increase in the turnover rate, a figure that is less than half the impact observed in high-skill industries.[29] An explanation is that workers in low-skill industries may switch markets for reasons not directly related to outside options,

where $p_{cognitive}$, p_{manual}, and $p_{inter-personal}$ are the productivity of each skills in Lise and Postel-Vinay (2020).

[26]The rank data is available upon request.

[27]This is calculated using $\log(5000/1007) * 0.011/0.27$.

[28]This is calculated using $\log(333/24) * 0.0458/0.175$.

[29]This is calculated using $\log(308/23) * 0.0282/0.27$.

suggesting that their market-switching decisions could be less influenced by demand factors.[30]

Another factor to consider is the potential bias of BGT vacancies towards high-skill jobs. Consequently, an increase in outside options reflected in online vacancies may not be as relevant for some workers in low-skill industries.[31]

In medium-skill industries, there is no significant response to changes in either employer concentration or outside options, although the direction of the point estimates aligns with those observed in the baseline analysis. Similar to low-skill industries, this lack of significant response in medium-skill industries may be partly attributed to the less precise measurement of outside options for these industries. Additionally, it is plausible that workers in medium-skill sectors tend to transition either to higher or lower-skilled industries, a phenomenon consistent with the findings in Groes et al. (2015).

When examining the combined effects of employer concentration and outside options, our analysis indicates that high-school-educated workers and those in low-skill industries may be more vulnerable to the rising power of employers in the labor market. Because of the importance of low-skill and high-skill industries for understanding the effects of employer concentration and outside options, we focus on the two industry groups to further interpret the results.

4.2 Analysis on the Low- and High-Skill Industry Groups

4.2.1 Low-Skill Industries

In low-skill industries, we observe a substantial decrease in the turnover rate due to employer concentration. This effect is particularly pronounced and could be attributed to the prevalence of high-school-educated workers in these sectors. These workers exhibit greater sensitivity to employer concentration, thereby resulting in a more substantial impact on turnover rates. To further dissect these findings, we stratify the turnover rates in low-skill industries based on the education level of workers, as this is the only available

[30] The relevant local market may also vary depending on the skill level of the industry. For instance, the labor market for low-skill industries might be more localized compared to that for high-skill industries. In Appendix Section A.9, we explore the effects of heterogeneity when local markets are defined at the county level. The findings indicate a marginally greater impact of outside options in low-skill industries, aligning with the hypothesis of smaller local markets for these sectors. Furthermore, the analysis reveals that the influence of employer concentration remains relatively unchanged when the instrumental variable for outside options is excluded.

[31] To the best of our knowledge, comprehensive data measuring the skill content of industry-specific vacancy postings across the entire labor market, beyond online vacancies, is not readily available. In Appendix Section A.4, we compare the distribution of the number of industry vacancies between the BGT data and the Job Openings and Labor Turnover Survey (JOLTS) data, finding no large discrepancies.

measure of skills in the QWI data.

Concretely, we estimate the effects of employer concentration on both high-school and college-educated workers within low-skill industries.[32] The results, presented in Panel A of Table 5, highlight the substantial effects of employer concentration within these industries. Columns (1) and (2) reveal that the effects of employer concentration in low-skill industries are more significant than those in all industries (Table 3 Columns 5 and 6). College-educated workers in low-skill industries experience a 48% more reduction in turnover rates compared to their counterparts in other industries. High-school-educated workers in these sectors still exhibit a more substantial decline in turnover rates than college-educated workers.

Furthermore, the impact of outside options in low-skill industries is only significant for college-educated workers. For high-school workers, while the point estimate remain similar to that in Table 3 Column (9), the decline in precision, possibly because of the smaller sample size, renders the effect insignificant. These findings highlight the importance of interacting education with industry skill contents. Specifically, high-school-educated workers in low-skill industries could suffer the most from an increase in employer concentration, while they receive limited benefits from more outside options, possibly due to factors such as switching costs, limited wage differentials, or mismatch with online job openings.

Given the theoretical framework linking labor market power to wages, we explore the effects of employer concentration and outside options on posted salaries in low-skill industries. The BGT data contains salary information for a subset of vacancy postings, which measures firms' willingness to share match surplus with workers before any bargaining takes place. Panel A, Columns (3) and (4) of Table 5, demonstrate that neither employer concentration nor outside options have a significant impact on posted salaries in these industries. These results suggest that increased employer concentration is not associated with higher wages in low-skill industries.[33]

4.2.2 High-Skill Industries

Turning our attention to high-skill industries, our analysis yields contrasting results, as summarized in Panel B of Table 5. In these sectors, employer concentration does not appear to exert a notable influence on the turnover rate. Instead, the pivotal factor driving turnover rates in high-skill industries is outside options, which significantly elevate them. This effect holds true for both high-school and college-educated workers. Interestingly, the impact

[32]As in Section 4.1, the sample includes workers of all ages.

[33]The insignificant point estimates do not imply that employer concentration has no effect on earnings, because realized earnings might be different. In addition, only a subset of vacancies has salary information.

of outside options on turnover rates is more pronounced among high-school-educated workers. This suggests that while high-school workers do not significantly respond to outside options in low-skill industries, they do so for outside options in high-skill industries, which could reflect the quality of outside option or better measurement of job opportunities.

Furthermore, when examining posted salaries in high-skill industries (Table 5 Panel B, Column 4), we find that outside options have a positive and significant effect on the salaries of college-educated workers. This outcome suggests that increased outside options could enable workers to renegotiate higher wages with firms, potentially motivating firms to offer more attractive compensation packages to retain talent. This phenomenon may also be driven by firms' proactive efforts to counter external job offers and secure valuable human capital.

In summary, our analysis confirms that employer concentration plays a more dominant role in reducing turnover rates within low-skill industries, while outside options emerge as a crucial driver of turnover dynamics in high-skill sectors. Furthermore, the level of education appears to have nuanced effects, with outside options contributing more significantly to the turnover rate of high-school-educated workers in high-skill industries. Additionally, while employer concentration does not significantly impact posted salaries, increased outside options can lead to higher salaries, especially for college-educated workers in high-skill industries.

4.3 Robustness

We conduct robustness analysis with respect to workers' age, the area of local labor markets, and the aggregation level of industries, respectively. We consider seven age groups (19-21, 19-24, 19-34, 19-44, 19-54, 19-64, 19-99), three areas (county, commuting zone, MSA), and two industry code levels (NAICS2, NAICS3).[34]

We summarize the results on the turnover rate. When we vary, e.g., the age groups, we keep the other specifications the same as in Section 4.1. The effects of both employer concentration and outside options are robust across age groups. As expected, the effects are the most significant for younger workers.

We turn to the robustness analysis with respect to the area of local markets. The effects are similar when we define local labor markets at the three-digit-NAICS-industry-by-MSA level, with the estimates equal to -0.0067 (0.0016) and 0.0367 (0.0066) for the HHI and outside options, respectively.

[34]Our choice of the robustness analysis is limited by data availability in the QWI and CPS. For example, the finest industry code level in the CPS is four-digit Census code.

When we define local markets at three-digit-NAICS-industry-by-county level, the estimates are -0.0071 (0.0014) and 0.0361 (0.0046) for the HHI and outside options, respectively. Both estimates are slightly larger in magnitude, which is consistent with employers exercising more labor market power locally and lower costs of switching jobs within county than within commuting zones.

Finally, utilizing local markets defined at the two-digit-NAICS-industry-by-commuting-zone level, we find that estimates for the HHI and outside options are -0.0067 (0.0015) and 0.0290 (0.0055), respectively. These figures are somewhat lower in magnitude compared to our baseline results. This difference might stem from increased switching costs across two-digit NAICS industries, leading to a less pronounced response in workers' turnover rates to vacancies in other industries within this classification. Nonetheless, it is important to note that as long as the HHI and outside options are consistently measured at the corresponding level, their effects do not exhibit significant variation.[35]

5 Discussion

The empirical analysis reveals three results: 1) Employer concentration decreases the turnover rate while outside option increases them; 2) The negative effects of employer concentration are stronger in low-skill industries; 3) The positive effects of outside option are stronger in high-skill industries.

Our heterogeneity analysis leads us to conclude that these findings are indicative of the presence of fewer switching opportunities and slower labor market dynamism. In this section, we forge a link between the influence of employer concentration and outside options on turnover rates and their consequent effects on realized wages. To achieve this, we extend the model presented in Section 2 to incorporate multiple sectors and bilateral switching, subsequently calibrating the model to the U.S. economy for the purpose of conducting counterfactual analyses. We relegate the details of the model to Appendix Section B.

Our calibration process effectively matches worker flows between two-digit NAICS industries, vacancy posting shares within these industries, and average wages across industries. In our counterfactual exercise, we observe that a 5% reduction in the turnover rate due to increased employer concentration results in a 1.1% decline in the average wage.

[35]It should be emphasized that this robustness pertains specifically to the analyses presented above. Adopting alternative definitions of local markets, such as states, could lead to more substantial changes in the effects of employer concentration and outside options. However, as discussed in Section 3.1, we argue that the most pertinent local market for the majority of workers is typically defined at the three-digit-NAICS-by-commuting-zone level.

This outcome signifies that changes in the turnover rate can explain approximately 40% of the overall wage-reducing effect stemming from increased employer concentration.[36] Therefore, the effect on the turnover rate could present an important mechanism through which employer concentration decreases wages.[37]

Our calibrated model also suggests that the effects are more pronounced in sectors characterized by higher concentration and lower productivity. This arises from the fact that less productive sectors experience fewer flows of workers toward more productive sectors, thereby receiving fewer job offers from those domains. Meanwhile, greater concentration restricts the number of offers from other firms within the same sector, further accentuating the decline in wages. These findings resonate with our empirical observations, where we ascertain that high-school-educated workers in low-skill industries are notably affected by employer concentration shocks.

5.1 Sector-Specific Minimum Wages

Given the large effects of employer concentration on turnover rates and wages, we explore the potential policy intervention of sector-specific minimum wages. In Appendix Section B.6, we demonstrate that such sector-specific minimum wages can serve as a lower bound on workers' share of surplus, without dissuading labor market mobility, as shown by Liu (2022b). This is attributed to the fact that more productive sectors tend to exhibit higher minimum wages, and these sector-specific minimum wages do not compress wages by industry.

In the event that we establish sector-specific minimum wages to mirror the value of working at the least productive firms within each sector, we find that a 5% reduction in the turnover rate would result in a mere 0.2% decline in the average wage. While higher minimum wages would lead to enhanced wage gains, they could also contribute to decreased employment levels. Thus, our analysis suggests that sector- or occupation-specific minimum wages hold the potential to address the varying impacts of employer concentration on different segments of the labor market. It's important to note that comprehensive research on the consequences of such minimum wage policies on wages and employment is a subject worthy of exploration, although it falls beyond the scope of this study.

[36] Specifically, Schubert et al. (2021) show that a similar increase in employer concentration to ours would decrease the average wage by 3%.

[37] The magnitude is consistent with theoretical studies with a similar framework. For example, Bagga (2023) employs a granular search model and show that the 20% of the decline in wages because of employer concentration is through declining turnover rates.

6 Conclusion

We estimate the effects of employer concentration and outside options on the turnover rate. Using instrumental variables that utilize plausibly exogenous firm-level nationwide growth in vacancies, we find that employer concentration decreases the turnover rate while outside options increase it. Moving from the 25th to 75th percentile of employer concentration implies a 5% decline in the turnover rate, while the same exercise for outside options increases the turnover rate by 39%. The effects of employer concentration are stronger for low-skill industries and high-school workers.

Furthermore, our quantitative analysis uncovers a relationship between turnover rates and wages. Specifically, we observe that the decline in the turnover rate contributes significantly to wage reductions following an increase in employer concentration, accounting for 40% of the overall wage decline. In light of these findings, we posit that the implementation of sector-specific minimum wages could offer a viable avenue for mitigating the adverse wage effects induced by employer concentration. Moreover, such sector-specific minimum wages have the potential to address the heterogeneous effects of employer concentration across sectors and worker skill levels.

References

Acemoglu, Daron and Jörn-Steffen Pischke, "The Structure of Wages and Investment in General Training," *Journal of Political Economy*, 1999, *107* (3), 539–572.

Altonji, Joseph G. and Nicolas Williams, "The Effects of Labor Market Experience, Job Seniority, and Job Mobility on Wage Growth," *NBER Working Paper*, 1992.

Arnold, David, "Mergers and Acquisitions, Local Labor Market Concentration, and Worker Outcomes," *Working Paper*, 2020.

Azar, José, Ioana Marinescu, and Marshall Steinbaum, "Labor Market Concentration," *Journal of Human Resources*, 2020, pp. 1218–9914R1.

_ , _ , Marshall I Steinbaum, and Bledi Taska, "Concentration in US Labor Markets: Evidence from Online Vacancy Data," *Labour Economics*, 2022, *66.*

Bagga, Sadhika, "Firm Market Power, Worker Mobility, and Wages in the US Labor Market," *Journal of Labor Economics*, 2023.

Bahn, Kate, "Understanding the Importance of Monopsony Power in the US Labor Market," *Technical Report, Washington Center for Equitable Growth*, 2018.

Bartel, Ann P. and George J. Borjas, "Wage Growth and Job Turnover: An Empirical Analysis," in Sherwin Rosen, ed., *Studies in Labor Markets*, University of Chicago Press, 1981.

Beaudry, Paul, David A. Green, and Benjamin Sand, "Does Industrial Composition Matter for Wages? A Test of Search and Bargaining Theory," *Econometrica*, 2012, *80* (3), 1063–1104.

Benmelech, Efraim, Nittai K. Bergman, and Hyunseob Kim, "Strong Employers and Weak Employees: How Does Employer Concentration Affect Wages," *Journal of Human Resources*, 2022, *57*, 200–250.

Berger, David, Kyle Herkenhoff, and Simon Mongey, "Labor Market Power," *American Economic Review*, 2022, *112* (4), 1147–1193.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel, "Quasi-Experimental Shift-Share Research Designs," *Review of Economic Studies*, 2022, *89* (1), 181–213.

Decker, Ryan A., John Haltiwanger, Ron S. Jarmin, and Javier Miranda, "Declining Dynamism, Allocative Efficiency, and the Productivity Slowdown," *American Economic Review*, 2017, *107* (5), 322–326.

Dodini, Samuel, Michael F. Lovenheim, Kjell G. Salvanes, and Alexander Willén, "Monopsony, Job Tasks, and Labor Market Concentration," *NBER Working Paper*, 2023.

Engbom, Niklas, "Firm and Worker Dynamics in an Aging Labor Market," *Society for Economic Dynamics 2018 Meeting Papers*, 2018.

Goldsmith-Pinkham, Paul, Issac Sorkin, and Henry Swift, "Bartik Instruments: What, When, Why, and How," *American Economic Review*, 2020, *110* (8), 2586–2624.

Groes, Fane, Philipp Kircher, and Iourii Manovskii, "The U-Shapes of Occupational Mobility," *Review of Economic Studies*, 2015, *82* (2), 659–692.

Guvenen, Fatih, Burhan Kuruscu, Satoshi Tanaka, and David Wiczer, "Multidimensional Skill Mismatch," *American Economic Journal: Macroeconomics*, 2020, *12* (1), 210–244.

Hershbein, Brad and Lisa B. Kahn, "Do Recessions Accelerate Routine-Biased Technological Change? Evidence from Vacancy Postings," *American Economic Review*, 2018, *108* (7), 1737–1772.

_ **, Claudia Macaluso, and Chen Yeh**, "Monopsony in the US Labor Market," *American Economic Review*, 2022, *112* (7), 2099–2138.

Hyatt, Henry and James Spletzer, "The Recent Decline in Employment Dynamics," *IZA Journal of Labor Economics*, 2013, *2* (5), 1–21.

Jarosch, Gregor, Jan Sebastian Nimczik, and Issac Sorkin, "Granular Search, Market Structure, and Wages," *Working Paper*, 2021.

Kambourov, Gueorgui and Iourii Manovskii, "Occupational Mobility and Wage Inequality," *Review of Economic Studies*, 2009, *76* (2), 731–759.

Lamadon, Thibaut, Magne Mogstad, and Bradley Setzler, "Imperfect Competition, Compensating Differentials, and Rent Sharing in the US Labor Market," *American Economic Review*, 2022, *112* (1), 169–212.

Lipsius, Ben, "Labor Market Concentration does not Explain the Falling Labor Share," *Working Paper*, 2018.

Lise, Jeremy and Fabien Postel-Vinay, "Multidimensional Skills, Sorting, and Human Capital Accumulation," *American Economic Review*, 2020, *110* (8), 2328–2376.

Liu, Andrew Yizhou, "The EITC and Occupational Mobility," *Working Paper*, 2022.

_ , "The Minimum Wage and Occupational Mobility," *International Economic Review*, 2022, *63* (2), 917–945.

Manning, Alan and Barbara Petrongolo, "How Local Are Labor Markets? Evidence from a Spatial Job Search Model," *American Economic Review*, 2017, *107* (10), 2877–2907.

Marinescu, Ioana and Roland Rathelot, "Mismatch Unemployment and the Geography of Job Search," *American Economic Journal: Macroeconomics*, 2018, *10* (3), 42–70.

_ **, Ivan Ouss, and Louis-Daniel Pape**, "Wages, Hires, and Labor Market Concentration," *Journal of Economic Behavior & Organization*, 2021, *184*, 506–605.

Molloy, Raven, Christopher L. Smith, Riccardo Trezzi, and Abigail Wozniak, "Understanding Declining Fluidity in the US Labor Market," *Brookings Papers on Economic Activity*, 2016, *46* (1), 183–237.

Postel-Vinay, Fabien and Jean-Marc Robin, "Equilibrium Wage Dispersion with Worker and Employer Heterogeneity," *Econometrica*, 2002, *70* (6), 2295–2350.

Prager, Elena and Matthew Schmitt, "Employer Consolidation and Wages: Evidence from Hospitals," 2019.

Pries, Michael J. and Richard Rogerson, "Declining Worker Turnover: The Role of Short-Duration Employment Spells," *American Economic Journal: Macroeconomics*, 2022, *14* (1), 260–300.

Pugsley, Benjamin Wild and Ayşegül Şahin, "Grown-Up Business Cycles," *Review of Financial Studies*, 2019, *32* (3), 1102–1147.

Rinz, Kevin, "Labor Market Concentration, Earnings, and Inequality," *Journal of Human Resources*, 2022, *57*, 251–283.

Rossi-Hansberg, Esteban, Pierre-Daniel Sarte, and Nicholas Trachter, "Diverging Trends in National and Local Concentration," in Martin Eichenbaum and Erik Hurst, eds., *NBER Macroeconomics Annual*, Vol. 35, University of Chicago Press, 2020.

Schubert, Gregor, Anna Stansbury, and Bledi Taska, "Employer Concentration and Outside Options," *Washington Center for Equitable Growth Working Paper*, 2021.

Shambaugn, Jay, Ryan Nunn, Audrey Breitwieser, and Patrick Liu, "The State of Competition and Dynamism: Facts about Concentration, Start-Ups, and Related Policies," *Brookings Report*, 2018.

Song, Jae, David J Price, Fatih Guvenen, Nicholas Bloom, and Till von Wachter, "Firming Up Inequality," *The Quarterly Journal of Economics*, 2019, *134* (1), 1–50.

Topel, Robert H. and Michael P. Ward, "Job Mobility and the Careers of Young Men," *The Quarterly Journal of Economics*, 1992, *107* (2), 439–479.

Tables and Figures

6.1 Tables

Table 1: Summary Statistics

Percentile	1	5	10	25	50	75	90	95	99
HHI	44	172	350	1013	2428	4664	6544	7812	10000
Outside Option	0	2	7	24	84	326	1239	2894	8722
Turnover Rate	1.6	3.6	5.8	12.3	22.7	34.2	46.9	56.1	81.6

Notes. Table 1 shows the summary statistics of local markets, which are define at three-digit-NAICS-industry-by-commuting-zone-by-year level. The HHI is constructed using the BGT data and Equation (8). We construct outside option indices using Equation (10). The turnover rate is given by Equation (7), which uses the quarterly QWI data.

Table 2: Instrumental Variables Summary Statistics

Percentile	1	5	10	25	50	75	90	95	99
HHI IV	2764	3683	3965	4262	4272	4501	5130	5788	7795
Outside Option IV	0	2	6	23	83	333	1290	2903	9033

Notes. Table 2 shows the summary statistics of the instrumental variables, which applies to local labor markets at the NAICS-three-digit-industry-by-commuting-zone level. Equation (13) and Equation (14) specify the HHI IV and outside option IV, respectively. We normalize the HHI instrumental variable to be from 0 to 10000 to compare with the HHI.

Table 3: The Effects of Labor Market Power on the Turnover Rate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(HHI)$	-0.0058	-0.0069	-0.0067	-0.0057	-0.0119	-0.0060	-0.0009	-0.0032	-0.0110
	(0.0005)	(0.0016)	(0.0017)	(0.0016)	(0.0025)	(0.0015)	(0.0028)	(0.0034)	(0.0037)
$\log(OO)$	0.0133	0.0335	0.0333	0.0483	0.0223	0.0322	0.0458	0.0092	0.0282
	(0.0029)	(0.0064)	(0.0065)	(0.0067)	(0.0054)	(0.0112)	(0.0133)	(0.0129)	(0.0136)
2SLS		Y	Y	Y	Y	Y	Y	Y	Y
Time Trend			Y						
Local Control			Y	Y					
High-School					Y				
College						Y			
High-Skill Ind.							Y		
Med-Skill Ind.								Y	
Low-Skill Ind.									Y
N	258,491	128,459	128,459	128,459	71,431	128,463	33,150	41,506	52,069
F-Stat		1479	1374	1402	950	1485	525	427	417

Notes. Table 3 shows the effects of employer concentration (Equation 8) and outside options (Equation 10) on the turnover rate, and Equation (7) shows how we use the QWI data to construct the turnover rate. Column (1) shows the results from the OLS regression (Equation 11). Column (2) uses the 2SLS regression and Equation (13) gives the specification of the instrumental variable for the HHI, while Equation (14) specifies the instrumental variable for outside options. Column (2) also controls for the predicted growth rate of total vacancy postings $\tilde{g}_{i,c,t}$. Column (3) adds local market time trends to Column (2) and Column (4) adds the lagged proportions of college-educated workers and vacancies requiring a college degree to Column (3). Columns (5) and (6) study the effects on the turnover rate of high-school workers and college workers, respectively. Columns (7) to (9) examine the effects on the turnover rate in high-skill, medium-skill, and low-skill industries, respectively, and we construct the industry skill index using the skill intensity in the O*NET data, with three dimensions of skills: cognitive, manual, and inter-personal. We take the weight of each skill dimension from Lise and Postel-Vinay (2020). We use heteroskedasticity-robust commuting-zone-clustered standard errors. The reported F-stat for the 2SLS regressions is the Kleibergen-Paap Wald F-statistic. The results of first-stage regressions are in Table A.14.

Table 4: Alternative Construction of Instrumental Variables

	(1)	(2)	(3)
log(HHI)	-0.0073	-0.0051	-0.0075
	(0.0016)	(0.0024)	
log(OO)	0.0338	0.0349	0.0364
	(0.0064)	(0.0065)	
Hansen J> 0.05			0.93
Large Employer	Y		
Drop Core Market		Y	
Split Sample			Y
N	128,129	128,170	
F-Stat	1499	467	

Notes. Table 4 shows the results using alternative construction of the instrumental variable for employer concentration. In Column (1), we only consider employers who operate in at least three local markets and who post at least 100 vacancies from 2010 to 2019. Column (2) further excludes the local markets that account for the highest number of vacancies for each employer, in addition to the criteria set in Column (1). Column (3) splits the sample evenly into two sub-samples and defines two instrumental variables using Equation (15). This random splitting process is conducted 100 times, and the table displays the median estimates derived from these iterations.

Table 5: The Effects of Labor Market Power in Industry Groups by Education

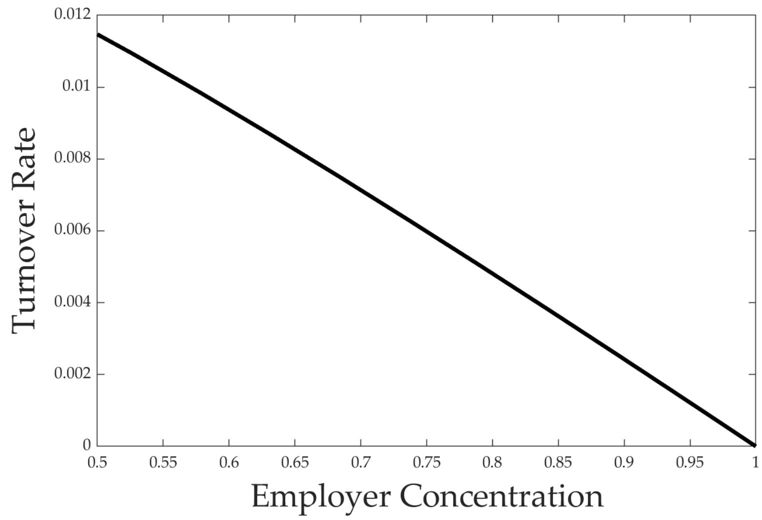
	Panel A: Low-Skill Industries			
	Turnover Rate		Posted Salary	
	(1)	(2)	(3)	(4)
log(HHI)	-0.0120	-0.0089	0.0181	0.0508
	(0.0040)	(0.0034)	(0.0233)	(0.0294)
log(OO)	0.0268	0.0455	0.0635	0.1025
	(0.0176)	(0.0114)	(0.0836)	(0.1079)
2SLS	Y	Y	Y	Y
High-School	Y		Y	
College		Y		Y
N	40,092	52,061	22,986	14,937
F-Stat	345	419	223	168

	Panel B: High-Skill Industries			
	Turnover Rate		Posted Salary	
	(1)	(2)	(3)	(4)
log(HHI)	-0.0088	0.0006	-0.0112	0.0101
	(0.0070)	(0.0023)	(0.0462)	(0.0151)
log(OO)	0.0461	0.0386	-0.2352	0.1059
	(0.0234)	(0.0103)	(0.1819)	(0.0433)
2SLS	Y	Y	Y	Y
High-School	Y		Y	
College		Y		Y
N	10,202	39,052	5,737	19,478
F-Stat	107	582	74	389

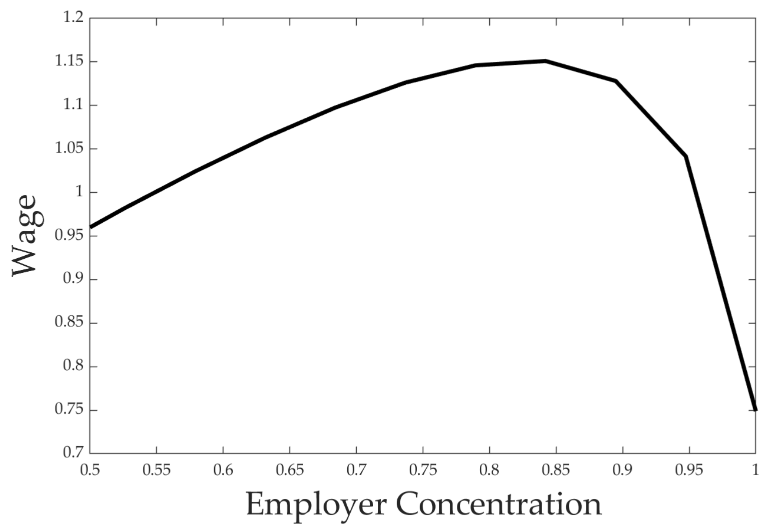
Notes. Table 5 shows the effects of employer concentration and outside options on the turnover rate (Columns 1 and 2) and posted salaries (Columns 3 and 4), separately for high-school and college workers. We use the 2SLS regression (Equation 11), and Equation (13) and Equation (14) construct the instrumental variables. Panel A restricts the sample to low-skill industries, and we construct the industry skill index using the skill intensity in the O*NET data, with three dimensions of skills: cognitive, manual, and inter-personal. We take the weight of each skill dimension from Lise and Postel-Vinay (2020). Panel B restricts the sample to high-skill industries. We use heteroskedasticity-robust commuting-zone-clustered standard errors. The reported F-stat for the 2SLS regressions is the Kleibergen-Paap Wald F-statistic.

6.2 Figures

Figure 1: Employer Concentration, Turnover Rate, and Wage

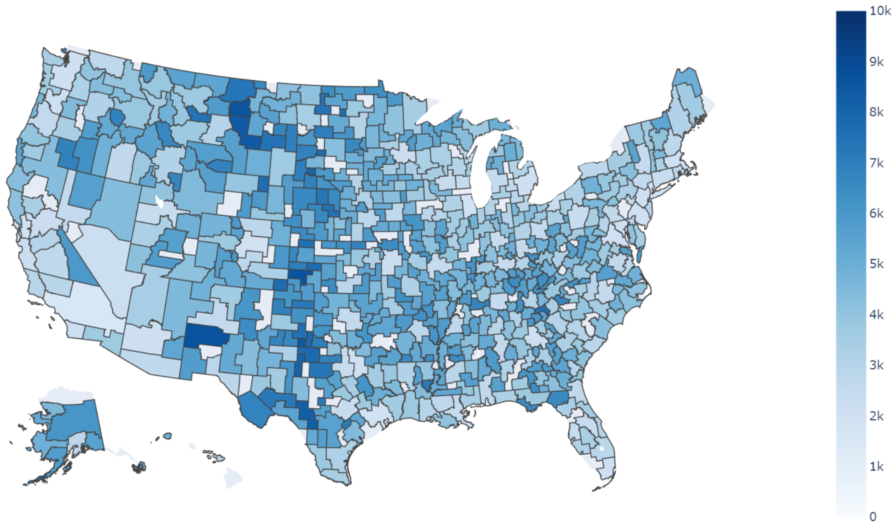


(a) Turnover Rate

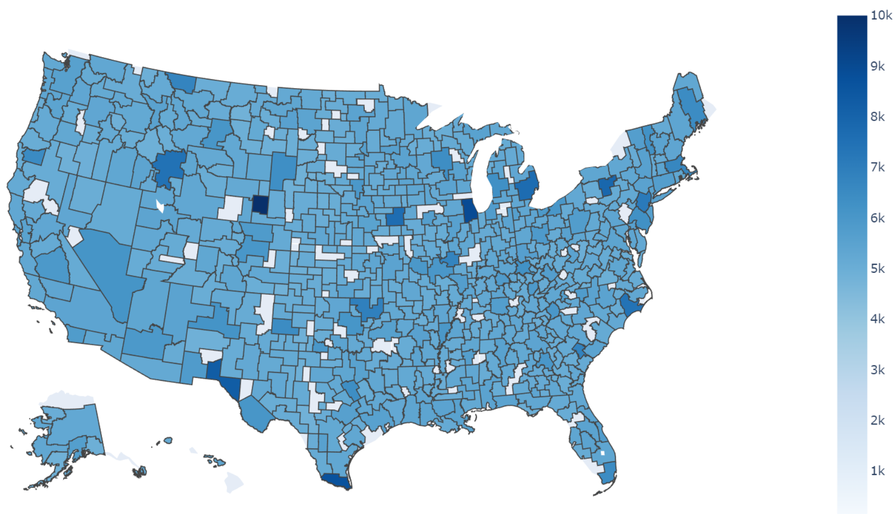


(b) Wage

Figure 2: Geographic Distributions of Employer Concentration



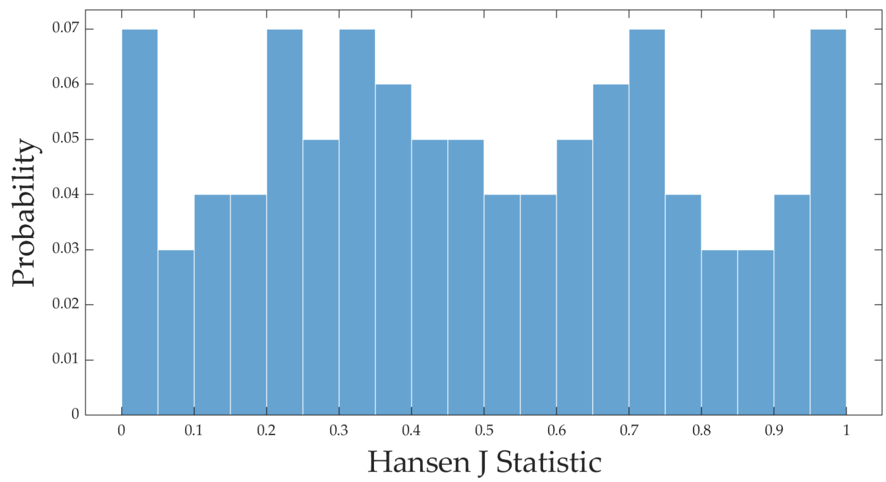
(a) HHI



(b) HHI IV

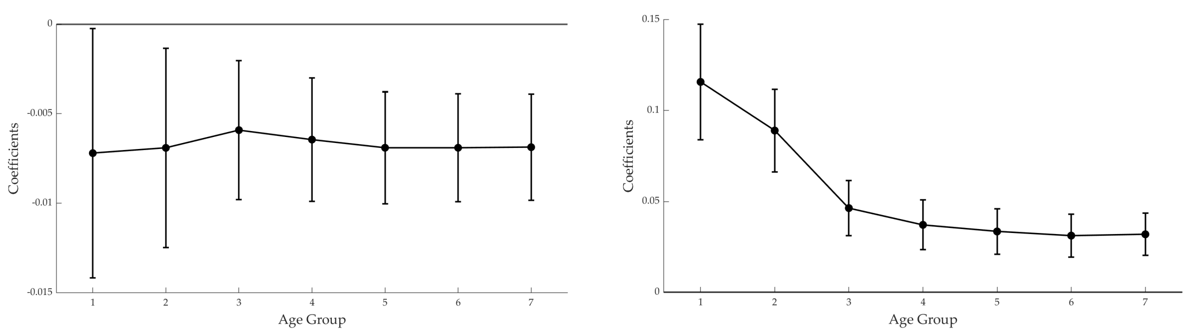
Notes. Figure 2 plots the HHI and HHI instrumental variable by 1990 commuting zone. We average the HHI and HHI IV from 2010 to 2019.

Figure 3: The Distribution of Hansen J Statistics



Notes. Figure 3 plots the distribution of Hansen J statistics when we split the sample evenly into two sub-samples and define two instrumental variables, each based on half of the sample (Equation 15). We repeat the random split 100 times.

Figure 4: The Effects by Age Groups



(a) Employer Concentration

(b) Outside Option

Notes. Figure 4 plots the estimates of employer concentration and outside options on the turnover rate using the 2SLS regression (Equation 11), and Equations (8) and (14) specify the instrumental variables. We define seven age groups (19-21, 19-24, 19-34, 19-44, 19-54, 19-64, 19-99). Figure 4 uses heteroskedasticity-robust commuting-zone-clustered standard errors.

Appendices

A Data Construction Details and Robustness Checks

A.1 Identification Assumptions

A.1.1 Employer Concentration Instrumental Variable

Equation (11) suggests that the exclusion restriction for the instrumental variable on the HHI is

$$Cov\left[HHI^{IV}_{i,c,t}, \epsilon_{i,c,t} | \gamma_{it}, \eta_{ct}\right] = \mathbb{E}\left[\sum_{t=1}^{T} \sum_{i \in N^{ind}} \sigma^2_{j,i,c,t-1} \left(\frac{(1+\tilde{g}_{j,i,c,t})^2}{(1+\tilde{g}_{i,c,t})^2} - 1 \right) | \gamma_{it}, \eta_{ct}\right] \rightarrow 0 \quad \text{(A.1)}$$

Equation (A.1) requires two assumptions to hold: First, the national firm-level vacancy growth is quasi-randomly assigned conditional on industry-by-time, commuting-zone-by-time, and commuting-zone-by-industry fixed effects. In other words, a local shock from a commuting-zone-by-industry submarket cannot cause a nationwide expansion or contraction of the firm. We show in Appendix Section A.6 that the variation in the instrumental variable uses almost exclusively changes in large employers' vacancies, which are arguably less likely to be affected by shocks to a single commuting-zone-by-industry local market.

Second, there needs to be sufficient firm-level shocks to the instrumental variable, and we note that the large F-statistics of the 2SLS results provides support for this assumption.

A.1.2 Outside Options Instrumental Variable

The exclusion restriction for the instrumental variable on outside options is

$$Cov\left[OO^{IV}_{i,c,t}, \epsilon_{i,c,t} | \gamma_{it}, \eta_{ct}\right] = \mathbb{E}\left[\sum_{t=1}^{T} \sum_{i \in N^{ind}} \pi_{ik} \frac{v_{k,c,2007}}{v_{k,2007}} v_{k,\not{c},t} \epsilon_{i,c,t} | \gamma_{it}, \eta_{ct}\right] \rightarrow 0 \quad \text{(A.2)}$$

Equation (A.2) requires two assumptions to hold: First, the national wide leave-one-out vacancy postings $v_{k,\not{c},t}$ is not affected by local vacancy postings in industry i and commuting zone c through a direct channel other than increasing the quality of local outside options $OO^{IV}_{i,c,t}$, conditional on controlling for fixed effects. One case that would violate the assumption is that a positive shock to the turnover rate in, e.g., Retail Trade industry in a commuting zone in Arkansas triggers changes in the average turnover rate in, e.g., Food industry in other commuting zones of the US. We note that our results are robust to varying local markets to be at the MSA or NAICS two-digit industry level, whose leave-one-out average turnover rates are arguably unlikely to be affected by local shocks.

Second, the nationwide leave-one-out mean turnover rates need to be correlated with local turnover rates of industry i in commuting zone c, and our large F-statistics shows that this is likely the case.

A.1.3 Correlation between the Instrumental Variables and Local Shocks

To support our identification argument, we follow Borusyak et al. (2022) and examine the cross-sectional correlation between the instrumental variables and measures of local shocks. Because the commuting-zone-by-time and industry-by-time fixed effects absorb many available variables that approximate local shocks, we rely on our data, namely QWI and BGT data, to construct local shocks. For example, we would like to use log GDP at the NAICS-three-digit-industry-by-commuting-zone level, which is not publicly available to the best of our knowledge. Commuting-zone level GDP would be absorbed by the fixed effects.

We use three variables to proxy local shocks: the lag of employment-to-population ratio, lag of log posted salary, and lag of the fraction of college workers. These variables could capture low frequency changes in local market conditions, while they should not correlate with our instrumental variables if these shocks are indeed local after controlling for fixed effects. The empirical specification is Equation (11) with the instrumental variables Equation (13) and Equation (14).

Table A.1 shows that there is no significant correlation except for the outside option IV on lag of employment-to-population ratio. Therefore, we do not find evidence of confounding factors that could violate the exclusion restriction.

Table A.1: Correlation of HHI IV and Outside Option IV with Local Shocks

	(1) Emp-Pop. Ratio	(2) College Frac.	(3) Salary
$\log(HHI^{IV})$	0.0000	0.0019	0.0013
	(0.0001)	(0.0019)	(0.0008)
$\log(OO^{IV})$	-0.0031	-0.0061	0.0101
	(0.0010)	(0.0147)	(0.0134)
N	136,531	128,654	92,170

In addition, Goldsmith-Pinkham et al. (2020) suggest examining the correlation between the initial vacancy shares and initial local controls to validate the exogeneity of the instrumental variable for outside options. Table A.2 shows that local markets vacancy shares do not significantly correlate with fraction of college workers or log salary in 2007. We note that other local shocks at the industry-by-time or commuting-zone-by-time level should be absorbed by fixed effects in the 2SLS regression. The exercise should further assuage concerns regarding the shift-share instrumental variable for outside options.

Table A.2: Correlation of Initial Vacancy Share and Initial Local Controls

	(1)
Fraction College	0.0024 (0.0016)
Log Salary	0.0006 (0.0004)
N	13,614

A.2 Using Occupation Flow Public Dataset to Construct Outside Options

In this section, we use the Occupation Flow Public Dataset by Schubert et al. (2021) to construct industry flows. Specifically, the flow probability between any two industry is defined as:

$$\pi_{ik} = \sum_{o \in i} \sum_{p \in k} \delta_o^i \delta_p^k \lambda_{op} \tag{A.3}$$

where λ_{op} is the worker flow between two occupations at 6-digit SOC level and δ_o^i is the share of occupation o vacancy postings in industry i. By construction, the outflows from an industry sum to one, so we can compare the results with those using CPS worker flows.

Before moving to the results, we discuss the advantage and disadvantage of using the public dataset. The advantage is that Equation (A.3) allows characterizing flow probability between any two three-digit NAICS industries, whereas we can only match a subset of three-digit NAICS industries using four-digit Census industry code in CPS.

The biggest disadvantage is that the public dataset, which is based on resume data, might not be representative of the flow probability in low-skill industries. For example, workers in low-skill industries might not use resumes as often as workers in high-skill industries. In the extreme case that the resume data misses all switches between jobs in low-skill industries, Equation (A.3) would assign zero probability to flows between low-skill industries. For example, suppose the vacancy postings increase in retail trade industry. For workers in, e.g., transportation industry, it would appear that the change in outside options is minimal. However, the turnover rate, measured using QWI data, is likely to respond in retail trade industry, leading to a small or imprecisely measured effect of outside options.

On the other hand, because the resume data likely over-samples switches between high-skill industries, the effects of outside options in those industries could be exaggerated.

In addition, Equation (A.3) aggregates from occupation flows to industry flows using online vacancy postings, which could further disproportionately represent high-skill jobs, leading to even larger measurement errors.

Table A.3 shows that the results indeed reflect the potential issues with using resume data to measure flow probabilities. The table replicates Table 3, but flow probabilities, and therefore, outside options, are constructed using Equation (A.3).

Table A.3: The Effects of Labor Market Power on the Turnover Rate: Using Resume Data to Construct Flow Probability

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(HHI)	-0.0050	-0.0054	-0.0052	-0.0047	-0.0106	-0.0045	0.0041	-0.0018	-0.0134
	(0.0005)	(0.0015)	(0.0016)	(0.0016)	(0.0023)	(0.0015)	(0.0032)	(0.0031)	(0.0034)
log(OO)	-0.0128	0.0634	0.0662	0.0694	0.0017	0.0354	0.4640	-0.0209	0.0319
	(0.0083)	(0.0219)	(0.0230)	(0.0238)	(0.0296)	(0.0159)	(0.0450)	(0.0309)	(0.0466)
2SLS		Y	Y	Y	Y	Y	Y	Y	Y
Time Trend			Y						
Local Control			Y	Y					
High-School					Y				
College						Y			
High-Skill Ind.							Y		
Med-Skill Ind.								Y	
Low-Skill Ind.									Y
N	288,381	139,549	139,549	139,549	77,875	139,568	39,014	42,959	55,748
F-Stat		1596	1470	1498	1116	1603	577	446	441

There are two main discrepancies between the results in Table A.3 and Table 3. First, the baseline 2SLS regression (Table A.3 Column 2) yields an estimate of outside options to be 0.0634 (0.0219), a number that is almost twice as large as that in Table 3 Column (2). A further examination suggests that the large estimate is driven by that for high-skill industries, shown as 0.4640 (0.0159) in Column (7), whereas the effect is only 0.0458 (0.0112) in Table 3 Column (7). The current estimate suggests that moving from the 25th to the 75th percentile of outside options would increase the turnover rate by 303% in high-skill industries, a number that is likely too large, given that the median turnover rate is 23%. The issue is consistent with the concern that the resume data over-estimates the effects of outside options in high-skill industries.

The second discrepancy is that the standard errors for outside options are larger. For example, the point estimate of outside options in low-skill industries (Table A.3 Column 9) is similar to that using CPS worker flows (Table 3 Column 9), but the former is imprecise and insignificant.

Except for the two discrepancies, most results are consistent using either way of constructing outside options: employer concentration decreases the turnover rate of high-school-educated workers and workers in low-skill industries more, while outside options increase the turnover rate of college-educated workers and workers in high-skill industries more.

This comparison should act as a cautionary note of the limitations inherent in using resume data to estimate flow probabilities between occupations or industries. Such caution is particularly relevant when the outcome variable pertains to the broader labor market dynamics, rather than being narrowly focused on high-skill occupations or industries. This distinction is crucial for ensuring accurate and representative labor market analyses.

A.3 Vacancy Postings Growth and Worker Quality

This section shows the correlation between vacancy postings growth and measures of worker quality in three-digit-NAICS-industry-by-commuting-zone local markets.

Our measures of worker quality include lags of fraction of college workers, fraction vacancies requiring a college degree, and log wage. We note that variation at the commuting-zone-by-time and industry-by-time levels are absorbed by fixed effects. Table A.4 shows no correlation between vacancy growth or its instrumental variable ($\tilde{g}_{i,c,t}$) in a local market and measures of worker quality. Combined with our robustness analysis by controlling for local worker quality, the evidence should assuage concerns that the effects of employer concentration and outside options are driven by changing worker composition.

Table A.4: Correlation Between Vacancy Growth and Worker Quality

	Vacancy Growth	Vacancy Growth IV
Log Wage	-0.0244	-0.0343
	(0.0175)	(0.0296)
Fraction College	-0.0339	-0.0272
	(0.0650)	(0.0941)
Vacancy College	0.0142	-0.0362
	(0.0265)	(0.0222)
N	384,316	384,316

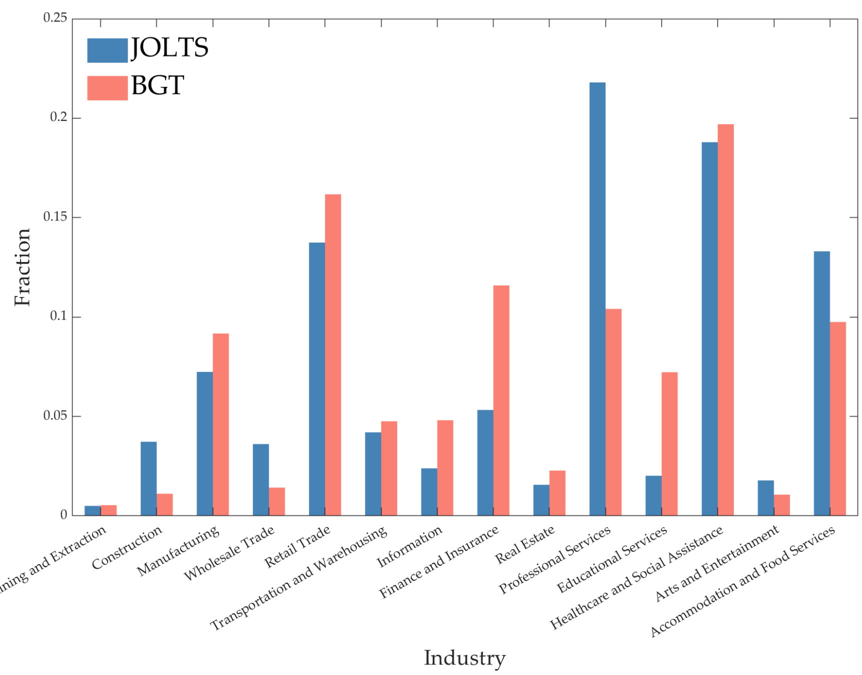
A.4 Comparing BGT and JOLTS Vacancy by Industry

Because the BGT data includes only online vacancy postings, it might not be representative of the full labor market, upon which the QWI turnover rates are based. Specifically, vacancies in BGT could over-represent job openings for high-skill workers.

We note that we are not aware of dataset that characterize the average skill content of job openings in an industry for the entire labor market. The data that has the *number* of job openings by industry is Job Openings and Labor Turnover Survey (JOLTS), which we use to compare with the BGT data in the number of vacancies by industry.

Figure A.1 shows that the two dataset do not differ drastically in the fraction of vacancies by industry. Construction, Finance and Insurance, Professional Services, and Educational Services see the largest difference. However, the differences are not systematic, because JOLTS has more openings in Construction and Professional Services while the BGT data has more openings in the other two industries.

Figure A.1: Comparison of BGT and JOLTS Job Openings by Industry



We note again that the similar does not rule out the possibility that the skill contents of the openings in these two dataset are different. However, to the extent that the BGT data include many openings in low-skill sectors, e.g., Accommodation and Food Services, we argue that the BGT data partially measures the job openings in the whole labor market, which resonates with the conclusion in Hershbein and Kahn (2018).

A.5 Details of the Robustness Analysis

A.5.1 Robustness with Respect to Age

Section 4.3 suggests that we define seven age groups: 19-21, 19-24, 19-34, 19-44, 19-54, 19-64, 19-99. For each age group, we construct the turnover rate at the three-digit-NAICS-industry-by-commuting-zone level, and the HHI is the same as in the baseline. We use turnover rates of the corresponding age group for outside options. Table A.5 shows the point estimates, which use heteroskedasticity-robust commuting-zone-clustered standard errors. The reported F-stat is the Kleibergen-Paap Wald F-statistic.

Table A.5: Robustness with Respect to Age

	Panel A: Turnover Rate						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\log(HHI)$	-0.0072	-0.0069	-0.0059	-0.0064	-0.0069	-0.0069	-0.0069
	(0.0035)	(0.0028)	(0.0020)	(0.0018)	(0.0016)	(0.0015)	(0.0015)
$\log(OO)$	0.1158	0.0890	0.0464	0.0371	0.0335	0.0312	0.0319
	(0.0162)	(0.0116)	(0.0077)	(0.0070)	(0.0064)	(0.0060)	(0.0059)
2SLS	Y	Y	Y	Y	Y	Y	Y
N	97,409	101,297	104,970	126,851	128,459	128,459	128,459
F-Stat	1443	1475	1488	1491	1479	1482	1483

A.5.2 Robustness with respect to Area

We define two areas of local labor markets: County and MSA. For each one, we restrict the QWI sample to workers between age 19 and 54. And then, we construct the turnover rate, short-duration employment rate, HHI, and outside options as in Equations (7), (8) and (10). Equations (13) and (14) specify the instrumental variables. Table A.6 shows the point estimates, which cluster standard errors at the corresponding aggregation level.

A.5.3 Robustness with respect to NAICS Code

We define one aggregation levels of NAICS industry code: NAICS2. We restrict the QWI sample to workers between age 19 and 54. And then, we construct the turnover rate, short-duration employment rate, HHI, and outside options as in Equations (7), (8) and (10). Equations (13) and (14) specify the instrumental variables. Table A.7 shows the point estimates, which use heteroskedasticity-robust commuting-zone-clustered standard errors.

Table A.6: Robustness with Respect to Area

	Turnover Rate	
	(1)	(2)
log(HHI)	-0.0071	-0.0067
	(0.0014)	(0.0016)
log(OO)	0.0361	0.0367
	(0.0046)	(0.0066)
2SLS	Y	Y
County	Y	
MSA		Y
N	247,899	157,267
F-Stat	2025	1423

Table A.7: Robustness with Respect to Industry Level of Aggregation

	Turnover Rate
	(1)
log(HHI)	-0.0067
	(0.0015)
log(OO)	0.0290
	(0.0055)
2SLS	Y
N	86,381
F-Stat	561

A.6 Vacancy Postings by Firms From 2010 to 2019

We aggregate the total vacancy postings by employer from 2010 to 2019. Table A.8 shows the distribution. The total vacancy postings are skewed towards the right, because the median firm posted 2 vacancies while firms in the 99th percentile posted 438 vacancies. Over 25% of employers only posted one vacancy in 10 years, which suggests the importance of large employers in driving employer concentration.

Table A.8: Distribution of Total Vacancy Postings by Employer

Percentile	1	5	10	25	50	75	90	95	99
Total Vacancies	1	1	1	1	2	5	17	47	438

We define large employers to be those whose vacancy postings are above the 99th percentile of vacancy postings distribution. We calculate the fraction of local markets with large and small employers, respectively, to understand the variation in our instrumental variable. Similarly, we decompose the HHI instrumental variable by large and small employers to see which firms contribute to the variation of the HHI instrumental variable.

Table A.9: Fractions of Markets with Large and Small Employers

	$HHI_{i,c,t}^{Large}$	$HHI_{i,c,t}^{Small}$	$HHI_{i,c,t}^{IV\ Large}$	$HHI_{i,c,t}^{IV\ Small}$
Fraction	92.4%	42.7%	37.2%	7.4%

Table A.9 shows that less than half of the markets have small employers, namely those whose total vacancies are below the 99th percentile. This suggests that the BGT data could under-represent the small employers. Meanwhile, the instrumental variable is primarily driven by vacancy postings of large employers, whose presence is five times larger than that of small employers, which makes our instrumental variable more likely to satisfy the exclusion restriction.

A.7 Construction of HHI and Outside Options by Education and Summary Statistics

When constructing the HHI and outside options by education, we utilize the education requirement in the BGT data. For high-school workers, we exclude vacancy postings that require a college degree, and calculate the HHI with the remaining vacancies. We separately aggregate worker flows in CPS based their education attainment, so that the worker flows are specific to high-school- or college-educated workers. After obtaining the worker flows, we calculate the outside options using Equation (10). Table A.10 shows the resulting HHI and outside options, as well as the turnover rate in the QWI data.

Table A.10: Summary Statistics by Education

Percentile	1	5	10	25	50	75	90	95	99
HHI: High-School	41	160	337	1007	2431	4634	6439	7661	10000
HHI: College	44	172	350	1013	2428	4664	6544	7812	10000
Outside Option: High-School	0	2	5	19	65	233	804	1739	5824
Outside Option: College	0	2	7	25	87	350	1358	3210	12022
Turnover Rate: High-School	1.7	4.1	6.5	12.1	19.8	29.2	41.7	51.9	80.3
Turnover Rate: College	1.5	3.7	6.0	11.0	18.3	27.3	39.5	49.3	76.2

A.8 Summary Statistics by Education and by Industry Skills

Table A.11 presents the summary statistics of the HHI, outside options, and turnover rate by industry skills.

Table A.11: Summary Statistics by Industry Skills

Percentile	1	5	10	25	50	75	90	95	99
HHI: High Skill Industries	63	201	369	979	2487	4876	6735	7951	10000
HHI: Mid Skill Industries	69	234	430	1043	2222	4129	6143	7396	10000
HHI: Low Skill Industries	29	113	255	1007	2543	5000	6800	7944	10000
Outside Option: High Skill Industries	0	2	7	24	84	333	1310	3090	11975
Outside Option: Mid Skill Industries	0	2	7	25	86	339	1289	3007	9206
Outside Option: Low Skill Industries	0	2	6	23	81	308	1138	2614	7368
Turnover Rate: High Skill Industries	1.1	2.7	4.6	9.6	17.5	29.2	40.5	52.0	95.0
Turnover Rate: Mid Skill Industries	1.5	4.1	6.9	12.6	19.9	29.2	42.0	55.3	88.3
Turnover Rate: Low Skill Industries	2.6	6.7	10.9	19.8	27.0	39.8	51.0	58.6	76.9

A.9 Heterogeneity Analysis Using County-Level Local Markets

The heterogeneity analysis in Section 4.1 reveals a smaller effect of outside options in low-skill industries. One possibility is that workers in low-skill industries search more locally, so that the attractiveness of job openings quickly diminishes as the distance increases. For example, these workers might not search for jobs that are more than 5 miles away, even if these jobs are in the same commuting zone.

We conduct heterogeneity analysis with county-by-three-digit-NAICS industry local markets, because county is the smallest area of local markets that we have turnover data. Table A.12 suggests that the estimates of outside options are larger for both high- and low-skill industries, which is consistent with a smaller switching cost between jobs within the same county. In addition, employer concentration has a larger impact on the turnover rate, possibly because increasing concentration implies fewer opportunities when the market size is small.

We note that workers in high-skill industries still respond more to outside options than those in low-skill industries, so market size cannot explain the smaller response to outside options in low-skill industries.

Another concern is that the instrumental variable for outside options could correlate with that for employer concentration. This would be case if some firms' vacancy postings are correlated in multiple industries, e.g., Walmart hires more software engineers and

Table A.12: The Effects of Labor Market Power on the Turnover Rate: County-Level Heterogeneity

	(1)	(2)	(3)
log(HHI)	-0.0066	0.0046	-0.0174
	(0.0024)	(0.0031)	(0.0031)
log(OO)	0.0507	0.0112	0.0310
	(0.0089)	(0.0076)	(0.0098)
2SLS	Y	Y	Y
High-Skill Ind.	Y		
Med-Skill Ind.		Y	
Low-Skill Ind.			Y
N	59,073	76,647	106,008
F-Stat	715	553	774

store associates to support the business. We evaluate the extent to which the effects of employer concentration are affected by the instrumental variable of outside options and vice versa by excluding one of the instrumental variables. For example, when using only the instrumental variable for employer concentration, we simply include the non-instrumented outside options in our 2SLS regression (Equation 11)

Table A.13 suggests similar estimates of the instrumental variables to those in the baseline. Despite the correlation between the instrumental variables, their effects on the turnover rate seem to be little affected by such correlation. Such robustness should lend support to a causal interpretation of our instrumental variable regression.

Table A.13: Excluding One Instrumental Variable

	(1) Exclude Outside Options IV	(2) Exclude HHI IV
log(HHI)	-0.0073	-0.0055
	(0.0016)	(0.0005)
log(OO)	0.0112	0.0359
	(0.0031)	(0.0061)
2SLS	Y	Y
N	128,459	258,491
F-Stat	2973	1873

A.10 The Results of First Stage Regressions

We show the results of first stage regressions for Table 3. All other results of first stage regressions are available upon request. We use heteroskedasticity-robust commuting-zone-clustered standard errors. The F-stat reported is the F-test of excluded instruments.

Table A.14: First Stage for Table 3

	Panel A: log(HHI)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(HHI^{IV})	0.1059	0.1048	0.1044	0.0923	0.1057	0.1076	0.0959	0.0830
	(0.0019)	(0.0020)	(0.0020)	(0.0021)	(0.0019)	(0.0033)	(0.0032)	(0.0029)
log(OO^{IV})	-0.2062	-0.2030	-0.2056	-0.1087	-0.2385	-0.4815	-0.3144	-0.1693
	(0.0228)	(0.0237)	(0.0234)	(0.0329)	(0.0232)	(0.0503)	(0.0464)	(0.0457)
Time Trend		Y						
Local Control		Y	Y					
High-School				Y				
College					Y			
High-Skill Ind.						Y		
Med-Skill Ind.							Y	
Low-Skill Ind.								Y
N	128,459	128,459	128,459	71,431	128,463	33,150	41,506	52,069
F-Stat	1479	1374	1402	950	1485	525	427	417

	Panel B: log(OO)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(HHI^{IV})	-0.0015	-0.0015	-0.0016	-0.0012	-0.0015	-0.0021	-0.0021	-0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0004)	(0.0005)	(0.0003)
log(OO^{IV})	0.5774	0.5787	0.5751	0.4495	0.5771	0.7179	0.5276	0.5358
	(0.0142)	(0.0145)	(0.0143)	(0.0159)	(0.0142)	(0.0199)	(0.0194)	(0.0159)
Time Trend		Y						
Local Control		Y	Y					
High-School				Y				
College					Y			
High-Skill Ind.						Y		
Med-Skill Ind.							Y	
Low-Skill Ind.								Y
N	128,459	128,459	128,459	71,431	128,463	33,150	41,506	52,069
F-Stat	1479	1374	1402	950	1485	525	427	417

B Model Details

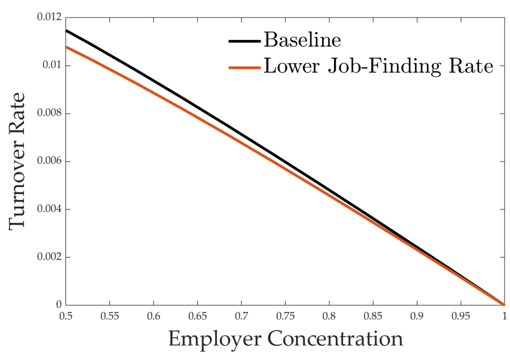
We first show the comparative statics for the example in Section 2. And then, we extend the theoretical framework to the full model in Section 5. We discuss the estimation and the counterfactual exercise of improving hiring technology.

B.1 Comparative Statics of Theoretical Framework

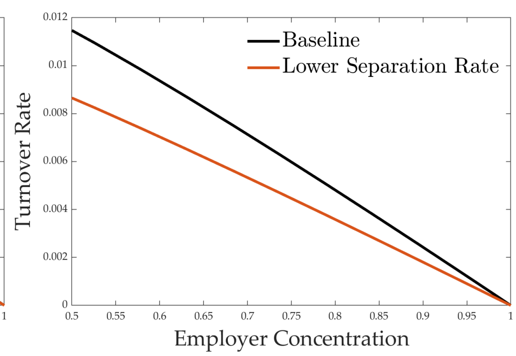
Section 2 argues that a lower job-finding rate or separation rate would reduce the impact of employer concentration, because when workers tend to stay with the current employer, and the distribution of outside offers have smaller impacts on turnovers. We demonstrate the argument numerically.

Figure B.1 plots the cases when we decrease the job-finding rate from 0.4 to 0.3 or the separation rate from 0.028 to 0.02. In both cases, the slope of the curve is reduced compared to that of the baseline ($\lambda = 0.4$ and $\delta = 0.028$), suggesting weaker effects of employer concentration on the turnover rate.

Figure B.1: Comparative Statics



(a) Lower Job-Finding Rate



(b) Lower Separation Rate

One can also prove analytically that the slope of the turnover-rate-employer-concentration curve is increasing in the job-finding rate and separation rate using Equation (5), namely $\partial^2 \overline{m} / \partial \sigma_2 \partial \lambda > 0$ and $\partial^2 \overline{m} / \partial \sigma_2 \partial \delta > 0$. This translates to the smaller (less negative) slope in Figure B.1.

B.2 Full Model Economy

We describe the full model in Section 5 in more detail. Time is continuous. There is a continuum of ex ante homogeneous workers and J sectors. In each sector, there are a finite number of infinitely lived firms, $i = 1, ..., M_j$, that differ in the firm-specific productivity $\{z_i\}_{i=1,...,M_j}$. The notion "firm" here is tied to the pre-determined vector of productivity. While the worker-firm pair could dissolve, the probability that a worker meets with firm i stays the same in the stationary equilibrium. Both firms and workers are risk-neutral with subjective discount rate ρ.

Unemployed workers receive unemployment benefit b and meet firm i with probability $\lambda(z_i)$. Upon receiving an offer from a firm, the worker and the firm determine the wage contract sequentially by mutual agreement as in Postel-Vinay and Robin (2002). Workers can renegotiate upon receiving an outside offer. The current and the poaching firm Bertrand-compete for the worker.

The outside offer can come from other firms in the same sector or employers in different sectors. For the former, the arrival rate of offers is dictated by $\{\lambda(z_i)\}$. Because the number of firms is finite, the fact that workers do not receive offers from the current employer has a non-trivial impact on the probability that they receive outside offers. Outside the worker's sector, firms could poach the worker, but the poaching rate is affected by the probability of switching $\left\{\pi_{j\to k}\right\}$ between sector j and k. Besides endogenous worker turnovers through poaching and job-finding, there are also exogenous turnovers through separation at the rate δ_s and labor market exit at the rate δ_d. New workers enter the labor market at the rate δ_d to keep the measure of workers constant.

Workers can learn on the job. In particular, an employed worker start at a firm with firm-specific human capital $x_{t=0} = \underline{x}(z)$, which evolves according to

$$dx_t = \mu(x, z)dt + \sigma(x, z)dW_t \tag{B.1}$$

Equation (B.1) implies that tenure affects workers' productivity. As workers' skills grow over time, their output also changes. However, the skill accumulation is not deterministic, as it is subject to random shocks given by the Brownian motion process $\{W_t\}$. For simplicity, we assume that workers' firm-specific human capital "resets" if they experience labor market turnovers. This assumption implies two things: 1) If a worker switch to another employer, the worker's firm-specific productivity starts at $\underline{x}(z)$ for that employer; 2) The worker does not retain the firm-specific human capital even if the worker is employed at the same firm in the future.

The first implication resonates with the notion that firm-specific human capitals differ from general human capitals (e.g., Acemoglu and Pischke, 1999). The second implication is stronger, but we note that when a worker is employed at the same employer repeatedly, the worker either was employed in another firm or unemployed. In both cases, the worker could spend sufficient time away from the employer that the firm-specific human capital has depreciated. Our assumption amounts to the extreme case that the depreciation rate is infinity.

Let us use one example to further illustrate what the assumption means. Suppose a retail worker works at Walmart first, switches to Target, and jumps back to Walmart. The worker's general knowledge of retail industry is retained. However, while the worker spends time away from Walmart, the store arrangement or item prices could have changed at Walmart, so that the worker needs to learn them even with past experience.

The initial human capital $\underline{x}(z)$ corresponds to hiring technology. As is clear later in the section, workers' output decreases if the firm-specific human capital is further below the firm's productivity z, which creates switching incentives. On the other hand, if the initial human capital is closer to the firm's productivity, the worker and the firm form a good match in the sense that the output and hence the joint surplus is high, in which case the worker is hard to poach. Hence, an exogenous increase in the initial human capital can be interpreted as an improvement in the hiring technology.

Let the joint match surplus for a worker with firm-specific human capital x at firm z in sector j be $S(x, z, j)$. Bertrand competition implies that the share of surplus allocated to the worker is endogenous. For example, suppose the initial wage contract is W. When the worker is poached by another employer with productivity z' in sector k, the worker stays if $S(x, z, j) \geqslant S(\underline{x}, z', k)$ and moves to the poacher otherwise. In both cases, the worker receives a new wage contract $W' = \min\left\{S(x, z, j), \max\left\{S(\underline{x}, z', k), W\right\}\right\}$. That is, the worker's new wage contract has a value equal to the joint surplus at the poacher if the worker stays or the joint surplus at the previous employer if the worker leaves.

Denote the worker's share of surplus by η, given by

$$\eta = \frac{S(\underline{x}, z', k) - U}{S(x, z, j) - U} \tag{B.2}$$

where U is the value of unemployment. We follow Lise and Postel-Vinay (2020) and assume that this share is constant when the worker does not receive outside offers.

B.3 Equilibrium

We first derive the expression for the joint surplus, given by

$$\begin{aligned}(\rho+\delta_s+\delta_d)S(x,z,j) =& y(x,z,j)+\mu(x,z)\partial_x S+\frac{1}{2}\sigma^2(x,z)\partial_{xx}S+\delta_s U\\ &+\sum_{z'\neq z}\alpha\lambda(z')\mathbb{E}\Big\{\mathbb{I}_{\{S(\underline{x},z',j)>S(x,z,j)\}}[W(x,z',j,\eta)-S(x,z,j)]\Big\}\\ &+\sum_{k\neq j}\pi_{j\to k}\sum_{i=1}^{M_k}\alpha\lambda(z_{ik})\mathbb{E}\Big\{\mathbb{I}_{\{S(\underline{x},z',k)>S(x,z,j)\}}[W(x,z',k,\eta)-S(x,z,j)]\Big\}\\ =& y(x,z,j)+\mu(x,z)\partial_x S+\frac{1}{2}\sigma^2(x,z)\partial_{xx}S+\delta_s U\end{aligned} \tag{B.3}$$

where $y(x,z,j)$ is the output and α is on-the-job-search efficiency. On the left-hand side, the joint surplus is discounted by the subjective discount rate, as well as the separation rate and the labor market exit rate. On the right-hand side, the match receives flow output $y(x,z,j)$, and workers' skill evolution implies that the value of the joint surplus is also changing overtime. When the worker is unemployed, the joint surplus becomes the value of unemployment. The second line in Equation (B.3) shows the value paid to the worker when there are offers from other firms in the same sector. Conditional on the joint surplus of the offer being greater than the current joint surplus, the worker would turnover to the other firm and get $W(x,z',j,\eta)$. Similarly, the third line represents the change in the joint surplus if the worker receives offers from firms in other sectors, where $\pi_{j\to k}$ is the probability of switching from sector j to sector k. The offer arrival rates are given by $\{\lambda(z')\}$ and $\{\lambda(z_{ik})\}$.

Bertrand competition is particularly useful because the value of switching to other employers, whether within the same sector or across sectors, drops out. The poacher always offers the worker the current joint surplus as the initial wage contract. Employer switching hence affects the allocation of workers but not the joint surplus. In particular, the share of surplus pledged to the worker is irrelevant for mobility.[38] Equation (B.3) line 2 makes it explicit that the worker does not receive offers from the same employer.

The value of unemployment solves

$$(\rho+\delta_d)U=b \tag{B.4}$$

Similar to the joint value, the value of finding a job drops out because the employer offers

[38] Workers' share of surplus is relevant for wages on the other hand.

the worker the value of unemployment. Together with worker homogeneity, the value of unemployment is independent of sectors.

For an employed worker, let $w(x,z,j,\eta)$ be the wage function that delivers the wage value $W(x,z,j,\eta) = U + \eta[S(x,z,j) - U]$, which satisfies

$$
\begin{aligned}
(\rho + \delta_s + \delta_d)W(x,z,j,\eta) =& w(x,z,j,\eta) + \mu(x,z)\partial_x W + \frac{1}{2}\sigma^2(x,z)\partial_{xx}W + \delta_s U \\
&+ \sum_{z' \neq z} \lambda(z')\mathbb{E}\Big\{\mathbb{I}_{\{S(x,z,j) \geq S(\underline{x},z',j)\}}\big[S(\underline{x},z',j) - W(x,z,j,\eta)\big]\Big\} \\
&+ \sum_{k \neq j} \pi_{j \to k} \sum_{i=1}^{M_k} \lambda(z_{ik})\mathbb{E}\Big\{\mathbb{I}_{\{S(x,z,j) \geq S(\underline{x},z',k)\}}\big[S(\underline{x},z',k) - W(x,z,j,\eta)\big]\Big\}
\end{aligned}
\tag{B.5}
$$

The worker's wage contract or value of employment changes because of flow wages, skill accumulation, separation, and labor market exit. On the second line, when the worker is poached by another employer in the same sector, the worker receives a new wage contract if the current employer successfully retains the worker. Otherwise, the worker leaves and receives a value of employment that is equal to the current wage contract. The third line is similar and corresponds to poaching from other sectors.

The wage function makes Equations (B.3) to (B.5) and $W(x,z,j,\eta) = U + \eta[S(x,z,j) - U]$ hold continuously, which implies that the wage function is

$$
\begin{aligned}
w(x,z,j,\eta) =& \eta y(x,z,j) + (1-\eta)b \\
&- \sum_{z' \neq z} \alpha\lambda(z')\mathbb{E}\Big\{\mathbb{I}_{\{S(x,z,j) \geq S(\underline{x},z',j)\}}\big[S(\underline{x},z',j) - \eta S(x,z,j) - (1-\eta)U\big]\Big\} \\
&- \sum_{k \neq j} \pi_{j \to k} \sum_{i=1}^{M_k} \alpha\lambda(z_{ik})\mathbb{E}\Big\{\mathbb{I}_{\{S(x,z,j) \geq S(\underline{x},z',k)\}}\big[S(\underline{x},z',k) - \eta S(x,z,j) - (1-\eta)U\big]\Big\} \\
=& \eta y(z,x,j) + (1-\eta)b
\end{aligned}
\tag{B.6}
$$

The second line and the third line drop because of the definition of η. Equation (B.6) shows that the wage function is simple and intuitive under Bertrand competition. It is the weighted average of the output and the unemployment benefit where the weight η is endogenous and depends on the worker's offer history. The wage function is increasing with outside offers because the share of surplus pledged to the worker increases. Skill accumulation is also important because it affects the flow output.

In the simple example in Section 2, we can solve analytically for the average wage as a function of the fraction of vacancy postings by firm 2 σ_2:

$$
\begin{aligned}
\overline{w} =& b\left[\frac{1}{(1+(\delta_s/\lambda)^{-1})(\sigma_2+\delta_s/\lambda)}+\frac{\sigma_2}{(1-\sigma_2+\delta_s/\lambda)(1+(\delta_s/\lambda)^{-1})}\right] \\
&+w'\left[\frac{\sigma_2}{(1+\delta_s/\lambda)(\sigma_2+\delta_2/\lambda)}+\frac{\sigma_2-\sigma_2^2}{(1-\sigma_2+\delta_s/\lambda)(1+\delta_s/\lambda)}\right]
\end{aligned}
\tag{B.7}
$$

The average wage is non-monotonic with respect to the vacancy share of firm 2. At one extreme when the share is 0, workers are either unemployed or employed in firm 1, where their wage is b regardless. At the other extreme when the share is 1, there is no poaching, so that all workers earn b as well.

Let the joint distribution of worker skills, firm productivity, and workers' share of surplus be $\{g(x,z,\eta,j)\}_{j=1,\dots,J}$. In the stationary equilibrium, the joint distribution solves

$$
\begin{aligned}
0 =& -\partial_x[\mu(x,z)g(x,z,\eta,j)]+\frac{1}{2}\partial_{xx}\left[\sigma^2(x,z)g(x,z,\eta,j)\right]-(\delta_s+\delta_d)g(x,z,\eta,j) \\
&-\sum_{z'\neq z}\alpha\lambda(z')g(x,z,\eta,j)-\sum_{k\neq j}\pi_{j\to k}\sum_{i=1}^{M_k}\alpha\lambda(z_{ik})g(x,z,\eta,j), \quad x>\underline{x}
\end{aligned}
\tag{B.8}
$$

The joint distribution changes because of skill accumulation and worker turnovers. Because workers reset their skills after switching employers, whenever $x > \underline{x}(z)$, there is no inflow of workers due to turnover.

At $x = \underline{x}(z)$, two cases occur. The first case relates to employed workers switching employers, corresponding to $\eta > 0$. There is inflow of workers from other employers that are poached away by firm z in sector j. The second case corresponds to unemployed workers finding jobs, i.e. $\eta = 0$.

A stationary equilibrium is defined as a collection of value functions $\{S, U, W\}$, a collection of job-finding rates $\{\lambda(z)\}$ and switching probabilities $\{\pi_{j\to k}\}$, and the joint distribution $\{g(x,z,j,\eta)\}$ such that Equations (B.3) to (B.6) are satisfied, together with Equation (B.8). We will regulate the job-finding rates and the switching probabilities directly by data instead of using equilibrium equations such as the free-entry condition.

This simplifies computation without affecting our purpose: we can easily impose the free-entry condition by adding costs of switching and vacancy postings, in which case the job-finding rates and the switching probabilities will be determined by those switching costs. However, since we are not interested in how changes in switching costs affect the equilibrium turnover rate and wages, we directly specify the job-finding rates and switching probabilities.

B.4 Model Estimation

We estimate the model using simulated method of moments. We include 13 industry groups based on 2-digit NAICS industry code, given in Table B.1. For each industry group, there are four levels of productivity, normalized to be $\{0.2, 0.4, 0.6, 0.8\}$. We calculate the productivity distribution of industry vacancy postings using the wages in the BGT vacancy postings, with the wage intervals being \$0-\$30000, \$30001-\$60000, \$60001-\$100000, >\$100000.

Table B.1: Industry Groups

NAICS Two-Digit Industry Code		
21	48 & 49	56
23	51	61
31 & 33	52 & 53	71 & 72 & 81
42	54	
44 & 45	55	

We set the discount rate ρ to be 0.002, corresponding to a risk-free rate of 2% per annum. We calculate the separation rate using CPS from 2010 to 2019, which is equal to 0.028. The labor market exit rate is 0.0028, implying a working life of 30 years.

We parameterize the drift of the firm-specific human capital to be

$$\mu(x, z) = \zeta \max\{z - x, 0\} \tag{B.9}$$

where ζ is the skill growth rate if the worker's human capital is below the firm's productivity z. Namely, the worker's firm-specific human capital evolves towards the firm's productivity. The volatility of the human capital growth is set to be a constant σ_x. We set the moment targets for ζ and σ_x to be the mean wage growth and the standard deviation of wage growth.

The production function has the following form:

$$y(x, z, j) = p_j - \gamma_1 \max\{z - x, 0\}^2 + \gamma_2 z x \tag{B.10}$$

p_j is industry-specific productivity. Workers with lower human capital have lower productivities, with the penalty parameter given by γ_1. High productivity firms and workers with high human capital are complementary if $\gamma_2 > 0$. We compute $\{p_j\}$ using the residual wage by industry. For γ_1 and γ_2, we target the mean and the standard deviation of the wage.

Within each industry, the job-finding rate is calculated using CPS from 2010 to 2019. The industry flow matrix is constructed using Footnote 9, where we normalize each row to sum to 1. Denote this matrix $\{\pi_{j,k}\}$. For unemployed workers in industry j, the probability of finding a job in industry k is hence $\pi_{j,k}\lambda_j$, where λ_j is the job-finding rate for industry j. For employed workers, the on-the-job-search efficiency is α which is calibrated to match the average turnover rate.

We specify the initial human capital to be a fraction of the firm productivity $x(z) = \chi z$, and we set the fraction to match the short-duration employment incidence rate. We estimate the unemployment benefit b to target the average wage markdown. The corresponding parameter values are in Table B.2.

Table B.2: Parameter Values

Parameter	Value	Parameter	Value
γ_1	4.45	b	0.48
γ_2	1.17	α	0.61
χ	0.54	ζ	0.024
σ_x	0.29		

Besides the targeted moments, our model matches well the unemployment rate (5.8%) and the industry employment share.

B.5 A Shock to Employer Concentration

We impose a shock to the employer concentration so that the turnover rate declines by 5%. Specifically, for each industry, we redistribute the vacancies to the firm with the largest measure of vacancies by decreasing the vacancy shares of other firms evenly. The 5% decline in the turnover rate is associated with a 1.1% decline in wages. Because Schubert et al. (2021) estimate that the employer concentration shock would decrease realized wages by 3%, we calculate that 40% of the decline is accounted for through the turnover channel.

B.6 Industry-Specific Minimum Wages

Two observations motivate our policy analysis of industry-specific minimum wages. First, the effects of employer concentration on the turnover rate and wages are heterogeneous by industry. Second, Liu (2022b) show that a uniform minimum wage would disincentivize mobility by compressing wages.

We hence consider setting minimum wages such that the lower-bounds on the workers' share of surplus Equation (B.2) need to implement the value of the least productive firms in each sector, where the dispersion comes from industry-specific productivity. This policy would increase workers' bargaining power without affecting employment, because the least productive firms are now indifferent between operating and exit the labor market.

We repeat the employer concentration shock as above, where the effect on the turnover rate decrease to 2% while the effect on wages decrease to 0.2%. This is because of an overall improvement in workers' outside option which offsets the effects of employer concentration.