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David Autor
Arindrajit Dube
Annie McGrew

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ABSTRACT

Labor market tightness following the height of the Covid-19 pandemic led to an unexpected compression in the US wage distribution that reflects, in part, an increase in labor market competition. Rapid relative wage growth at the bottom of the distribution reduced the college wage premium and counteracted nearly 40% of the four-decade increase in aggregate 90-10 log wage inequality. Wage compression was accompanied by rapid nominal wage growth and rising job-to-job separations—especially among young non-college (high school or less) workers. Comparing across states, post-pandemic labor market tightness became strongly predictive of real wage growth among low-wage workers (wage-Phillips curve), and aggregate wage compression. Simultaneously, the wage-separation elasticity—a key measure of labor market competition—rose among young non-college workers, with wage gains concentrated among workers who changed employers. Seen through the lens of a canonical job ladder model, the pandemic increased the elasticity of labor supply to firms in the low-wage labor market, reducing employer market power and spurring rapid relative wage growth among young noncollege workers who disproportionately moved from lower-paying to higher-paying and potentially more-productive jobs.

David Autor
Department of Economics, E52-438
Massachusetts Institute of Technology
77 Massachusetts Avenue
Cambridge, MA 02139
and NBER
dautor@mit.edu

Arindrajit Dube
Department of Economics
University of Massachusetts
Crotty Hall
412 N. Pleasant Street
Amherst, MA 01002
and NBER
adube@econs.umass.edu

Annie McGrew
University of Massachusetts Amherst
amcgrew@umass.edu

An appendix is available at http://www.nber.org/data-appendix/w31010

Introduction

A vast economic and sociological literature studies the contributions of technology, trade, and institutions to four decades of rising inequality in the United States (Katz and Murphy, 1992; Katz et al., 1999; DiNardo et al., 1996; Autor et al., 2008, 2016). The role played by the competitive structure of the labor market, and its empirical manifestation in worker reallocation across jobs, has received comparatively less attention. Yet, there is reason to suspect a connection. A growing literature documents the importance of imperfect labor market competition in US workers' pay determination: facing labor supply curves that are far from perfectly elastic, many firms are able to mark down wages below competitive levels (Manning, 2021; Bassier et al., 2022; Datta, 2022; Lamadon et al., 2022; Yeh et al., 2022). The secular decline in job-to-job separations in the United States, especially since 2000 (Bjelland et al., 2011; Hyatt and Spletzer, 2013), may be one symptom of this phenomenon: workers whose wages are set infra-marginally will be less likely to separate from their current job in response to wage fluctuations. A corollary of this observation is that if the firm-level labor supply elasticity—or its doppelgänger, the 'quit elasticity'—were to rise, the magnitude of wage markdowns would fall and the worker reallocation rate from lower-paying to higher-paying employers would increase.[1]

This paper studies the rapid evolution of the US labor market in the years immediately before and after the Covid-19 pandemic to understand the role of rising labor market tightness in driving wage compression, boosting the quit elasticity, and augmenting competition in the low-wage labor market. We begin with an overview of how the Covid-19 pandemic and subsequent recovery have disrupted longstanding trends in aggregate wage inequality. Following the pandemic, substantial nominal wage growth at the bottom of the distribution reversed around 38% of the rise in 90-10 log wage inequality since 1980 and led to a fall in the college-high school wage premium. The reduction in the 90-10 log wage ratio following the pandemic was nearly half (46%) of the reduction during the Great Compression of 1940–1950 period. Importantly, we find that this wage compression was accompanied by a rise in the rate of job-to-job separations—especially among young non-college workers.

To understand the role of market competition in these wage patterns, we exploit cross-state variation in post-pandemic labor market tightness, where tightness is measured using variation in state-level unemployment and employment-to-employment (EE) separation rates. In tighter labor markets, wage compression was greater with faster real wage growth among low-wage workers, particularly among young non-college workers. Job-shopping ap-

[1] We use the term 'quit elasticity' throughout the paper to refer to what is formally the employment-to-employment (EE) separation elasticity. We also use the terms EE separations and job-to-job separations interchangeably.

pears to play a key role in wage growth: alongside unemployment, job-to-job separation rates exhibit independent power for predicting cross-state wage growth, reflecting movements along state-level wage-Phillips curves (Moscarini and Postel-Vinay, 2017). At the same time, we find only limited indication that the tighter labor markets experienced faster price inflation.

We explore the potential role of labor market competition in driving these trends by assessing whether the EE separation elasticity, a key indicator of employer market power, has risen in the post- versus pre-pandemic labor market. The EE separation elasticity is informative because it reflects the ability of employers to retain workers who, according to observable characteristics, are paid relatively low wages (for a recent discussion of the theory and a review of evidence, see Langella and Manning (2021)). Canonical job ladder models, discussed in Section 2, predict that the EE separation elasticity will increase when the unemployment rate falls, and when the 'contact rate' between currently employed workers and external firms rises (Burdett and Mortensen, 1998). In both cases, the transition rate of employed workers from lower- to higher-wage jobs will grow. We also discuss non-model-based reasons for why the separation elasticity may have grown following the pandemic, including: decreased worker-firm attachment spurred by mass job loss during the pandemic; increased household liquidity deriving from pandemic transfer programs; and shifting perceptions about the availability of higher-wage jobs.

Empirically, we show that the quit elasticity for young workers and for non-college workers has risen. We further document that the wage compression is entirely accounted for by wage growth associated with job changes rather than same-job wage growth. This pattern of wage growth suggests that increased competition has led to a reallocation of jobs from low-wage to higher-wage employers. We interpret this collage of evidence as indication that the Covid-19 pandemic increased the elasticity of labor supply to firms in the low-wage labor market, reducing employer market power and spurring rapid relative wage growth among young non-college workers who disproportionately moved from lower-paying to higher-paying and potentially more-productive jobs. These forces arose in 2020 at the onset of the pandemic and remained strong through through mid-2022. Labor market tightness has subsequently declined since its peak in 2022 and has largely ceased to spur further relative wage gains among low-wage workers, further job separations, or further aggregate wage and price growth. Despite this moderation, nothing in our data suggests that the 'unexpected compression' has begun to unwind.

A number of recent papers explore the relationship between labor market tightness and employer market power. Hirsch et al. (2018), Webber (2022), and Bassier et al. (2022) document the countercyclicality of employer labor market power, as measured by the elasticity of quits to wages. These papers do not, however, link the change in market power to reallocation or wage inequality. Similarly, focusing on the pre-pandemic labor market, Bivens and Zipperer (2018) and Baker and Bernstein (2013) show that higher employment rates are associated with greater wage compression but do not consider the role of labor market competition and job change in mediating that role.[2] The rapid change in labor market conditions following the pandemic provides a fertile ground for exploring the tightness-competition-reallocation mechanism. Our work is also related to Cerrato and Gitti (2022), who show that a steepening post-pandemic price-Phillips curve contributes to rising inflation. While our focus is on wage inequality rather than price levels, our results for the price-Phillips curve also suggest a steepening in the 2021-2022 period. However, we find this to be temporary: overall, state-level tightness appears to have contributed very modestly to state-level price growth over the 2020-2023 period. Our primary empirical analysis draws on the Current Population Survey (CPS), which offers representative, timely survey data on employment and wages. Because precision is limited by the relatively small sample sizes available in the CPS, the evidence here is a first step toward a more detailed analysis.

The remainder of the paper is structured as follows. Section 1 discusses the data and methodology. Section 2 provides a formal framework for understanding the link between employer market power, worker reallocation, and labor market tightness. Section 3 presents evidence on employment trends by education and occupational characteristics, as well as complementary evidence on wage trends. Section 4 explores the mediating role of job-to-job separations. In this section, we decompose wage change by job change status, and provide estimates of the quit elasticity, wage-Phillips curve (overall, as well for different quantiles and demographic groups), and the role of possible industry shifts. Section 5 considers the relationship between labor market tightness, price growth, and real wage growth. Section 6 offers conclusions and next steps.

1 Data sources

Our primary data source is monthly Current Population Survey (CPS) data from January 2015 through June 2023, sourced from IPUMS (Flood et al., 2021). To measure within-person wage changes, we match individuals across CPS samples observed one year apart. We drop all observations with imputed wages for wage calculations.

For wages at the tails of the distribution, we implement several procedures. Some of these are designed to produce consistent comparisons over time, while taking into account

[2]These papers were written before post-pandemic labor market conditions provided an opportunity to illuminate these mechanisms.

changes in topcoding conventions used by the Census Bureau during the study period. The Census bureau winsorizes weekly earnings at \$2884.61, equivalent to annualized earnings of \$150,000 (or hourly wages of \$75). We estimate the hourly wage of salaried workers as the quotient of their weekly earnings and hours usually worked per week at their main job. We winsorize all hourly wages at \$2.13, the minimum wage for tipped workers in 1991. We topcode all hourly earnings at or above \$75 as this translates into annualized earnings of \$150,000 (assuming 40 hours work weeks, for 50 weeks). Following convention, we replace top-coded earnings with the estimated conditional mean above it—assuming wages in the upper tail follow a Pareto distribution (1.5 x 75 =112.50) (Acemoglu and Autor, 2011).[3]

As of April 2023, the Census Bureau imposed a "dynamic" topcode in which the hourly wages of the top 3% of earners are replaced with the weighted average of their reported earnings. The Census has implemented this procedure only for individuals who entered the survey for the first time in January 2023. Since wages are only observed in MIS 4 and 8, this new top coding procedure only affects individuals who are month-in-sample (MIS) 4 after March 2023. Mixing the prior and new topcoding makes the estimates very difficult to compare, and fragile. For this reason, from April 2023 onwards, we only use the subsample using the older topcoding procedure. In other words, we use only wage observations from MIS 8, which do not include the new dynamic topcoding procedure. To account for the fact that we lose half of the wage observations after March 2023, we double the weights on MIS 8 observations in that period.

We include all individuals aged 16-64 in our analysis. For our longitudinal estimates, we impose further restrictions, including only individuals who report consistent gender throughout the panel and no more than a two-year age change between matched observations. All wages are deflated using the national CPI-U data from the US Bureau of Labor Statistics. We construct a state-level CPI-U measure using a combination of regional and metro-level information to assess geographic variation in price growth; the details of which are explained in Section 5. While the CPS can be used to estimate state-level unemployment rates, we instead use state unemployment rate measures from the Bureau of Labor Statistics' Local Area Unemployment Statistics (LAUS), which combine CPS estimates with other data sources to increase precision (`https://bls.gov/lau`).

The CPS interviews sample members eight times. Respondents are interviewed for four consecutive months, are rotated out for eight months, and then are included in the sample for another four months. In months in sample (MIS) 4 and 8, respondents are asked to report

[3] Before 2003, the Census winsorized annualized earnings at \$100,000. For pre-2003 data, we topcode all nominal hourly earnings greater than \$50, the hourly equivalent of \$100,000 in annual earnings, at ($1.5\times 50 =$ \$75).

their wage. In the 2^{nd} through 4^{th} and 6^{th} though 8^{th} MIS, respondents who were employed in the previous month are asked if they are working for the same employer. This question in the CPS allows us to capture job changes more accurately than using month-to-month and year-to-year changes in CPS respondents' industry and occupation codes. This technique is frequently used to proxy for job changes, but introduces significant measurement error.[4] Measurement error arises because the Census Bureau assigns industry codes to each CPS respondent based on their self-reported ('write-in') job description.[5] If a worker is not entirely consistent in describing their job across successive surveys, or if the Census Bureau re-tunes its textual coding algorithm, this introduces spurious industry transitions that overstate the true frequency of job changes.

In contrast, the CPS captures *actual* job change with high precision using the following query, which is coded in the IPUMS variable *EMPSAME*: "Last month, it was reported that [name/you] worked for [company name]. [Do/Does] [you/he/she] still work for [company name]?"[6] We define job-movers as those who respond "no" to this question. Evidence for the reliability of this measure, provided in Section 4, is that it closely accords with published job change frequencies from the Bureau of Labor Statistics' Job Opening and Labor Turnover Survey (JOLTS). JOLTS employs a large monthly sample of establishments to precisely capture job openings, hires, and separations. Unfortunately, as noted above, this question is only asked during interview months MIS $\in \{2, 3, 4, 6, 7, 8\}$. This means that job changes are not observable in MIS $\in \{1, 5\}$ nor during the eight months when respondents are out of rotation. Because of this, this measure cannot be used to reliably track job changes occurring between a worker's two wage observations, which are recorded one year apart. To address this limitation, we implement a measurement correction procedure in order to decomposure annual wage gains between switchers and stayers. This measurement error correction is described in Section 4.4.[7]

In section 3, we document wage and employment trends over time. There were sizeable compositional changes in the employed US workforce during the pandemic and its immediate aftermath, when non-employment was high and selective. To account for such compositional

[4] For example, the Federal Reserve Bank of Atlanta's Wage Growth Tracker (`https://www.atlantafed.org/chcs/wage-growth-tracker)` codes a worker as having changed jobs if she is in a different occupation or industry than a year ago or has changed employers or job duties in the past three months.

[5] The exact CPS survey question for a worker's industry is: "What kind of business or industry is this?" Census follows a parallel procedure for assigning occupation codes.

[6] `https://www.census.gov/programs-surveys/cps/technical-documentation/questionnaires.html`

[7] Fujita et al. (2020) detect an increase in the incidence of missing answers to the CPS question behind the IPUMS variable EMPSAME between 2007-2009 due to changing Census technology and policies. However, the increase in missing answers levels out around 2015. Thus, this bias in the CPS measure primarily affects the *level* of the measure after 2014. The effect on changes over time after 2014 in self-reported separations, which is the object of interest here, should be relatively modest.

changes, for all analyses in this section, we reweight each month's sample by using inverse probability weighting to match the characteristics of the workforce in the first quarter of 2020. Variables used for reweighting include indicators for six age groups, five education categories, five racial categories, Hispanic ethnicity, gender, nativity (US- vs. foreign-born), and region. We also adjust for 2020 demographic composition in the figures which document employment-to-employment separation trends in Section 4.1. In analyses where we compute wage quantiles, we account for the non-classical measurement error in reported wages that stems from bunching at round numbers. Round-number bunching occurs both because wages are, in reality, frequently bunched at round numbers and because survey respondents further round their wages when reporting (Dube et al., 2018). This rounding creates substantial flat spots in measured nominal wage quantiles, which may exhibit no changes for many months when bunched on a round number (e.g., \$15/hr), followed by a sudden, substantial change when moving to a new round number (e.g., \$16/hr). To uncover the underlying wage distribution, we smooth wage quantiles, first by calculating national wage quantiles by month, and then by predicting wage quantile by rank using a lowess regression. The resulting, smoothed-wage quantiles are far more stable, as illustrated by the leftmost panel of Figure 11 which is the smoothed analog to Figure A1. For cross-group analyses, we construct smoothed-wage quantiles by group and time period.

2 Conceptual framework: Labor market tightness, competition, and reallocation

To structure the analysis, we provide a conceptual model that links labor market tightness, employer competition, and worker reallocation in an imperfectly competitive labor market setting, which we contrast with the fully-competitive and market-clearing canonical model. In both perfectly and imperfectly competitive settings, rising labor market tightness—stemming from either greater demand for labor or fewer workers looking for a job—generates higher wages. However, the imperfectly competitive model makes four additional predictions about the market-level impacts of rising tightness: 1) a compression in wages paid to similar workers; 2) increased worker reallocation from low-paid to higher-paid employers; 3) concentration of wage gains among job-movers rather than job-stayers; and 4) greater responsiveness of worker separations to wage levels, i.e., a higher quit elasticity.

We begin with the benchmark, static model of labor market competition in Figure 1, viewed from the market level (panel A) and the firm level (panel B). Consider an inward shift of the market labor supply curve from LS to LS'. In panel A, the market-clearing wage rises and the equilibrium quantity of employed labor falls. Viewed from the perspective of price-taking firms in panel B, the labor supply curve firm shifts upward and employment falls accordingly. Because perfect competition enforces a law of one price for labor (of given skill level), the wage increase is identical across all firms employing workers of that skill level.

Contrast this with a monopsonistically competitive setting where the wage and employment impacts of a uniform increase in elasticity can differ between high and low productivity firms. This setting involves a large number of firms, J, where workers have idiosyncratic preference shocks over jobs, ν_j, that have a Type I Extreme Value distribution (Card et al., 2018). When worker preferences are $U_{ij} = \epsilon^L \ln(w_j) + \nu_{ij}$, the residual (firm-level) labor supply has a constant elasticity:

$$l_j(w_j) = L \times \frac{w_j^{\epsilon^L}}{\sum_{k=1}^{J} w_k^{\epsilon^L}}$$

$$\ln l_j(w_j) = \ln L - \ln\left(\sum_{k=1}^{J} w_k^{\epsilon^L}\right) + \epsilon^L \ln(w_j)$$

where L is the total number of workers in the market, and ϵ^L is the labor supply elasticity. Due to the large-J assumption, the term $\sum_{k=1}^{J} w_k^{\epsilon^L}$ is taken as a constant by any given firm. The inverse labor supply function of each firm can be written as:

$$\ln(w_j) = \left[\frac{\ln(\sum_{k=1}^{J} w_k^{\epsilon^L}) - \ln(L)}{\epsilon^L}\right] + \frac{1}{\epsilon^L} \ln(l_j). \tag{1}$$

When an increase in labor market competition raises the labor supply elasticity, ϵ^L, the firm-level inverse labor supply curve becomes flatter as the slope $\frac{1}{\epsilon^L}$ falls. Additionally, in equilibrium, the intercept of the labor supply curve increases as the labor supply curve shifts upwards to ensure firm employment is consistent with market labor supply (which is fixed) – this is explained in further detail below.

Figure 2 depicts the result of an increase in the labor supply elasticity for high- and low-productivity firms. This figure plots the changes in employment and wages at two firms that face identical firm-specific labor supply curves but differ in productivity—specifically, the panel-B firm has higher marginal labor productivity (at given employment) than the panel-A firm. As we show next, this leads to wage compression between the high- and low-productivity firms and to employment reallocation from the low- to high-productivity firm.

To illustrate these results with minimal complexity, we parameterize the firm's production function as $y_j = p_j \times \ln(l_j)$, where p_j is a firm-specific productivity shifter. The MRPL is $\frac{p_j}{l_j}$, and profit maximization sets wages at $w_j = \frac{\epsilon^L}{1+\epsilon^L} \times \frac{p_j}{l_j}$. If we take two firms $j \in \{H, L\}$

where $p_H > p_L$, relative wages can be written as:

$$\frac{w_L}{w_H} = \frac{l_H}{l_L} \cdot \frac{p_L}{p_H}$$

Further substituting in the expression for the labor supply function $l_j(w_j)$ and rearranging terms yields the following equilibrium relative wages:

$$\frac{w_L^*}{w_H^*} = \left(\frac{p_L}{p_H}\right)^{\frac{1}{\epsilon^L+1}} \tag{2}$$

Taking logs and differentiating with respect to ϵ^L yields:

$$\frac{\partial\left(\ln(w_L^*) - \ln(w_H^*)\right)}{\partial \epsilon^L} = \frac{\ln(p_H) - \ln(p_L)}{\left(\epsilon^L + 1\right)^2} > 0.$$

This positive derivative indicates that as ϵ^L increases, the wage gap between low- and high-productivity firms becomes less negative, meaning that the wage distribution compresses. This result is seen in Figure 2, where an increase in ϵ^L spurs an increase in wages at both low and high-productivity firms, but more so at the former than the latter. That rising competition leads to wage compression is the first prediction of the monopsony model.

Rising competition also induces labor reallocation from low- to high-productivity firms. At the level of an individual monopsonistically competitive firm (where the term $\sum_{k=1}^{J} w_k^{\epsilon^L}$ is held constant), an increase in the labor supply elasticity (i.e., ϵ^L in equation (1)) reduces the firm's marginal factor cost, spurring an unambiguous increase in employment. But this partial equilibrium logic does not carry over to the market level, since not all employers can raise employment simultaneously. The labor supply curve facing each firm must therefore shift inward in order to ensure firm employment is consistent with market labor supply. In effect, rising competition decreases the slope and increases intercept of the inverse labor supply curve, as shown in Figure 2, so that at the new market equilibrium, the marginal factor cost is lower than in the original equilibrium *only* for firms with a sufficiently high level of productivity. Firms at or above this threshold increase hiring (Panel B of Figure 2) while those below it reduce hiring (Panel A of Figure 2).

This reallocation can be shown analytically in our model. Rearranging equation (2) to obtain relative employment at the low versus high-productivity firm yields:

$$\frac{l_L^*}{l_H^*} = \left(\frac{p_L}{p_H}\right)^{\frac{\epsilon^L}{\epsilon^L+1}} \tag{3}$$

Taking logs and differentiating (3) with respect to ϵ^L yields:

$$\frac{\partial \left(\ln(l_L^*) - \ln\left(l_H^*\right)\right)}{\partial \epsilon^L} = \frac{\ln\left(p_L\right) - \ln\left(p_H\right)}{\left(\epsilon^L + 1\right)^2} < 0$$

The negative sign of this derivative indicates that, when the labor supply elasticity rises, relative employment falls at the lower-productivity firm. Since market labor supply is fixed at L, an equilibrium reduction in *relative* employment at lower productivity firms implies that there is labor reallocation from low- to high-productivity firms. Thus, a second prediction of the monopsonistic competition model is that a tightening of competitive conditions causes more-productive, higher-paying employers to become relatively larger.

A third prediction of this model is that the wage gains stemming from a tightening labor market are particularly concentrated among movers. The reason, also seen in Figure 2, is that while both firm-stayers and firm-movers experience a wage gain as the labor supply elasticity rises, movers benefit both from rising market wages at all firms and from a boost to their marginal products as they move from low- to high-productivity firms.

The fourth prediction of the monopsony model is that the elasticity of worker separations with respect to (low) wages rises as the labor market tightens. This prediction emerges when we embed our static labor supply model in a search framework, which we do next.

2.1 Why labor market tightness increases the elasticity of labor supply

The critical ingredient in the framework above is that the firm-specific labor supply curves become *more elastic* as the labor market tightens. Why would this occur? The static model is silent on the matter but this implication follows directly from a dynamic job ladder model (Burdett and Mortensen, 1998; Bontemps et al., 1999; Moscarini and Postel-Vinay, 2018). Consider a dynamic wage posting model with search frictions where workers engage in on-the-job search. In this model, the rate of job separations at wage w can be written as $S(w) = \delta + \chi + \lambda_e\left(1 - F(w)\right)$, where δ is the exogenous separation rate to non-employment, χ is the exogenous separation rate into another—possibly worse-paying—job, sometimes called a "Godfather shock" (i.e., a job offer you cannot refuse), λ_e is the outside offer arrival rate for current employees (the contact rate), and $F(w)$ is the wage offer distribution. Due to frictional wage dispersion, this distribution is non-degenerate.

In this setting, the rate at which current employees separate to better-paying jobs, $\lambda_e\left(1 - F(w)\right)$, is an endogenous function of the wage at the current employer, w, holding fixed λ_e and $F(w)$. Taking logs and differentiating, the overall quit (or EE separation) elasticity is $\epsilon^{EE} = -\lambda_e f(w) w / (\chi + \lambda_e\left(1 - F\left(w\right)\right))$, which depends only on the employer's own wage *rank* in the aggregate distribution, $F(w)$. One implication of this observation, used below, is that the elasticity of EE separations, with respect to a variable that is monotone in wage rank, w, is also a function only of the rank.

This model makes clear predictions for how the quit elasticity responds to market conditions, represented by λ_e and $F(w)$. Zooming out from the firm- to the market-level, employers post V vacancies while workers exert total job-seeking effort of $JS = u + \phi(1-\delta)(1-u)$. Here, $\phi > 0$ is the relative efficiency of on-the-job search, so that the contact rate of the employed relative to the unemployed is: $\lambda_e = \phi\lambda_u$. We represent the total number of contacts in the market with a constant-returns matching function, $m(JS, V)$, and the offer arrival rate to employed workers as $\lambda_e = \frac{m(JS,V)}{JS} = m(1,\theta)$, where $\theta = \frac{V}{JS}$ corresponds to labor market tightness. Rearranging the total job-search effort equations as $JS = (1-\phi(1-\delta))u + \phi(1-\delta)$ makes it clear that $\frac{\partial JS}{\partial u} > 0$.[8] Thus, θ is also monotonically rising in the conventional tightness measure $\tilde{\theta} = V/u$.

The offer arrival rate to employed workers, $\lambda_e = \frac{m(JS,V)}{JS} = m(1,\theta)$, is then rising in market tightness. By implication, for a given equilibrium wage distribution, the quit elasticity ϵ^{EE} increases (becomes more negative) as market tightness (θ or $\tilde{\theta}$) rises. These comparative statics highlight how rising tightness, by increasing competition for new hires, raises the quit elasticity, which is the fourth implication of our conceptual framework. We note that market tightness may increase due to either a positive demand shock, raising V, or a fall in u—perhaps reflecting a contraction in the labor force. Both factors are plausible candidates for the increase in labor market tightness following the pandemic.

We have so far ignored the changes in the wage offer distribution $F(w)$. Endogenizing the wage offer distribution and allowing it to depend on firm-level productivity does not change the model's key features, however, as we show in Appendix A2. The reason is that, while the separation elasticity, ϵ^{EE}, depends on the wage distribution (an endogenous object), the effect of an increase in the contact rate, λ_e, on the separation elasticity depends only on the rank of the firm's wage (or productivity, p), $r = F(w) = H(\kappa^{-1}(w))$, which is a primitive of the model (here $w = \kappa(p)$ is the mapping between productivity and wage, and is assumed to be monotonic).

Moreover, consistent with the logic of the static monopsony model above, a rise in the contact rate affects EE separations more at low- than at high-productivity employers, reallocating workers from the former to the latter. To see this formally, observe that the EE separation rate is equal to $\chi + \lambda_e(1 - F(w)) = \chi + \lambda_e(1 - H(p))$. Since $(1 - F(w))$

[8] The derivative, $\frac{\partial JS}{\partial u} = 1-\phi(1-\delta)$, is positive if $\phi < \frac{1}{1-\delta}$, which for small enough δ means that $\phi <= 1$. The term ϕ is assumed to be strictly greater than zero, since a zero value would imply an absence of on-the-job search and result in the Diamond paradox—where even an infinitesimal amount of search friction results in all firms setting wages at the single monopsonist level (Diamond, 1971). Thus, $0 < \phi \leq 1$ and $\frac{\partial JS}{\partial u} > 0$.

is monotonically decreasing in w, an increase in the contact rate, λ_e, differentially raises separations at low-wage, low-productivity firms (i.e., low-ranked firms with small $H(.)$) as compared to high-wage, high-productivity firms. Intuitively, for workers who are already at the highest-paid quantile of the wage distribution, an increase in the contact rate never triggers a separation; by contrast, this same increase boosts the odds that a low-paid worker gets a better offer. Figure 3 illustrates this logic by plotting the EE separation by firm wage-rank locus for λ_e equal to 0.02 and 0.04. The 'rotation' of the equilibrium separations-wage locus, as the contact rate rises, reflects the reallocation of lower-wage workers toward higher rungs of the job ladder. Figure 4 further shows how, in steady state, a tighter labor market, represented by a higher contact rate, yields a larger fraction of the workforce employed at more-productive (i.e., high-ranked) firms.

2.2 Empirical implications

We will empirically assess these relationships, first by documenting trends in wage compression, next by estimating EE separation elasticities with respect to residual wages in the pre- and post-pandemic periods, and finally by assessing whether a rise in separations is associated with a reallocation of workers from lower- to higher-paid jobs—measured both by wage gains among movers and by worker reallocation out of low-wage quantiles and low-wage sectors. The job ladder model also provides guidance on how to empirically measure labor market tightness for this exercise. While empirical work often measures tightness by the unemployment rate, $u = \frac{\delta}{\delta+\lambda_u}$, this measure does not capture movements in job-finding rates among the employed, $\lambda_e = \phi\lambda_u$.[9] The job ladder model implies that, to capture both λ_u and λ_e, an empirical measure of labor market tightness should include both the unemployment rate and the job-to-job separation rate.

Alongside the direct role of labor market tightness implied by theory, we suspect that other pandemic-specific factors may have contributed to an increase in the separation elasticity. For example, while most industrialized countries used public payments to employers to retain workers during lock-downs (Giupponi et al., 2022), the US, instead, vastly increased the scope and generosity of unemployment benefits programs for millions of workers who were temporarily or permanently laid off during the pandemic.[10] This dissolution of worker-firm ties may have increased workers' 'footlooseness' following the initial shock, especially in low-wage sectors such as hospitality, which experienced the deepest pandemic-related con-

[9]As shown in Moscarini and Postel-Vinay (2017), conditional on the outside option, greater ease of job finding among the unemployed that does not *also* raise job-finding rate among those at work has no impact on wages.

[10]Simultaneously, the US Paycheck Protection Program kept a comparatively modest number of workers, 1–2 million, employed during the pandemic (Autor et al., 2022).

traction. These pandemic dislocations may have also altered workers' perceptions of the availability of better-paying jobs. Literature suggests that workers at particularly low-wage jobs may systematically underestimate the true availability of outside options (Jäger et al., 2022). Plausibly, a temporary shutdown could enable workers to discover better outside options: both directly, by increasing workers' own search activity, and indirectly, by watching their coworkers find new jobs (Porter and Rigby, 2021). Finally, by substantially increasing household liquidity—particularly among low-income households (Cox et al., 2020)—the transfer payments made by supplementary unemployment benefits (Federal Pandemic Unemployment Compensation) and household stimulus benefits (Economic Impact Payments) may have raised reservation wages and enabled more job shopping.[11] Furthermore, if liquidity constraints prevent low-wage workers from bargaining for higher wages, pandemic stimulus payments may have facilitated job switching or wage bargaining among low-wage workers (Caratelli, 2022). Our CPS data do not directly illuminate the role of these factors, but they are likely to be captured by our analysis to the degree that they contribute to rising labor market tightness.

We first turn to evidence describing the evolution of the US labor market during and after the pandemic. We next test the distinct predictions of the competitive and monopsonistic models for the contribution of tightening aggregate and regional labor markets to the unexpected compression.

3 The unexpected compression

3.1 Employment drop and rebound

The onset of the pandemic saw the sharpest drop in US employment of the post-WWII era. Figure 5 plots the 3-month rolling average Employment-to-Population (EPOP) ratio and the labor force participation rate from January 2015 through June of 2023. EPOP fell sharply at the onset of the pandemic, plunging by an unprecedented 9.2 percentage points from 71.6% in January 2020 to 62.4% in May 2020. The labor force participation rate (employment plus unemployment) saw a smaller, but still stark, fall over the same period, from 74.4% in January 2020 to 71.7% in May 2020.[12]

[11] Generous unemployment benefit replacement rates appear to have had only a modest impact on job finding rates among the unemployed, however, including through the liquidity channel (Ganong et al., 2022; Coombs et al., 2022).

[12] Figure 5 displays percentage changes in employment and labor force participation, normalized by their January 2020 values, while in the text, we discuss percentage point changes (since EPOP is already a percentage). As shown in the figure, EPOP fell by 12.8% between January and May 2020, while labor

The employment drop was particularly pronounced among less-educated workers, as shown in Figure 6, consistent with the fact that pandemic business shutdowns disproportionately affected low-paid, front-line service workers. Between January and May of 2020, EPOP fell by 7 percentage points among those with a college (Bachelor's) degree or more, versus 10.3 points among those with a high school diploma or less (from 84.3% to 77.4% in the former group, and from 60.18% to 49.9% in the latter).[13]

The subsequent rebound was equally-and-oppositely pronounced. By mid 2022, EPOP among adults with only a high-school education had already attained 100% of its early-2020 level, which it has since slightly surpassed.[14] The college-degree EPOP rate did not have nearly as much ground to make up after the pandemic, but as of mid-2023, it also had returned to its pre-pandemic level (Montes et al., 2022).

The disproportionate fall and rebound of less-educated workers is mirrored in the pattern of employment change by occupation. Ranking occupations by their average wage level in January 2020, Figure 7 shows that employment in the (population-weighted) bottom earnings tercile occupations decreased by more than 18% between January 2020 and May 2020. Those occupations in the top tercile lost a mere 4% of employment, while those in the middle tercile lost 8%. By early 2022, occupations in all three terciles had essentially reattained their immediate pre-pandemic employment levels, a pattern that has persisted through the close of our data series in mid-2023. The rapidity of this rebound stands in contrast with the protracted recovery from the 2007 financial crisis, particularly for low-wage workers (Hoynes et al., 2012; Carnevale et al., 2016).

3.2 Wage distribution changes

The disproportionate exposure of less-educated workers performing low-wage occupations to adverse pandemic employment shocks would normally augur further wage divergence between the top and bottom of the distribution—compounding four decades of rising US wage inequality (Hoffmann et al., 2020). Indeed, in the early days of the pandemic, one of this paper's authors predicted a slack post-pandemic labor market for non-college workers, with accompanying wage stagnation at the bottom of the distribution (Autor and Reynolds, 2020). We thus feel comfortable labeling as *unexpected* the remarkable wage *compression* underway in the post-pandemic labor market.

Since 2020, both real and relative wages have grown substantially more at the bottom

force participation fell by 3.7%.

[13] Thus, the proportional fall in EPOP was over twice as large – 17% vs. 8.3% – for the less-educated group.

[14] Except where otherwise noted, the term 'high-school workers' refers to those with a high school diploma or less (i.e., less than high-school or high-school educated). This group does *not* include workers with some college (i.e., more than high school but less than a four-year college degree).

of the distribution (10^{th} percentile) than at the median or top (90^{th} percentile), as shown in Figure 8.[15] Despite substantial post-pandemic inflation (which we account for using the benchmark Consumer Price Index for all Urban Consumers (CPI-U)), real hourly earnings at the 10^{th} percentile of the wage distribution rose by 8.1% between January 2020 and June 2023.[16] During the same period, real hourly earnings rose by about 1% at the median, while they fell by 1.5% at the 90th percentile of the wage distribution.

Figure 9 compares the change in the log of the 90-10 wage ratio over the 2020–2023 period to other key historical episodes. Using data on hourly wages from the decennial Census, the first bar in Figure 9 shows that this ratio fell by 0.24 log points between 1940 and 1950–the period known as the Great Compression (Goldin and Margo, 1992). According to Goldin and Margo (1992), the distribution of wages expanded slightly in the 1950s and 60s, but expanded significantly after 1970. The late 1970s mark the beginning of the Great Divergence, a decades-long period of increasing inequality. Between 1979 and 2019, the 90-10 ratio increased by 0.29 log points (2nd bar of Figure 9). The post-pandemic period marks a departure from this decades-long increase in inequality, as shown in the 3rd bar of Figure 9—between 2020 and mid-2023, the 90-10 ratio fell by 0.11 log points. These estimates suggest that the recent wage compression was about 46% as large as the Great Compression, and that it reversed approximately 38% of the *rise* in the log 90/10 ratio over the previous four decades.[17]

A noteworthy pattern in Figure 8 is that the 10^{th} percentile of the wage distribution was rising strongly in the five years prior to the pandemic, a phenomenon discussed in depth by Aeppli and Wilmers (2022), Dey et al. (2022), and Shambaugh and Strain (2021). This pattern might indicate that wage compression following the pandemic primarily reflects an acceleration of pre-pandemic wage trends. An alternative (or complementary) explanation is that wage compression prior to the pandemic was substantially driven by state minimum wage laws, many of which were adopted in the preceding decade (Cengiz et al., 2019). Figure 10 explores these possibilities by contrasting trends in 10^{th}, 50^{th}, and 90^{th} percentiles in the 31 states that set minimum wages above the federal level, (panel A: 'minimum-wage states'), with analogous trends in the 20 states that did not, (panel B: 'non-minimum-wage states').

[15]Figure A2 shows these wage percentiles without demographic compositional adjustments.

[16]Figure A3 shows that trends in relative wage growth at the bottom of the wage distribution are robust to excluding workers who receive tips, commissions, or overtime pay, who could bias wage trends upwards by earning more than is reported in the CPS.

[17]Table A1 reports the 90-10 ratios and their change over each of these time periods in levels and in logs. It also reports the estimates in the most recent period with and without adjustment for pre-pandemic demographic characteristics. The adjustment is done using inverse probability weighting as described in Section 1, but does not materially alter the change in the log 90-10 ratio: the adjusted change in the recent period (-0.116) is very similar to the raw change (-0.108).

Prior to the pandemic, the rise in the 10^{th} percentile was limited to minimum-wage states; no such trend was visible in the non-minimum-wage states. Yet, in both groups, the 10^{th} percentile jumped sharply in late 2020 and remained at its elevated level through late 2022. Trends in the 50^{th} and 90^{th} percentiles were, however, comparable between minimum- and non-minimum-wage states. While institutional forces likely drove wage compression in a subset of states prior to the pandemic, the evidence in Figure 10 suggests that the sharp post-pandemic wage compression in both minimum- and non-minimum-wage states is not, primarily, a continuation of this trend.[18] This conclusion is reinforced by a comparison of Figures 11 and A4, which report wage growth across the wage distribution for the periods 2020–2023 and 2015–2019, respectively. This figures make clear that wage compression was substantially greater during 2020–2023 than 2015–2019.

To provide a picture of real wage changes across the full wage distribution, Figure 11 plots nominal wage changes by percentile between January 2020 and May 2023.[19] The figure overlays the contemporaneous change in the CPI-U, thus delineating real wage gains from losses. The first panel shows that, over this nearly 3.5 year period, real wage gains were positive up to the 60^{th} percentile and were negative for the remainder. Focusing only on the most recent 24 months of data (May 2021 through May 2023), real wage gains accrued to the the bottom 40% of the wage distribution while other percentiles lost in real terms. Finally, in the twelve months between May 2022 and May 2023, real wage gains accrued relatively evenly throughout the distribution, with only slightly faster growth at the bottom. Thus, most of the wage compression was concentrated between January 2020 through May 2022. The period since mid-2022 has seen fairly broad-based wage growth, and we certainly have not seen any reversals in the reduction in inequality.

A limitation of the CPS real earnings measure is that it may not capture changes in non-wage compensation that coincided with the pandemic. Barrero et al. (2022) estimate that the recent, rapid rise of remote work arrangements has improved the amenity value, and hence raised the real compensation, of the jobs held by highly educated workers. Simultaneously, the disamenities associated with low-paid, in-person jobs have arguably intensified: greater disease exposure risk, thinner staffing levels, and a seeming epidemic of irate customers. It appears plausible that trends in real wage compression modestly overstate trends in real compensation.[20]

[18] Examining wage quantiles by sex reveals that the pre-pandemic wage compression was sharper among men than women (Figure A5). Since women comprise a disproportionate share of the workers paid at or below the minimum wage (U.S. Bureau of Labor Statistics, 2021), it is equally clear that the minimum wage was not the only force driving lower-tail wage compression prior to the pandemic.

[19] Figure A6 shows the same wage changes by percentile, but without adjusting for compositional changes.

[20] Larrimore et al. (2022) analyze changes in earnings levels during the pandemic—inclusive of fiscal relief provided by the array of Covid-19 policy responses enacted in that period. They find that the real median

3.3 Between-group inequality

We next document how wage compression is reshaping wage inequality among age-by-education skill groups. Thirty years of literature has analyzed the expansion of these differentials (Katz and Murphy, 1992; Katz et al., 1999; Card and Lemieux, 2001; Acemoglu and Autor, 2011; Autor, 2014; Hoffmann et al., 2020; Vogel, 2023). Figure 12 documents the pronounced wage growth of high-school and some-college workers relative that of workers with a four-year degree. Akin to the pre-pandemic compression of the lower tail of the distribution, wage differential between college and high-school workers was contracting prior to the pandemic (Aeppli and Wilmers, 2022), particularly between 2015 and 2017.[21] But the post-pandemic compression is faster and more abrupt than the preceding trend. As shown in Figure 13, this post-pandemic jump in the real wages of high-school workers was equally rapid in states with and without minimum wages set above the federal level.[22]

Figure 14 plots wage trends by age, documenting that younger workers have seen the largest wage gains since the onset of the pandemic. Further breaking down the data by age and education in Figure 15 makes clear that wage compression among young non-college workers drives these trends.[23] Of the four groups depicted—high-school vs. college-educated × above vs. below age 40—young high-school workers constitute the only group that has *not* seen its post-pandemic earnings gains entirely eroded by inflation. Our subsequent analysis of mechanisms focuses primarily, though not exclusively, on the contrast between young high-school workers and the balance of the workforce.

This pattern of wage compression is not limited to educational wage differentials. Grouping occupations into terciles based on wage ranks in 2019, Figure 16 shows that wage growth since early 2020 has been strongest in the lowest occupational wage tercile and weakest in the top occupational wage tercile. Paralleling the patterns above, pre-pandemic wage growth in low-wage occupations exceeded that of mid- and high-wage occupations, but this trend sharply accelerated with the pandemic: since early 2020, average earnings in the lowest tercile of occupations have grown relative to earnings in high-wage and mid-wage occupations

incomes of the bottom quintile of earners rose by over 60% in 2020, and that these earnings increases offset relief reductions during the 2021 recovery.

[21] Figure A7 shows real-wage trends for more-detailed educational categories—less than a high school degree, high school degree, some college, Bachelor's degree, and greater than Bachelor's. The wage gap between some-college and four-year college-graduate workers has closed even more rapidly than the pure college/high school wage gap. We focus primarily on the pure college/high school gap since the some-college category is an unstable amalgam of workers with two-year degrees or incomplete two- and four-year college enrollments.

[22] Figure 13 also documents that the jump in the wage of college workers starting in 2020 is initially several points larger in states with supra-federal minimum wage laws. But this differential disappears by early 2023

[23] A comparison of earnings trends between non-college workers and college or more is reported in Figure A8.

by eleven and five percentage points, respectively. Low-wage occupations tend to be those that are intensive in non-routine manual tasks—occupations which have also experienced fast wage growth since 2020, as documented in Figure A9. Occupations in this category are dominated by in-person services, such as food preparation, building and grounds, cleaning, personal care, and personal service. These occupations suffered a disproportionate share of layoffs early in the pandemic.

Finally, Figures 17 and 18 report real wage trends by sex and race, examining the gains of Black and Hispanic workers relative to white, non-Hispanic workers. The wage trends for men and women were very similar prior to the pandemic, but the gender wage gap fell slightly (by around two percentage points) since 2020. The earnings gap between Black/Hispanic and white workers closed even more–by approximately five percentage points after the onset of the pandemic. Distinct from the quantile, education, and occupational wage differentials above, there was no trend in the racial earnings gap prior to the pandemic. A question for future investigation is whether the earnings trends among education, age, and occupational groups fully account for the post-pandemic compression of the racial gap, or if a distinct, race-specific component remains.

4 Competition at work? Testing the role of intensifying labor market competition

Given the sharp drop in demand for low-wage workers during the pandemic, what explains the substantial real earnings growth at the bottom of the distribution since 2020? We focus on mechanisms in this section. Guided by the theoretical model in Section 2, we consider four margins of adjustment that inform whether the recent wage compression primarily reflects a shift between two competitive equilibria or, instead, a *tightening* of competitive conditions within an imperfectly competitive labor market. Specifically, the imperfectly competitive model predicts:

1. A rise in employment-to-employment (EE) transitions among low-wage workers, and an accompanying rise in wages among groups with rising transition rates (section 4.1)
2. A rise in the elasticity of quits with respect to (low) wages (section 4.2)
3. A reallocation of employment from low-wage to high-wage firms and sectors (section 4.3)
4. A concentration of wage gains among job-movers versus job-stayers (section 4.4)

4.1 Tightness and wage growth

We turn to the first prediction by documenting changes in EE transitions. Using CPS data, we classify workers as having made an EE transition if they are (a) employed in two consecutive survey months and (b) report having changed employers or primary jobs between those months. The upper panel of Figure 19 plots three-month moving averages of EE separation rates for the full sample of employed working-age adults, comparing years 2021, 2022, and 2023 to a pre-pandemic baseline average of 2017 through 2019. EE transitions rose modestly in the second half of 2021 and remained elevated relative to their pre-pandemic level until 2023, at which point they returned approximately to baseline. The lower panel of Figure 19 presents complementary evidence on voluntary job separation rates ('quit rates') from the Bureau of Labor Statistics' Job Openings and Labor Turnover Survey (JOLTS). Reassuringly, there is a tight correspondence between the CPS-based and JOLTS-based measures of separations. In the CPS data, the monthly separation rate rose from approximately 2.2% during 2017–2019 to approximately 2.5% in mid 2022, before drifting back to its pre-pandemic level. In the JOLTS data, which exhibits smaller monthly fluctuations due to its larger sample frame, the corresponding rise is from 2.2% in 2017–2019 to 2.9% in the first half of 2022, then gradually diminishing to 2.5% in the first half of 2023.

Figure 20 reports analogous separation rates for education-by-age subgroups. The four panels of this figure reveal that the aggregate increase in EE transitions in Figure 19 is driven primarily by young high-school workers. The monthly EE separation rate among this group rose from 3.2%, on average, from 2017 through 2019 to a high of 4.0% in 2021 before returning to its pre-pandemic level by 2023. The EE separation rate also rose for older high-school workers in the post-pandemic period although to a smaller extent than their younger counterparts. Among college-educated workers, however, there is almost no visible rise in separations following the onset of the pandemic.[24] Figure 21 rounds out this evidence by using JOLTS data to track voluntary separation rates, by sector, for years 2015–2023. The sharp post-pandemic rise in job separations is most pronounced in the hospitality sector, which employs a disproportionate share of young and less-educated workers (we calculate that between 2015 and 2023, young high-school workers make up 41% of the hospitality industry, compared to 21% of the overall sample). Consistent with the CPS evidence, quit rates in hospitality remain elevated through the first half of 2022 and then gradually return to pre-pandemic levels.

In the job-ladder model, rising job-to-job separation rates signal an overall tightening of the labor market, which enables workers to move from from lower- to higher- (residual)

[24] Figure A10 reports EE separation rates separately for high-school and some-college workers. The rise in transitions is concentrated among workers without a college education.

wage employers, leading to aggregate wage gains. Our first step in exploring this prediction is to estimate the state-level relationship between tightness and wage growth. Following the theoretical treatment above, we measure labor market tightness using both state-level EE separation rates and state unemployment rates. To efficiently combine these measures, we standardize both, reverse the sign of the unemployment rate, and take the average of the two.

As documented in Figure 22, labor market tightness in 2021 through mid-2023 varied substantially across states, with a cross-state standard deviation of 0.66 percentage points. The labor market was generally tighter in low population density states, such as Maine and Montana, and was relatively slack in states that maintained prolonged pandemic lockdowns, including Massachusetts, New York, and California. Figure 23 shows the time path of our composite tightness measure (panel A) and its two components (panel B). Tightness fell by roughly four standard deviations at the outset of the pandemic, but rebounded quickly, rising above pre-pandemic levels throughout 2022. Subsequently, tightness returned to approximately its pre-pandemic level during the first half of 2023. The evolution of tightness reflects movements in both unemployment and EE transitions: the national unemployment rate, after spiking in 2020, returned to its low pre-pandemic level by 2022, while the EE separation rate remained substantially elevated relative to the pre-pandemic baseline until the onset of 2023. The zenith of tightness occurs in 2022 when EE separations are elevated while unemployment is low.

We estimate the relationship between state-level tightness and wage changes—the wage-Phillips curve—over the post-pandemic period (2021 Q1 – 2023 Q2) by stacking wage observations from nine successive adjacent quarters, denoting stacks by subscript k, so each stack has two quarters, $t_k \in \{0, 1\}$.[25] We fit the following equation:

$$\ln W_{iskt_k} = \beta \left(\text{Tightness}_{skt_k=0} \times \mathbb{1}\left[t_k = 1\right] \right) + X_i' \gamma_k + \alpha_{kt_k} + \delta_{sk} + e_{iskt_k}, \tag{4}$$

where $\ln W_{iskt_k}$ is the log wage for worker i in state s in stack k and sub-period t_k, and the vectors α_{kt_k} and δ_{sk} contain stack-by-time and stack-by-state fixed effects, respectively. Our variable of interest is an interaction between tightness at the start of the quarter ($t_k = 0$) and an indicator for the end of the quarter ($t_k = 1$). The coefficient of interest, β, estimates the relationship between the *change* in state-level annualized log wages and the *level* of tightness.[26] So that β can be read as an annualized relationship, the outcome variable, quarterly wages, is multiplied by four. Additional specifications include individual

[25] The first stack includes data from 2021 Q1 and Q2, the second contains data from 2021 Q2 and Q3, and the final (9^{th}) stack includes data from 2023 Q1 and 2023 Q2.

[26] While our outcome variable is quarterly wages (not wage growth), the interaction between Tightness and an indicator for the second quarter allows us to interpret β as the effect of tightness on wage *growth*.

controls, X_i, for education, age, sex, race, sector (manufacturing, finance, business services, or professional services). Goda and Soltas (2022) show that long Covid-19 illness reduced labor supply, which we control for using state-specific Covid-19 death rates (from CDC (2020)). The coefficients for these control variables are all stack-specific. Standard errors are clustered at the state level. We also estimate equation (4) for wage quartiles and age-education demographic groups, pooling all main effects across groups while allowing β to differ by demographic group.[27]

Our approach to estimating wage-Phillips curves echoes that of Katz and Krueger (1999), who studied the evolution of wages and prices in the high-pressure labor market of the 1990s, with two key differences. First, the tightness measure applied here incorporates *both* state-level EE separation rates and state-level unemployment rates (as opposed to solely the unemployment rate). Second, whereas the wage-Phillips curve estimated in Katz and Krueger (1999) is expectations-augmented by imposing an estimated *price*-coefficient on the wage-Phillips curve, our estimate directly regresses wage changes on labor market tightness. This direct approach proves important because, as predicted by theory and confirmed above, tightness appears to disproportionately affect wage growth among low-wage workers.

Estimates of equation (4) for all working-age adults and for demographic subgroups are reported in Table 1 and Figure 24. Panel A of the figure corresponds to the estimated cross-state wage-Phillips curve for all working-age adults. In the most demanding specification, reported in column 5 of Table 1, the well-determined slope of 0.023 (se = 0.010) implies that a one-standard deviation increase in tightness predicts additional annual wage growth of 2.3% over the post-pandemic period. Given the considerable cross-state dispersion of the tightness measure depicted in Figure 22, this is an economically sizable relationship.

Panel B of Figure 24 extends this exercise by separately reporting wage-Phillips curves estimates for the 1^{st} quartile of the wage distribution and for the remaining three quartiles combined, with corresponding regression estimates reported in Table A2. The slope estimate for the bottom-quartile wage-Phillips curve is over eleven times as steep as the corresponding estimate for the combined upper-three quartiles: 0.095 (se = 0.035) versus 0.008 (se = 0.014), respectively. This pattern constitutes a first piece of evidence that the wage compression documented in the previous section is associated with labor market tightness. Panel C presents a second piece of evidence: the cross-state wage-Phillips curve for high-school workers under age 40 has a slope of 0.096 (se = 0.032); for the complementary set of all other working-age adults, however, this curve is shallow and statistically insignificant at 0.007 (se = 0.011). Table 1 further documents that these relationships are concentrated

[27] While individual controls and stack-by-state fixed effects are common between groups in the subgroup regression equations, stack-by-time fixed effects vary by group.

in the bottom half of the wage distribution, particularly among workers without four-year college degrees, and are highly robust to the inclusion of demographic control variables. Conversely, estimates of the wage-Phillips curve for the upper half of the wage distribution and for workers with four-year degrees are generally imprecise and opposite-signed. Thus, labor market tightness is strongly predictive of wage gains at the bottom of the distribution in the post-pandemic era.

These steep wage-Phillips curves were not nearly as pronounced in the pre-pandemic era. Table A3 reports analogous estimates for the 2015–2019 period and finds no significant relationship between labor market tightness and wage growth for the full sample of working-age adults. For the subgroups exhibiting the steepest wage-Phillips curves after 2020 (1^{st} wage-quartile earners and high-school workers under age 40), pre-pandemic estimates show an insignificant or a significant yet weaker relationship. We also test that this *steepening* of the wage-Phillips curve is statistically distinguishable from zero. Post-pandemic, the overall wage-Phillips curve coefficient increased significantly by 0.031 (se = 0.013). The coefficient for 1^{st} wage-quartile earners increased significantly by 0.071 (se = 0.031). For high-school workers under age 40, estimates increased by 0.006 (se = 0.042), though not significantly.

The steepening of the wage-Phillips curve and the differences across the distribution underscore how profoundly the low-wage labor market has changed since the onset of the pandemic. To illustrate this point, Figure A11 plots the estimated wage-Phillips curve coefficients in each year between 1995 and 2023, with separate coefficients reported for overall mean wages and for two low-wage groups: first quartile earners and high-school educated workers under age 40. The specification for this figure comes from equation 4 estimated separately by year and group. For the the two low-wage groups, the wage-tightness coefficient is strongly procyclical, reaching an apex during the high-pressure Roaring Nineties (Krueger and Solow, 2002), a nadir during the Great Recession (circa 2008), a rebound after approximately 2010, and a second peak in the immediate post-pandemic years. This steepening of the wage-Phillips curve in the post-pandemic era is consistent with the non-linear Phillips curve proposed by Benigno and Eggertsson (2023) and Crust et al. (2023). Similarly, Burya et al. (2023) show that the wage-Phillips curve is weaker in areas where firms have more market power, supporting our finding that the relationship between wage growth and tightness is stronger when the labor market is more competitive (evidenced by a rise in separation elasticity in the next section).

We documented above that state minimum wage regulations likely contributed to lower-tail wage compression prior to the pandemic (Figure 10). To abstract from these effects, Table A4 repeats the main wage-Phillips curve estimations using a trimmed sample that omits the bottom 15 percentiles of earners in each state and period—workers whose wages are the most likely to be shaped by the minimum. Results for the trimmed sample are highly comparable to those in Table 1, with slightly *larger* point estimates for low-earnings groups. This pattern suggests that the state-level correlation between wage compression and labor market tightness is unlikely to be driven by state minimum wage policies.

As a second robustness test, Tables A5 and A6 replicate the Table 1 estimates using the two standardized components of the tightness measure—unemployment and EE separations—as standalone predictors in separate models. The unemployment measure is the unambiguously the stronger standalone predictor. But in the case of the lowest wage quartile, the opposite is true. The combined tightness measure is strengthened by both components.

4.2 Separation elasticities

The job-ladder model predicts that a tightening labor market will spur a rise in the quit elasticity—the sensitivity of job-to-job separations to wage levels—and differentially so for low-paid workers. In the theoretical model, low-paid workers are those who earn less than comparable workers employed by other employers. In the data, it is difficult to distinguish workers who receive low wages *despite* their skills from workers who receive low wages *because* of their skills. Bassier et al. (2022) surmount this problem by using matched worker-firm data to estimate the elasticity of quits to the firm-specific component of wages (distinct from the worker skill component). This is not feasible in Current Population Survey data, which are based on household surveys. We use two alternative approaches. The first estimates the response of worker separations to workers' own wage levels purged of the influence of standard Mincerian covariates (in effect, their wage residuals). A second approach uses industry wage premia to proxy for rents paid to workers, motivated by the evidence that (normally) unobserved worker skill differentials do not fully account for industry wage premia; instead, these premia represent an aggregation of firm-specific wage components that differ systematically by industry (Katz and Summers, 1989; Card et al., 2022).

We estimate the wage-separation elasticity with the following model:

$$\Delta J_{it}^{k} = \alpha_{T(t)}^{k} + \beta_{T(t)}^{k} \ln w_{i,t-1} + X_{it}^{'}\lambda_{T(t)}^{k} + \epsilon_{it}, \tag{5}$$

The dependent variable, ΔJ^k, is an indicator for whether worker i made a job-to-job separation during the past 3-months ($k = 3$). The key independent variable, $\ln w_{i,t-1}$, is the log of hourly earnings reported by the respondent in MIS 4, prior to any possible employment transition occurring over the next 12 months before the next wage observation in MIS 8. The covariate vector X includes indicators for gender, race, ethnicity, citizenship, state, metro area status, five education categories (less than HS, HS, some college, BA, and greater than BA), and four age groups (under 25, 25-39, 40-54, 55+). We anticipate a *rise* in the magnitude of the separation elasticity from a tightening labor market. We allow for this by fitting equation (5) separately for two time intervals: pre-pandemic job changes in 2015–2019; and post-pandemic job changes in 2021–2023. These time intervals are subscripted as $T(t) = 1$ for $t \in [2015, 2019]$ and $T(t) = 2$ for $t \in [2021, 2023]$.

The disparate timing of the job change questions in the CPS complicates estimation of own-wage separation elasticities. Specifically, job changes occurring in the 8 month interval between a worker's 4th and 5th month in the CPS rotation, as well as those occurring as they reenter the rotation in MIS 5, are not observed.[28] For the case of 3-month separations, we code $\Delta J_i^{k=3} = 1$ if worker i reported a job-to-job separation in MIS 6 through 8 (the months in which job-to-job separations are directly reported by the respondent) while excluding observations where workers have different industry *and* occupation affiliations between MIS 5 and 6—since these likely signal an intervening job change. Accordingly, $\beta^{k=3}$ estimates the hazard of quitting a job in MIS 6, 7, or 8 *conditional* on being *unlikely* to have changed jobs between MIS 4 and 5. To obtain the elasticities corresponding to equation 5, we divide $\beta^k_{T(t)}$ by the mean separation rate in the estimation sample, $E(\Delta J^k_{it})_{T(t)}$. We note that use of industry and occupation changes to proxy for (and condition out) job changes during the intervening months between MIS 5 and 6 is an imperfect fix, but there are no obviously superior solutions given the data.

Estimates for the wage separation elasticity are reported in Tables 2a and 2b. The first column of each table corresponds to estimates of eqn (5) for 3-month job changes. We detect no change in the *overall* separation elasticity between the pre (2015–2019) and post (2021–2023) periods. Among the high-school under-40 group, however, the magnitude of the separation elasticity increases substantially in the post period. Echoing the pattern for the state-level wage-Phillips curves, the impact of labor market tightness in making separations more sensitive to wages is concentrated among young, less-educated workers

The person-level wage residual calculated from cross-sectional data incorporates both firm-specific rents (the explanatory variable of interest) and unobserved worker quality—a confound that will attenuate separation elasticity estimates based on equation (5). As an alternative measure of on-the-job rents, we use the estimated log wage premium $\tilde{w}_j$ in each worker's industry j of current employment. Industry wage premia (IWP) are estimated from cross-sectional regressions of log hourly wages on gender, age, age squared, and age cubed,

[28] The industry wage premium approach, discussed below, surmounts this problem because the premium is a function only of one's industry, which is reported in each period.

as well as dummy variables for race, ethnicity, citizenship, education, metro area status, and 3-digit industry, where the coefficients on the industry dummies capture the estimated premia. These IWP models are fit separately by education-age groups with the following estimating equation:[29]

$$\Delta J^k_{it} = \alpha_{T(t)} + \beta_{1,T(t)} \ln \tilde{w}_{j(i,t-1)} + X'_{it}\lambda_{T(t)} + \epsilon_{it}. \tag{6}$$

Distinct from equation (5), this model uses $\tilde{w}_{j(i)}$ in place of $\tilde{w}_i$. Additionally, since industry affiliation—used to calculate the wage premia—are observed each month, we use monthly separations ($k = 1$) as the dependent variable (rather than 3-month ($k = 3$) separations), clustering standard errors at the industry level. Elasticities from these specifications are obtained by dividing $\beta_{1,T(t)}$ by $E(\Delta J^1_{it})_{T(t)}$. Estimates of equation (6) are reported in columns 2 and 3 of Tables 2a and 2b. Consistent with our findings thus far, we see an increase in the magnitude of the separation elasticity among young non-college workers from -0.546 (se = 0.133) to -0.766 (se = 0.152).

An additional prediction of the job ladder model is that the separation elasticity is not constant across the wage distribution but instead is larger at lower wage levels, where outside offers are more likely to generate a voluntary worker move (see section 2.1). Harnessing this prediction, we fit equation (6) non-linearly, using a quadratic specification for the main explanatory variable, $\tilde{w}_{j(i,t-1)}$.[30] Implied elasticities are then calculated by dividing the derivative of ΔJ^1_{it} with respect to $\tilde{w}_{j(i,t-1)}$ by the predicted value of ΔJ^1_{it} at several values of $\ln \tilde{w}$. Results are summarized in Figures 25 and 26 and are enumerated in Table 3, which reports estimated elasticities at $\ln \tilde{w} \in \{-0.3, 0.0, 0.3\}$ in both the pre- and post-pandemic period, as well as the contrast between the two.[31]

While the aggregate EE separation elasticity at its midpoint ($\tilde{w}_j = 0$) did not meaningfully change between the pre- and post-pandemic periods, this elasticity steepened at *low* wage levels ($\tilde{w}_j = -0.3$), from -0.717 (se = 0.216) in the pre-pandemic period to -0.895 (se = -0.209) in the post-pandemic period, as shown in Figure 25. This increase was most pronounced among the lowest paid worker groups, as predicted by theory. Panel A of Figure 26 reveals that the quit elasticity at the mean wage premium among young non-college

[29] Table 4 of Card et al. (2022) reports that approximately 20% of the variance ($0.122^2/0.240^2$) in cross-sectional industry wage premia reflects differences in employer pay across industries, with most of the remainder due to skill sorting. These unobserved skill differences contribute to variation in $\tilde{w}_j$ and hence will attenuate estimates of the quit elasticity—though this attenuation can be calculated using estimates reported in Card et al. (2022).

[30] Tables A7 and A8 report the coefficients on $\ln \tilde{w}_{j(i,t-1)}$ and its square from equation (6). Table A9 reports these estimates using a Poisson regression specification.

[31] Table A10 reports the estimated elasticities evaluated along the industry wage premia using a Poisson regression specification.

workers rose in magnitude from -0.515 (se $= 0.132$) to -0.833 (se $= 0.147$). At $\tilde{w}_j = -0.3$, the increase was steeper still, growing from -0.262 (se $= 0.224$) to -0.942 (se $= 0.304$). This increase is statistically significant at $p = 0.10$, as reported in Table 3. In contrast, there is no evident change in the quit elasticity for older high-school workers or for four-year college grads in either age bracket. Thus, the job-to-job separation elasticity differentially rose in magnitude among low-wage workers employed in 'low-rent' jobs, i.e. jobs that pay particularly low wages conditional on observable worker characteristics. As highlighted by Table A11, this rise in the elasticity (in absolute value) was especially pronounced until mid-2022, where it began to slightly weaken.[32]

4.3 Job changes and wage changes

In the job-ladder model, job separations spike as the labor market tightens and workers transition to higher-paid jobs. Accordingly, wage gains stemming from a tightening labor market should be concentrated among job movers. We test these predictions as follows: First, we explore whether the rate of net worker mobility from lower-paid to higher-paid industries increased following the pandemic. Ideally, we would be able to see if workers are more likely to move into higher-paying employers (not just industries). However, this is infeasible with household data, since we cannot estimate firm-specific wage premia. Instead, we can calculate industry wage premia and use that to test whether workers are moving from higher to lower paid industries, with industry premia serving as an aggregation of firm wage premia. In Section 4.4, we then test whether wage gains are concentrated among job movers by decomposing annual wage growth between movers and stayers.

As in Section 4.2, industry wage premia, $\tilde{w}_j$, are measured as industry fixed effects, obtained from a cross-section Mincerian wage regression, estimated separately by subgroup. We subdivide industries into four groups based on ranked wage premia, $Q(\tilde{w}_j)$, with each group containing 25% of employment in 2015–2019.[33] The following linear probability model characterizes the probability that a worker who is employed in the lower half of the industry wage premium distribution in year $t-1$ is employed in the upper half of the distribution in the following year t:

[32] Figure A12 reports estimated separation elasticities at six-month intervals from the first half of 2015 through the first half of 2023. In panel A, the overall separation elasticity at low industry premium levels ($\ln \tilde{w} = -0.3$) rose in absolute magnitude from approximately 2018 forward, rose further during the pandemic recovery in 2021 and 2022, and then substantially weakened from the second half of 2022 forward. Panel B shows this pattern was especially pronounced for young non-college workers.

[33] Quartile groupings are kept constant after 2019, allowing industries at various wage levels to grow or contract as a share of employment.

$$E\left[\mathbb{1}\left[Q(\tilde{w}_{j(i),t}) = 3 \vee 4\right] \middle| Q(\tilde{w}_{j(i),t-1}) = 1 \vee 2\right] = \alpha_{T(t)=1} + \alpha_{T(t)=2}. \tag{7}$$

The coefficients $\alpha_{T(t)=1}$ and $\alpha_{T(t)=2}$ in equation (7) capture the probability of upward industry mobility during years 2015–2019 and 2021–2023, respectively. Figure 27 and Table 4 report estimates for both the full sample of employed workers and the subsample of non-college workers under age 40.

Movements across the two halves of the industry premium distribution in a given month are relatively rare: we estimate this probability at 0.52% prior to 2020 for the full sample of workers. Following the pandemic, this probability rose to 0.54%, an increase that is not statistically or economically significant. Mobility among young non-college workers was 62% higher than across the full sample of workers in the pre-pandemic period: 0.84% versus 0.52% during 2015–2019. In the post-pandemic period, as our conceptual framework anticipates, the mobility of young non-college workers increased disproportionately, widening the mobility gap between the two groups. As shown in the third set of bars in Figure 27, upward industry wage mobility among young non-college workers rose significantly after the pandemic, from 0.84% to 1.00% (compared with 0.52% to 0.54% for the overall sample).[34] If this rise in upward industry mobility were accompanied by a comparable increase in downward industry mobility, the net effect would be a wash. This is not the case, however. Figure 27 finds no increase in downward mobility, either overall or among young non-college workers (this is also confirmed in panel C of Table 4).[35]

Figure 28 and Table 5 refine this exercise by analyzing movements into and out of the bottom quartile of industries. The probability of upward mobility from the bottom quartile is nearly double that of the probability of movement out of the bottom half of the distribution. The probability of exit from the bottom-quartile among the full population rose only modestly from pre- to post-2020: 0.99% before and 1.04% after. Among young non-college workers, the gain was larger (and highly precise): a 23% increase, from 1.44% to 1.77%. There was no corresponding increase in downward mobility. These findings indicate that the rise in the EE separation elasticity documented above reflects a net reallocation of young non-college workers away from particularly low-premium (i.e., low-rent) sectors.[36]

[34]These probabilities likely overstate the frequency of upward movements because measurement error in industry assignments will generate false transitions. But the estimated *change* in this probability should be unbiased unless measurement error changes.

[35]Downward mobility is not simply the mirror of upward mobility for two reasons. First, on average, workers tend to move upward in the wage distribution as they age—particularly young workers—so we expect some upward mobility at the person level. Second, high-premium industries may expand and low-premium industries contract, leading to a rise in aggregate upward industry mobility.

[36]In comparing upward and downward mobility rates across sectors, it is critical to account for size differences among the underlying risk sets. Since, by definition, there are three times as many workers in the top-three

Figure 29 and Table 6 provide a third perspective on sectoral mobility by charting movements in and out of the typically low-paid hospitality sector. According to our IWP estimates, the hospitality sector lies slightly below the 10^{th} percentile of the residual industry wage distribution. The share of hospitality workers in the overall sample fell from 8.0% in 2015–2019, to 7.4% in 2021–2023. The corresponding fall for young non-college workers was from 18.5% to 18.0%. Among the overall working population, the exit rate from hospitality rose from 1.4% to 1.5% with a small decrease in the adjusted entry rate. Among young non-college workers, the exit rate rose further, from 1.49% to 1.73%, with a small (and statistically insignificant) increase in the adjusted entry rate.[37] For both groups, the net exit rate from the hospitality industry increased in the post-pandemic period.

To further investigate the timing of these movements, Tables A12, A13, and A14 and Figures A13, A14 , and A15 present estimates over two post-pandemic periods: 2021 Q1 to 2022 Q2, and 2022 Q3 to 2023 Q2. Net movements out of the bottom quartile and out of the hospitality industry have broadly weakened from the third quarter of 2022 to mid-2023. For the overall sample, movements out of the bottom half of the IWP distribution have also weakened in the most recent period. However, the movement of young non-college workers out of the bottom half of the IWP distribution has increased slightly in the most recent period. Since wage compression has been abating since mid-2022, weakened mobility estimates in the most recent period are consistent with expectations.

In short, evidence from all three measures of industry mobility suggests that the unexpected, post-pandemic compression of the US wage distribution reflects—at least in part—rising net flows of young non-college workers into higher-wage industries. If workers were reallocating to better paid jobs in the post-pandemic period, then the wage growth of job movers should be larger than the wage growth of job stayers. This is the prediction we test next.

quartiles than in the bottom quartile, the exit rate from the top-three quartiles of the distribution would need to exceed the exit rate from the bottom quartile by a factor of three in order to maintain the initial, steady-state distribution. Thus, in constructing up-down comparisons in Table 5 and Figure 28, we adjust for relative sizes of the risk sets by multiplying downward movements by the factor $(1-p)/p$, where p is the fraction of workers in the bottom quartile ($p = 0.25$).

[37] Movements into the hospitality sector in Figure 29 and Table 6 are also scaled by $(1-p)/p$, where p is the fraction of workers in the hospitality industry in 2015–2019 ($p = 0.079$ for the overall sample and $p = 0.185$ for the young non-college sample).

4.4 The contribution of job mobility to wage growth

A key challenge in decomposing the role of job-movers and job-stayers in overall wage growth is that the Current Population Survey does not provide reliable measures of job change at annual frequencies. Job change is observed for only a subset of eight months that an individual is in the CPS sample, while wage changes are observed only for two survey months that are a year apart. We address this limitation by using a quarterly measure of job change to estimate the annual job-to-job separation rate under the assumption of a constant hazard rate.[38]

In order to decompose the wage change into job-mover and job-stayer components, let $\Delta w_T = \Delta w_T^M \Delta J_T + \Delta w_T^S (1 - \Delta J_T)$ denote the mean wage change for a demographic group during a time interval T. This is equal to the wage change among job-movers, Δw_T^M, times the estimated (12-month) job switch rate, ΔJ_T, plus the wage change among job-stayers, Δw_T^S, multiplied by the complement of the switch rate. Using this identity, we can decompose the change in wage growth between two periods, 2015–2019 ($T = 1$) and 2021–2023 ($T = 2$), using the following equation:

$$\Delta w_2 - \Delta w_1 = \underbrace{\left(\Delta w_2^M - \Delta w_1^M\right) \Delta J_1}_{Movers} + \underbrace{\left(\Delta w_2^S - \Delta w_1^S\right) (1 - \Delta J_1)}_{Stayers} + \underbrace{(\Delta J_1 - \Delta J_2) \left(\Delta w_2^M - \Delta w_2^S\right)}_{Switch\ rate}. \quad (8)$$

Given estimates of $\left\{\Delta w_T^M, \Delta w_T^S, \Delta J_T\right\}$, equation (8) apportions the observed change in wage growth across time periods for a given demographic group into three components: the change in the wage growth of job-movers, scaled by the switch rate; the change in the wage growth of job-stayers, scaled by the complement of the switch rate; and the change in the switch rate, scaled by the difference between the mover and stayer wage growth. These three groups represent the proportion of the wage compression ($\Delta w_2 - \Delta w_1$) that is attributed to the change in mover wage growth, the proportion due to the change in stayer wage growth, and the proportion due to a change in the probability of switching.

We observe overall wage change (Δw_T) and wage change for movers (Δw_T^M) directly in the data. We define Δw_T^M as the annual wage change for individuals who reported switching jobs in MIS 6, 7, or 8.[39] We then need to estimate ΔJ_T and Δw_T^S. Estimating Δw_T^S is a bit

[38]We are able to calculate a quarterly job change measure because job changes in the CPS are measured 3-months consecutively in MIS 2,3,4 and 6,7,8. We use MIS 6,7,8 for our quarterly switch measure because those are the months in between the two wage observations in MIS 4 and 8.

[39]We focus on MIS 6,7,8 because these are the only months in which we observe job change in between our

more complicated than estimating Δw_T^M because people who did not change jobs in MIS 6, 7 or 8 could have changed jobs in the eight months between MIS 4 and 5 during which job change is unobserved in our dataset. Because of this, we use overall wage change (Δw_T), the wage change among movers (Δw_T^M) and the annual probability of switching jobs (ΔJ_T) to infer the wage change among job stayers (Δw_T^S).

Thus, in order to estimate Δw_T^S, we first must estimate ΔJ_T. To do this, we leverage the fact that we see job change information for three out of the 12 months in between our two wage observations.[40] Define ΔJ_T^3 as the quarterly switch rate so that $\Delta J_T^3 = 1$ if an individual switched jobs in MIS 6,7 or 8 and $\Delta J_T^3 = 0$ otherwise (individuals who did not switch jobs in those months). The annual switch rate would then be the sum of the probability of switching in the last quarter of the year (MIS 6,7,8) and the probability of staying in the last quarter of year times the probability of switching in the first three quarters of the year conditional on staying in the last quarter. Under the assumption of constant hazard, the switch probability is then: $\Pr[\Delta J_T = 1] = \Pr[\Delta J_T^3 = 1] + (\Pr[\Delta J_T^3 = 0]) * \Pr\left[\Delta J_T = 1 | \Delta J_T^3 = 0\right]$ where $\Pr\left[\Delta J_T = 1 | \Delta J_T^3 = 0\right] = 1 - \left(\Pr\left(\Delta J_T^3 = 0\right)\right)^3$ is the probability of a job change in the past year given no change in the last quarter (MIS 6,7,8).

Estimates of all the terms of equation (8) are reported in panels A and B of Table 7 for young non-college workers, as well as their complementary group. Quarterly separation rates, $\Pr\left[\Delta J_T^3\right] = 1$, are reported in row 1 of panel A. Row 2 reports the 3-quarter switch probability, $\Pr\left[\Delta J_T = 1 | \Delta J_T^3 = 0\right]$. Estimates for the annual switch probability, $\Pr\left[\Delta J_T = 1\right]$, and its counterpart, $\Pr\left[\Delta J_T = 0\right]$, are reported in rows 3 and 4, respectively, of panel A.

The estimates in panel A show that the annual probability of changing jobs increased by over two percentage points for young non-college workers (from 27.23% to 29.66%) while it increased by less than a percentage point (from 19.82% to 20.48%) for all other workers between the two periods. Average annual wage changes in each period among workers—both overall (Δw^M) and by job-change status (Δw_T^M and Δw_T^S)—are reported in panel B of Table 7. Here we can see that the only group to experience annual wage growth between the 2015–2019 and 2021–2023 period was young non-college workers who switched jobs.

Finally, in panel C, we plug estimates from panels A and B to the wage decomposition in equation (8). Panel C of Table 7 reports the estimates of the components in equation 8 separately for young non-college workers and their complementary group. Figure 30 summarizes these results. Panel A of this figure plots the wage decomposition for each group (as reported in panel C of Table 7). The darker set of bars represent the decomposition

two wage observations in MIS 4 and 8.

[40] We observe wages in MIS 4 and 8 and job change in MIS 6,7, and 8, but there is an eight month gap in between MIS 4 and 5.

for young non-college workers while the lighter colored bars for the complementary set of workers—those who are not young non-college workers. The first set of bars in this figure shows the delta in average annual wage change among CPS respondents between the 2015–2019 and 2021–2023 periods. For the high-school under-40 group, this rate was 0.94 log points lower in 2021–2023, reflecting the impact of rising inflation. This slowdown is more than accounted for by the fall in the average wages of job-stayers which accounted for -1.93 log points of overall wage growth for young high-school workers (the 2^{nd} set of bars). By contrast, and consistent with the predictions of the job ladder model, the average wage change for movers and the job change rate increased among young high-school workers as the labor market tightened. Thus, job moving positively contributed to overall wage growth for young, non-college workers (the 3^{rd} and 4^{th} sets of bars). Specifically, the increase in wage growth for job movers in the 2021–2023 period contributed 0.85 log points to wage growth among young high-school workers while the rising move rate contributed another 0.14 log points. Put together, moving jobs contributed 0.99 log points in total to wage growth for young non-college workers. Average wage growth for all other workers (light colored bars) became substantially more negative after the pandemic and, in contrast to young-high school workers, this decrease was not counteracted by wage growth associated with job moving. Thus, the increasing gains from job moving—higher average wage gains for movers and a higher move rate—were concentrated among young non-college workers.

In order to understand the role of switching jobs in the wage *compression*, the second panel of Figure 30 reports the difference between the components of wage decomposition for young non-college workers and all other workers. Comparing overall wage changes for each group between the 2015–2019 and 2021–2023 periods, the first bar in this panel shows that wage growth was 1.31 log points greater among young high-school workers than among other workers. Wage changes among job-movers, as well as changes in the job move rate, disproportionately benefited young high-school workers. Of the 1.31 log point differential increase in wage growth among young high-school workers, -0.13 log points are explained by lower wage growth among young high-school stayers (scaled by the initial stay rate), 1.32 log points by greater wage growth among young high-school movers (scaled by the initial move rate), and 0.12 log points by a differential increase in the move rate among young high-school workers (scaled by the difference in wage growth among job-movers versus job-stayers). Job movers completely account for the differential post-2020 wage growth among young high-school workers relative to other workers (Figure 30).

These findings shed light on how tight labor markets lead to higher wages. Standard macroeconomic models of the labor market (Blanchard and Galí, 2010; Mortensen and Pissarides, 1994) typically assume that the higher labor demand associated with increasing tightness improves workers' bargaining positions, which leads them to renegotiate for higher wages. Strikingly, a large part of the wage growth we have seen is not of this variety. Wage growth among job stayers has risen much less than wage growth among movers. This type of adjustment highlights the importance of changes in competition—especially through on-the-job search and frictional wage dispersion—as important building blocks to understand how labor market tightness affects wages.

5 Nominal wage, tightness, and inflation

The tightening labor market during 2021–2023 was central to the increase in labor market competition—and the resulting compression in wages—following the pandemic. The same 2021–2023 period *also* saw a rapid rise in prices, at a rate unprecedented since the Great Inflation of the 1970s and early 1980s, with the headline CPI-U inflation reaching a 12-month peak of 9.0 in June 2022. Was the labor market tightness that produced the unexpected wage compression also responsible for this surge in inflation?

We estimate the relationship between state-level tightness and price inflation between 2021 and the first half of 2023 using a regional price-Phillips curve, paralleling our previous analysis of the wage-Phillips curve. We use the headline CPI-U, which includes the full basket of goods and services, for the purpose of quantifying real wage trends while allowing for regional variation in prices. Annualized headline CPI inflation over this period was 12.5%. It is widely recognized, however, that the headline inflation surge was, in part, driven by volatile global energy prices, exacerbated by the Russia-Ukraine conflict of 2022. We therefore focus on CPI-less-energy as the key price index for our Phillips curve analysis (similarly to Cerrato and Gitti (2022)). Over the same period, (annualized) CPI-less-energy inflation was 11.5% nationally. We assess how much our measure of labor market tightness is associated with regional differences in price inflation using this index.

To construct state-level price changes, we apply the 23 CBSA-level CPI-U deflators to the main metro areas in each state; the state average of CBSA-level CPI-U deflators to other (non-main) metro areas within each state; and census division-level CPI-U deflators to the remainder of areas. Using pooled worker-level CPS observations for each quarter, we fit the following equation, analogous to the specification for estimating the wage-Phillips curve:

$$\ln P_{iskt_k} = \beta \left(\text{Tightness}_{skt_k=0} \times \mathbb{1}\left[t_k = 1\right] \right) + X_i' \gamma_k + \alpha_{kt_k} + \delta_{sk} + e_{iskt_k}, \tag{9}$$

where $\ln P_{iskt_k}$ is the log price level facing worker i in state s in stack k and sub-period t_k. Recall that due to the inclusion of stack-by-time and stack-by-state fixed effects, with an interaction between tightness at the start of the quarter ($t_k = 0$) and an indicator for the end of the quarter ($t_k = 1$), the β coefficient estimates the relationship between the *change* in state-level annualized log prices and the *level* of labor market tightness.

Figure 31 plots the price-Phillips curve, as well as the wage-Phillips curves for high-school workers under 40 and for the workforce overall, superimposed on the binscatters associated with each curve. The price-Phillips curve has a slope of 0.003 (se = 0.006), roughly an eighth of the 'overall' wage-Phillips curve slope, 0.023 (se = 0.01). Both of these estimates are less than one-quarter as large as the wage-Phillips curve slope for young workers without a college education, which is estimated at 0.095 (se = 0.032). This contrast highlights that tightness-fueled wage gains accrue disproportionately to low-wage workers.

Table 8 reports price-Phillips curve estimates using our primary tightness measure as well as its two components. The coefficients on tightness (row 1 of Table 8) are around 0.003 depending on the exact set of controls, implying that a one standard deviation increase in tightness is associated with a very modest 30 basis point rise in inflation. Although this price-Phillips curve estimate is close to zero when pooled over the entire post-pandemic period, panel A of Table A15 shows that tightness had a statistically significant impact on non-energy price inflation from 2021 until mid-2022: during this time, the price- and wage-Phillips curve estimates were similar in magnitude (panels A and B). The price-Phillips curve estimate steepened from a (wrong-signed) -0.0093 in the pre-pandemic period to 0.0079 in the 2021-22 period, before reverting back to -0.0087 in the 2022-23 period.

What do these estimates imply about the contribution of labor market tightness to price inflation? Using the price-Phillips curve estimate from the full post period of 2021 Q1 through 2023 Q2, we calculate that tightness contributed around 18 percent of the *excess* inflation in this period, meaning the inflation at and above the 2021 Q1 value of 2.1 percent.[41] This calculation is, however, based on an estimated price-Phillips curve coefficient that is statistically indistinguishable from zero. Focusing only on the period between 2021 Q1 and 2022 Q2, when the price-Phillips curve relationship was statistically significant, these estimates suggest that tightness contributed to 39% of the excess inflation in that sub-period. After 2022 Q2, we cannot confidently attribute any further inflation acceleration to tightness given wrong-signed and imprecise coefficient. These illustrative exercises suggest that labor market tightness contributed meaningfully to inflation dynamics over the full 2021–2023 period, though the majority of the rise in inflation during this period stems from other

[41] In order to calculate the contribution of inflation to tightness, we estimate quarterly predicted inflation rates from our PPC estimates. For example, in each quarter, we multiply our PCC coefficient for the full post-pandemic period (.0031) by the change in tightness from the previous quarter. These quarterly predicted changes in inflation are summed up to calculate the cumulative change in predicted inflation over this period—.5 percentage points compared to a 2.8 percentage point actual increase in cumulative inflation over this period. Thus, tightness explains (.5/2.8 =) 18% of the increase in inflation over this period. We repeat this exercise for 2021 Q1 - 2022 Q2 period using the PPC from that sample (.0079).

sources.

Estimating price-Phillips curves using unemployment rates alone (instead of the composite tightness measure) yields slightly stronger and more precise estimates (row 2 of Table 8). Conversely, using EE separation rates alone yields imprecise estimates (row 3). This pattern parallels the wage-Phillips curve estimates in Table A6, which show that the EE separation rate is by itself predictive of wage growth only or low-wage workers, i.e., the group for whom EE separations have risen the most.

We had previously presented real wage trends across the earnings distribution using *national* price deflators (Figure 11). Figure 32 provides a regional perspective on real wage gains across the distribution by deflating wage levels using our constructed *state-level* headline CPI. Conclusions about the level and distribution of real wage changes during the two-, and nearly three-year intervals ending in June 2023 are essentially unaffected when using regional rather than national price indices. For the twelve months immediately preceding June 2023, the adjustment makes a slight difference: absent this adjustment, workers in the bottom 90% of the wage distribution experienced wage gains; with this regional adjustment, only those in the bottom 70^{th} percentile did. This implies, consistent with the estimates in Table 8, that tightness-driven real wage growth was modestly offset in regional labor markets by tightness-driven price growth.

Table 9 incorporates this insight to estimate how labor market tightness has affected real wage growth net of regional price change by wage quantile and demographic group.[42] For the workforce overall, applying regional price deflators versus the national price deflator does not substantially change our inference on the estimated effect of tightness on real wage levels (as suggested by Figure 31). Low-wage workers saw pronounced real wage gains in tighter regional labor markets, even after accounting for regional differences in inflation. The tightening labor market following the height of the pandemic is strongly associated with relative and real wage changes that disproportionately benefit low-wage workers.

6 Conclusion

Labor market tightness following the height of the Covid-19 pandemic led to an unexpected compression in the US wage distribution that reflects, in part, an increase in labor market competition. Disproportionate wage growth at the bottom of the distribution reduced the college wage premium and reversed almost 40% of the rise in 90-10 log wage inequality since

[42] To gauge the impact of applying regional rather than national price adjustment, one can compare the Table 9 wage-Phillips curve estimates with analogous, nationally price-deflated estimates presented in Table 1.

1980, as measured by the 90-10 ratio. The Unexpected Compression as measured by the fall in the 90-10 log wage ratio was nearly half of the Great Compression of the 1940s. The rise in wages was particularly strong among workers under 40 years of age and without a college degree.

Wage compression, associated with rapid nominal wage growth, was accompanied by rising job-to-job separations—especially among young non-college workers. These two phenomena are closely linked. State-level, post-pandemic labor market tightness became strongly predictive of aggregate wage compression, substantial real wage growth among low-wage workers, and re-allocation toward higher-paying sectors. Tightness was associated with higher local area price inflation in 2021 through early 2022 and modestly contributed to inflation in the full post-pandemic period. Importantly, even accounting for its impact on inflation, labor market tightness spurred real wage growth for the lowest-earning quartile of workers.

The post-pandemic rise in labor market tightness—and the consequent wage compression—represent a profound shift in US labor market conditions, seen most clearly in the rise of the wage-separation elasticity among young non-college workers. The collage of evidence above leads us to tentatively conclude that the pandemic increased the elasticity of labor supply to firms in the low-wage labor market, reducing employer market power and spurring rapid relative wage growth among young non-college workers who disproportionately moved from lower-paying to higher-paying and potentially more-productive jobs.

This evidence has several limitations. One is that the relatively small size of the monthly CPS sample provides, at most, adequate precision for testing some of the key empirical implications of the imperfectly competitive model. Additionally, the infeasibility of accurately tracking workers' job changes over the course of a year requires us to focus on industry change rather than job change as a measure of worker mobility, though job change is the object of interest underscored by theory. Third, and most critically, our evidence on the rise of the quit elasticity relies on using either own-wage residuals or estimated industry premia to proxy for rents—that is, the wage premia (or deficits) that workers receive, relative to their competitive wage level. A stronger test of the evolution of the quit elasticity would employ establishment-level measures of wage premia that are purged of workers' own skill levels (or fixed effects). Our ongoing work seeks to overcome these limitations by using large samples of matched worker-establishment data to perform fine-grained analyses of worker separations across individual establishments, both in the cross-section and in the years before and after the onset of the pandemic.

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Figure 1: Effect of Inward Labor Shift in Competitive Labor Market

A. Market-level impact *B. Price-taking firm response*

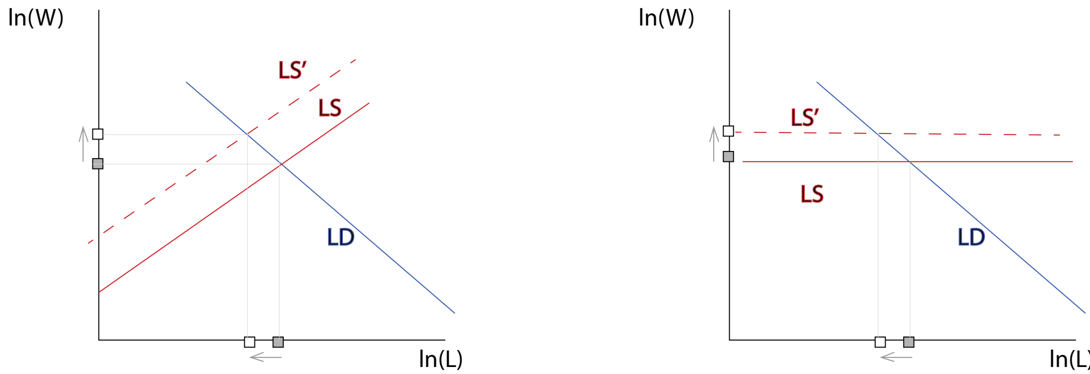


Figure 2: Effect of Rotation of Labor Supply Curve in Monopsonistic Labor Market

A. Low-productivity monopsonistic firm *B. High-productivity monopsonistic firm*

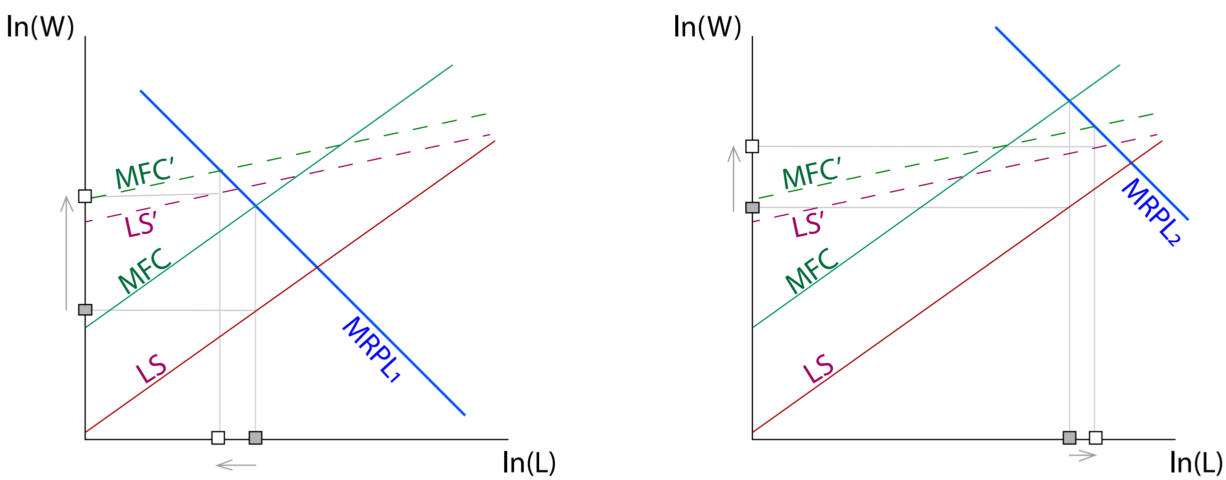
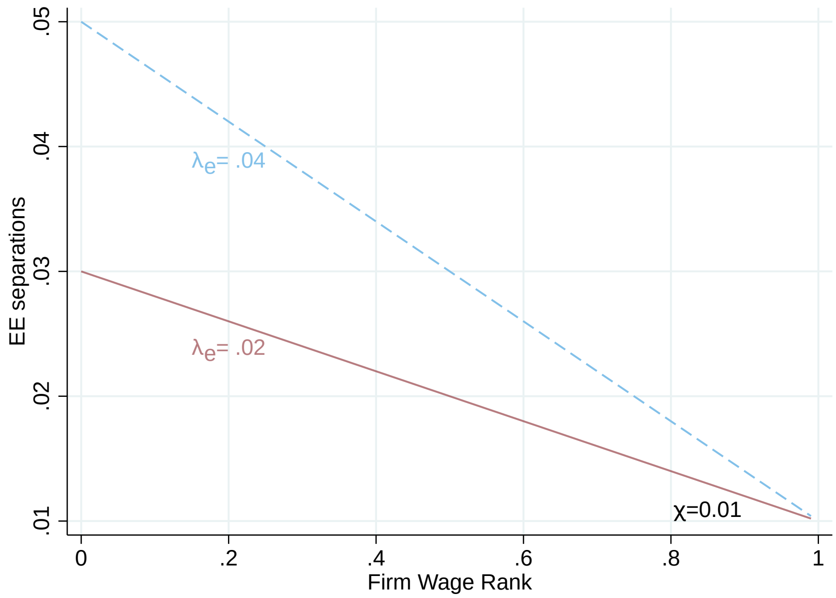
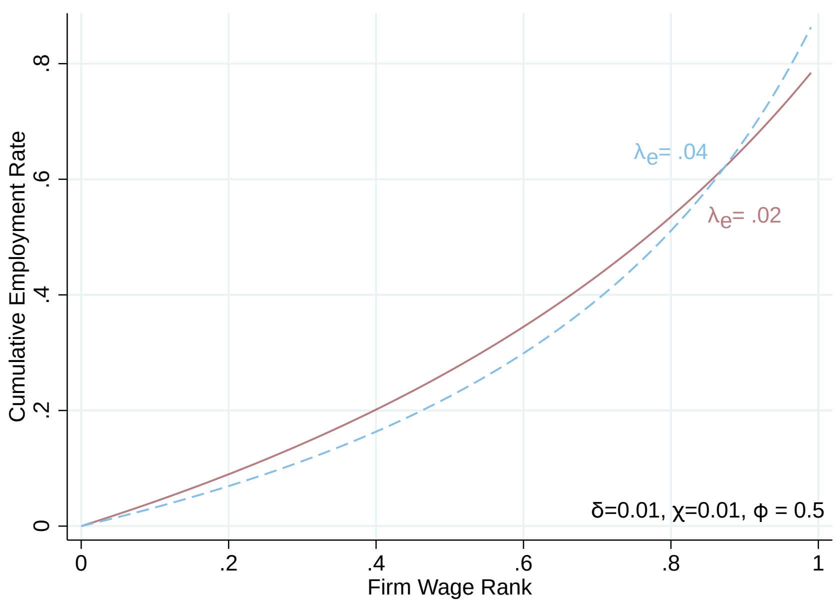


Figure 3: Shift in Job-to-Job Separations and Firm Wage Rank Locus in Response to a Higher Contact Rate



Note: Figure plots the EE separation rate as a function of firm wage rank from the dynamic job ladder model presented in Section 2.1 and further elaborated in Appendix Section A2. The EE separation equation is $EE(w) = \chi + \lambda_e(1-r)$, where EE is the employment-to-employment separation rate, χ is the exogenous separation rate to another job, r is firm wage rank, and λ_e is the contact rate. This equation is plotted for $\chi = 0.01$ and separately for $\lambda_e = .02$ and $\lambda_e = .04$.

Figure 4: Reallocation of Steady-State Employment by Firm Wage Rank in Response to a Higher Contact Rate



Note: Figure plots the cumulative employment rate in steady state as a function of firm wage rank from the dynamic job ladder model presented in Section 2.1 and further elaborated in Appendix Section A2. The equation estimated in this figure is equation 10 (in levels) for $\delta = 0.01$, $\chi = 0.01$, and $\phi = 0.5$. Cumulative employment is plotted separately for different contact rates ($\lambda_e = .02$ and $\lambda_e = .04$).

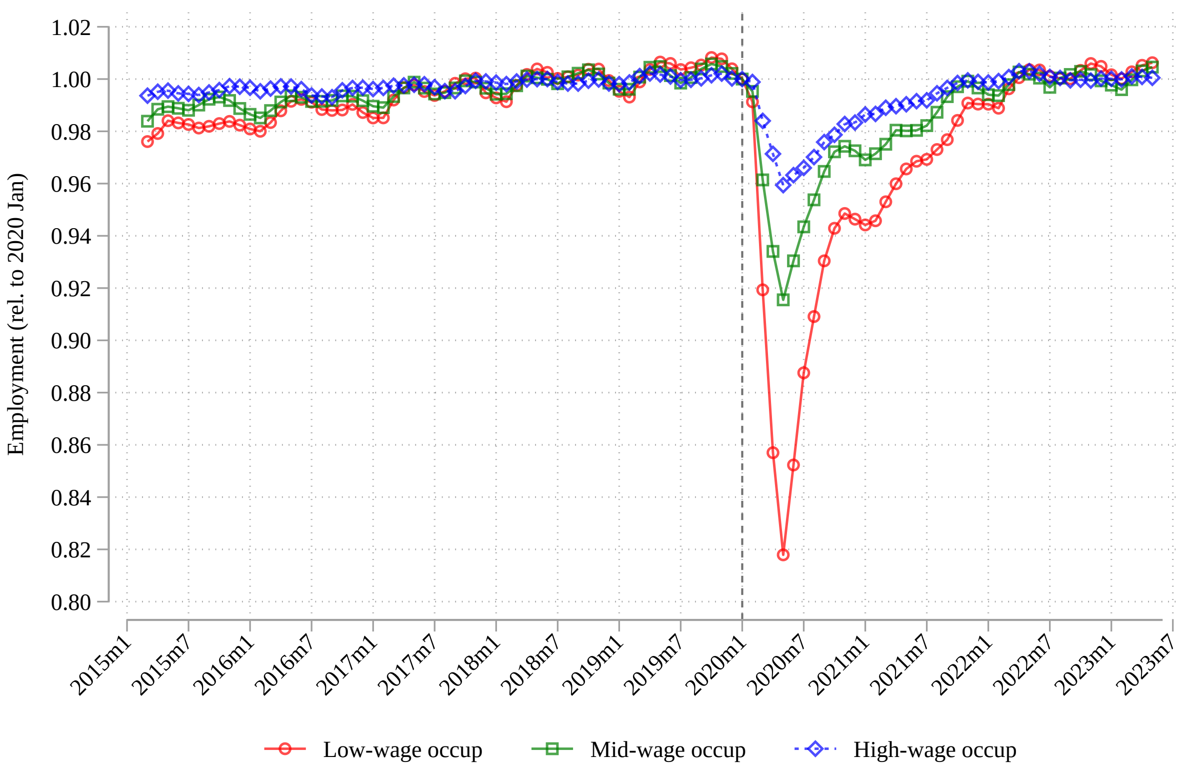
Figure 5: Employment and Labor Force Participation Rates, Relative to January 2020

Note: CPS monthly data. Adjusted to maintain demographic composition in January–March 2020 using inverse probability weighting based on age, education, race/ethnicity, gender, country of birth, and region. Employment is smoothed with a 3-month moving average.

Figure 6: Employment-to-Population Rates by Education, Relative to January 2020

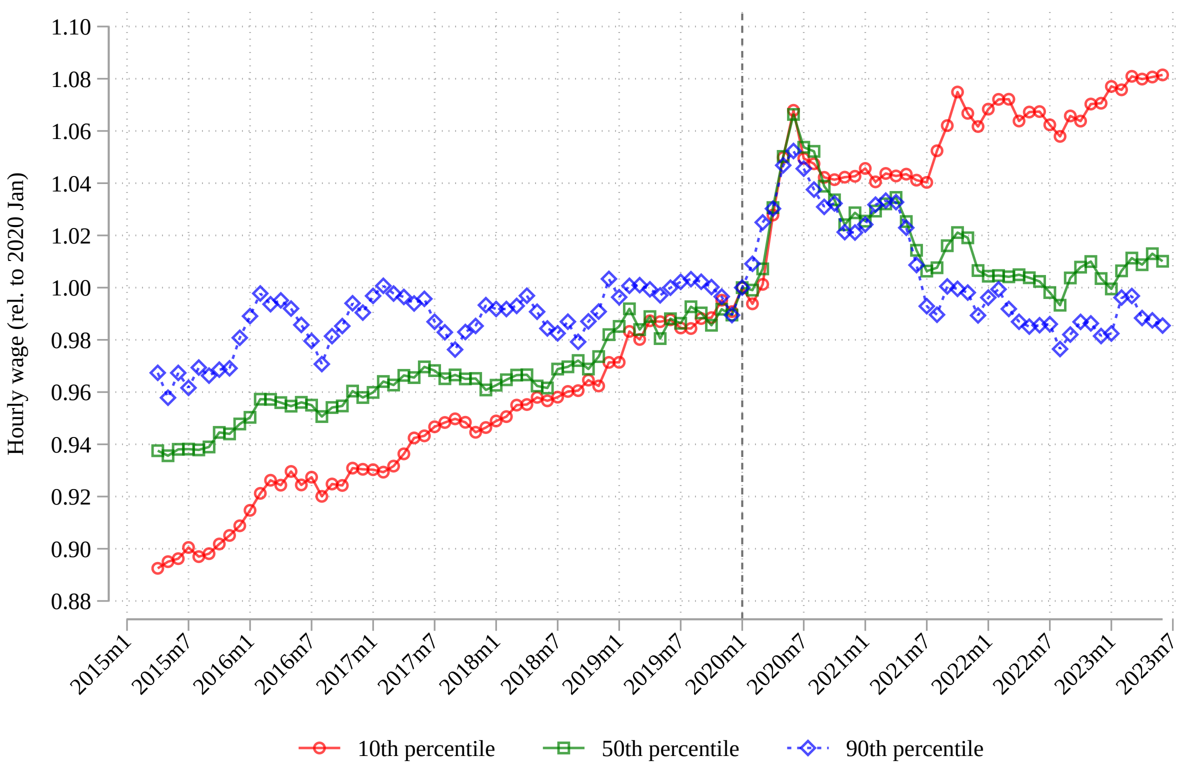
Note: CPS monthly data. Adjusted to maintain demographic composition in January–March 2020 using inverse probability weighting based on age, education, race/ethnicity, gender, country of birth, and region. Employment is smoothed with a 3-month moving average.

Figure 7: Employment Trends for Low-, Mid-, and High-Wage Occupations, Relative to January 2020



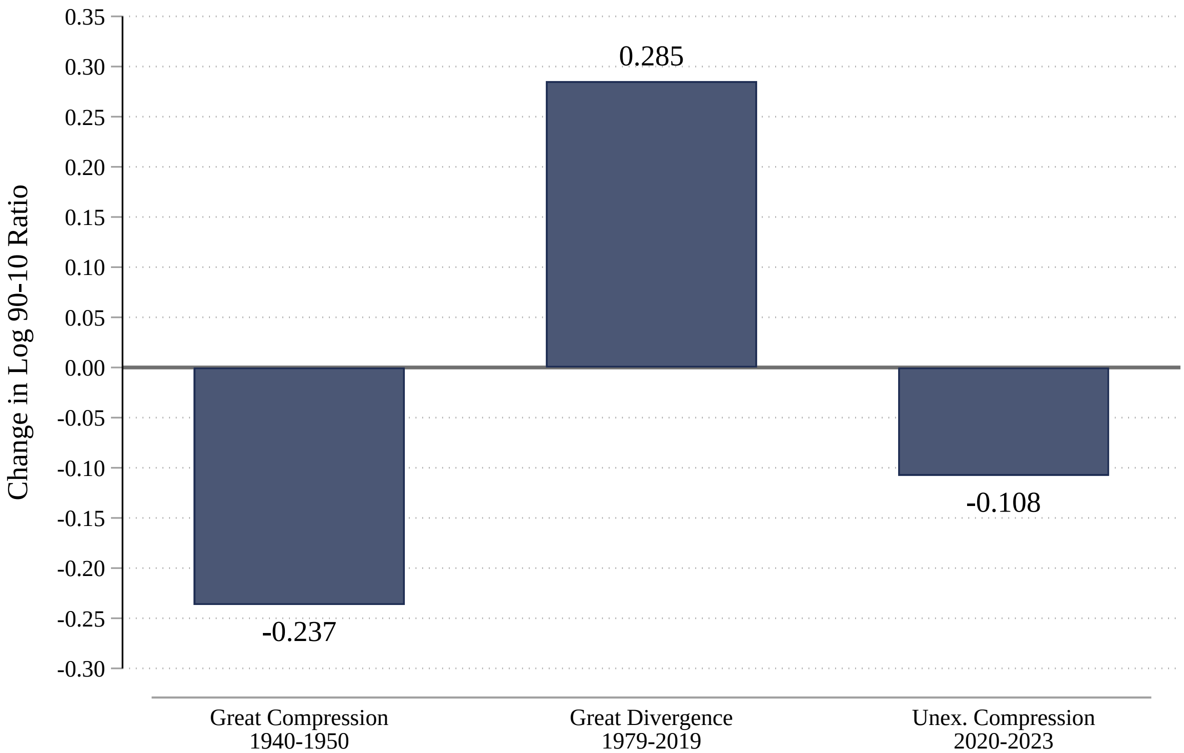
Note: CPS monthly data. Adjusted to maintain demographic composition in January–March 2020 using inverse probability weighting based on age, education, race/ethnicity, gender, country of birth, and region. Employment is smoothed with a 3-month moving average. Occupational wage terciles are measured pre-pandemic, in 2019.

Figure 8: Real Hourly Wages by Quantile, Relative to January 2020



Note: CPS monthly data. Adjusted to maintain demographic composition in January–March 2020 using inverse probability weighting based on age, education, race/ethnicity, gender, country of birth, and region. Wages are real (2023_{q2} USD). We construct wage quantiles by month. Wage percentiles smoothed with lowess and 3-month moving average.

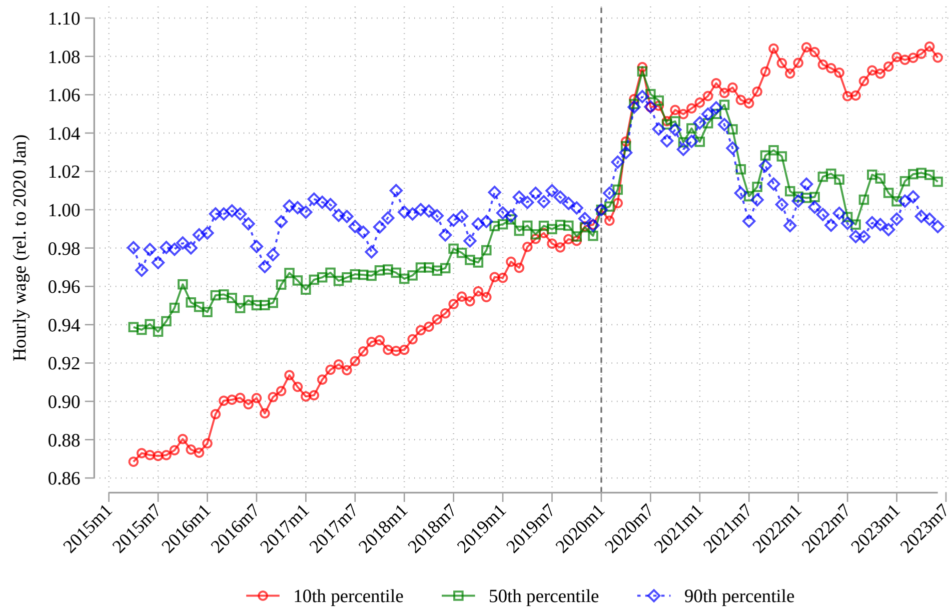
Figure 9: Change in Log 90/10 Ratio Over Time



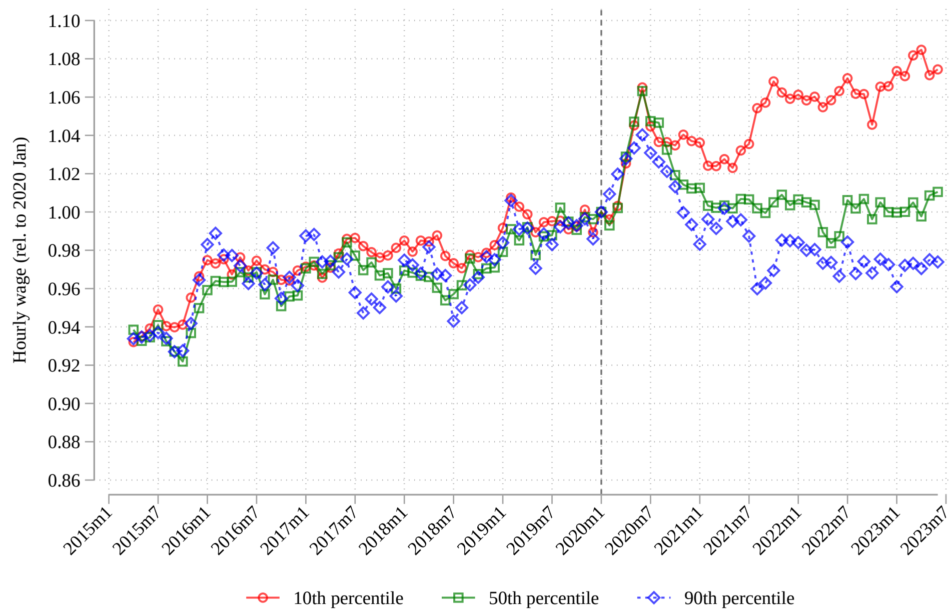
Note: Figure displays the change in the log 90-10 ratio for different time periods. The first bar compares the years 1940 and 1950, while the second bar compares years 1979 and 2019. The last bar compares the first quarter of 2020 to the second quarter of 2023. Percentiles are smoothed using lowess for the latter two time periods. Data for 1940 and 1950 are from the Decennial Census. CPS monthly data is obtained for 1979 from NBER and for 2019-2023 from IPUMS. Estimates in this figure correspond to Table A1.

Figure 10: Real Hourly Wages by Quantile and State Minimum Wage Status, Relative to January 2020

A. State minimum wage above federal level

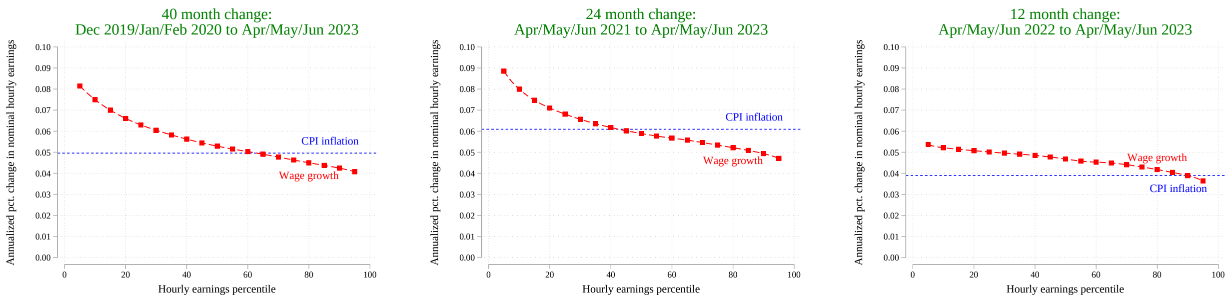


B. Federal or no minimum wage



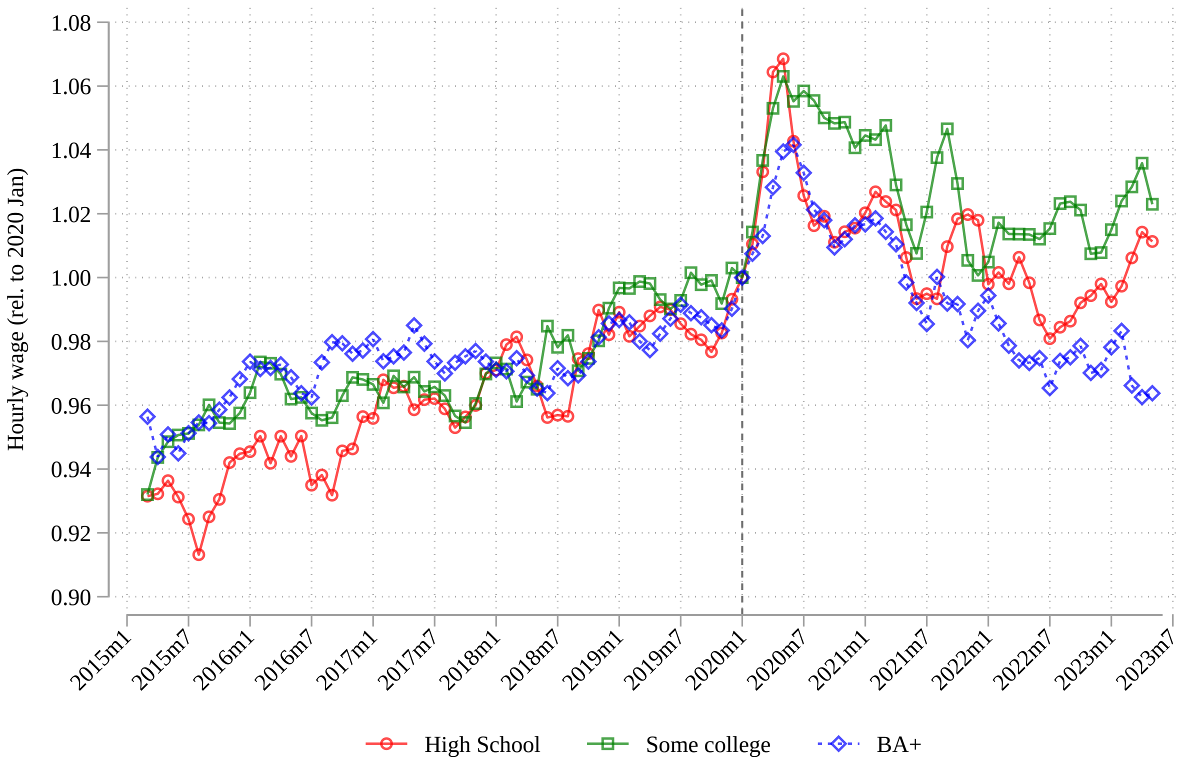
Note: CPS monthly data. Adjusted to maintain demographic composition in January–March 2020 using inverse probability weighting based on age, education, race/ethnicity, gender, country of birth, and region. Wages are real (2023_{q2} USD). We construct wage quantiles by state minimum wage status and month. Wage percentiles are smoothed with lowess and a 3-month moving average. Thirty-one US states (including Washington DC) have a minimum wage above the federal level. Fifteen states have a minimum wage equal to the federal level, \$7.25, and 5 states have no minimum wage.

Figure 11: Annualized Percent Change in Nominal Hourly Earnings by Earnings Percentile Over 40, 24, and 12 Months - Adjusted for Composition



Note: CPS monthly data. Adjusted to maintain demographic composition in January–March 2020 using inverse probability weighting based on age, education, race/ethnicity, gender, country of birth, and region. Wage percentiles are smoothed with lowess. Inflation is calculated using annualized, seasonally unadjusted CPI-U.

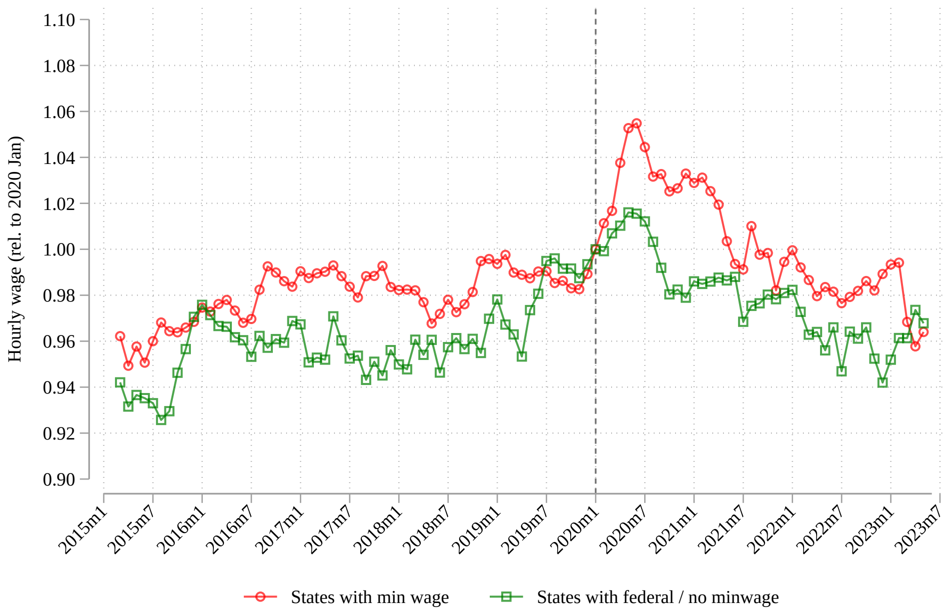
Figure 12: Real Hourly Wages by Education, Relative to January 2020



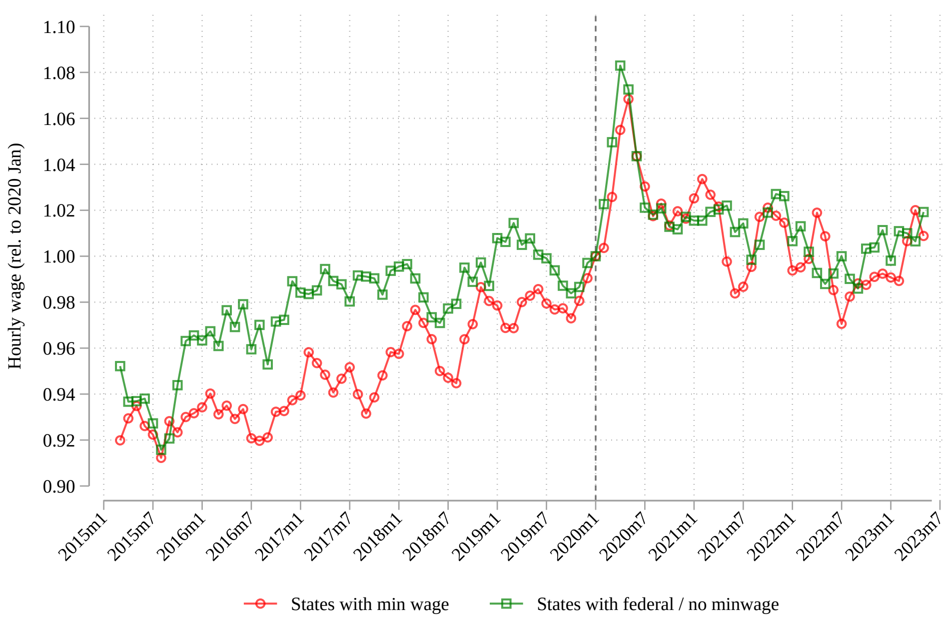
Note: CPS monthly data. Adjusted to maintain demographic composition in January–March 2020 using inverse probability weighting based on age, education, race/ethnicity, gender, country of birth, and region. Wages are real (2023_{q2} USD) and smoothed with a 3-month moving average.

Figure 13: Real Hourly Wages by Education and State Minimum Wage Status, Relative to January 2020

A. BA+ educated workers

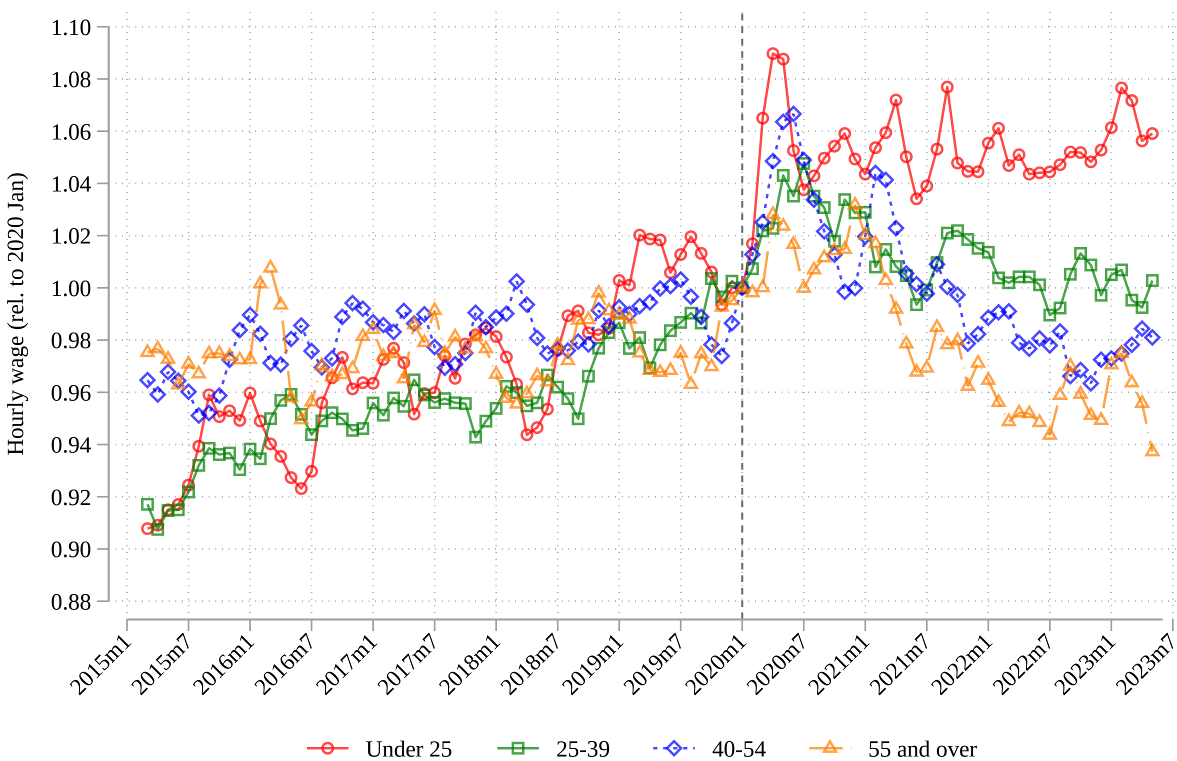


B. High-school educated workers



Note: CPS monthly data. Adjusted to maintain demographic composition in January–March 2020 using inverse probability weighting based on age, education, race/ethnicity, gender, country of birth, and region. Wages are real (2023_{q2} USD) and smoothed with a 3-month moving average. Thirty-one US states (including Washington DC) have a minimum wage above the federal level. Fifteen states have a minimum wage equal to the federal level, \$7.25, and 5 states have no minimum wage.

Figure 14: Real Hourly Wages by Age, Relative to January 2020

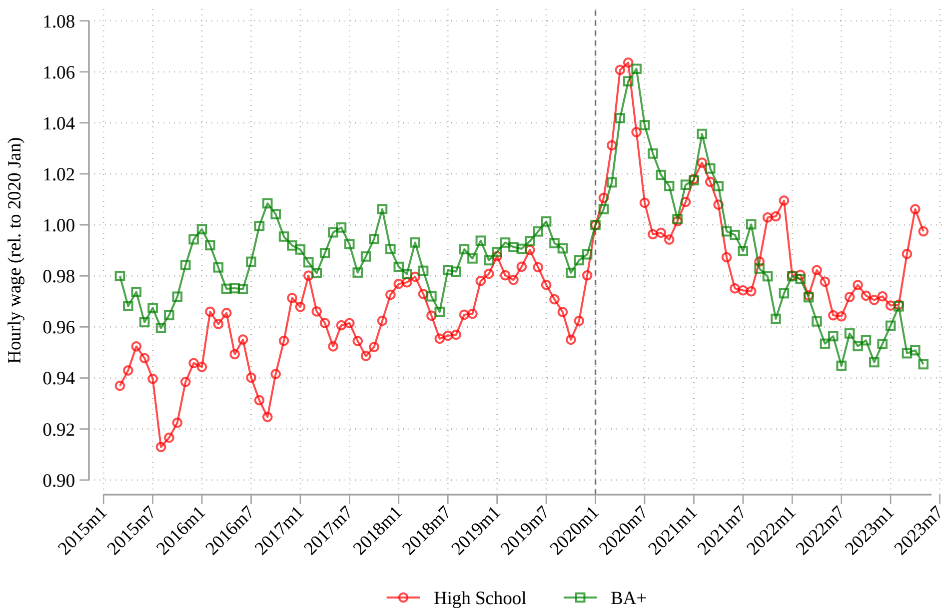


Note: CPS monthly data. Adjusted to maintain demographic composition in January–March 2020 using inverse probability weighting based on age, education, race/ethnicity, gender, country of birth, and region. Wages are real (2023_{q2} USD) and smoothed with a 3-month moving average.

Figure 15: Real Hourly Wages by Age and Education, Relative to January 2020

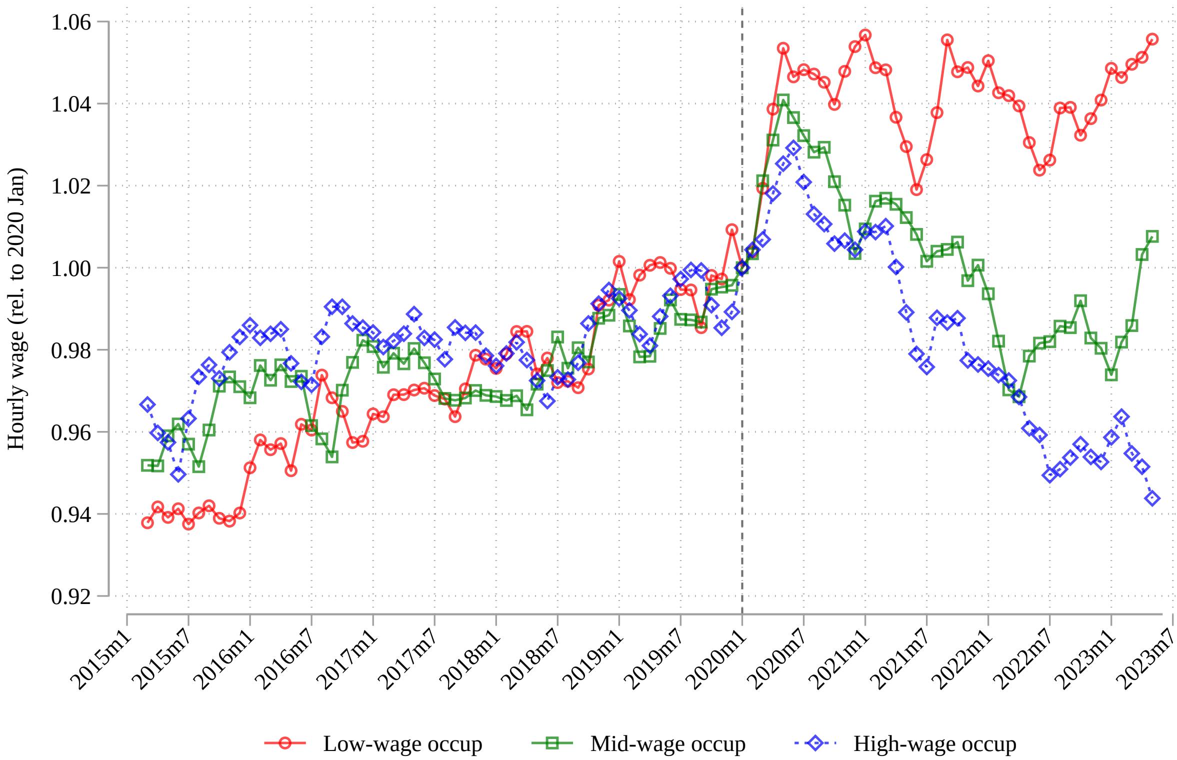
A. Workers under age 40

B. Workers age 40 and above



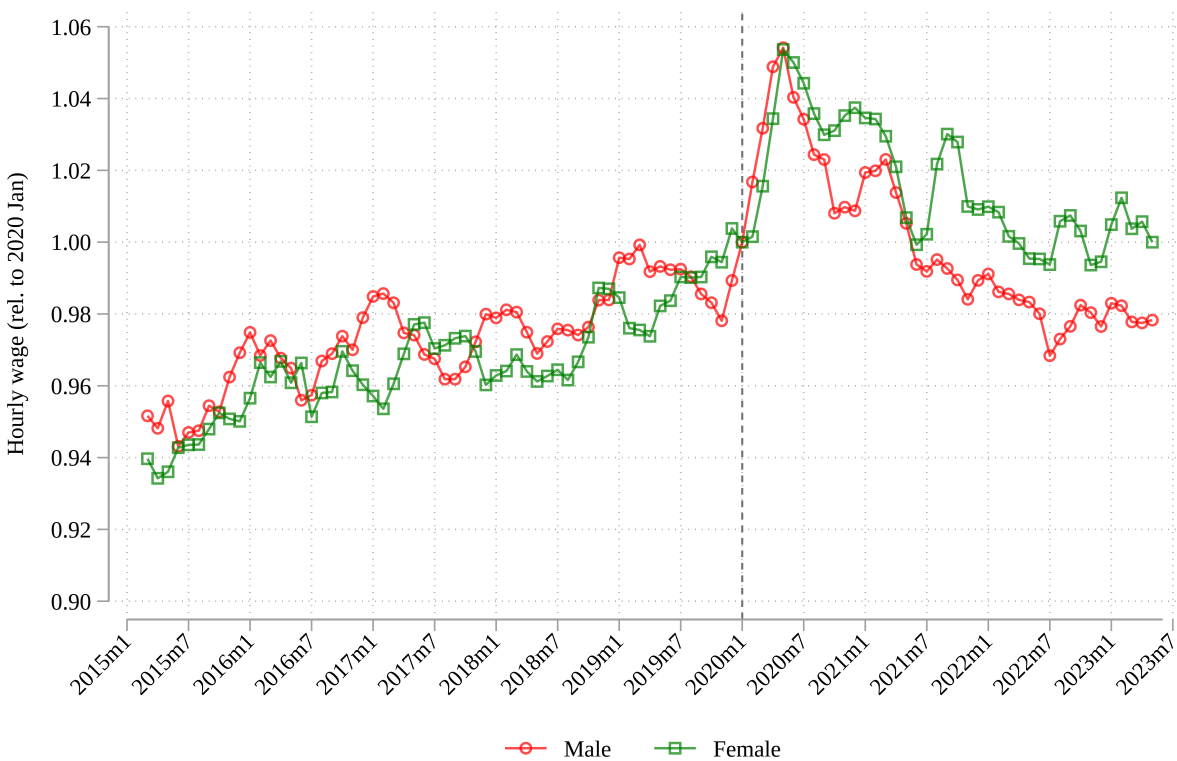
Note: CPS monthly data. Adjusted to maintain demographic composition in January–March 2020 using inverse probability weighting based on age, education, race/ethnicity, gender, country of birth, and region. Wages are real (2023_{q2} USD) and smoothed with a 3-month moving average.

Figure 16: Real Hourly Wages by Occupational Wage Tercile, Relative to January 2020



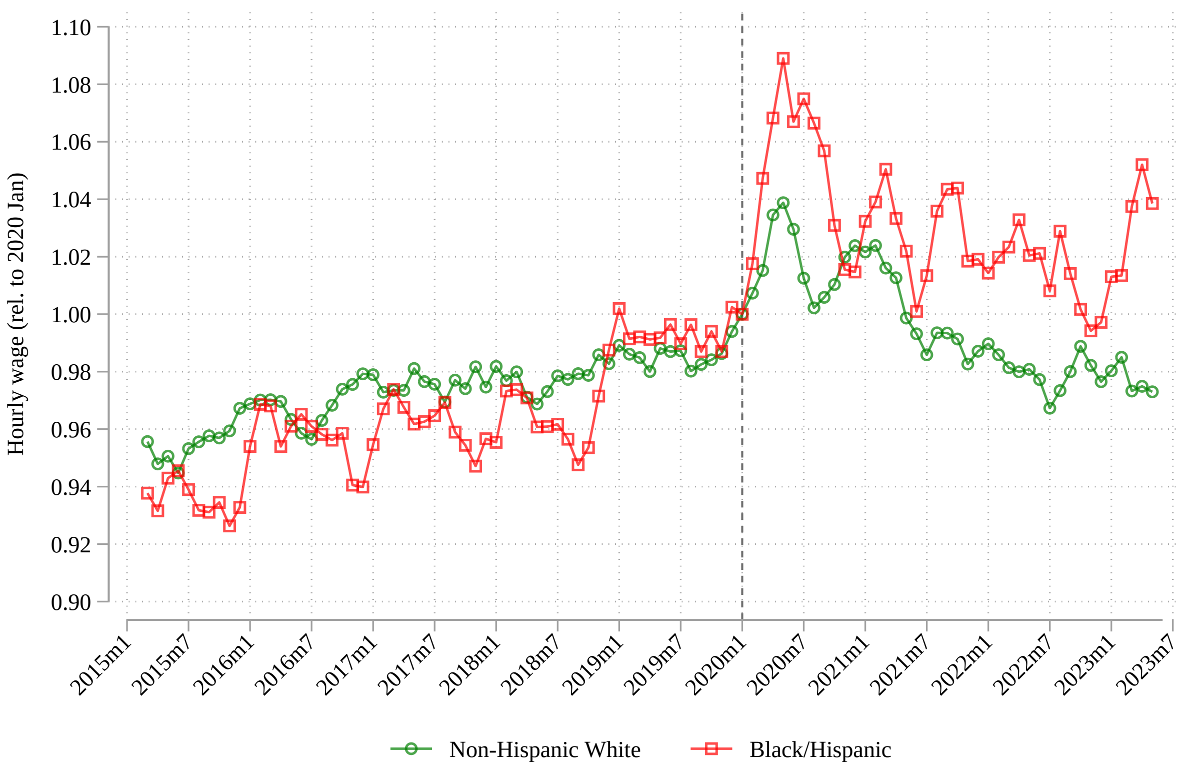
Note: CPS monthly data. Adjusted to maintain demographic composition in January–March 2020 using inverse probability weighting based on age, education, race/ethnicity, gender, country of birth, and region. Wages are real (2023_{q2} USD) and smoothed with a 3-month moving average. Occupational wage terciles are measured pre-pandemic, in 2019.

Figure 17: Real Hourly Wages by Sex, Relative to January 2020



Note: CPS monthly data. Adjusted to maintain demographic composition in January–March 2020 using inverse probability weighting based on age, education, race/ethnicity, gender, country of birth, and region. Wages are real (2023_{q2} USD) and smoothed with a 3-month moving average.

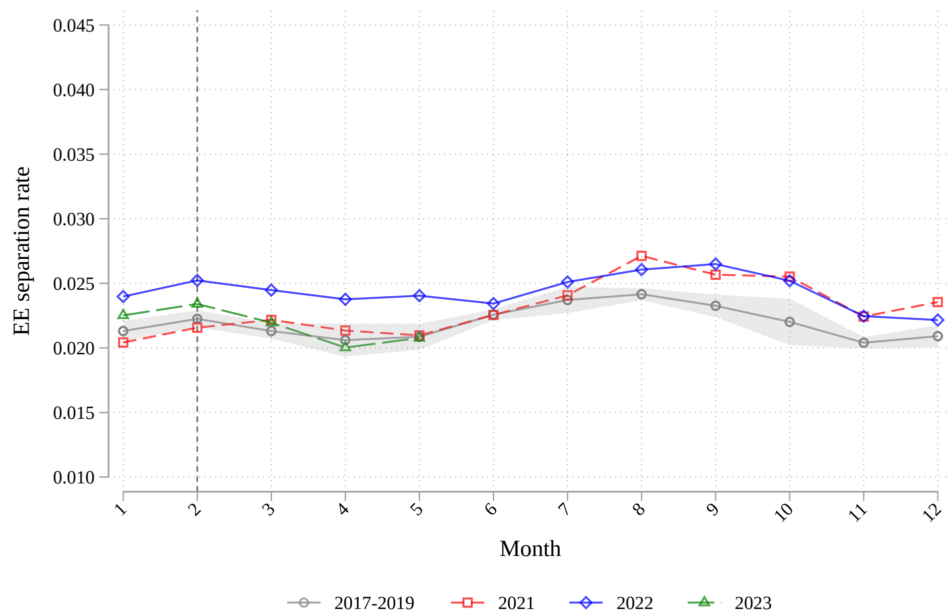
Figure 18: Real Hourly Wages by Race, Relative to January 2020



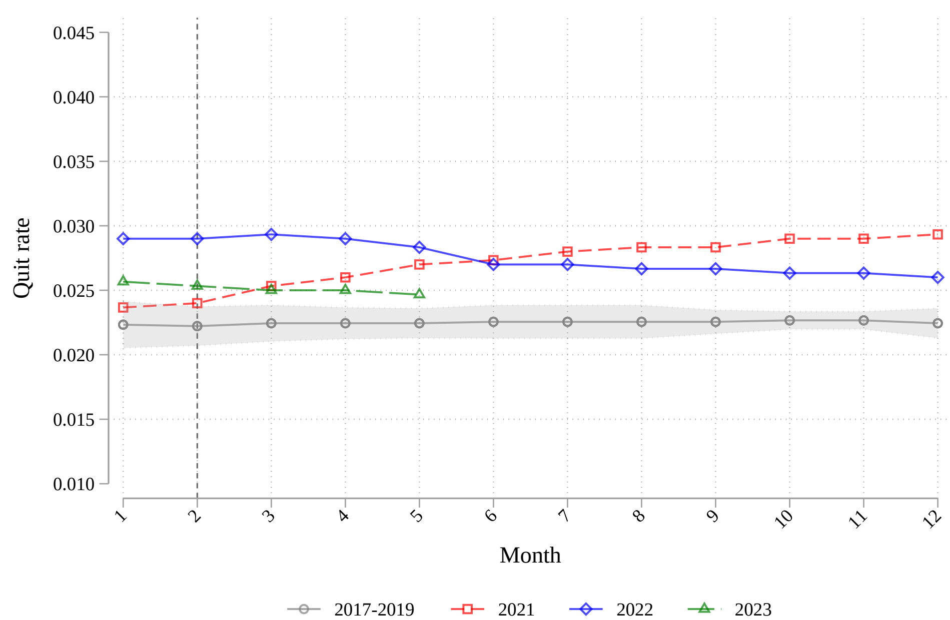
Note: CPS monthly data. Adjusted to maintain demographic composition in January–March 2020 using inverse probability weighting based on age, education, race/ethnicity, gender, country of birth, and region. Wages are real (2023_{q2} USD) and smoothed with a 3-month moving average.

Figure 19: Job Transitions by Month and Year

A. EE Separation Rate

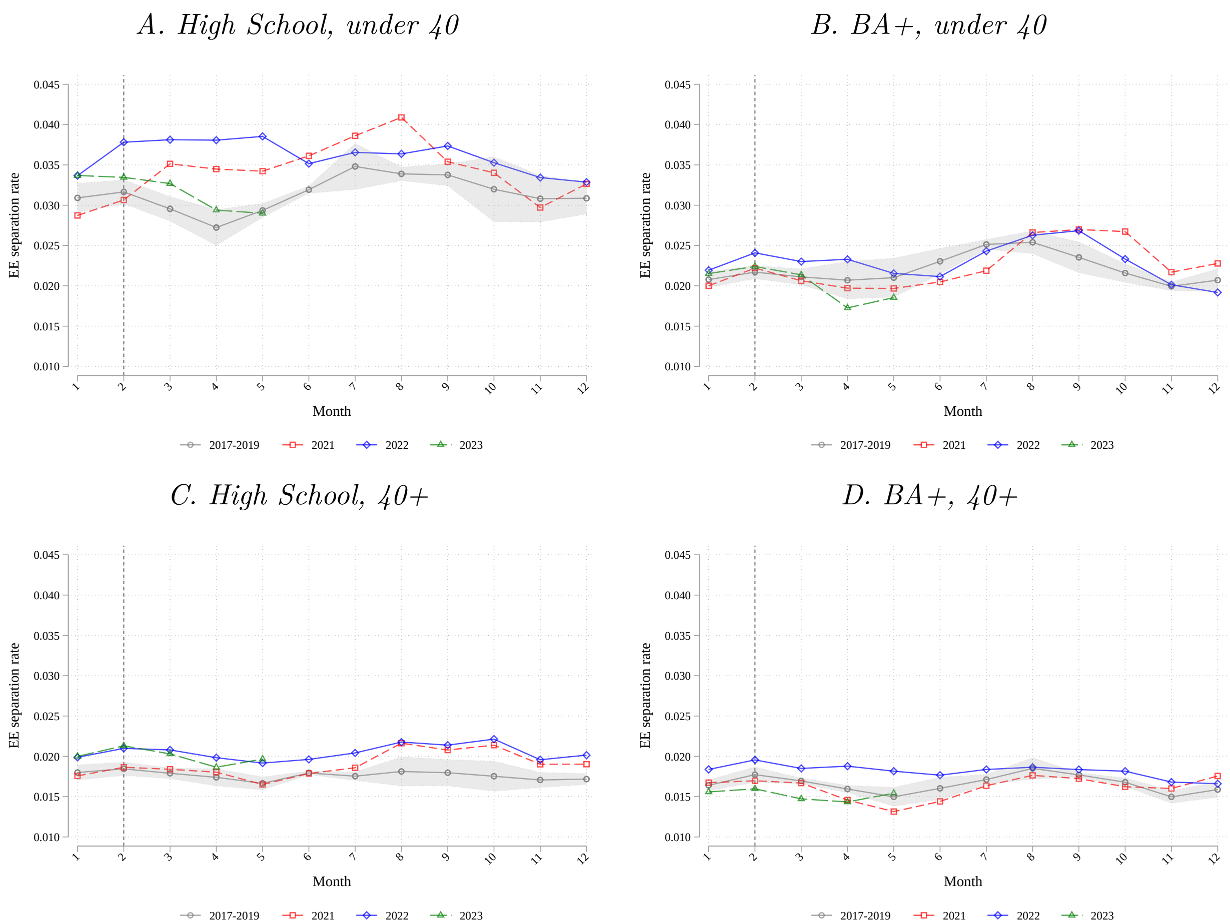


B. Quit Rate



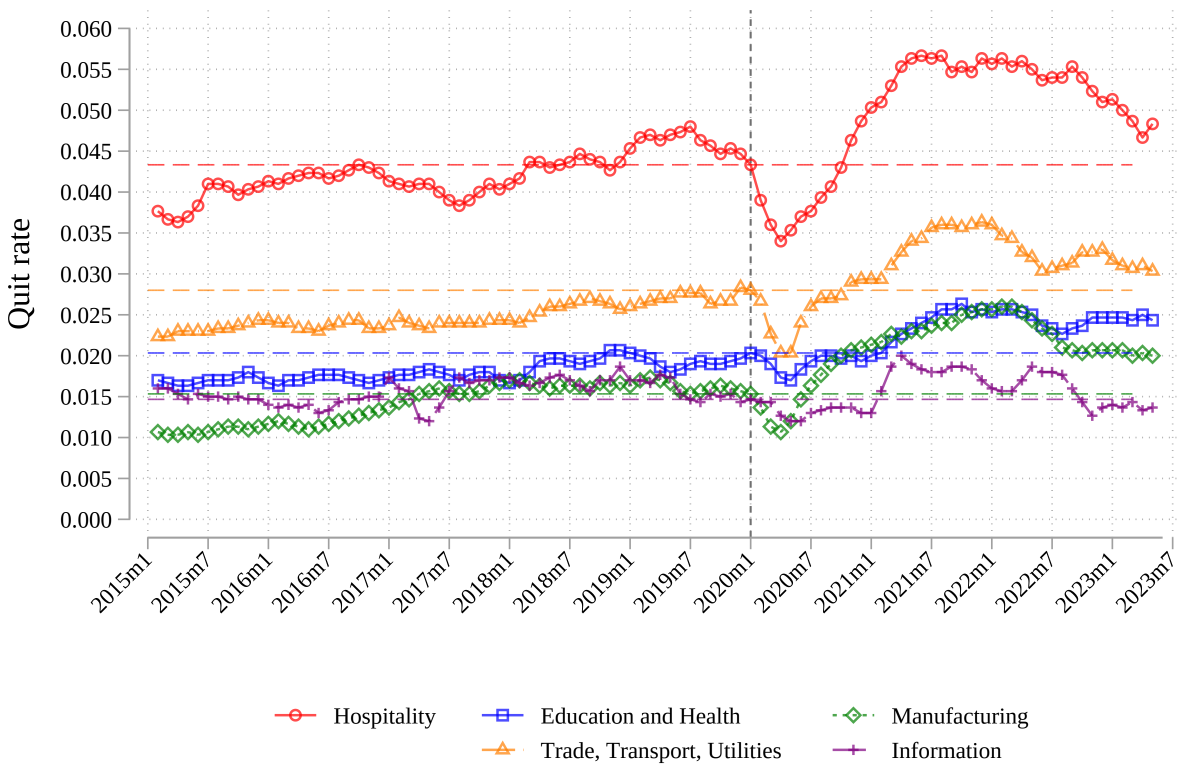
Note: Employment-to-employment (EE) separation rate obtained from CPS monthly data. Quit rate obtained from BLS Job Openings and Labor Turnover Survey (JOLTS) data. EE separation rates and quit rates are smoothed with a 3-month moving average. Shaded areas represent the 95% confidence interval for the monthly EE separation (panel A) or quit rate (panel B) during the 2017–2019 period.

Figure 20: EE Separation Rates by Month and Year: Age and Education



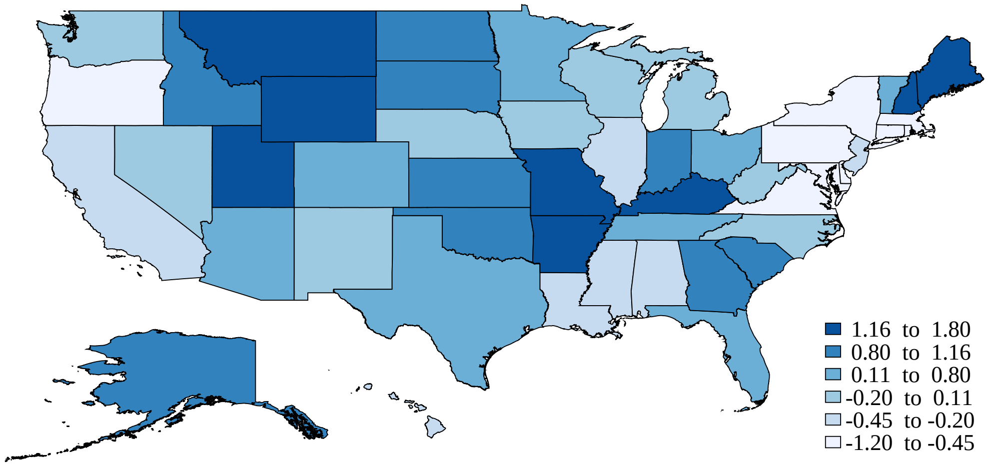
Note: CPS monthly data. Employment-to-employment (EE) separation rate is smoothed with a 3-month moving average. Shaded area represents the 95% confidence interval for the monthly EE separation rate during the 2017–2019 period.

Figure 21: Quit Rate Trends by Sector



Note: BLS Job Openings and Labor Turnover Survey (JOLTS) data. Quit rate is seasonally adjusted and smoothed with a 3-month moving average. Dashed lines represent the industry quit rate in January 2020. Manufacturing sector includes durable and non-durable goods manufacturing. Trade sector includes wholesale trade, retail trade, transportation, warehousing, and utilities. Information sector includes financial activities. Education and health sectors include education services, healthcare, and social assistance. Hospitality sector includes accommodation and food services, arts, entertainment, and recreation.

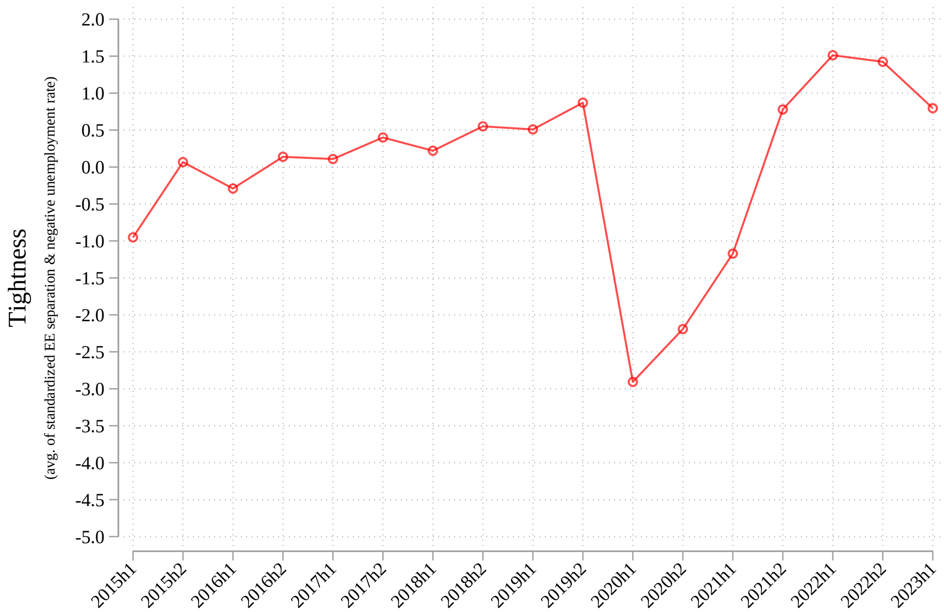
Figure 22: Cross-State Variation in Tightness, 2021–2023



Note: Cross-state variation in tightness over the $2021_{q1} - 2023_{q2}$ period. Tightness is calculated as the state-level average of the standardized EE separation rate and the negative, standardized unemployment rate. EE separation rates obtained from CPS monthly data. Seasonally-adjusted state unemployment rates obtained from BLS LAUS.

Figure 23: Tightness Over Time

A. Tightness

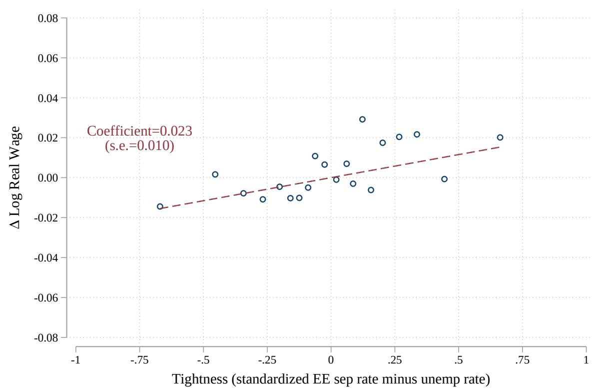


B. Components of tightness

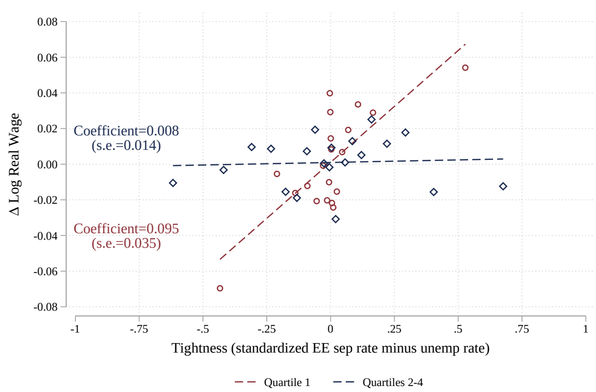
Note: Tightness measure and its components between 2015–2023. Estimates are reported in six-month intervals. EE separations and unemployment are standardized relative to their respective mean and standard deviation over the entire sample period. Tightness is calculated as the state-level average of the standardized EE separation rate and the negative, standardized unemployment rate. EE separation rates obtained from CPS monthly data. Seasonally-adjusted state unemployment rates obtained from BLS LAUS.

Figure 24: Wage-Phillips Curves, Using Cross-State Variation in Tightness (Standardized EE Separation Rate and Negative Unemployment Rates)

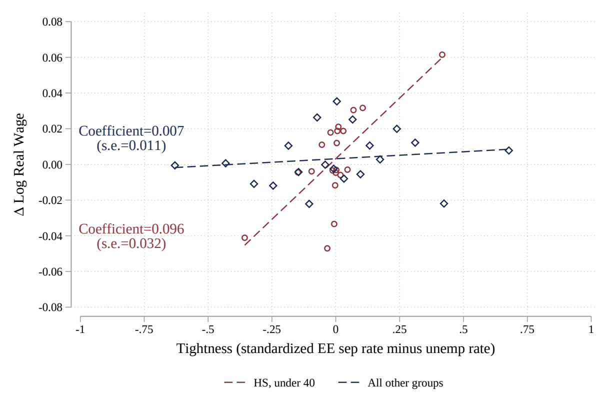
A. Overall



B. 1st quartile vs. all others

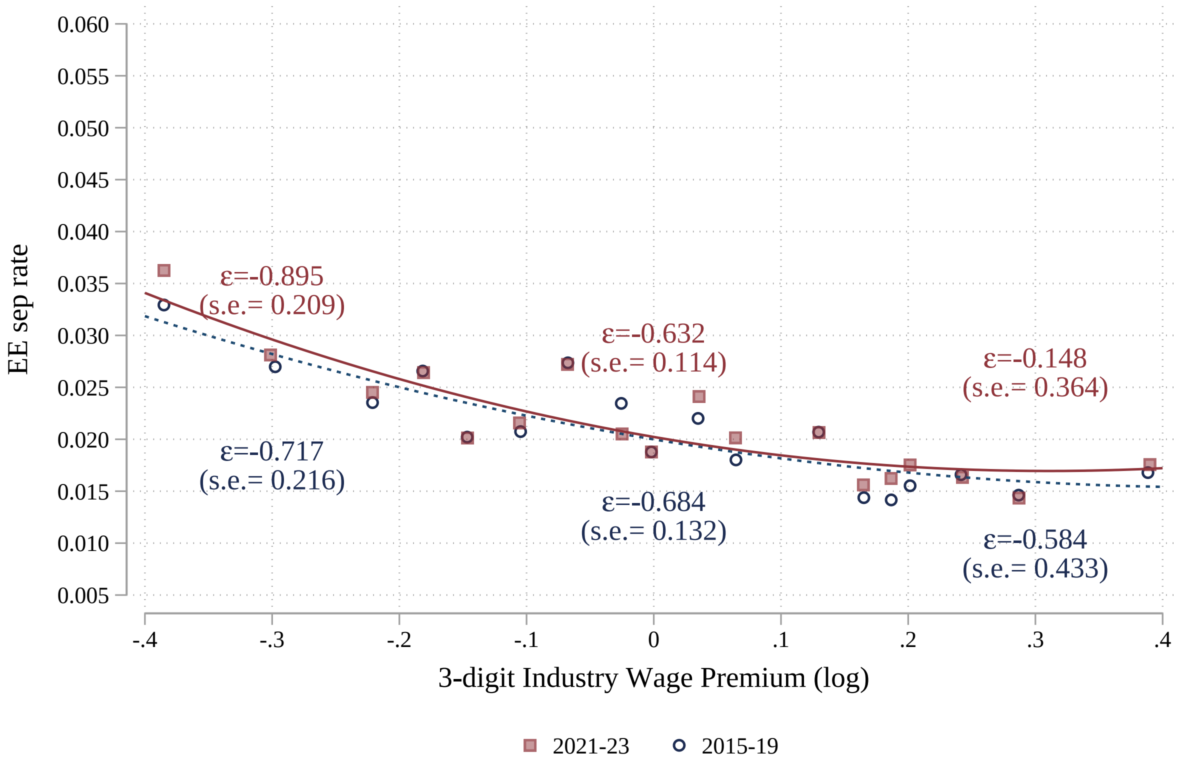


C. High School, under 40 vs. all others



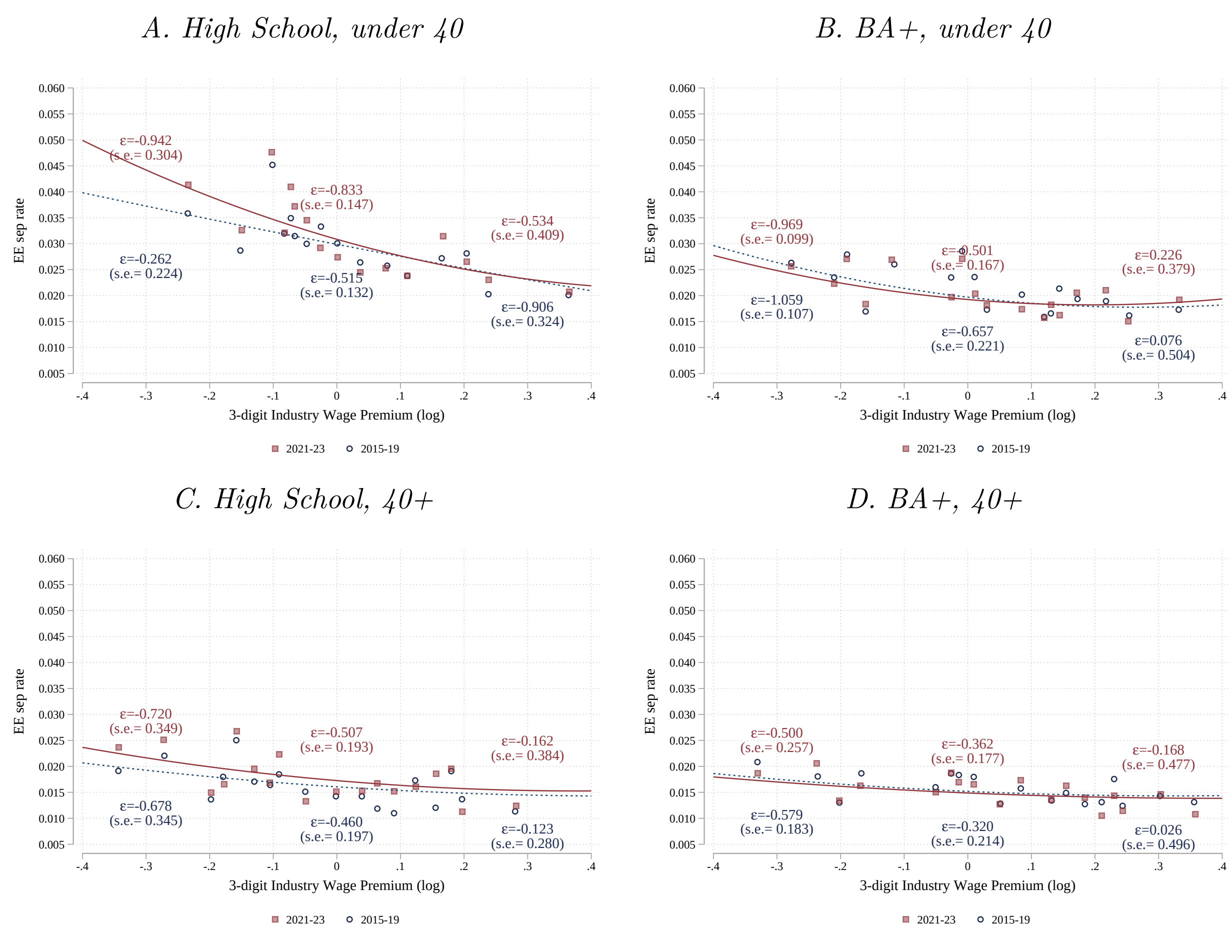
Note: Binscatters show the relationship between tightness (in quarter $t_k = 0$) and log real wage change (between quarter $t_k = 0$ and the following quarter $t_k = 1$) based on the regression equation 4. Tightness is an average of the standardized EE separation rate and the negative, standardized unemployment rate, measured at the state level. Panel A shows the overall wage change associated with tightness (reported in Tables 1 and A2). Panel B contrasts wage gains for workers in the bottom wage quartile versus all other quartiles. Panel C contrasts wage gains for high-school workers under age 40, versus all other workers. Specifications for Panel B and C correspond with Table A2. All data obtained from CPS monthly data except for seasonally-adjusted state unemployment rates, which are obtained from BLS LAUS. The y-axis is average annualized log real wage change. Wage quartiles are estimated by state and quarter. Standard errors clustered at the state level.

Figure 25: Job-to-Job Separation by Residual Log Industry Wage



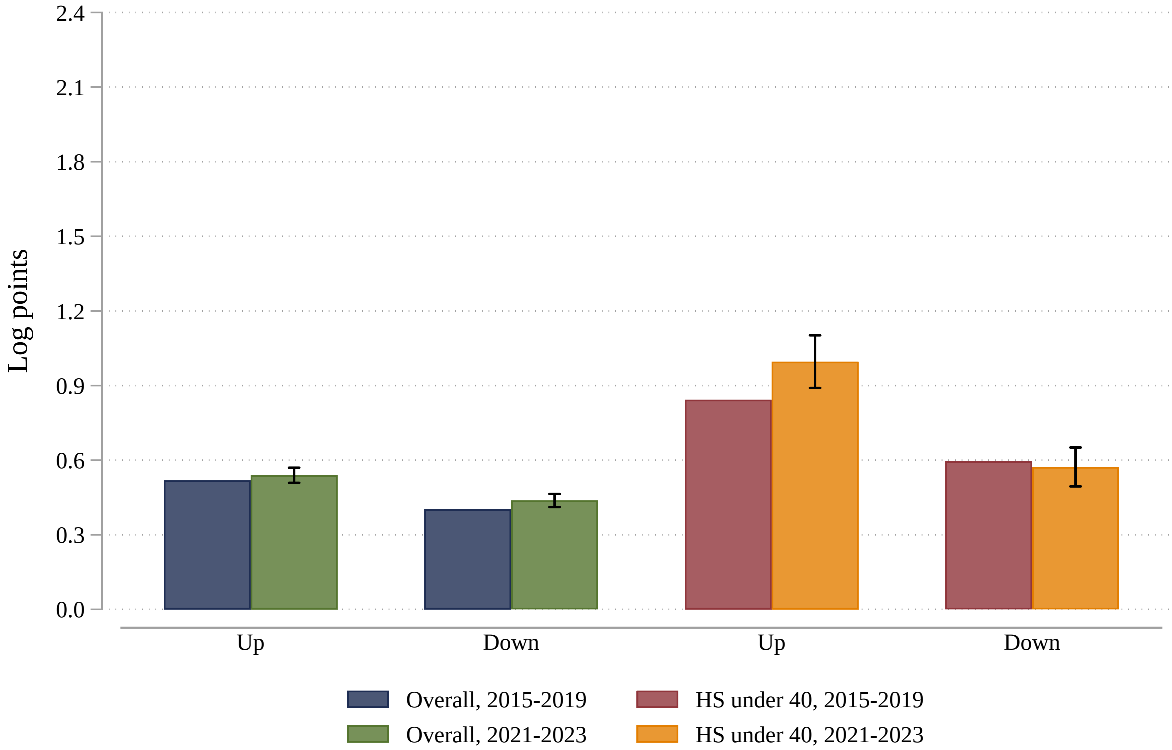
Note: Binscatter shows the quadratic relationship between industry wage premia (IWP) and EE separations, before and after the pandemic. Elasticities at $x = \{-0.3, 0, 0.3\}$ are calculated in two steps: first, we regress an indicator for EE separation at time t on IWP at time $t-1$ and its square as well as on demographic controls and state fixed effects (based on equation 6). Second, we evaluate the derivative of EE separation with respect to IWP at x and divide by the conditional mean of EE separation at x to get the elasticity at x. Demographic controls from the regression in step one include dummy variables for sex, race, ethnicity, age group, education, citizenship, and metro area status. The IWP are calculated from a regression of log real wage on demographic controls and 3-digit industry fixed effects for the pre-pandemic period, 2015–2019. The dependent variable, EE separation, is obtained from CPS monthly data. Standard errors are clustered at the industry level. Coefficients from the regression in step one are reported in Table A7 and the elasticities in this figure, as well as their difference between the 2015–2019 and 2021–2023 periods, are reported in Table 3.

Figure 26: Job-to-Job Separation by Residual Log Industry Wage: by Age and Education



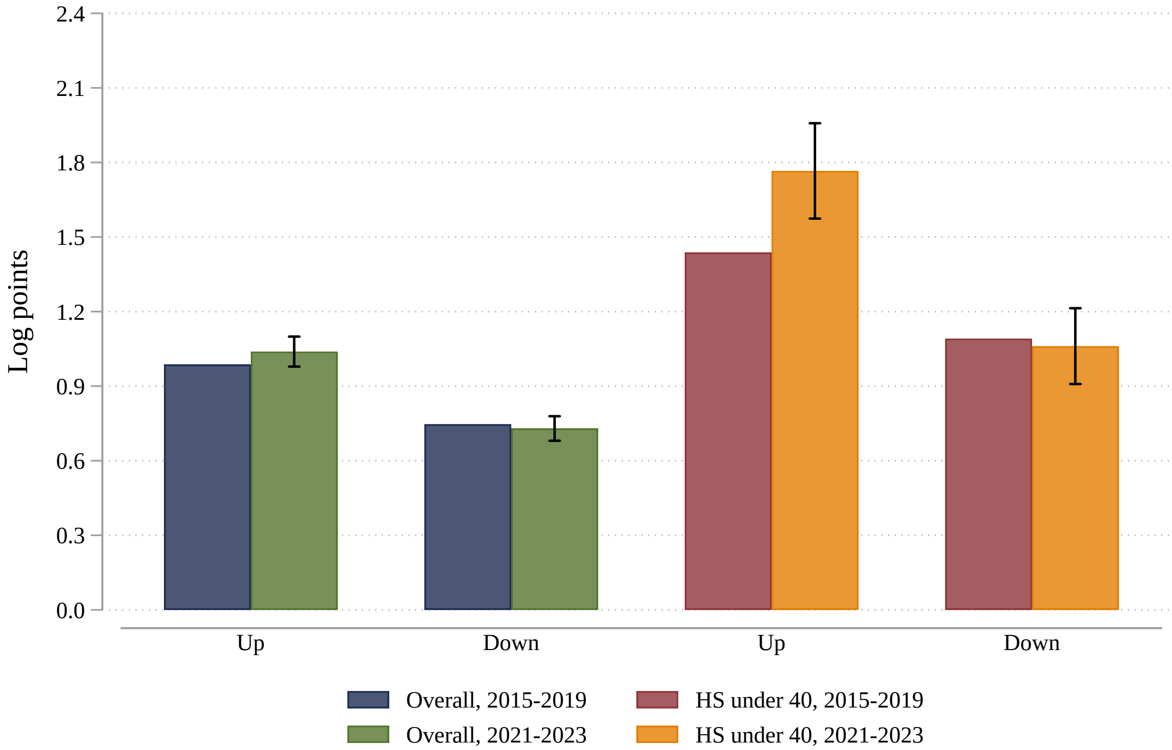
Note: Binscatters show the quadratic relationship between industry wage premia (IWP) and EE separations, before and after the pandemic, by age and education group. Elasticities at $x = \{-0.3, 0, 0.3\}$ are calculated in two steps: first, we regress an indicator for EE separation at time t on 3-digit IWP at time $t-1$ and its square as well as on demographic controls and state fixed effects (based on equation 6). Second, we evaluate the derivative of EE separation with respect to IWP at x and divide by the conditional mean of EE separation at x to get the elasticity at x. Demographic controls from the regression in step one include dummy variables for sex, race, ethnicity, age group, education, citizenship, and metro area status. The IWP are calculated separately for each subgroup from a regression of log real wage on demographic controls and 3-digit industry fixed effects for the pre-pandemic period, 2015–2019. The dependent variable, EE separation, is obtained from CPS monthly data. Standard errors are clustered at the industry level. Coefficients from the regression in step one are reported in Table A7 for panel A and in Table A8 for panels B through D. The elasticities in this figure, as well as their difference between the 2015–2019 and 2021–2023 periods for each subgroup, are reported in Table 3.

Figure 27: Movement Between Top Half and Bottom Half of the 3-Digit Industry Wage Premium Distribution



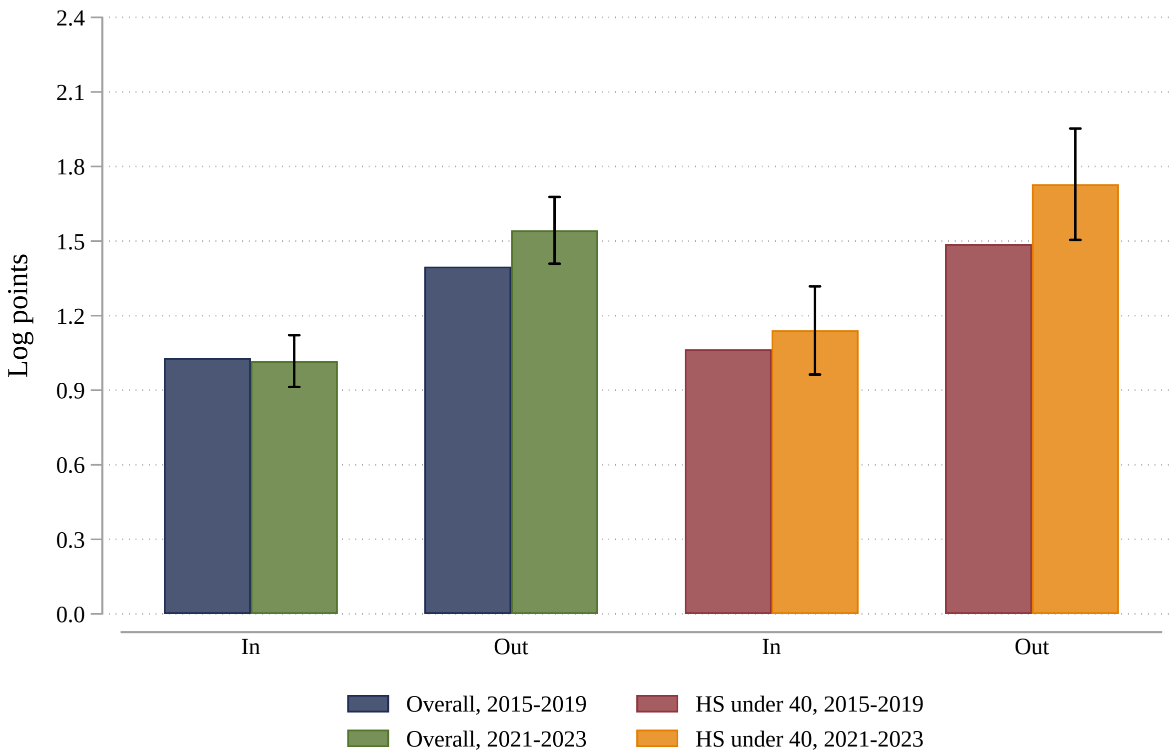
Note: Movement between the top and bottom halves of the 3-digit industry wage premium (IWP) distribution, by period, for all workers and for HS under 40 workers. The sample is limited to workers employed in both the current and the previous month. *Up* represents the likelihood of switching from the bottom half of the 3-digit IWP distribution to the top half. *Down* represents the likelihood of switching from the top half of the 3-digit IWP distribution to the bottom half. Movements in 2015–2019 correspond to column 1 of Table 4 and movements in 2021–2023 correspond to column 2 of Table 4. The error bars represent the 95% confidence intervals for the difference in movement between periods, corresponding to column 3 of Table 4.

Figure 28: Movement Into and Out of Bottom Quartile of the 3-Digit Industry Wage Premium Distribution



Note: Movement into and out of the bottom quartile of the industry wage premium (IWP) distribution, by period, for all workers and HS under 40 workers. *Up* represents the likelihood of switching from the bottom quartile of the 3-digit IWP distribution to the top three quartiles. *Down* represents the likelihood of switching from the top three quartiles of the 3-digit IWP distribution to the bottom quartile. Movements in 2015–2019 correspond to column 1 of Table 5 and movements in 2021–2023 correspond to column 2 of Table 5. The error bars represent the 95% confidence interval for the difference in movement between periods, corresponding to column 3 of Table 5. To account for the size differentials in exit and entry rates, *Down* bars and confidence intervals are re-scaled by $(1-p)/p$ where p is the share of workers in the bottom quartile ($p = 0.25$).

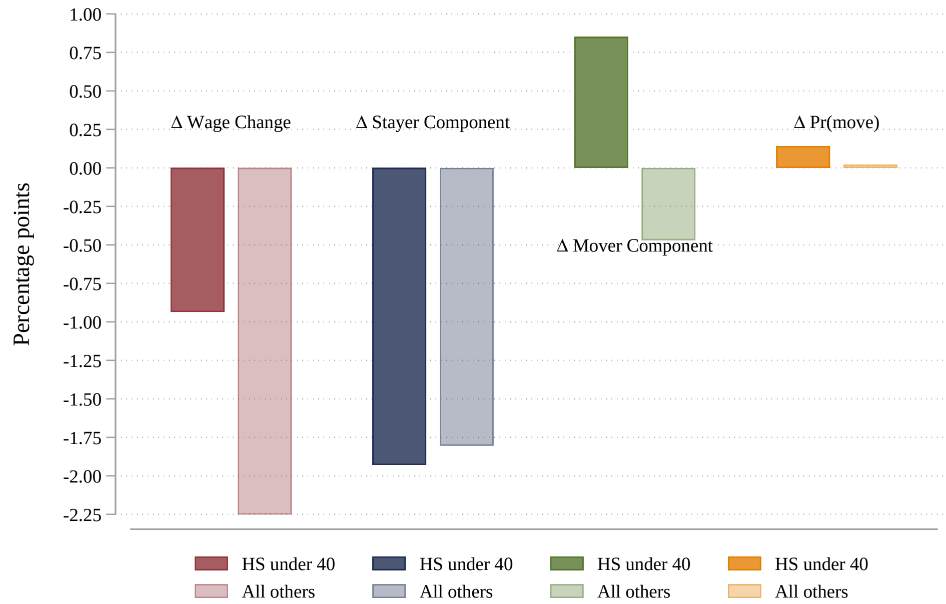
Figure 29: Movement Into and Out of the Hospitality Industry



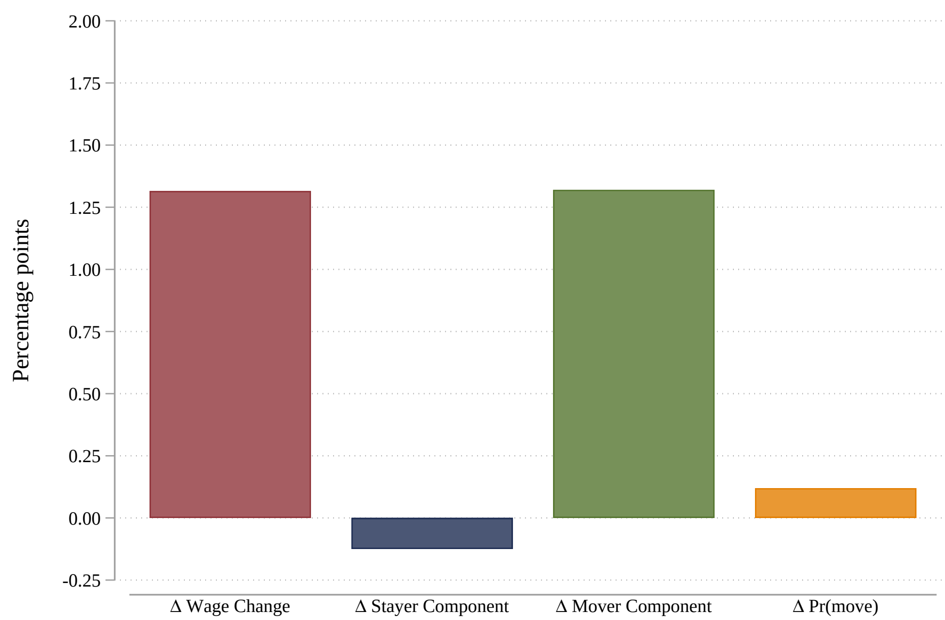
Note: Movement into and out of the hospitality sector, by period, for all workers and HS under 40 workers. The sample is limited to workers employed in both the current and the previous month. An individual is considered to have moved into or out of the hospitality industry only if their industry changed from the previous month and if they indicated switching jobs since the previous month. *In* represents the likelihood of entering the hospitality sector. *Out* represents the likelihood of leaving the hospitality sector. Movements in 2015–2019 correspond to column 1 of Table 6 and movements in 2021–2023 correspond to column 2 of Table 6. The error bars represent the 95% confidence interval for the difference in movement between periods, corresponding to column 3 of Table 6. To account for the size differentials in exit and entry rates, *In* bars and confidence intervals are re-scaled by $(1-p)/p$ where p is the share of workers in hospitality in 2015–2019. For the overall sample, $p = 0.079$, and for HS under 40, $p = 0.185$.

Figure 30: Decomposition of the Change in Annual Wage Growth During 2021–2023 vs. 2015–2019

A. Levels: High school under 40 workers, all other workers

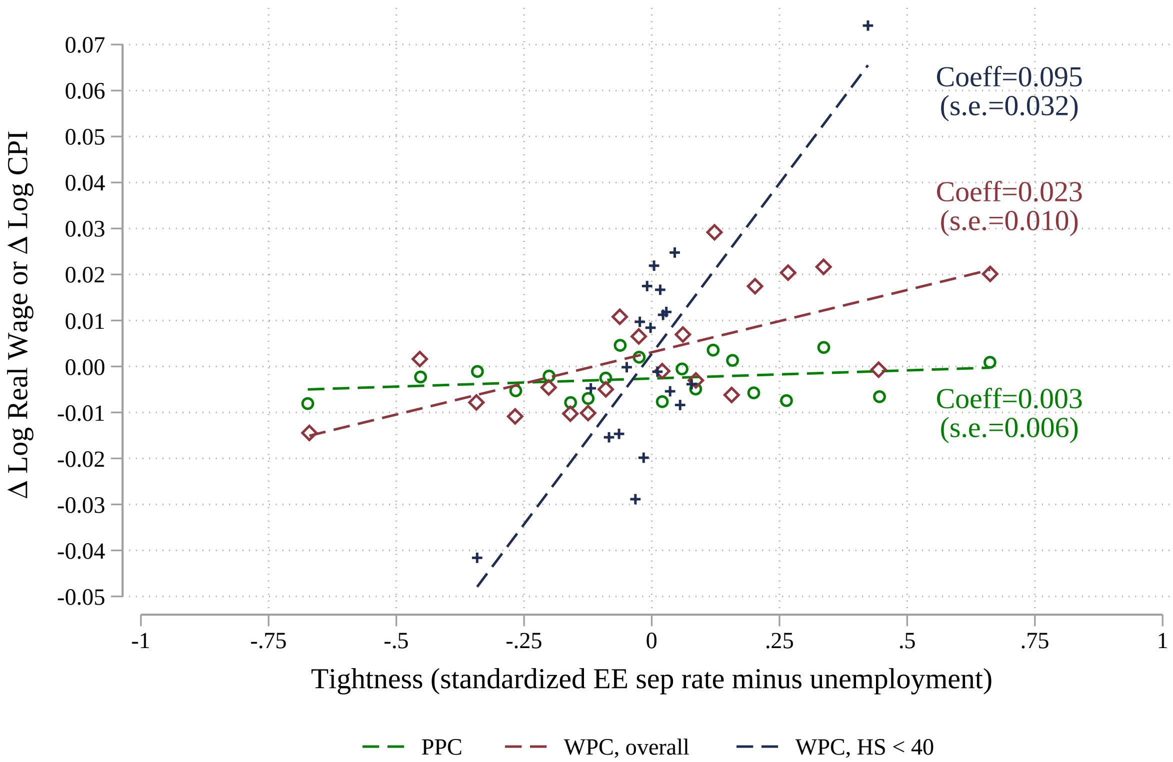


B. Difference: High school under 40 vs. all other workers



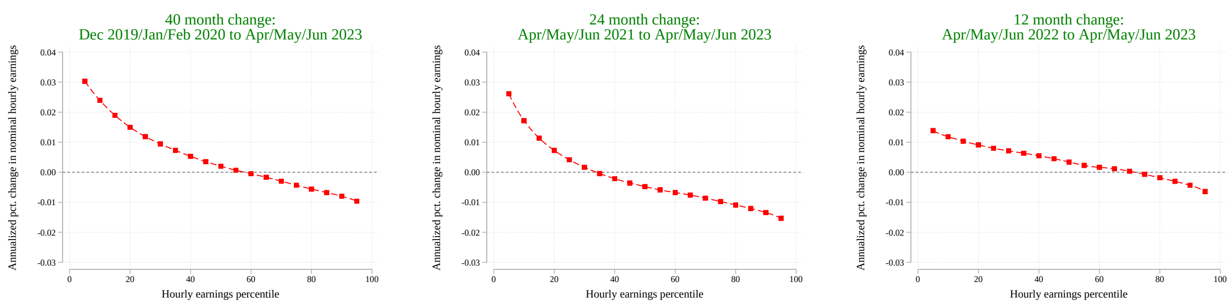
Note: See Section 4.4 for the details underlying the decomposition. Panel A corresponds to estimates in panel C of Table 7. Panel B reports the difference between the components of the wage decomposition for the two groups (simply the difference between the two columns of panel C of Table 7).

Figure 31: Wage- and Price-Phillips Curves, Using Cross-State Variation in Tightness



Note: Binscatter shows the relationship between tightness (in quarter $t_k = 0$) and log real wage or CPI change between quarter $t_k = 0$ and the following quarter $t_k = 1$ based on regression equations 4 and 9. Estimates correspond to the specification in column 5 of Tables 1 and 8. All data are obtained from CPS monthly files with the exception of CPI excluding energy obtained from BLS, seasonally-adjusted state unemployment rates obtained from BLS LAUS, and Covid-19 death rates obtained from CDC (2020). The y-axis is average annualized log real wage change, or average annualized log non-energy CPI change. Wage quartiles are estimated by state and quarter. We assign CBSA-level CPI to main metro areas in each state, state average of CBSA-level CPI in other metro areas within the state, and census division-level CPI for remaining non-metro areas. Standard errors clustered at the state level.

Figure 32: Annualized Percent Change in Real Hourly Earnings by Earnings Percentile Over 40, 24, and 12 Months - Adjusted for Composition and constructed *state-level* CPI



Note: CPS monthly data. Adjusted to maintain demographic composition in January–March 2020 using inverse probability weighting based on age, education, race/ethnicity, gender, country of birth, and region. Wage percentiles smoothed with lowess. CPI-U is obtained from BLS. We apply CBSA-level CPI-U deflators to main metro areas in each state, state average of CBSA-level CPI-U deflators in other metro areas within the state, and census division-level CPI-U deflators for the remaining, non-metro areas.

Table 1: Coefficient on Tightness from Regressions of Wage Change on State Labor Market Tightness

	(1)	(2)	(3)	(4)	(5)
Overall	0.0315^{**}	0.0244^{**}	0.0260^{**}	0.0231^{**}	0.0231^{**}
	(0.0136)	(0.0118)	(0.0103)	(0.0097)	(0.0097)
Within wage quartiles					
1^{st} Quartile	0.1269^{***}	0.1271^{***}	0.1220^{***}	0.1216^{***}	0.1216^{***}
	(0.0387)	(0.0384)	(0.0378)	(0.0378)	(0.0378)
2^{nd} Quartile	0.0958^{***}	0.0967^{***}	0.0945^{***}	0.0930^{***}	0.0930^{***}
	(0.0309)	(0.0306)	(0.0293)	(0.0290)	(0.0290)
3^{rd} Quartile	-0.0737^{***}	-0.0743^{***}	-0.0705^{***}	-0.0713^{***}	-0.0713^{***}
	(0.0201)	(0.0201)	(0.0200)	(0.0199)	(0.0199)
4^{th} Quartile	-0.0163	-0.0192	-0.0168	-0.0157	-0.0157
	(0.0283)	(0.0282)	(0.0271)	(0.0268)	(0.0268)
Within age and education groups					
High School, under 40	0.0928^{***}	0.1146^{***}	0.1057^{***}	0.0953^{***}	0.0953^{***}
	(0.0354)	(0.0347)	(0.0340)	(0.0321)	(0.0321)
High School, 40+	0.1298^{**}	0.1215^{**}	0.1153^{**}	0.1084^{**}	0.1084^{**}
	(0.0539)	(0.0518)	(0.0524)	(0.0506)	(0.0506)
Some College, under 40	0.1027^{***}	0.0772^{***}	0.0756^{***}	0.0642^{**}	0.0642^{**}
	(0.0340)	(0.0273)	(0.0263)	(0.0252)	(0.0252)
Some College, 40+	0.0181	0.0099	0.0036	-0.0059	-0.0059
	(0.0293)	(0.0289)	(0.0274)	(0.0265)	(0.0265)
BA+, under 40	-0.0706^{**}	-0.0720^{**}	-0.0599^{**}	-0.0471	-0.0471
	(0.0314)	(0.0314)	(0.0301)	(0.0303)	(0.0303)
BA+, 40+	-0.0281	-0.0351	-0.0385	-0.0386	-0.0386
	(0.0304)	(0.0318)	(0.0297)	(0.0301)	(0.0301)
Controls:					
Age		X	X	X	X
Demographics			X	X	X
Sector				X	X
Covid Death Rate					X

Note: N=326,923. Table reports estimates for β from equation 4. Dependent variable is the log real wage and the main explanatory variable, tightness, is an average of the standardized EE separation rate and negative standardized unemployment rate, both measured at the state level. Each column reports three regression estimates, one per panel (overall, within wage quartiles, and within age and education groups). All specifications include stack-by-state and stack-by-time effects, where stack denotes a pair of adjacent quarters. Subgroup regressions (lower two panels) include group-specific stack-by-time effects. Wage quartiles are estimated by state and quarter. Age controls include five age group dummies. Demographic controls include 3 education dummies, 5 race dummies, and a dummy for sex. Sector controls include dummies for Manufacturing, Professional Services, Finance, and Business Services. Column 5 additionally controls for state Covid-19 death rate per 100,000 people as of June 2023. All data are obtained from CPS monthly files with the exception of seasonally-adjusted state unemployment rates obtained from BLS LAUS, and Covid-19 death rates obtained from CDC (2020). Standard errors in parentheses are clustered on state. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table 2a: Employment-to-Employment Separation Elasticity Estimates

	Individual-level Wage	Industry Wage Premium	
	(1)	(2)	(3)
Overall			
2015–2019	-0.2725^{***}	-1.0112^{***}	-0.6788^{***}
	(0.0437)	(0.1834)	(0.1357)
	N=80,729	*N=1,921,670*	*N=1,921,670*
2021–2023	-0.2700^{***}	-0.9803^{***}	-0.6096^{***}
	(0.0660)	(0.2221)	(0.1380)
	N=33,746	*N=735,378*	*N=735,378*
High School Educated, Under 40 Years Old			
2015–2019	-0.3169^{**}	-0.7891^{***}	-0.5460^{***}
	(0.1290)	(0.1366)	(0.1334)
	N=10,020	*N=284,569*	*N=284,569*
2021–2023	-0.5508^{***}	-1.0302^{***}	-0.7662^{***}
	(0.1817)	(0.1395)	(0.1523)
	N=3,825	*N=110,086*	*N=110,086*
High School Educated, 40 Years and Older			
2015–2019	-0.3742^{***}	-0.4712^{**}	-0.4246^{**}
	(0.1245)	(0.2235)	(0.1776)
	N=14,232	*N=334,735*	*N=334,735*
2021–2023	-0.1973	-0.5882^{***}	-0.4751^{**}
	(0.1906)	(0.2228)	(0.1902)
	N=5,112	*N=117,190*	*N=117,190*
Aggregation Level	Individual	3-digit Ind.	3-digit Ind.
Time Interval	3-month	Monthly	Monthly
Controls	X		X

Note: Separation elasticities are estimated in two steps: first by regressing an indicator for EE separation on logged real wage (column 1) or industry wage premia (columns 2 and 3), and then by dividing the coefficient on wage from these regressions by the mean EE separation rate for the corresponding period and subgroup. Column 1 is based on equation 5 – the independent variable is log real wage and the dependent variable is a 3-month measure of EE separation. Columns 2 and 3 are based on equation 6 – the independent variable is the 3-digit industry wage premia (IWP), calculated from a regression of log real wage on demographic controls and industry fixed effects, and the dependent variable is a monthly measure of separation. Estimates are run without (col 2) and with controls (col 3). Columns 1 and 3 include as controls indicators for state, age group, gender, race, ethnicity, education, citizenship, and metro area status. Standard errors in parentheses are clustered by industry in columns 2 and 3.

* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table 2b: Employment-to-Employment Separation Elasticity Estimates

	Individual-level Wage	Industry Wage Premium	
	(1)	(2)	(3)
Bachelor's Degree or Higher, Under 40 Years Old			
2015–2019	−0.2604**	−0.8795***	−0.8154***
	(0.1051)	(0.2528)	(0.2248)
	N=14,644	*N=319,962*	*N=319,962*
2021–2023	−0.2826**	−0.6788***	−0.6243***
	(0.1368)	(0.2388)	(0.1986)
	N=7,046	*N=135,359*	*N=135,359*
Bachelor's Degree or Higher, 40 Years and Older			
2015–2019	−0.1631*	−0.4283**	−0.4030**
	(0.0838)	(0.1797)	(0.1707)
	N=19,346	*N=409,955*	*N=409,955*
2021–2023	0.0089	−0.3993**	−0.4071**
	(0.1417)	(0.1716)	(0.1587)
	N=9,330	*N=173,475*	*N=173,475*
Aggregation Level	Individual	3-digit Ind.	3-digit Ind.
Time Interval	3-month	Monthly	Monthly
Controls	X		X

Note: Separation elasticities are estimated in two steps: first by regressing an indicator for EE separation on logged real wage (column 1) or industry wage premia (columns 2 and 3), and then by dividing the coefficient on wage from these regressions by the mean EE separation rate for the corresponding period and subgroup. Column 1 is based on equation 5 – the independent variable is log real wage and the dependent variable is a 3-month measure of EE separation. Columns 2 and 3 are based on equation 6 – the independent variable is the 3-digit industry wage premia (IWP), calculated from a regression of log real wage on demographic controls and industry fixed effects, and the dependent variable is a monthly measure of separation. Estimates are run without (col 2) and with controls (col 3). Columns 1 and 3 include as controls indicators for state, age group, gender, race, ethnicity, education, citizenship, and metro area status. Standard errors in parentheses are clustered by industry in columns 2 and 3.
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table 3: Employment-to-Employment Separation Elasticity Estimates at Different Values of Industry Wage Premia

	(1) IWP=-0.3	(2) IWP=0	(3) IWP=0.3
Overall			
2015–19	-0.7166^{***}	-0.6837^{***}	-0.5842
	(0.2160)	(0.1322)	(0.4331)
2021–23	-0.8954^{***}	-0.6318^{***}	-0.1483
	(0.2086)	(0.1135)	(0.3643)
Difference	-0.1788	0.0518	0.4360
	(0.2999)	(0.1741)	(0.5653)
High School Educated, Under 40 Years Old			
2015–19	-0.2621	-0.5151^{***}	-0.9064^{***}
	(0.2238)	(0.1321)	(0.3245)
2021–23	-0.9415^{***}	-0.8328^{***}	-0.5335
	(0.3040)	(0.1472)	(0.4086)
Difference	-0.6794^{*}	-0.3177	0.3729
	(0.3770)	(0.1975)	(0.5211)
High School Educated, 40 Years and Older			
2015–19	-0.6779^{**}	-0.4596^{**}	-0.1232
	(0.3449)	(0.1968)	(0.2803)
2021–23	-0.7198^{**}	-0.5070^{***}	-0.1617
	(0.3491)	(0.1929)	(0.3838)
Difference	-0.0419	-0.0474	-0.0384
	(0.4902)	(0.2752)	(0.4746)
Bachelor's Degree or Higher, Under 40 Years Old			
2015–19	-1.0592^{***}	-0.6572^{***}	0.0757
	(0.1070)	(0.2211)	(0.5041)
2021–23	-0.9687^{***}	-0.5013^{***}	0.2256
	(0.0992)	(0.1666)	(0.3795)
Difference	0.0905	0.1559	0.1500
	(0.1457)	(0.2766)	(0.6303)
Bachelor's Degree or Higher, 40 Years and Older			
2015–19	-0.5790^{***}	-0.3196	0.0264
	(0.1833)	(0.2135)	(0.4964)
2021–23	-0.4998^{*}	-0.3624^{**}	-0.1682
	(0.2569)	(0.1767)	(0.4774)
Difference	0.0792	-0.0428	-0.1946
	(0.3152)	(0.2769)	(0.6878)

Note: See Tables A7 and A8 and Figures 25 and 26 for notes. Standard errors in parentheses clustered by industry. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table 4: Mobility Rates from the Bottom Half of the 3-digit Industry Wage Premia Distribution, 2021–2023 v. 2015–2019

	(1) 2015–2019	(2) 2021–2023	(3) Difference
A. Exit rate from bottom half of IWP			
Overall	0.00519***	0.00539***	0.00020
N=1,490,780	(0.00008)	(0.00013)	(0.00016)
HS, under 40	0.00843***	0.00996***	0.00153***
N=223,749	(0.00026)	(0.00047)	(0.00054)
B. Exit rate from top half of IWP			
Overall	0.00403***	0.00438***	0.00035***
N=1,512,842	(0.00007)	(0.00011)	(0.00013)
HS, under 40	0.00596***	0.00573***	−0.00024
N=225,467	(0.00022)	(0.00033)	(0.00040)
C. Net exit rate from bottom half of IWP			
Overall	0.00116***	0.00101***	−0.00015
N=3,003,622	(0.00010)	(0.00017)	(0.00020)
HS, under 40	0.00247***	0.00424***	0.00177***
N=449,216	(0.00034)	(0.00057)	(0.00066)

Note: Table reports the likelihood of moving between the bottom and top half of the industry wage premium (IWP) distribution. IWP are calculated separately for subgroup (overall vs. HS under 40) in 2015-2019 by regressing log real wage on age, age^2, age^3, dummy variables for race, ethnicity, education, citizenship, metro area status, and industry. The sample is limited to those who were employed in the current and previous month. An individual is considered to have moved from the bottom to top (top to bottom) half of the IWP distribution if their industry at time t is in the top (bottom) half of the IWP and their industry in the previous month (time $t-1$) was in the bottom (top) half of the IWP distribution *and* they reported switching jobs since the previous month. Panel A reports the likelihood of moving from the bottom to top half of the IWP distribution, panel B reports the likelihood of moving from the top half to bottom half, and panel C represents the net movement between the two halves. Panel C is simply the difference between the first two panels. The first column presents these statistics for 2015-2019, the second for 2021-2023, and the third column is the difference between the first and second columns. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table 5: Mobility Rates from the Bottom Quartile of the 3-digit Industry Wage Premia Distribution, 2021–2023 v. 2015–2019

	(1) 2015–2019	(2) 2021–2023	(3) Difference
A. Exit rate from the bottom quartile of IWP			
Overall	0.00987***	0.01039***	0.00052*
N=734,422	(0.00016)	(0.00027)	(0.00031)
HS, under 40	0.01438***	0.01766***	0.00328***
N=115,785	(0.00047)	(0.00086)	(0.00098)
B. Exit rate from the top three quartiles of IWP			
Overall	0.00747***	0.00730***	−0.00018
N=2,269,200	(0.00014)	(0.00021)	(0.00025)
HS, under 40	0.01091***	0.01061***	−0.00030
N=333,431	(0.00043)	(0.00065)	(0.00078)
C. Net exit rate from bottom quartile of IWP			
Overall	0.00240***	0.00309***	0.00069*
N=3,003,622	(0.00020)	(0.00033)	(0.00039)
HS, under 40	0.00347***	0.00705***	0.00358***
N=449,216	(0.00062)	(0.00106)	(0.00123)

Note: Table reports the likelihood of moving between the bottom quartile and top three quartiles of the industry wage premium (IWP) distribution. IWP are calculated for the period 2015-2019 separately for each subgroup (overall vs. HS under 40) by regressing log real wage on age, age^2, age^3, and indicators for race, ethnicity, education, citizenship, metro area status, and industry. The sample is limited to those who were employed in the current and previous month. An individual is considered to have moved from the bottom quartile to the top three quartiles (top to bottom) of the IWP distribution if their current industry is in the top three (bottom) quartiles of the IWP and their industry in the previous month was in the bottom (top three) quartile of the IWP distribution *and* they reported switching jobs since the previous month. Panel A reports the likelihood of moving out of the bottom quartile of the IWP distribution, panel B reports the likelihood of moving into the bottom quartile and panel C represents the net movement out of the bottom quartile. Estimates in panel B are calculated by multiplying the mean exit rate from the top three quartiles by $(1-p)/p$ where p is the share of workers in the bottom quartile ($p = .25$). We do this to account for the size differentials between exit and entry rates into the bottom quartile. Panel C is then the difference between the first two panels. The first column presents these statistics for 2015-2019, the second for 2021-2023, and the third column is the difference between the first and second columns. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table 6: Mobility Rates from the Hospitality Sector, 2021–2023 v. 2015–2019

	(1) 2015–2019	(2) 2021–2023	(3) Difference
A. Exit rate from Hospitality sector			
Overall	0.01397***	0.01543***	0.00146**
N=212,536	(0.00034)	(0.00060)	(0.00069)
HS, under 40	0.01488***	0.01729***	0.00241**
N=81,837	(0.00057)	(0.00099)	(0.00114)
B. Exit rate from non-Hospitality sector			
Overall	0.01029***	0.01017***	−0.00012
N=3,019,354	(0.00029)	(0.00045)	(0.00053)
HS, under 40	0.01064***	0.01140***	0.00077
N=461,737	(0.00048)	(0.00077)	(0.00090)
C. Net exit rate from Hospitality sector			
Overall	0.00368***	0.00526***	0.00158*
N=3,019,354	(0.00043)	(0.00072)	(0.00084)
HS, under 40	0.00424***	0.00588***	0.00164
N=461,737	(0.00073)	(0.00123)	(0.00143)

Note: Table shows the entrance and exit rates for the hospitality industry. The sample is limited to individuals working in the current and previous month. The hospitality sector is composed of all the industries within the Bureau of Labor Statistics' sector category "Accommodation and Food Service". An individual is considered a hospitality mover if their industry switched from a non-hospitality to a hospitality industry (or vice versa) from one month to the next, and they reported switching employers. Panel A reports the likelihood of exiting hospitality, panel B reports the likelihood of entering hospitality, and panel C represents the net exit rate from the hospitality sector. For panel B, the mean exit rate from non-hospitality industries is multiplied by $(1-p)/p$ to account for the size differentials between exit and entry rates, where p is the share of workers in hospitality in 2015-2019. For the overall sample, the hospitality share is $p = 0.079$, and for HS under 40, $p = 0.185$. The mean exit rate from non-hospitality overall in 2015-2019 is 0.0009, so the estimate presented in the table is $0.0103 \approx 0.0009 * 11.7$. Panel C is the difference between the first two panels. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table 7: Decomposition of the Change in Annual Wage Growth During 2021—2023 vs. 2015—2019

	High-School under-40		All others	
	(1) 2015-2019	(2) 2021-2023	(3) 2015-2019	(4) 2021-2023
A. Job Change and Industry Change Rates (% points)				
Pr(Mover in last qtr)	7.64	8.42	5.37	5.57
Pr(Mover in past 3 qtrs)	21.21	23.20	15.27	15.79
Pr(Mover in past year)	27.23	29.66	19.82	20.48
Pr(Stayer in past year)	72.77	70.34	80.18	79.52
B. Mean Log Wage Changes by Switcher Status (log points)				
E(Wage change)	4.63	3.69	3.46	1.20
E(Wage change | Job move)	4.67	7.80	6.25	3.88
E(Wage change | No job move)	4.61	1.96	2.77	0.52
C. Decomposition of Wage Change: 2021-23 vs. 2015-19 (log points)				
Contribution of job-movers		0.85		-0.47
Contribution of job-stayers		-1.93		-1.80
Contribution of move rate		0.14		0.02
Total		-0.94		-2.25

Note: Panels A and B in table report inputs in calculating the decomposition from equation (8). The components of the decomposition are reported in panel C. Panel A reports the quarterly probability of moving (row 1), the 3-quarter probability of moving (row 2) as well as the annual probability of moving (row 3) and its complement (row 4). Panel B then reports annual wage growth overall (row 1), for job movers (row 2), and for job stayers (row 3). Panel C reports the estimates for the decomposition: the contribution of the wage growth associated with job moving (row 1), the wage growth associated with job staying (row 2) and the wage growth associated with a change in the move rate (row 3) to overall wage growth for young non-college workers and their complementary group (row 4). See Section 4.4 for additional details underlying the decomposition.

Table 8: Price-Phillips Curve Estimates:
Regressions of Δ Log CPI on Various Measures of State Labor Market Tightness

	(1)	(2)	(3)	(4)	(5)
Tightness	0.0031	0.0030	0.0030	0.0028	0.0028
	(0.0064)	(0.0064)	(0.0064)	(0.0063)	(0.0063)
Std. 1-Unemployment	0.0071^{**}	0.0071^{**}	0.0070^{**}	0.0069^{**}	0.0069^{**}
	(0.0032)	(0.0032)	(0.0032)	(0.0031)	(0.0031)
Std. EE Separation	-0.0023	-0.0023	-0.0022	-0.0023	-0.0023
	(0.0039)	(0.0039)	(0.0038)	(0.0038)	(0.0038)
Controls:					
Age		X	X	X	X
Demographics			X	X	X
Sector				X	X
Covid Death Rate					X

Note: N=588,976. Table reports estimates for β from equation 9 for tightness and its components. Dependent variable is the log CPI (excluding energy). We assign CBSA-level CPI to main metro areas in each state, state average of CBSA-level CPI in other metro areas within the state, and census division-level CPI for remaining non-metro areas. Each column reports regression estimates using different explanatory variables. The explanatory variables are tightness (an average of the standardized EE separation rate and negative standardized unemployment rate) and both of its standardized components, each measured at the state level. All specifications include stack-by-state and stack-by-time effects, where stack denotes a pair of adjacent quarters. Age controls include five age group dummies. Demographic controls include 3 education dummies, 5 race dummies, and a dummy for sex. Sector controls include dummies for Manufacturing, Professional Services, Finance, and Business Services. Column 5 additionally controls for state Covid-19 death rate per 100,000 people as of June 2023. All data are obtained from CPS monthly files with the exception of CPI excluding energy obtained from BLS, seasonally-adjusted state unemployment rates obtained from BLS LAUS, and Covid-19 death rates obtained from CDC (2020). Standard errors in parentheses are clustered on state. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table 9: Coefficient on Tightness from Regressions of Wage Change on State Labor Market Tightness - using constructed *state-level* CPI

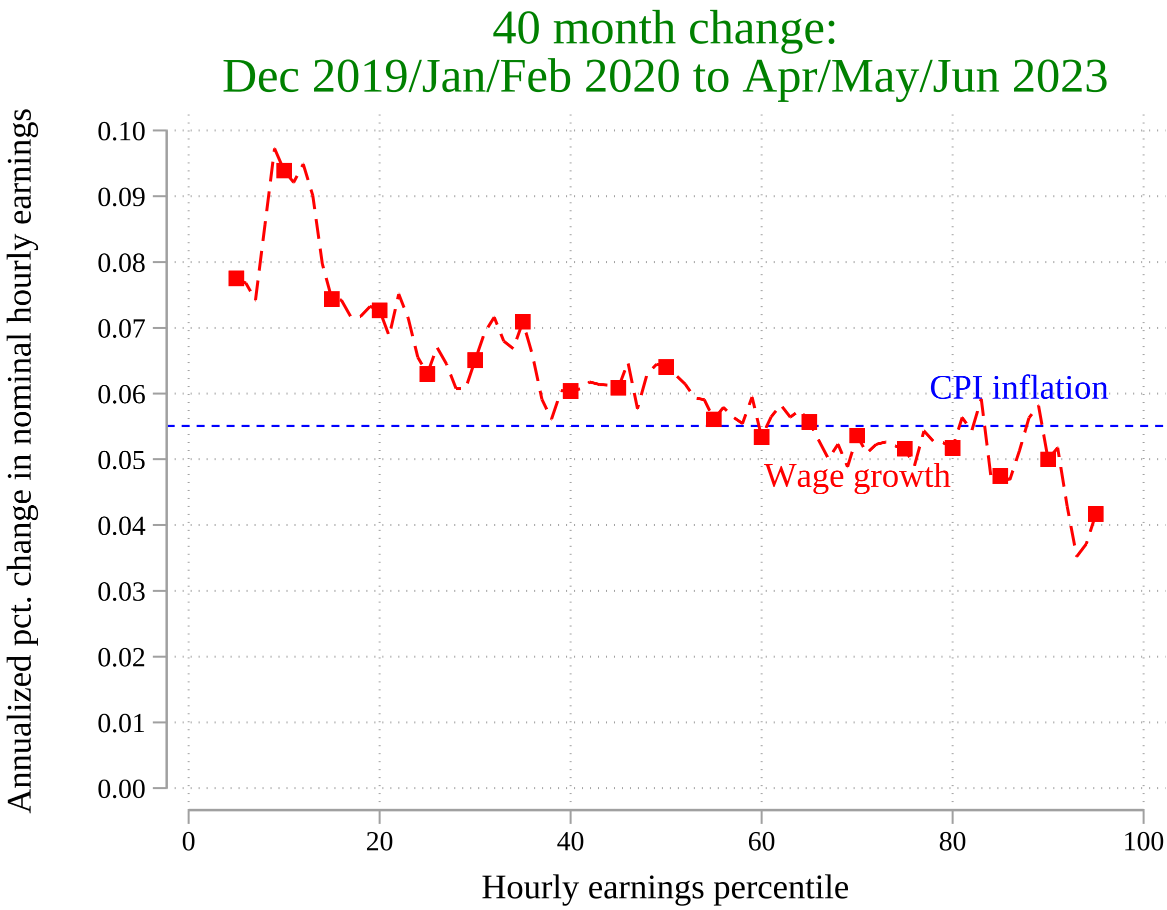
	(1)	(2)	(3)	(4)	(5)
Overall	0.0277**	0.0206*	0.0222**	0.0194*	0.0194*
	(0.0136)	(0.0119)	(0.0110)	(0.0103)	(0.0103)
Within wage quartiles					
1^{st} Quartile	0.1240***	0.1246***	0.1196***	0.1191***	0.1191***
	(0.0379)	(0.0376)	(0.0369)	(0.0369)	(0.0369)
2^{nd} Quartile	0.0922***	0.0930***	0.0906***	0.0892***	0.0892***
	(0.0308)	(0.0305)	(0.0290)	(0.0286)	(0.0286)
3^{rd} Quartile	−0.0775***	−0.0782***	−0.0744***	−0.0753***	−0.0753***
	(0.0200)	(0.0199)	(0.0197)	(0.0197)	(0.0197)
4^{th} Quartile	−0.0202	−0.0232	−0.0208	−0.0197	−0.0197
	(0.0280)	(0.0280)	(0.0270)	(0.0268)	(0.0268)
Within age and education groups					
High School, under 40	0.0893**	0.1111***	0.1022***	0.0917***	0.0917***
	(0.0357)	(0.0352)	(0.0345)	(0.0326)	(0.0326)
High School, 40+	0.1252**	0.1169**	0.1106**	0.1036**	0.1036**
	(0.0549)	(0.0528)	(0.0533)	(0.0515)	(0.0516)
Some College, under 40	0.0962***	0.0708***	0.0691***	0.0578**	0.0578**
	(0.0340)	(0.0273)	(0.0266)	(0.0254)	(0.0254)
Some College, 40+	0.0153	0.0071	0.0008	−0.0088	−0.0088
	(0.0290)	(0.0285)	(0.0270)	(0.0260)	(0.0260)
BA+, under 40	−0.0715**	−0.0729**	−0.0606**	−0.0479*	−0.0479*
	(0.0307)	(0.0305)	(0.0291)	(0.0289)	(0.0289)
BA+, 40+	−0.0326	−0.0397	−0.0430	−0.0430	−0.0430
	(0.0298)	(0.0311)	(0.0291)	(0.0294)	(0.0294)
Controls:					
Age		X	X	X	X
Demographics			X	X	X
Sector				X	X
Covid Death Rate					X

Note: N=326,923. Table reports estimates for β from equation 4. Dependent variable is the log real wage and the main explanatory variable, tightness, is an average of the standardized EE separation rate and negative standardized unemployment rate, both measured at the state level. Real wages are deflated using CPI at the most regional level available. We deflate wages with CBSA-specific CPI-U for available main metro areas, state average of CBSA-level CPI-U for other metro areas, and census-division level CPI-U for non-metro areas. Each column reports three regression estimates, one per panel (overall, within wage quartiles, and within age and education groups). All specifications include stack-by-state and stack-by-time effects, where stack denotes a pair of adjacent quarters. Subgroup regressions (lower two panels) include group-specific stack-by-time effects. Wage quartiles are estimated by state and quarter. Age controls include five age group dummies. Demographic controls include 3 education dummies, 5 race dummies, and a dummy for sex. Sector controls include dummies for Manufacturing, Professional Services, Finance, and Business Services. Column 5 additionally controls for state Covid-19 death rate per 100,000 people as of June 2023. All data are obtained from CPS monthly files with the exception of seasonally-adjusted state unemployment rates obtained from BLS LAUS, and Covid-19 death rates obtained from CDC (2020). Standard errors in parentheses are clustered on state. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Appendix

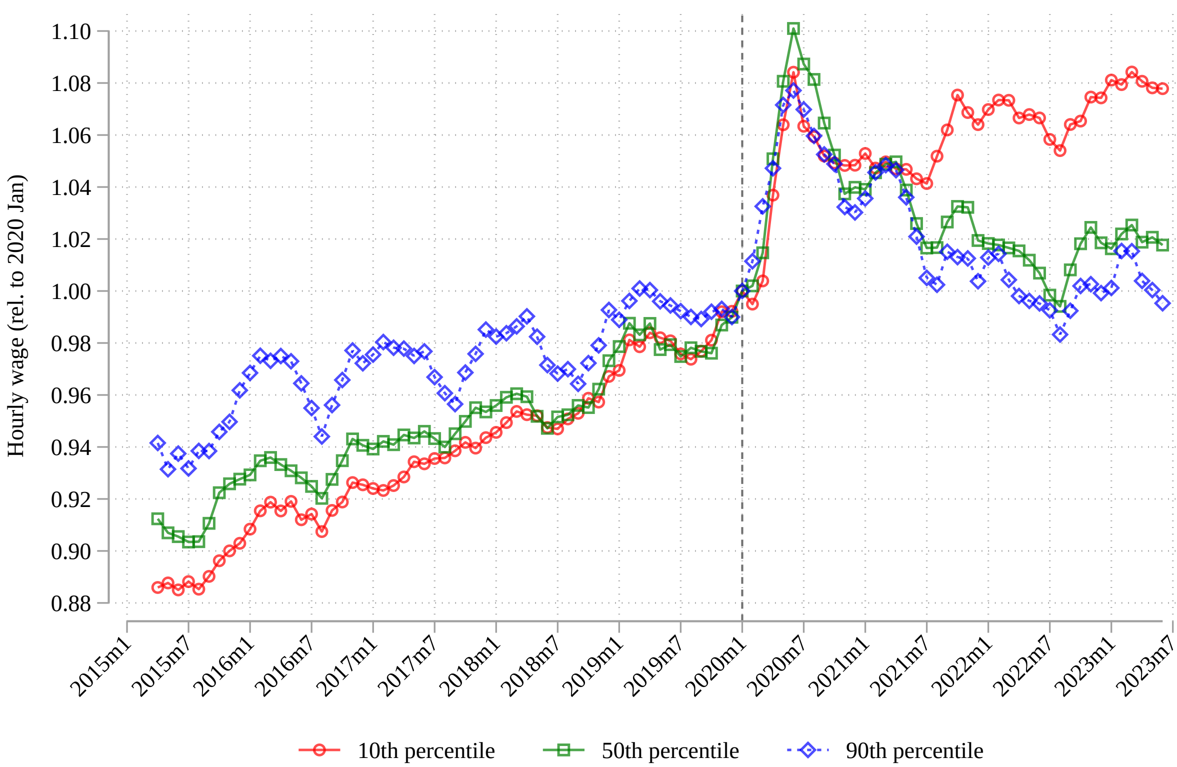
A1 Appendix Figures and Tables

Figure A1: Changes in Nominal Wage and Inflation Rate Along the (Unsmoothed) Distribution



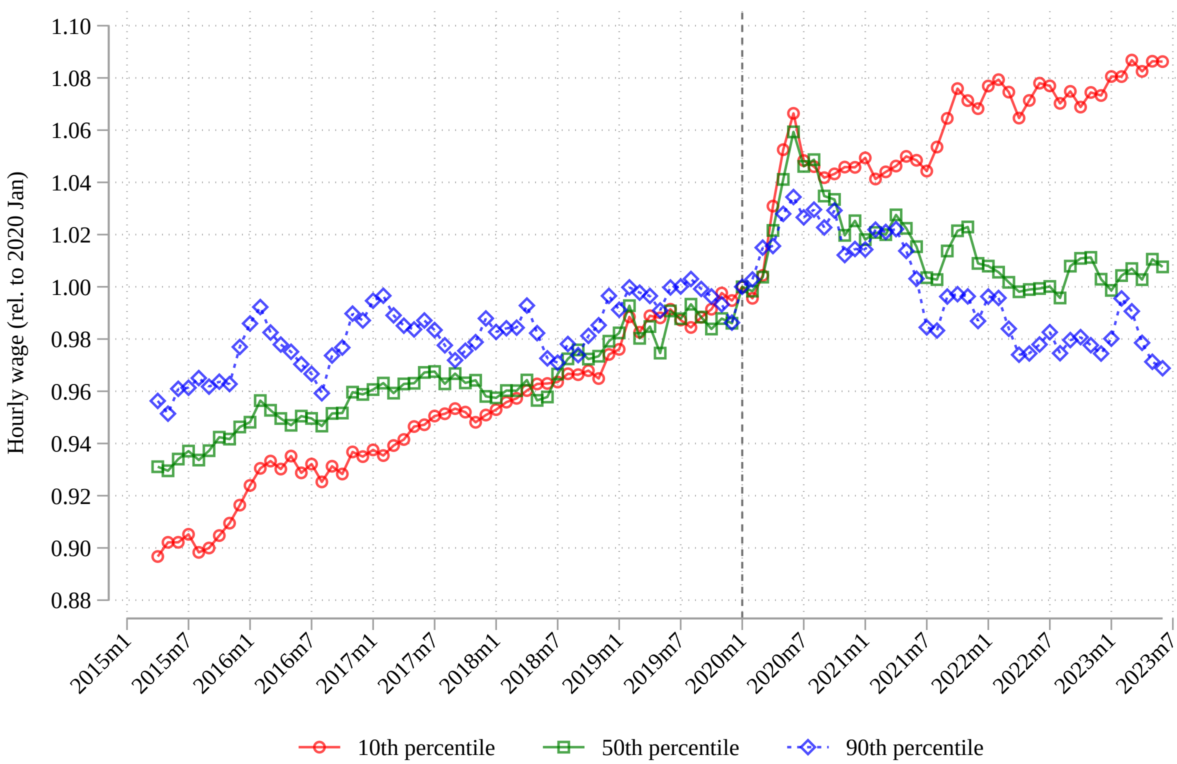
Note: CPS monthly data. Adjusted to maintain demographic composition in January–March 2020 using inverse probability weighting based on age, education, race/ethnicity, gender, country of birth, and region. Inflation is calculated using annualized, seasonally unadjusted CPI-U.

Figure A2: Real Hourly Wages by Quantile, Relative to January 2020
(Not Adjusted for Composition)



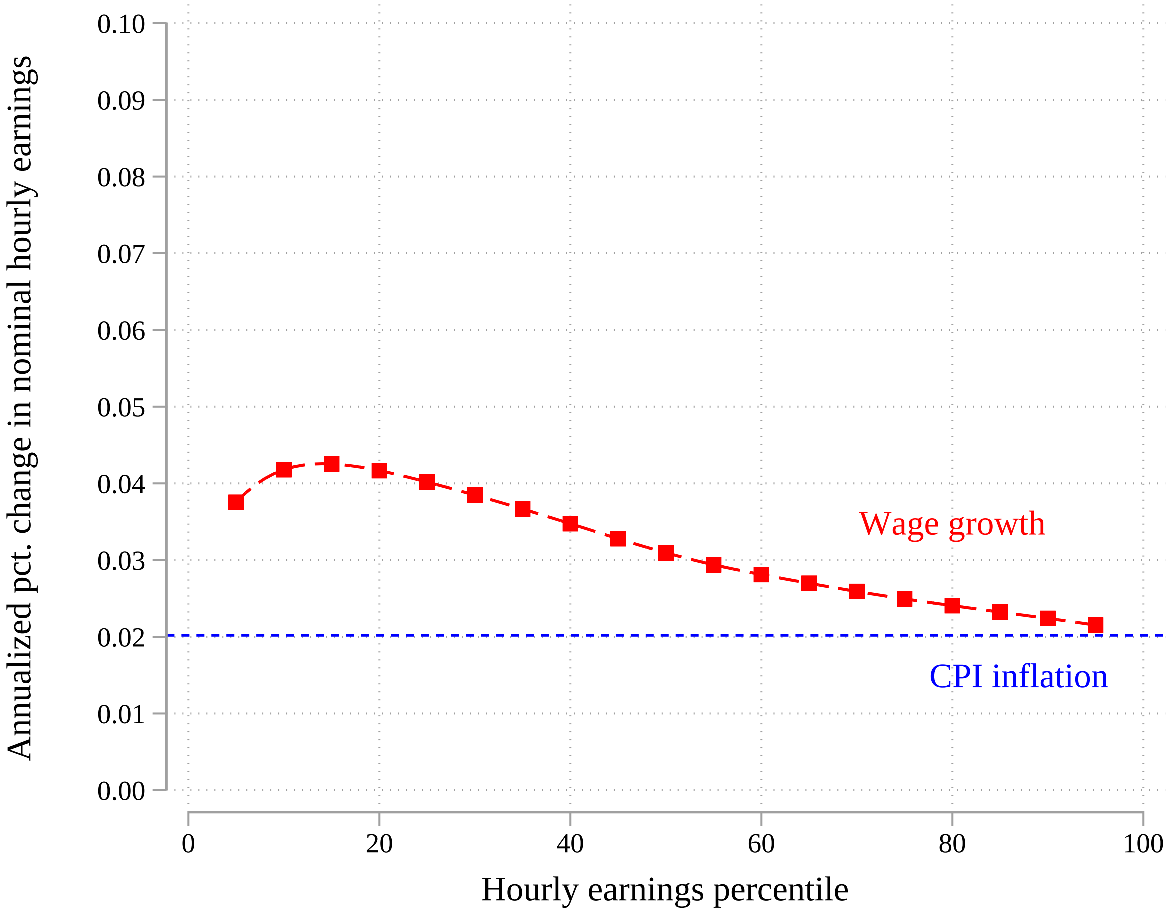
Note: CPS monthly data. Not adjusted to maintain demographic composition in January–March 2020. Wages are real (2023_{q2} USD). We construct wage quantiles by month. Wage percentiles are smoothed with lowess and a 3-month moving average.

Figure A3: Real Hourly Wages by Quantile, Relative to January 2020 (Excluding Tipped Workers)



Note: CPS monthly data. Adjusted to maintain demographic composition in January–March 2020 using inverse probability weighting based on age, education, race/ethnicity, gender, country of birth, and region. Wages are real (2023_{q2} USD).We construct wage quantiles by month. Wage percentiles are smoothed with lowess and a 3-month moving average. Workers who report receiving overtime pay, tips, or commissions are excluded.

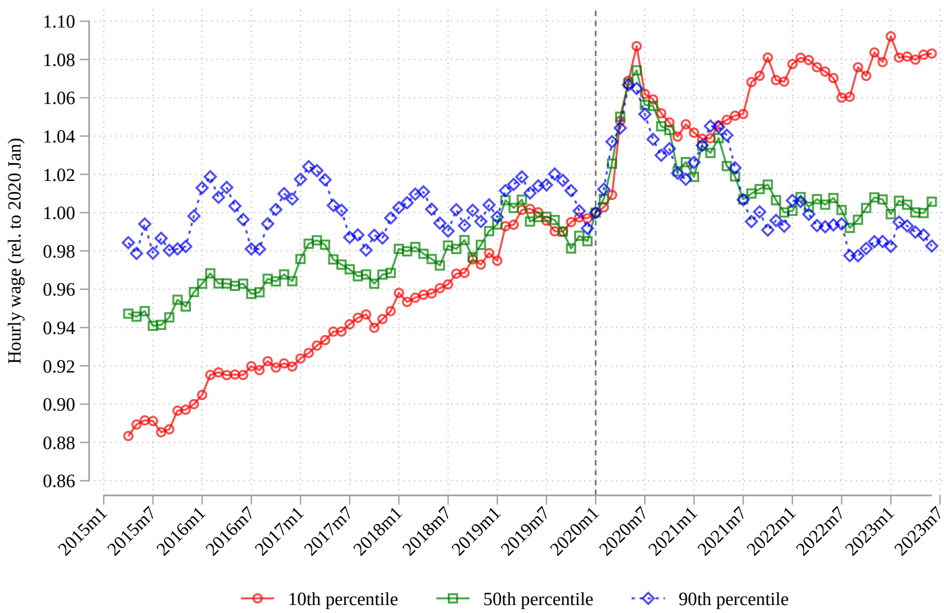
Figure A4: 48 Month Changes in Nominal Wage and Inflation Rate Along the Distribution: Oct/Nov/Dec 2015 through Oct/Nov/Dec 2019



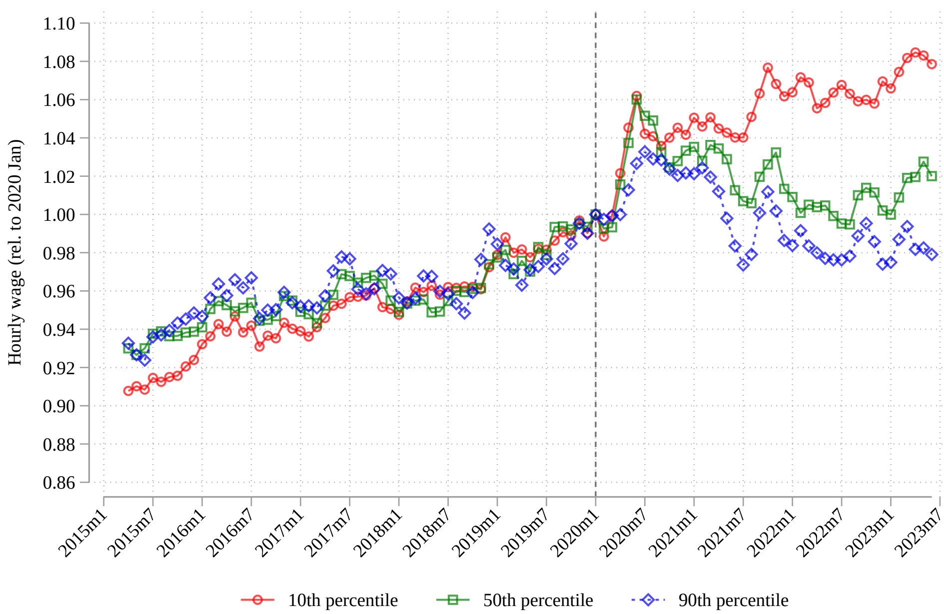
Note: CPS monthly data. Adjusted to maintain demographic composition in January–March 2020 using inverse probability weighting based on age, education, race/ethnicity, gender, country of birth, and region. Wage percentiles smoothed with lowess. Inflation is calculated using annualized, seasonally unadjusted CPI-U. Start and end point observations pool data from October through December 2015 and October through December 2019, respectively.

Figure A5: Real Hourly Wages by Quantile and Sex, Relative to January 2020

A. Male workers

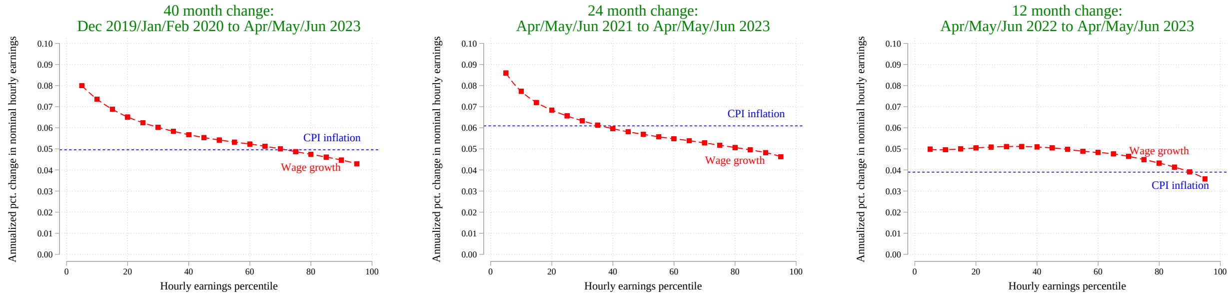


B. Female workers



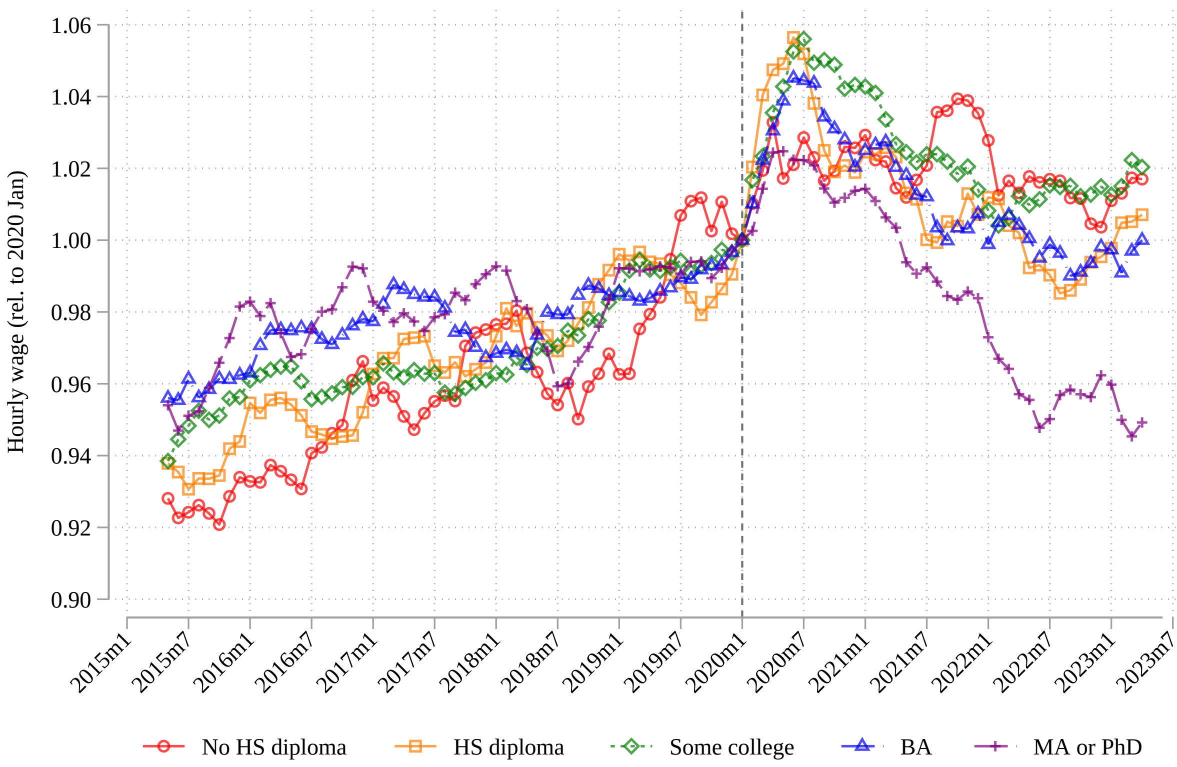
Note: CPS monthly data. Adjusted to maintain demographic composition in January–March 2020 using inverse probability weighting based on age, education, race/ethnicity, gender, country of birth, and region. Wages are real (2023_{q2} USD). We construct wage quantiles by sex and month. Wage percentiles are smoothed with lowess and a 3-month moving average.

Figure A6: Annualized Percent Change in Nominal Hourly Earnings by Earnings Percentile Over 40, 24 and 12 Months, Not Adjusted for Composition



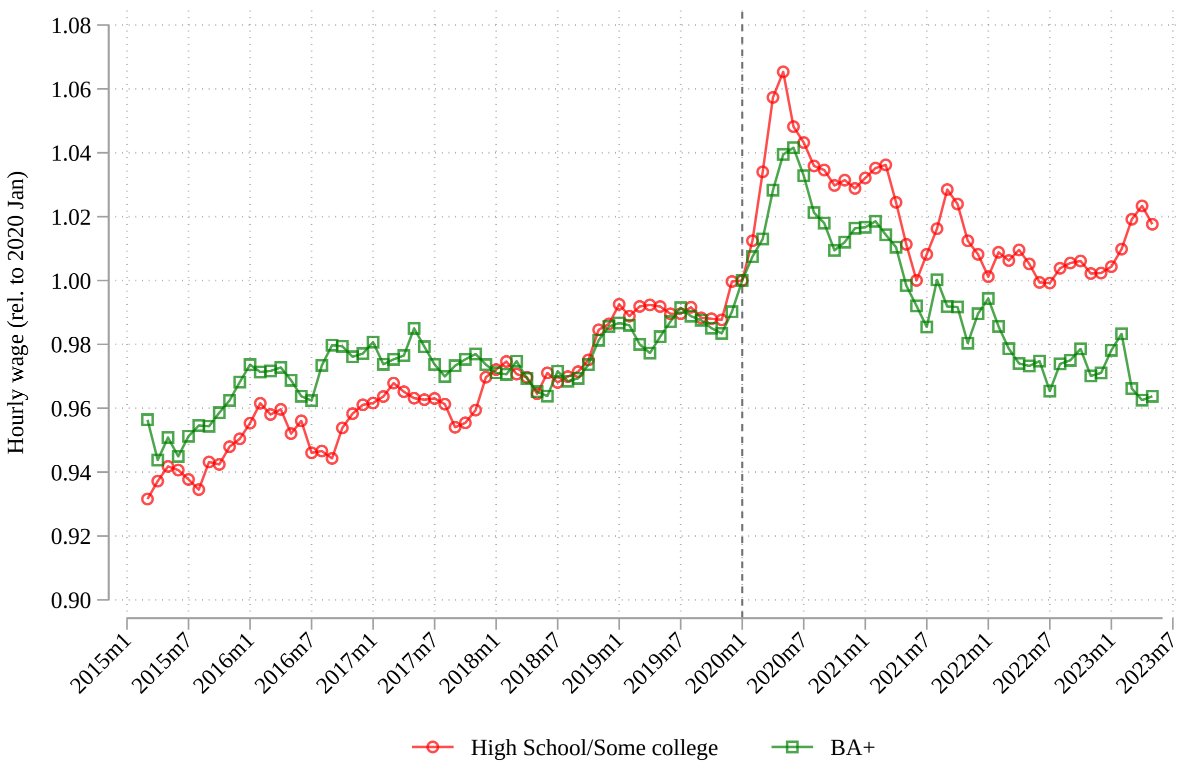
Note: CPS monthly data. Not adjusted to maintain demographic composition in January–March 2020. Wage percentiles are smoothed with lowess. Inflation is calculated using annualized, seasonally unadjusted CPI-U.

Figure A7: Real Hourly Wages by Education Levels (5 Education Categories), Relative to January 2020



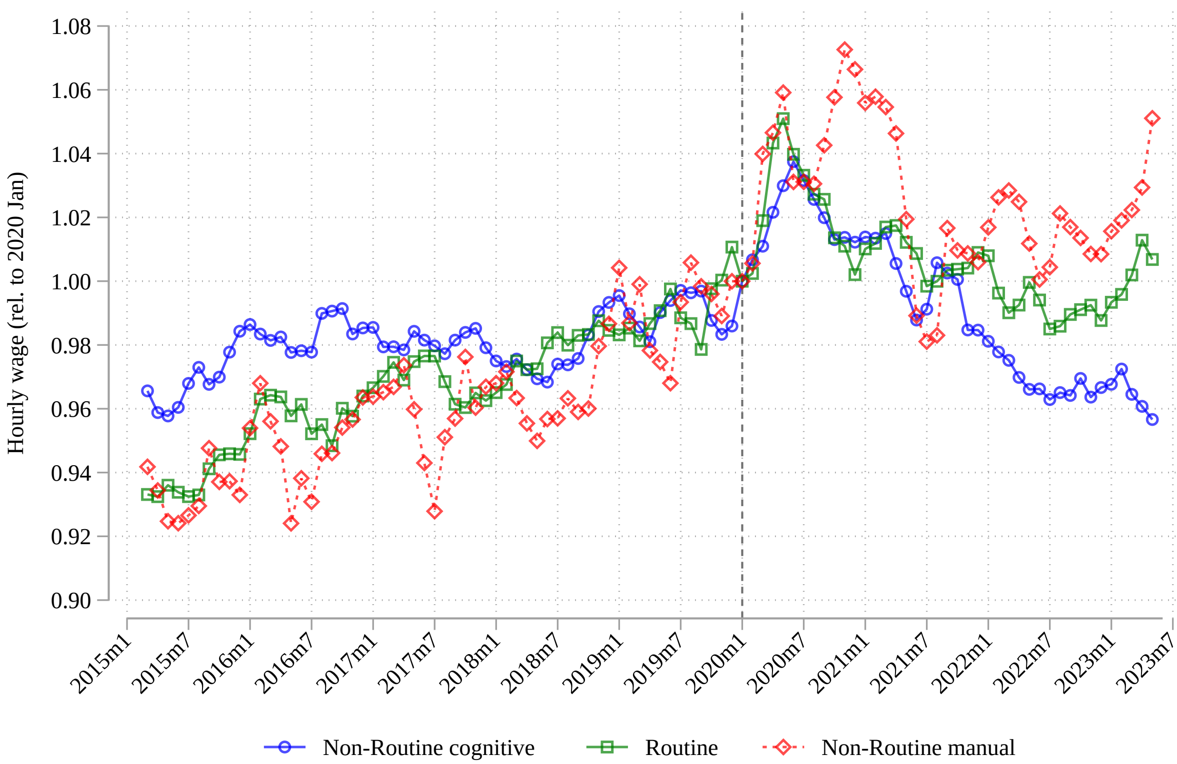
Note: CPS monthly data. Adjusted to maintain demographic composition in January–March 2020 using inverse probability weighting based on age, education, race/ethnicity, gender, country of birth, and region. Wages are real (2023_{q2} USD) and smoothed with a 6-month moving average.

Figure A8: Real Hourly Wages by Education Levels (Non-BA vs. BA+), Relative to January 2020



Note: CPS monthly data. Adjusted to maintain demographic composition in January–March 2020 using inverse probability weighting based on age, education, race/ethnicity, gender, country of birth, and region. Wages are real (2023_{q2} USD) and smoothed with a 3-month moving average.

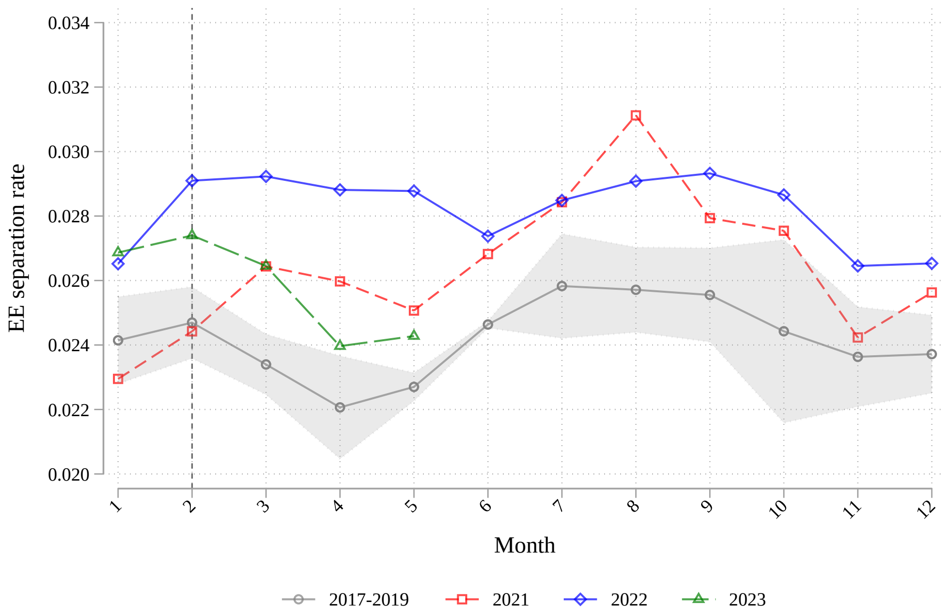
Figure A9: Real Hourly Wages by Types of Occupation Using Task Measures, Relative to January 2020



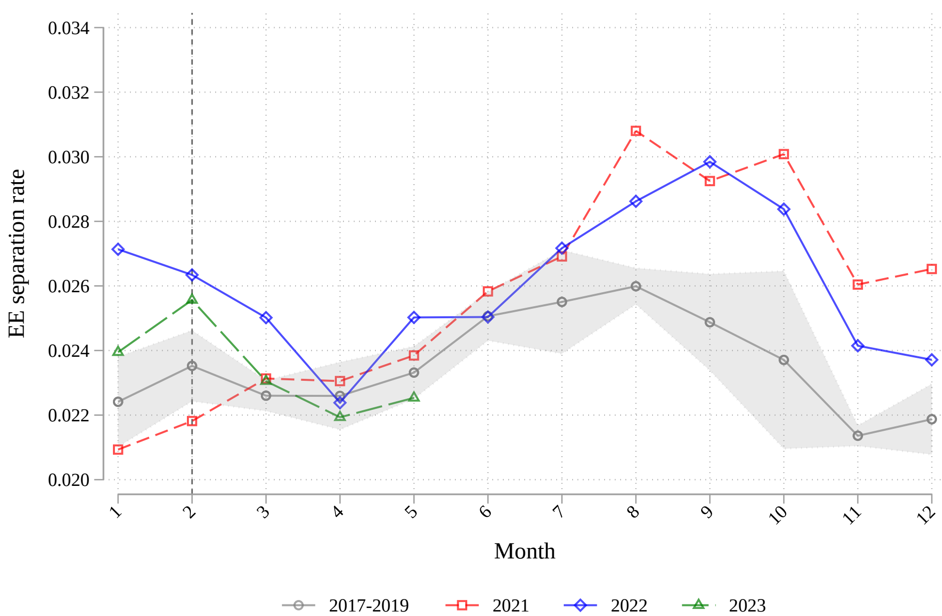
Note: CPS monthly data. Adjusted to maintain demographic composition in January–March 2020 using inverse probability weighting based on age, education, race/ethnicity, gender, country of birth, and region. Wages are real (2023_{q2} USD) and smoothed with a 3-month moving average. Occupation task types were identified following Jaimovich and Siu (2020).

Figure A10: EE Separation Rates by Month and Year: Non-BA Workers

A. High School education

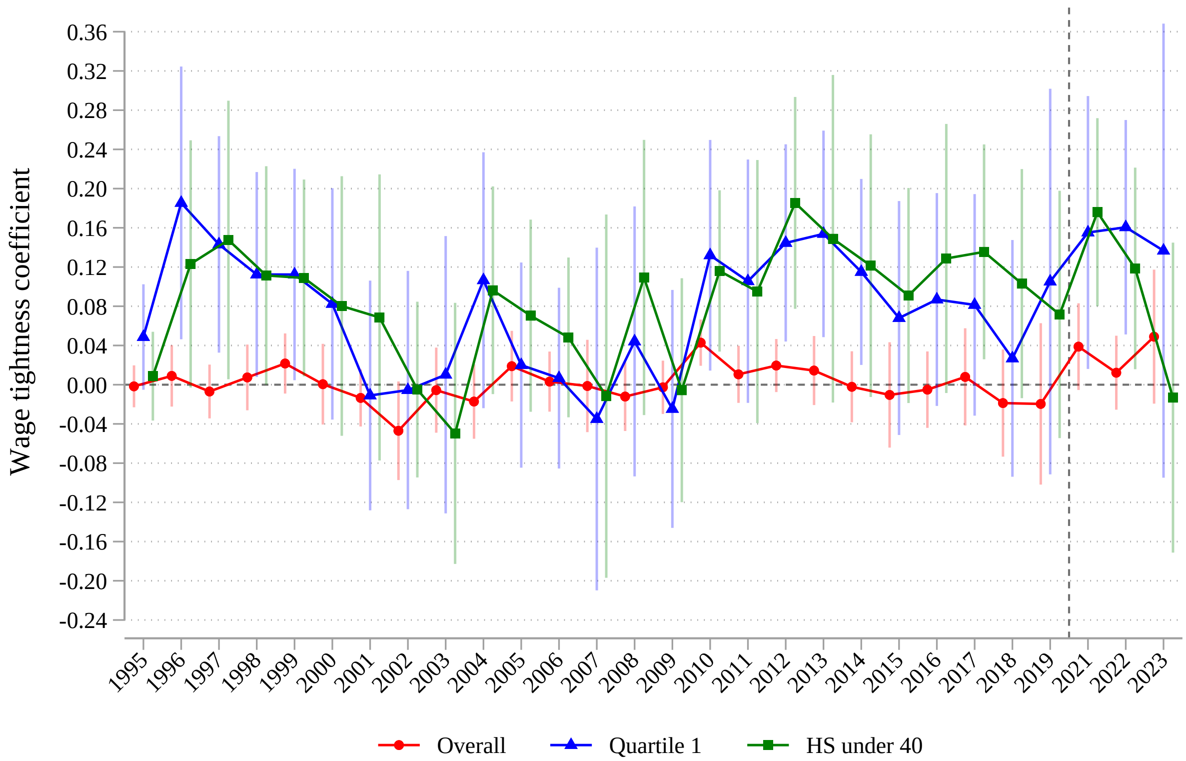


B. Some college education



Note: CPS monthly data. Employment-to-employment (EE) separation rate is smoothed with a 3-month moving average. Shaded area represents the 95% confidence interval for the monthly EE separation rate during the 2017–2019 period.

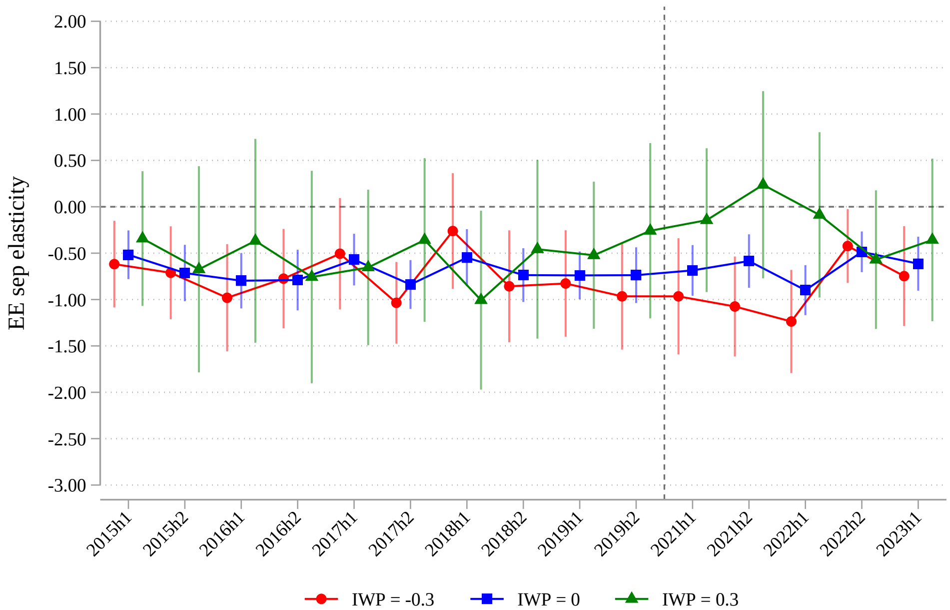
Figure A11: Wage Tightness Coefficient over Time



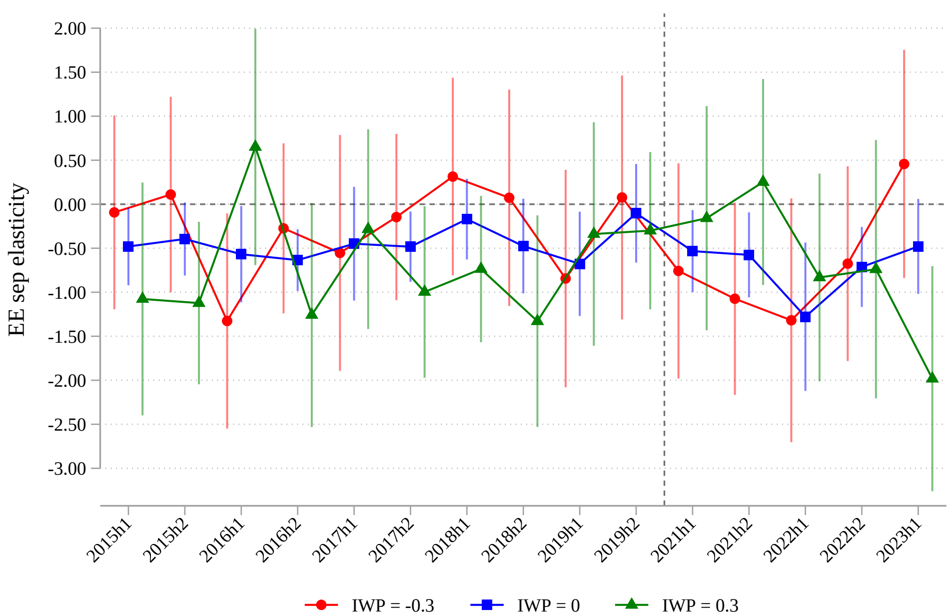
Note: Figure shows the evolution of the wage-Phillips curve coefficient (β from equation 4) over time, pooled annually. Each series reports key coefficients from regression estimates by year, and by group (overall, by wage quartiles, by age and education groups). The dashed line represents the 2020 pandemic, excluded from our estimates. Vertical lines represent 95% confidence intervals. All specifications include stack-by-state and stack-by-time effects, where stack denotes a pair of adjacent quarters. Subgroup regressions include group-specific stack-by-time effects. Wage quartiles are estimated by state and quarter. Age controls include five age group dummies. Demographic controls include 3 education dummies, 5 race dummies, and a dummy for sex. Sector controls include dummies for Manufacturing, Professional Services, Finance, and Business Services. We additionally controls for state Covid-19 death rate per 100,000 people as of June 2023. All data obtained from CPS monthly data except for seasonally-adjusted state unemployment rates which were obtained from BLS LAUS. The y-axis is average annualized log real wage change. Standard errors clustered at the state level.

Figure A12: EE Separation Elasticity over Time

A. Overall

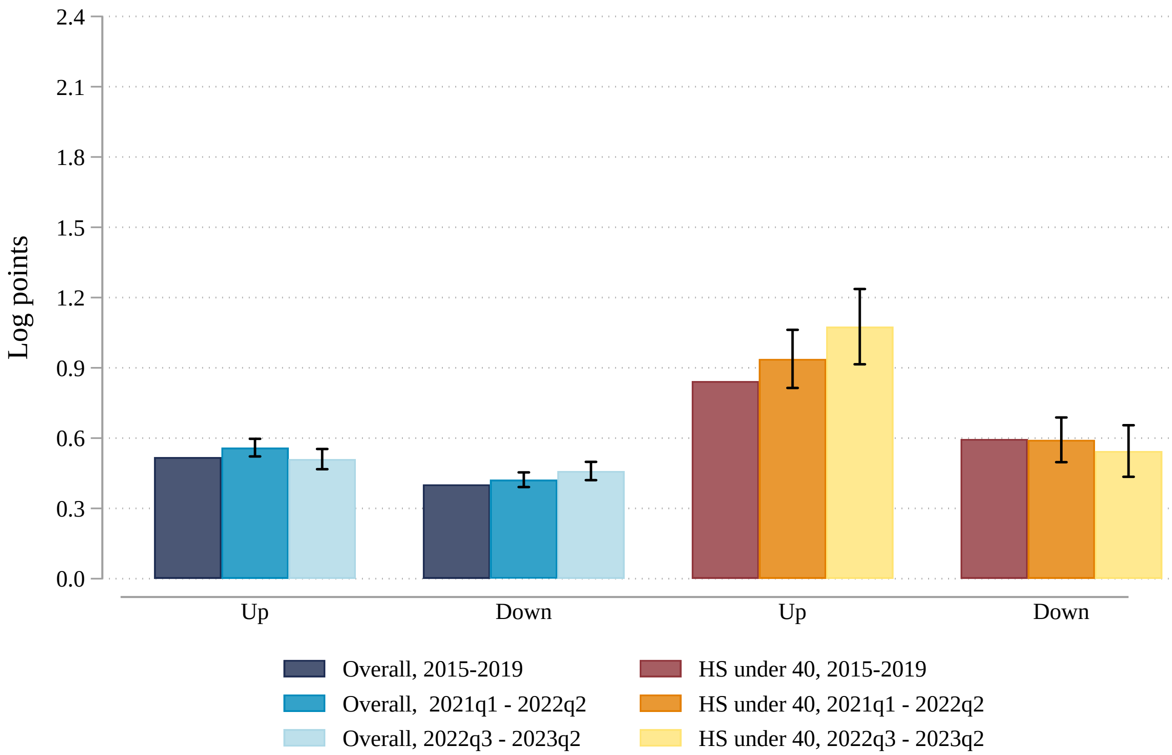


B. High School, under 40



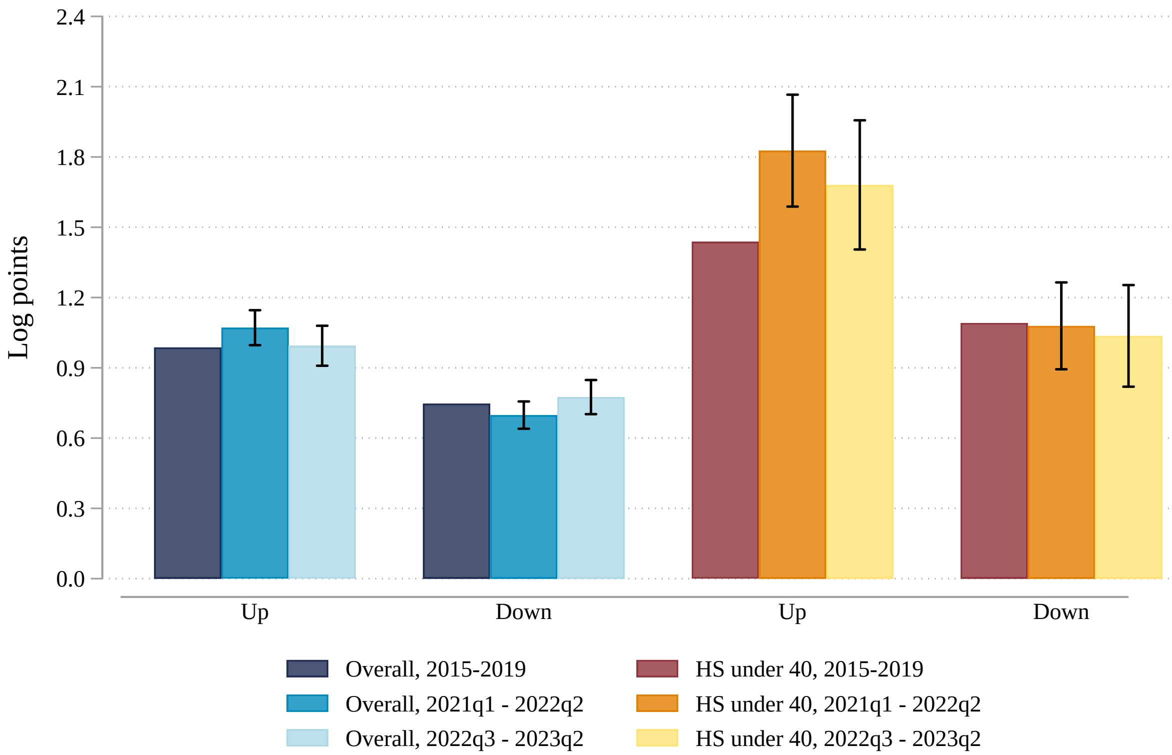
Note: EE separation elasticity estimates in 6-month intervals, evaluated along different points of the industry wage premia (IWP) distribution. Elasticities at $x = \{-0.3, 0, 0.3\}$ are calculated in two steps: first, we regress an indicator for EE separation at time t on 3-digit IWP at time $t-1$ and its square as well as on demographic controls and state fixed effects (based on equation 6). Second, we evaluate the derivative of EE separation with respect to IWP at x and divide by the conditional mean of EE separation at x to get the elasticity at x. Demographic controls from the regression in step one include dummy variables for sex, race, ethnicity, age group, education, citizenship, and metro area status. The IWP are calculated from a regression of log real wage on demographic controls and 3-digit industry fixed effects for the first half of 2015. Elasticities are calculated for each 6-month interval. The dependent variable, EE separation, is obtained from CPS monthly data. Standard errors are clustered at the industry level.

Figure A13: Movement Between Top Half and Bottom Half of the 3-Digit Industry Wage Premium Distribution



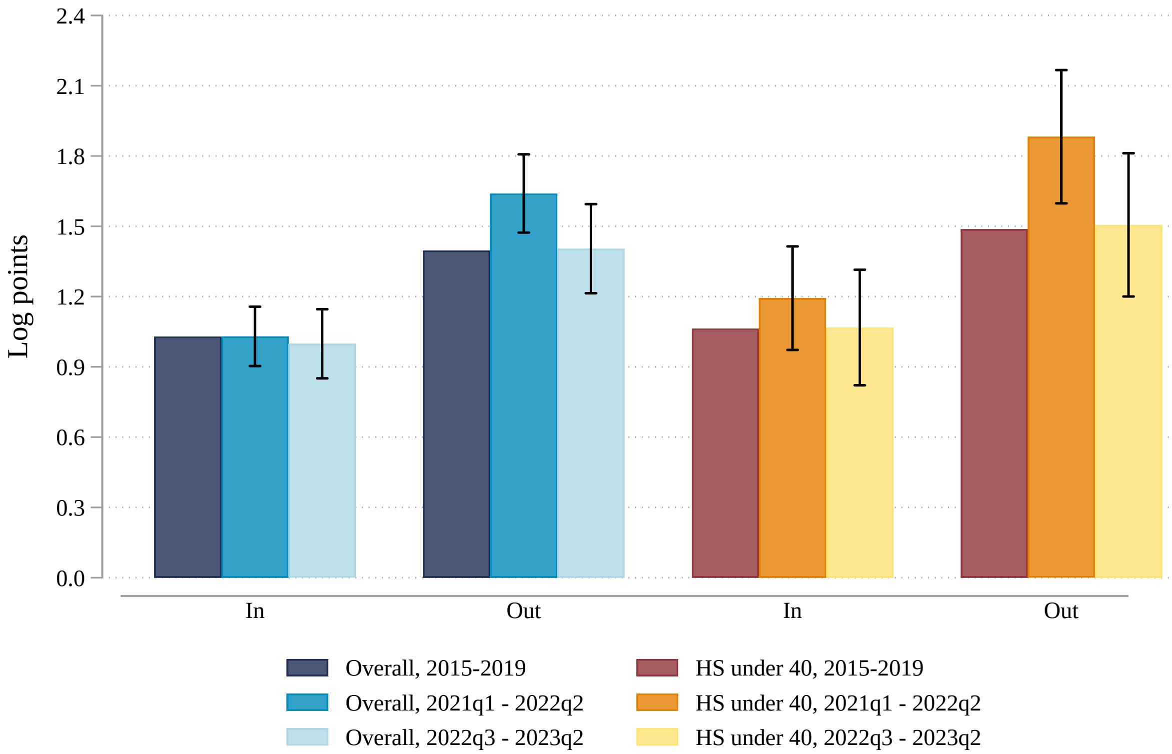
Note: Movement between the top and bottom halves of the 3-digit industry wage premium (IWP) distribution, by period, for all workers and for HS under 40 workers. The sample is limited to workers employed in both the current and the previous month. *Up* represents the likelihood of switching from the bottom half of the 3-digit IWP distribution to the top half. *Down* represents the likelihood of switching from the top half of the 3-digit IWP distribution to the bottom half. Movements in 2015–2019 correspond to column 1 of Table A12, movements in $2021_{q1} - 2022_{q2}$ correspond to column 2 of Table A12, and movements in $2022_{q3} - 2023_{q2}$ correspond to column 3 of Table A12. The error bars represent the 95% confidence intervals for the difference in movement relative to the 2015–2019 period, corresponding to columns 2 and 3 of Table A12.

Figure A14: Movement Into and Out of Bottom Quartile of the 3-Digit Industry Wage Premium Distribution



Note: Movement into and out of the bottom quartile of the industry wage premium (IWP) distribution, by period, for all workers and HS under 40 workers. *Up* represents the likelihood of switching from the bottom quartile of the 3-digit IWP distribution to the top three quartiles. *Down* represents the likelihood of switching from the top three quartiles of the 3-digit IWP distribution to the bottom quartile. Movements in 2015–2019 correspond to column 1 of Table A13, movements in $2021_{q1} - 2022_{q2}$ correspond to column 2 of Table A13, and movements in $2022_{q3} - 2023_{q2}$ correspond to column 3 of Table A13. The error bars represent the 95% confidence intervals for the difference in movement relative to the 2015–2019 period, corresponding to columns 2 and 3 of Table A13. To account for the size differentials in exit and entry rates, *Down* bars and confidence intervals are re-scaled by $(1-p)/p$ where p is the share of workers in the bottom quartile ($p = 0.25$).

Figure A15: Movement Into and Out of the Hospitality Industry



Note: Movement into and out of the hospitality sector, by period, for all workers and HS under 40 workers. The sample is limited to workers employed in both the current and the previous month. An individual is considered to have moved into or out of the hospitality industry only if their industry changed from the previous month and if they indicated switching jobs since the previous month. *In* represents the likelihood of entering the hospitality sector. *Out* represents the likelihood of leaving the hospitality sector. Movements in 2015–2019 correspond to column 1 of Table A14, movements in $2021_{q1} - 2022_{q2}$ correspond to column 2 of Table A14, and movements in $2022_{q3} - 2023_{q2}$ correspond to column 3 of Table A14. The error bars represent the 95% confidence intervals for the difference in movement relative to the 2015–2019 period, corresponding to columns 2 and 3 of Table A14. To account for the size differentials in exit and entry rates, *In* bars and confidence intervals are re-scaled by $(1 - p)/p$ where p is the share of workers in hospitality in 2015–2019. For the overall sample, $p = 0.079$, and for HS under 40, $p = 0.185$.

Table A1: 90-10 Ratio Over Time

	90/10	ln(90/10)
A. The Great Compression		
1940	5.000	1.609
1950	3.946	1.373
Δ	-1.054	-0.237
B. The Great Divergence		
1979	3.549	1.267
2019	4.720	1.552
Δ	1.172	0.285
C. The Unexpected Compression		
2020	4.792	1.567
2023	4.302	1.448
2023 (Adj)	4.257	1.448
Δ	-0.490	-0.108
Δ (Adj)	-0.525	-0.116

Note: Panel A compares the years 1940 and 1950, while panel B compares 1979 and 2019. Panel C compares the first quarter of 2020 to the second quarter of 2023. Panel A uses 1940 and 1950 Decennial Census data. Panels B and C use CPS monthly data from NBER (1979) and IPUMS (2019-2023). For each analysis, the sample is limited to individuals between 16-64 years old. For the latter two periods, imputed wages are excluded and percentiles are smoothed using lowess. For each panel, the first two rows display the 90-10 ratio (column 1) and its log (column 2) for the start and end of the time period. The third row of panels A and B and the 4th row of panel C report the difference in the (log) ratio between the start and end of the time period. The third row of panel C displays the level and log ratios in 2023 adjusted for the demographic composition in 2020. The adjustment is done using inverse probability weighting based on age, education, ethnicity, gender, and region. The last row is the change in the ratio between 2020 and the demographically-adjusted 2023.

Table A2: Coefficient on Tightness from Regressions of Wage Change on State Labor Market Tightness

	(1)
Overall	0.0231**
	(0.0098)
Within wage quartiles	
1^{st} Quartile	0.0953***
	(0.0346)
$2^{nd} - 4^{th}$ Quartiles	0.0084
	(0.0138)
Within age and education groups	
HS under 40	0.0963***
	(0.0319)
All other groups	0.0070
	(0.0111)
Controls:	
Age	X
Demographics	X
Sector	X
Covid Death Rate	X

Note: N=326,923. Table reports estimates corresponding to Figure 24. Dependent variable is the log real wage and the main explanatory variable, tightness, is an average of the standardized EE separation rate and negative standardized unemployment rate, both measured at the state level. Table reports three regression estimates, one per panel (overall, within wage quartiles, and within age and education groups) based on equation 4. All specifications include stack-by-state and stack-by-time effects, where stack denotes a pair of adjacent quarters. Subgroup regressions (lower two panels) include group-specific stack-by-time effects. Wage quartiles are estimated by state and quarter. Age controls include five age group dummies. Demographic controls include 3 education dummies, 5 race dummies, and a dummy for sex. Sector controls include dummies for Manufacturing, Professional Services, Finance, and Business Services. This specification additionally controls for state Covid-19 death rate per 100,000 people as of June 2023. All data are obtained from CPS monthly files with the exception of seasonally-adjusted state unemployment rates obtained from BLS LAUS, and Covid-19 death rates obtained from CDC (2020). Standard errors in parentheses are clustered on state. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table A3: Coefficient on Tightness from Regressions of Wage Change on State Labor Market Tightness - Pre-pandemic vs. Post-pandemic

	(1)	(2)	(3)
A. Overall			
2015–2019	-0.0149	-0.0152	-0.0090
	(0.0148)	(0.0138)	(0.0105)
2021–2023	0.0291*	0.0218	0.0224**
	(0.0153)	(0.0135)	(0.0108)
B. 1st Quartile			
2015–2019	0.0476	0.0495	0.0475
	(0.0325)	(0.0324)	(0.0322)
2021–2023	0.1236***	0.1233***	0.1186***
	(0.0402)	(0.0400)	(0.0390)
C. High School, under 40			
2015–2019	0.0505*	0.0769***	0.0737**
	(0.0290)	(0.0293)	(0.0297)
2021–2023	0.0819**	0.0967***	0.0793**
	(0.0374)	(0.0367)	(0.0343)
Controls:			
Age		X	X
Demographics			X
Sector			X
Covid Death Rate			X

Note: N=1,181,780. Table reports estimates for β from equation 4, over the 2015–2023 sample period. Dependent variable is the log real wage and the main explanatory variable, tightness, is an average of the standardized EE separation rate and negative standardized unemployment rate, both measured at the state level.. Each column reports key coefficients from six regression estimates: by period (pre-pandemic, post-pandemic) and by group (overall, by wage-quartiles, by age and education groups). All specifications include stack-by-state and stack-by-time effects, where stack denotes a pair of adjacent quarters. Subgroup regressions (lower two panels) include group-specific stack-by-time effects. Wage quartiles are estimated by state and quarter. Age controls include five age group dummies. Demographic controls include 3 education dummies, 5 race dummies, and a dummy for sex. Sector controls include dummies for Manufacturing, Professional Services, Finance, and Business Services. Column 3 additionally controls for state Covid-19 death rate per 100,000 people as of June 2023. All data are obtained from CPS monthly files with the exception of seasonally-adjusted state unemployment rates obtained from BLS LAUS, and Covid-19 death rates obtained from CDC (2020). Standard errors in parentheses are clustered on state. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table A4: Coefficient on Tightness from Regressions of Wage Change on State Labor Market Tightness - 15^{th} percentile trimmed

	(1)	(2)	(3)	(4)	(5)
Overall	0.0345^{**}	0.0290^{**}	0.0275^{**}	0.0252^{**}	0.0252^{**}
	(0.0152)	(0.0135)	(0.0110)	(0.0105)	(0.0105)
Within wage quartiles					
1^{st} Quartile	0.2044^{***}	0.2034^{***}	0.1932^{***}	0.1920^{***}	0.1920^{***}
	(0.0333)	(0.0334)	(0.0308)	(0.0307)	(0.0307)
2^{nd} Quartile	0.0991^{***}	0.1001^{***}	0.0969^{***}	0.0959^{***}	0.0959^{***}
	(0.0279)	(0.0279)	(0.0259)	(0.0256)	(0.0256)
3^{rd} Quartile	-0.0704^{***}	-0.0705^{***}	-0.0659^{***}	-0.0666^{***}	-0.0666^{***}
	(0.0190)	(0.0189)	(0.0181)	(0.0179)	(0.0179)
4^{th} Quartile	-0.0132	-0.0154	-0.0132	-0.0123	-0.0123
	(0.0301)	(0.0300)	(0.0284)	(0.0281)	(0.0281)
Within age and education groups					
High School, under 40	0.1411^{***}	0.1638^{***}	0.1529^{***}	0.1436^{***}	0.1436^{***}
	(0.0443)	(0.0433)	(0.0396)	(0.0380)	(0.0380)
High School, 40+	0.0994^{**}	0.0926^{*}	0.0852^{*}	0.0789^{*}	0.0789^{*}
	(0.0487)	(0.0474)	(0.0475)	(0.0465)	(0.0465)
Some College, under 40	0.1152^{***}	0.1026^{***}	0.1011^{***}	0.0922^{***}	0.0922^{***}
	(0.0421)	(0.0384)	(0.0350)	(0.0349)	(0.0349)
Some College, 40+	0.0623^{**}	0.0558^{*}	0.0458	0.0384	0.0384
	(0.0309)	(0.0311)	(0.0299)	(0.0288)	(0.0288)
BA+, under 40	-0.0769^{***}	-0.0789^{***}	-0.0652^{**}	-0.0553^{**}	-0.0553^{**}
	(0.0292)	(0.0301)	(0.0281)	(0.0273)	(0.0273)
BA+, 40+	-0.0279	-0.0341	-0.0357	-0.0375	-0.0375
	(0.0274)	(0.0279)	(0.0258)	(0.0261)	(0.0261)
Controls:					
Age		X	X	X	X
Demographics			X	X	X
Sector				X	X
Covid Death Rate					X

Note: N=279,382. Table reports estimates for β from equation 4. Dependent variable is the log real wage and the main explanatory variable, tightness, is an average of the standardized EE separation rate and negative standardized unemployment rate, both measured at the state level. Each column reports three regression estimates, one per panel (overall, within wage quartiles, and within age and education groups). All specifications include stack-by-state and stack-by-time effects, where stack denotes a pair of adjacent quarters. Subgroup regressions (lower two panels) include group-specific stack-by-time effects. Wage quartiles are estimated by state and quarter. The bottom 15^{th} percentile of earners in each state and quarter are trimmed from sample. Age controls include five age group dummies. Demographic controls include 3 education dummies, 5 race dummies, and a dummy for sex. Sector controls include dummies for Manufacturing, Professional Services, Finance, and Business Services. Column 5 additionally controls for state Covid-19 death rate per 100,000 people as of June 2023. All data are obtained from CPS monthly files with the exception of seasonally-adjusted state unemployment rates obtained from BLS LAUS, and Covid-19 death rates obtained from CDC (2020). Standard errors in parentheses are clustered on state. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table A5: Coefficient on Unemployment from Regressions of Wage Change on State Standardized Negative Unemployment Rate

	(1)	(2)	(3)	(4)	(5)
Overall	0.0179***	0.0157**	0.0108*	0.0105*	0.0105*
	(0.0067)	(0.0065)	(0.0066)	(0.0062)	(0.0062)
Within wage quartiles					
1^{st} Quartile	0.0562	0.0577	0.0534	0.0535	0.0535
	(0.0448)	(0.0445)	(0.0437)	(0.0438)	(0.0438)
2^{nd} Quartile	0.1140***	0.1142***	0.1092***	0.1080***	0.1080***
	(0.0320)	(0.0316)	(0.0306)	(0.0302)	(0.0302)
3^{rd} Quartile	−0.0403	−0.0407	−0.0377	−0.0384	−0.0384
	(0.0271)	(0.0272)	(0.0268)	(0.0268)	(0.0268)
4^{th} Quartile	−0.0573**	−0.0592**	−0.0558**	−0.0539**	−0.0539**
	(0.0270)	(0.0269)	(0.0260)	(0.0258)	(0.0258)
Within age and education groups					
High School, under 40	0.0616**	0.0870***	0.0827***	0.0753***	0.0753***
	(0.0252)	(0.0232)	(0.0227)	(0.0217)	(0.0217)
High School, 40+	0.1530***	0.1468***	0.1486***	0.1398***	0.1398***
	(0.0541)	(0.0524)	(0.0507)	(0.0481)	(0.0481)
Some College, under 40	0.1040***	0.0956***	0.0889***	0.0813***	0.0813***
	(0.0289)	(0.0236)	(0.0223)	(0.0220)	(0.0220)
Some College, 40+	0.0071	0.0006	−0.0034	−0.0091	−0.0091
	(0.0207)	(0.0214)	(0.0210)	(0.0207)	(0.0207)
BA+, under 40	−0.1054***	−0.1085***	−0.1030***	−0.0909***	−0.0909***
	(0.0179)	(0.0170)	(0.0166)	(0.0169)	(0.0169)
BA+, 40+	−0.0710**	−0.0775***	−0.0776***	−0.0703**	−0.0703**
	(0.0285)	(0.0287)	(0.0272)	(0.0273)	(0.0273)
Controls:					
Age		X	X	X	X
Demographics			X	X	X
Sector				X	X
Covid Death Rate					X

Note: N=326,923. Table reports estimates analogous to β from equation 4, but for negative standardized unemployment rate rather than tightness. The dependent variable is still log real wage. Each column reports three regression estimates, one per panel (overall, within wage quartiles, and within age and education groups). All specifications include stack-by-state and stack-by-time effects, where stack denotes a pair of adjacent quarters. Subgroup regressions (lower two panels) include group-specific stack-by-time effects. Wage quartiles are estimated by state and quarter. Age controls include five age group dummies. Demographic controls include 3 education dummies, 5 race dummies, and a dummy for sex. Sector controls include dummies for Manufacturing, Professional Services, Finance, and Business Services. Column 5 additionally controls for state Covid-19 death rate per 100,000 people as of June 2023. All data are obtained from CPS monthly files with the exception of seasonally-adjusted state unemployment rates obtained from BLS LAUS, and Covid-19 death rates obtained from CDC (2020). Standard errors in parentheses are clustered on state. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table A6: Coefficient on EE Separation Rate from Regressions of Wage Change on State Standardized EE Separation Rate

	(1)	(2)	(3)	(4)	(5)
Overall	0.0116	0.0079	0.0120	0.0101	0.0101
	(0.0100)	(0.0093)	(0.0076)	(0.0072)	(0.0072)
Within wage quartiles					
1^{st} Quartile	0.0566*	0.0559*	0.0548*	0.0545*	0.0545*
	(0.0291)	(0.0290)	(0.0282)	(0.0282)	(0.0282)
2^{nd} Quartile	−0.0013	−0.0009	0.0007	0.0004	0.0004
	(0.0188)	(0.0188)	(0.0181)	(0.0179)	(0.0179)
3^{rd} Quartile	−0.0283*	−0.0284*	−0.0275*	−0.0276*	−0.0276*
	(0.0151)	(0.0151)	(0.0145)	(0.0145)	(0.0145)
4^{th} Quartile	0.0237	0.0227	0.0223	0.0220	0.0220
	(0.0180)	(0.0180)	(0.0178)	(0.0177)	(0.0177)
Within age and education groups					
High School, under 40	0.0283	0.0282	0.0246	0.0217	0.0217
	(0.0231)	(0.0229)	(0.0227)	(0.0216)	(0.0216)
High School, 40+	−0.0004	−0.0026	−0.0081	−0.0077	−0.0077
	(0.0279)	(0.0277)	(0.0271)	(0.0265)	(0.0265)
Some College, under 40	0.0079	−0.0051	−0.0020	−0.0054	−0.0054
	(0.0210)	(0.0190)	(0.0174)	(0.0173)	(0.0173)
Some College, 40+	0.0087	0.0068	0.0047	0.0014	0.0014
	(0.0183)	(0.0183)	(0.0178)	(0.0170)	(0.0170)
BA+, under 40	0.0138	0.0147	0.0200	0.0218	0.0218
	(0.0176)	(0.0162)	(0.0155)	(0.0156)	(0.0156)
BA+, 40+	0.0228	0.0217	0.0193	0.0148	0.0148
	(0.0209)	(0.0208)	(0.0197)	(0.0201)	(0.0201)
Controls:					
Age		X	X	X	X
Demographics			X	X	X
Sector				X	X
Covid Death Rate					X

Note: N=326,923. Table reports estimates analogous to β from equation 4, but for the standardized EE separation rate rather than tightness. The dependent variable is still log real wage. Each column reports three regression estimates, one per panel (overall, within wage quartiles, and within age and education groups). All specifications include stack-by-state and stack-by-time effects, where stack denotes a pair of adjacent quarters. Subgroup regressions (lower two panels) include group-specific stack-by-time effects. Wage quartiles are estimated by state and quarter. Age controls include five age group dummies. Demographic controls include 3 education dummies, 5 race dummies, and a dummy for sex. Sector controls include dummies for Manufacturing, Professional Services, Finance, and Business Services. Column 5 additionally controls for state Covid-19 death rate per 100,000 people as of June 2023. All data are obtained from CPS monthly files with the exception of seasonally-adjusted state unemployment rates obtained from BLS LAUS, and Covid-19 death rates obtained from CDC (2020). Standard errors in parentheses are clustered on state. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table A7: Relationship Between Employment-to-Employment Separation and Industry Wage Premia

	Overall		HS, under 40		All others	
	(1)	(2)	(3)	(4)	(5)	(6)
Period 1: 2015–2019						
Ind. Wage Premium	-0.0208^{***}	-0.0141^{***}	-0.0236^{***}	-0.0155^{***}	-0.0162^{***}	-0.0131^{***}
	(0.0031)	(0.0027)	(0.0040)	(0.0040)	(0.0031)	(0.0029)
Ind. Wage Premium^2	0.0230^{*}	0.0069	-0.0001	-0.0111	0.0178^{*}	0.0078
	(0.0119)	(0.0099)	(0.0123)	(0.0111)	(0.0099)	(0.0087)
	N=1,921,670		*N=284,569*		*N=1,629,695*	
Period 2: 2021–2023						
Ind. Wage Premium	-0.0212^{***}	-0.0132^{***}	-0.0350^{***}	-0.0258^{***}	-0.0143^{***}	-0.0107^{***}
	(0.0031)	(0.0024)	(0.0040)	(0.0046)	(0.0030)	(0.0025)
Ind. Wage Premium^2	0.0337^{***}	0.0174^{*}	0.0319^{*}	0.0207	0.0237^{**}	0.0143^{*}
	(0.0130)	(0.0095)	(0.0178)	(0.0173)	(0.0102)	(0.0085)
	N=735,378		*N=110,086*		*N=622,652*	
Controls		X		X		X

Note: Table reports coefficients on industry wage premium (IWP) and its square from a regression of an indicator for EE separation at time t on 3-digit industry wage premia at time $t-1$ and its square as well as demographic controls and state fixed effects (based on equation 6). Demographic controls include dummy variables for sex, race, ethnicity, age group, education, citizenship, and metro area status. The 3-digit industry wage premia are calculated from a regression of log real wage on demographic controls and industry fixed effects for the pre-pandemic period, 2015-2019. Estimates for the age and education groups included in "All others" (columns 5 and 6) are reported in Table A8. Estimates from this table are used for calculating the elasticities reported in Figure 25, panel A of Figure 26, and in the first two panels of Table 3. These elasticities are calculated by evaluating the derivative of EE separation w.r.t IWP at $x = \{-.3, 0, .3\}$ and dividing by the conditional mean of EE separation at $x = \{-.3, 0, .3\}$ to estimate the elasticity at $x = \{-.3, 0, .3\}$. The third row of each column in Table 3 reports the difference between the coefficients in rows 1 and 2. Standard errors in parentheses are clustered by industry.
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table A8: Relationship Between Employment-to-Employment Separation and Industry Wage Premia: All others

	HS, 40+		BA, under 40		BA, 40+	
	(1)	(2)	(3)	(4)	(5)	(6)
Period 1: 2015–2019						
Ind. Wage Premium	-0.0081^{**}	-0.0074^{**}	-0.0142^{***}	-0.0130^{***}	-0.0053	-0.0048
	(0.0039)	(0.0032)	(0.0047)	(0.0044)	(0.0034)	(0.0032)
Ind. Wage Premium^2	0.0092	0.0093	0.0265^{***}	0.0240^{***}	0.0089	0.0087
	(0.0078)	(0.0075)	(0.0093)	(0.0085)	(0.0081)	(0.0075)
	N=334,735		*N=319,962*		*N=409,955*	
Period 2: 2021–2023						
Ind. Wage Premium	-0.0107^{***}	-0.0088^{***}	-0.0106^{***}	-0.0097^{***}	-0.0053^{*}	-0.0054^{**}
	(0.0040)	(0.0033)	(0.0036)	(0.0032)	(0.0029)	(0.0027)
Ind. Wage Premium^2	0.0118	0.0104	0.0267^{***}	0.0232^{***}	0.0060	0.0052
	(0.0101)	(0.0096)	(0.0075)	(0.0069)	(0.0090)	(0.0083)
	N=117,190		*N=135,359*		*N=173,475*	
Controls		X		X		X

Note: Table reports coefficients on industry wage premium (IWP) and its square from a regression of an indicator for EE separation at time t on 3-digit industry wage premia at time $t-1$ and its square as well as demographic controls and state fixed effects (based on equation 6). Demographic controls include dummy variables for sex, race, ethnicity, age group, education, citizenship, and metro area status. The 3-digit industry wage premia are calculated from a regression of log real wage on demographic controls and industry fixed effects for the pre-pandemic period, 2015-2019. Estimates in this table correspond to the age and education groups included in category "All others" (columns 5 and 6) of Table A8. Estimates from this table are used for calculating the elasticities reported in panels B through D of Figure 26 and in the last three panels of Table 3. These elasticities are calculated by evaluating the derivative of EE separation w.r.t IWP at $x = \{-.3, 0, .3\}$ and dividing by the conditional mean of EE separation at $x = \{-.3, 0, .3\}$ to estimate the elasticity at $x = \{-.3, 0, .3\}$. The third row of each column in Table 3 reports the difference between the coefficients in rows 1 and 2. Standard errors in parentheses are clustered by industry.

* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table A9: Relationship Between Employment-to-Employment Separation and Industry Wage Premia - Poisson Estimates

	Overall	HS, under 40	HS, 40 +	BA+, under 40	BA+, 40+
	(1)	(2)	(3)	(4)	(5)
Period 1: 2015–2019					
Ind. Wage Premium	-0.6755^{***}	-0.5361^{***}	-0.4421^{**}	-0.5884^{***}	-0.3048
	(0.1463)	(0.1463)	(0.1937)	(0.2125)	(0.2054)
Ind. Wage Premium^2	-0.1395	-0.6806	0.4548	0.5774	0.4054
	(0.5222)	(0.4571)	(0.4543)	(0.4102)	(0.4398)
	N=1921670	*N=284569*	*N=334,735*	*N=319,962*	*N=409,955*
Period 2: 2021–2023					
Ind. Wage Premium	-0.5806^{***}	-0.8066^{***}	-0.4807^{**}	-0.4332^{**}	-0.3536^{**}
	(0.1179)	(0.1489)	(0.1916)	(0.1696)	(0.1692)
Ind. Wage Premium^2	0.3454	0.2579	0.4293	0.6861^{**}	0.2193
	(0.4702)	(0.6241)	(0.5512)	(0.3388)	(0.4673)
	N=735378	*N=110086*	*N=117,190*	*N=135,359*	*N=173,475*

Note: Table reports coefficients on industry wage premium and its square from a Poisson regression of an indicator for EE separation at time t on 3-digit industry wage premia at time $t-1$ and its square as well as demographic controls and state fixed effects (based on equation 6). Demographic controls include dummy variables for sex, race, ethnicity, age group, education, citizenship, and metro area status. The 3-digit industry wage premia are calculated from a regression of log real wage on demographic controls and industry fixed effects for the pre-pandemic period, 2015-2019. Standard errors in parentheses are clustered by industry. Estimates from this table are used for calculating the elasticities reported in Table A10. The elasticities at $x = \{-.3, 0, .3\}$ are estimated by evaluating the derivative of EE separation w.r.t IWP at $x = \{-.3, 0, .3\}$. The third row of each panel in Table A10 reports the difference between the coefficients in rows 1 and 2. Standard errors in parentheses are clustered by industry.
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table A10: Employment-to-Employment Separation Elasticity Estimates at Different Values of Industry Wage Premia - Poisson Estimates

	(1) IWP=-0.3	(2) IWP=0	(3) IWP=0.3
Overall			
2015–19	-0.5918^{**}	-0.6755^{***}	-0.7592^{*}
	(0.2453)	(0.1463)	(0.4230)
2021–23	-0.7879^{***}	-0.5806^{***}	-0.3734
	(0.2267)	(0.1179)	(0.3682)
Difference	-0.1961	0.0948	0.3858
	(0.3337)	(0.1876)	(0.5602)
High School Educated, Under 40 Years Old			
2015–19	-0.1278	-0.5361^{***}	-0.9444^{***}
	(0.2616)	(0.1463)	(0.3533)
2021–23	-0.9614^{**}	-0.8066^{***}	-0.6519
	(0.4009)	(0.1489)	(0.4050)
Difference	-0.8336^{*}	-0.2705	0.2925
	(0.4782)	(0.2085)	(0.5368)
High School Educated, 40 Years and Older			
2015–19	-0.7150^{*}	-0.4421^{**}	-0.1692
	(0.3786)	(0.1937)	(0.2834)
2021–23	-0.7382^{*}	-0.4807^{**}	-0.2231
	(0.3810)	(0.1916)	(0.3835)
Difference	-0.0233	-0.0386	-0.0539
	(0.5365)	(0.2722)	(0.4763)
Bachelor's Degree or Higher, Under 40 Years Old			
2015–19	-0.9349^{***}	-0.5884^{***}	-0.2419
	(0.0903)	(0.2125)	(0.4509)
2021–23	-0.8448^{***}	-0.4332^{**}	-0.0215
	(0.0836)	(0.1696)	(0.3650)
Difference	0.0900	0.1552	0.2205
	(0.1229)	(0.2716)	(0.5795)
Bachelor's Degree or Higher, 40 Years and Older			
2015–19	-0.5480^{***}	-0.3048	-0.0615
	(0.1513)	(0.2054)	(0.4480)
2021–23	-0.4852^{**}	-0.3536^{**}	-0.2220
	(0.2211)	(0.1692)	(0.4069)
Difference	0.0628	-0.0488	-0.1605
	(0.2676)	(0.2658)	(0.6045)

Note: See Table A9 for notes. Standard errors in parentheses clustered by industry. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table A11: Employment-to-Employment Separation Elasticity Estimates at the Mean of Industry Wage Premia over Varying Periods

	Overall	HS, under 40	HS, 40 +	BA+, under 40	BA+, 40+
	(1)	(2)	(3)	(4)	(5)
2015–2019	-0.6837^{***}	-0.5151^{***}	-0.4596^{**}	-0.6572^{***}	-0.3196
	(0.1322)	(0.1321)	(0.1968)	(0.2211)	(0.2135)
	N=1,921,670	*N=284,569*	*N=334,735*	*N=319,962*	*N=409,955*
$2021_{q1} - 2022_{q2}$	-0.7033^{***}	-0.9096^{***}	-0.6545^{***}	-0.5255^{***}	-0.3618^{*}
	(0.1234)	(0.1817)	(0.2045)	(0.1913)	(0.2091)
	N=461,472	*N=68,460*	*N=74,006*	*N=84,763*	*N=107,934*
$2022_{q3} - 2023_{q2}$	-0.5172^{***}	-0.7075^{***}	-0.2939	-0.4503^{**}	-0.3610^{*}
	(0.1154)	(0.1928)	(0.3318)	(0.1930)	(0.1937)
	N=273,906	*N=41,626*	*N=43,184*	*N=50,596*	*N=65,541*

Note: Table reports EE separation elasticity coefficients over the pre-pandemic period, and two separate post-pandemic periods. These elasticities are calculated in two steps: first, we regress an indicator for EE separation at time t on 3-digit IWP at time $t-1$ and its square as well as on demographic controls and state fixed effects (based on equation 6). Second, we evaluate the derivative of EE separations w.r.t IWP at the mean, $x = \{0\}$, and divide by the conditional mean of EE separation at $x = \{0\}$ to estimate the elasticity at $x = \{0\}$. Their specification corresponds to column 2 of Table 3. The dependent variable, EE separation, is obtained from monthly CPS data. The 3-digit industry wage premia are calculated from a regression of log real wage on demographic controls and industry fixed effects for the pre-pandemic period, 2015-2019. Standard errors in parentheses are clustered by industry.
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table A12: Mobility Rates from the Bottom Half of the 3-digit Industry Wage Premia Distribution, 2021–2023 v. 2015–2019

	(1)	(2)	(3)	(4)	(5)
				Difference	Difference
	2015–2019	$2021_{q1} - 2022_{q2}$	$2022_{q3} - 2023_{q2}$	$2021_{q1} - 2022_{q2}$	$2022_{q3} - 2023_{q2}$
A. Exit rate from bottom half of IWP					
Overall	0.00519***	0.00559***	0.00510***	0.00041**	−0.00008
N=1,490,780	(0.00008)	(0.00017)	(0.00020)	(0.00019)	(0.00022)
HS, under 40	0.00843***	0.00938***	0.01076***	0.00095	0.00233***
N=223,749	(0.00026)	(0.00058)	(0.00078)	(0.00063)	(0.00082)
B. Exit rate from top half of IWP					
Overall	0.00403***	0.00422***	0.00460***	0.00020	0.00057***
N=1,512,842	(0.00007)	(0.00014)	(0.00019)	(0.00016)	(0.00020)
HS, under 40	0.00596***	0.00593***	0.00545***	−0.00004	−0.00051
N=225,467	(0.00022)	(0.00043)	(0.00052)	(0.00049)	(0.00056)
C. Net exit rate from bottom half of IWP					
Overall	0.00116***	0.00137***	0.00051*	0.00021	−0.00065**
N=3,003,622	(0.00010)	(0.00022)	(0.00027)	(0.00025)	(0.00029)
HS, under 40	0.00247***	0.00346***	0.00531***	0.00099	0.00284***
N=449,216	(0.00034)	(0.00071)	(0.00092)	(0.00079)	(0.00098)

Note: Table reports the likelihood of moving between the bottom and top half of the industry wage premium (IWP) distribution. IWP are calculated separately for subgroup (overall vs. HS under 40) in 2015-2019 by regressing log real wage on age, age^2, age^3, dummy variables for race, ethnicity, education, citizenship, metro area status, and industry. The sample is limited to those who were employed in the current and previous month. An individual is considered to have moved from the bottom to top (top to bottom) half of the IWP distribution if their industry at time t is in the top (bottom) half of the IWP and their industry in the previous month (time $t-1$) was in the bottom (top) half of the IWP distribution *and* they reported switching jobs since the previous month. Panel A reports the likelihood of moving from the bottom to top half of the IWP distribution, panel B reports the likelihood of moving from the top half to bottom half, and panel C represents the net movement between the two halves. Panel C is simply the difference between the first two panels. The first column presents these statistics for 2015-2019, the second for $2021_{q1} - 2022_{q2}$, and the third for $2022_{q3} - 2023_{q1}$. The third and fourth columns respectively report estimates for the columns 2 and 3 relative to the pre-pandemic estimates in column 1. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table A13: Mobility Rates from the Bottom Quartile of the 3-digit Industry Wage Premia Distribution, 2021–2023 v. 2015–2019

	(1)	(2)	(3)	(4)	(5)
				Difference	Difference
	2015–2019	$2021_{q1} - 2022_{q2}$	$2022_{q3} - 2023_{q2}$	$2021_{q1} - 2022_{q2}$	$2022_{q3} - 2023_{q2}$
A. Exit rate from the bottom quartile of IWP					
Overall	0.00987***	0.01071***	0.00994***	0.00084**	0.00007
N=734,422	(0.00016)	(0.00035)	(0.00041)	(0.00038)	(0.00044)
HS, under 40	0.01438***	0.01827***	0.01681***	0.00389***	0.00243*
N=115,785	(0.00047)	(0.00112)	(0.00133)	(0.00122)	(0.00141)
B. Exit rate from the top three quartiles of IWP					
Overall	0.00747***	0.00698***	0.00775***	−0.00049*	0.00028
N=2,269,200	(0.00014)	(0.00026)	(0.00035)	(0.00030)	(0.00037)
HS, under 40	0.01091***	0.01079***	0.01036***	−0.00012	−0.00055
N=333,431	(0.00043)	(0.00084)	(0.00102)	(0.00095)	(0.00111)
C. Net exit rate from bottom quartile of IWP					
Overall	0.00116***	0.00137***	0.00051*	0.00021	−0.00065**
N=3,003,622	(0.00010)	(0.00022)	(0.00027)	(0.00025)	(0.00029)
HS, under 40	0.00247***	0.00346***	0.00531***	0.00099	0.00284***
N=449,216	(0.00034)	(0.00071)	(0.00092)	(0.00079)	(0.00098)

Note: Table reports the likelihood of moving between the bottom quartile and top three quartiles of the industry wage premium (IWP) distribution. IWP are calculated for the period 2015-2019 separately for each subgroup (overall vs. HS under 40) by regressing log real wage on age, age^2, age^3, and indicators for race, ethnicity, education, citizenship, metro area status, and industry. The sample is limited to those who were employed in the current and previous month. An individual is considered to have moved from the bottom quartile to the top three quartiles (top to bottom) of the IWP distribution if their current industry is in the top three (bottom) quartiles of the IWP and their industry in the previous month was in the bottom (top three) quartile of the IWP distribution *and* they reported switching jobs since the previous month. Panel A reports the likelihood of moving out of the bottom quartile of the IWP distribution, panel B reports the likelihood of moving into the bottom quartile and panel C represents the net movement out of the bottom quartile. Estimates in panel B are calculated by multiplying the mean exit rate from the top three quartiles by $(1-p)/p$ where p is the share of workers in the bottom quartile ($p = .25$). We do this to account for the size differentials between exit and entry rates into the bottom quartile. Panel C is then the difference between the first two panels. The first column presents these statistics for 2015-2019, the second for $2021_{q1} - 2022_{q2}$, and the third for $2022_{q3} - 2023_{q1}$. The third and fourth columns respectively report estimates for the second and third columns relative to the pre-pandemic estimates in column 1. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table A14: Mobility Rates from the Hospitality Sector, 2021–2023 v. 2015–2019

	(1)	(2)	(3)	(4)	(5)
				Difference	Difference
	2015–2019	$2021_{q1} - 2022_{q2}$	$2022_{q3} - 2023_{q2}$	$2021_{q1} - 2022_{q2}$	$2022_{q3} - 2023_{q2}$
A. Exit rate from Hospitality sector					
Overall	0.01397***	0.01640***	0.01404***	0.00243***	0.00007
N=212,536	(0.00034)	(0.00078)	(0.00091)	(0.00085)	(0.00097)
HS, under 40	0.01488***	0.01882***	0.01506***	0.00394***	0.00018
N=81,837	(0.00057)	(0.00134)	(0.00145)	(0.00145)	(0.00156)
B. Exit rate from non-Hospitality sector					
Overall	0.01029***	0.01030***	0.00999***	0.00001	−0.00031
N=3,019,354	(0.00029)	(0.00058)	(0.00070)	(0.00065)	(0.00075)
HS, under 40	0.01064***	0.01193***	0.01068***	0.00130	0.00004
N=461,737	(0.00048)	(0.00102)	(0.00116)	(0.00113)	(0.00126)
C. Net exit rate from Hospitality sector					
Overall	0.00368***	0.00610***	0.00406***	0.00242**	0.00038
N=3,019,354	(0.00043)	(0.00096)	(0.00111)	(0.00105)	(0.00119)
HS, under 40	0.00424***	0.00689***	0.00438**	0.00265	0.00014
N=461,737	(0.00073)	(0.00167)	(0.00180)	(0.00182)	(0.00194)

Note: Table shows the entrance and exit rates for the hospitality industry. The sample is limited to individuals working in the current and previous month. The hospitality sector is composed of all the industries within the Bureau of Labor Statistics' sector category "Accommodation and Food Service". An individual is considered a hospitality mover if their industry switched from a non-hospitality to a hospitality industry (or vice versa) from one month to the next, and they reported switching employers. Panel A reports the likelihood of exiting hospitality, panel B reports the likelihood of entering hospitality, and panel C represents the net exit rate from the hospitality sector. For panel B, the mean exit rate from non-hospitality industries is multiplied by $(1-p)/p$ to account for the size differentials between exit and entry rates, where p is the share of workers in hospitality in 2015-2019. For the overall sample, the hospitality share is $p = 0.079$, and for HS under 40, $p = 0.185$. Panel C is the difference between the first two panels. The first column presents these statistics for 2015-2019, the second for $2021_{q1} - 2022_{q2}$, and the third for $2022_{q3} - 2023_{q1}$. The third and fourth columns respectively report estimates for the second and third columns relative to the pre-pandemic estimates in column 1. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table A15: Price Phillips Curve Estimates: Over Varying Time Intervals

	(1) Tightness	(2) Std. 1-Unemp	(3) Std. EE Sep	(4) 1-Unemp	(5) EE Sep
A. Δ Log CPI (excluding energy)					
2018–2019	-0.0093^{*}	-0.0033^{**}	-0.0057	-0.5665^{**}	-1.3873
N=567,666	(0.0051)	(0.0016)	(0.0040)	(0.2670)	(0.9649)
$2021_{q1} - 2022_{q2}$	0.0079^{***}	0.0042^{***}	0.0013	0.7170^{***}	0.3237
N=344,055	(0.0029)	(0.0011)	(0.0028)	(0.1905)	(0.6675)
$2022_{q3} - 2023_{q2}$	-0.0087	-0.0020	-0.0058	-0.3301	-1.4026
N=244,921	(0.0060)	(0.0058)	(0.0047)	(0.9885)	(1.1384)
B. Δ Log real wage					
2018 − 2019	-0.0025	-0.0006	-0.0018	-0.1085	-0.4395
N=303,629	(0.0091)	(0.0038)	(0.0083)	(0.6410)	(2.0054)
$2021_{q1} - 2022_{q2}$	0.0093^{*}	0.0039	0.0050	0.6683	1.2219
N=188,047	(0.0053)	(0.0028)	(0.0102)	(0.4678)	(2.4689)
$2022_{q3} - 2023_{q2}$	0.0217^{*}	0.0069	0.0122	1.1636	2.9572
N=138,876	(0.0127)	(0.0073)	(0.0087)	(1.2408)	(2.1124)
Controls:	X	X	X	X	X

Note: Table reports estimates for β from equations 4 and 9, over different periods and measures of tightness. Dependent variable is the log CPI (excluding energy) in panel A, and the log real wage in panel B. In panel A, we apply CBSA-level CPI to main metro areas in each state, state average of CBSA-level CPI in other metro areas within the state, and census division-level CPI for remaining non-metro areas. Each column reports regression estimates using different explanatory variables (each measured at the state level): tightness (an average of the standardized EE separation rate and negative standardized unemployment rate), each of its standardized components, the EE separation rate, and 1 - unemployment rate. All specifications include stack-by-state and stack-by-time effects, where stack denotes a pair of adjacent quarters. All specifications include controls. Age controls include five age group dummies. Demographic controls include 3 education dummies, 5 race dummies, and a dummy for sex. Sector controls include dummies for Manufacturing, Professional Services, Finance, and Business Services. We additionally control for state Covid-19 death rate per 100,000 people as of June 2023. All data are obtained from CPS monthly files with the exception of CPI excluding energy obtained from BLS, seasonally-adjusted state unemployment rates obtained from BLS LAUS, and Covid-19 death rates obtained from CDC (2020). Standard errors in parentheses are clustered on state. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

A2 Additional Theoretical Derivations of the Dynamic Wage Posting Model

We have so far ignored the changes in the wage offer distribution $F(w)$. Endogenizing the wage offer distribution, $F(w)$, does not change the model's key features. Consider the case where firms vary in productivity, p_j, which is distributed as $H(p)$. Assume further that wages are monotonic in productivity, $w = \kappa(p)$ with $\kappa'(p) > 0$, which will hold in a wide class of models, including wage posting models with heterogeneous employers (Bontemps et al., 1999).[43] The wage offer distribution then simply inherits the productivity distribution of active firms, with $F(w) = H(\kappa^{-1}(w))$.

A key result of the model, which we verify empirically, is that a rise in the contact rate affects EE separations more at low- than at high-wage employers—in other words, the quit elasticity rises differentially at low wage levels. The separation elasticity, ϵ^{EE}, with respect to the wage, depends on the wage level—whose distribution is, of course, an endogenous object. However, the effect of an increase in the contact rate, λ_e, on the EE elasticity with respect to the firm wage rank depends only on the rank, $r = F(w) = H(k^{-1}(w))$, which, in turn, is a primitive of the model. Specifically, the EE elasticity as a function of r can be written as:

$$\tilde{\epsilon}^{EE} = -\frac{r\lambda_e}{\chi + (1-r)\lambda_e}.$$

The key observation is that a higher contact rate, due to either rising vacancies or falling labor supply, makes EE separations more sensitive to firm wage rank (increases the magnitude of the separation elasticity), as seen in the 'twisting' of the EE separations-firm wage locus shown in Figure 3. Empirically, rising tightness should spur a relatively larger increase in separations at low-ranked firms. In turn, this fuels a relative increase in wages, concentrated at low-wage firms, as in the static model.[44] In short, rising tightness reduces frictional wage inequality through two channels: wages rise more at lower-ranked firms, and workers move disproportionately from lower- to higher-ranked firms.

This model also shows how a tighter labor market yields, in steady state, a larger fraction of the workforce employed at more-productive firms.[45] Define $L(p)$ as the cumulative share of potential workers (normalized at 1) who are employed by employers with productivity of

[43] Under wage posting, employers set wages based on the labor supply elasticity, which is the sum of the quit and the recruit elasticities. In steady state, this can be approximated as twice the absolute value of the quit elasticity (Manning, 2021).

[44] The dynamic model in this section does not explicitly describe the wage setting process, where wages are marked down based on the labor supply elasticity. However, the impact of increasing contact rate on the rise in offered wages comes out of standard wage posting models, as in Bontemps et al. (1999).

[45] Moscarini and Postel-Vinay (2018) develop this point in their discussion of the job ladder model.

p or less. Further denoting $1 - F_t(\kappa(p))$ as $\overline{F}_t(\kappa(p))$, the law of motion for this share can be written as:

$$\begin{aligned} L_{t+1}(p) = & \underbrace{(1-\delta)(1-\chi)L_t(p) + [(1-\delta)\chi(1-u_t) + \lambda_u u_t] F_t(\kappa(p))}_{\text{Inflow}} - \\ & \underbrace{\left[\lambda_e \overline{F}_t(\kappa(p))\right](1-\delta)(1-\chi)L_t(p)}_{\text{Outflow}}. \\ = & (1-\delta)(1-\chi)\left[1 - \lambda_e \overline{F}_t(\kappa(p))\right] L_t(p) + [(1-\delta)\chi(1-u_t) + \lambda_u u_t] F_t(\kappa(p)). \end{aligned}$$

In steady state, we have:

$$L(p) = \frac{F(\kappa(p))[(1-\delta)\chi + \delta]}{1 - (1-\delta)(1-\chi)\left[1 - \lambda_e \overline{F}(\kappa(p))\right]} \times \frac{\lambda_u}{\lambda_u + \delta},$$

Since $\chi * \delta \approx 0$ and $\lambda_e = \phi\lambda_u$:

$$L(p) \approx \frac{F(\kappa(p))}{\left[\left(\frac{1}{\chi+\delta} - 1\right)\phi\lambda_u \overline{F}(\kappa(p)) + 1\right]} \times \frac{\lambda_u}{\lambda_u + \delta},$$

$$\tilde{L}(r) \approx \frac{r}{\left[\left(\frac{1-\gamma}{\gamma}\right)\phi\lambda_u(1-r) + 1\right]} \times \frac{\lambda_u}{\lambda_u + \delta}.$$ [46]

Taking logs,

$$\ln \tilde{L}(r) = \ln(r) - \ln\left[\left(\frac{1-\gamma}{\gamma}\right)\phi\lambda_u(1-r) + 1\right] + \ln(\lambda_u) - \ln(\lambda_u + \delta), \tag{10}$$

and differentiating with respect to $\ln \lambda$, we get the following condition:

$$\frac{d \ln \tilde{L}(r)}{d \ln \lambda_u} = \frac{\left(\frac{1-\gamma}{\gamma}\right)\phi\lambda_u(1-r)}{\left(\frac{1-\gamma}{\gamma}\right)\phi\lambda_u(1-r) + 1} + \frac{\delta}{\lambda_u + \delta}. \tag{11}$$

This expression reveals how the steady state allocation of labor evolves with tightness, as measured by λ_u, as well as $\lambda_e = \phi\lambda_u$. At the top of the distribution, where $r = F(w) = 1$, the derivative in equation 11 is positive: greater tightness unambiguously raises employment at the highest-ranked firm. Tightness may not raise employment at firms with low productivity rank, r, however. Evaluating this expression at $r = 0$ and substituting $\phi\lambda_u$ for λ_e, we see that there will be a relative reduction in employment at the bottom of the distribution when the following condition holds:

[46] $\gamma = \chi + \delta$

$$\frac{\left(\frac{1-\gamma}{\gamma}\right)\phi\lambda_u}{\left(\frac{1-\gamma}{\gamma}\right)\phi\lambda_u+1} > \frac{\delta}{\lambda_u+\delta}.$$

Increased tightness is more likely to reallocate labor upward from lower- to higher-ranked firms when (1) on-the-job search is more efficient (ϕ is large), and (2) endogenous job-to-job changes are a large fraction of all separations ($\phi\lambda_u$ is large relative to δ and χ).

Figure 4 in the body of the paper illustrates this point for an increase in λ_e from 0.02 to 0.04, with $\delta = \chi = 0.01, \phi = 0.5$. Using these parameter values, the overall employment rate rises with market tightness, driven by upward reallocation to higher-ranked firms. As shown in the figure, cumulative employment *below* the 90^{th} percentile of firm productivity is lower in a tighter market while cumulative employment *above* the 90^{th} percentile of firm productivity is higher. Tightness also boosts the overall employment rate (by over 10 percentage points, from 0.65 to 0.76), meaning that it raises employment at high-ranked firms, in absolute terms, while decreasing it at low-ranked firms.