The Distributional Dynamics of Wages Over the Business Cycle

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Job Market Paper

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Abstract

Examining cyclical variations in the wage distribution of the U.S. from 1980-2019, I document two novel facts. In recessions, the wage distribution: (i) becomes more positively skewed, and (ii) shrinks at the bottom and widens at the top. These facts indicate that a higher fraction of overall dispersion concentrates at top segments of the cross-sectional distribution of wages. I build a bargaining model of random search that incorporates two-sided heterogeneity, aggregate uncertainty, on-the-job search, and targeted recruiting by firms to explore the mechanisms underlying these stylized facts. In recessions, matches require higher skills from workers to be worth forming, so firms target their vacancies towards high-skill workers. Job offers then fall upon the high-skilled, improving their bargaining position and preventing wages at the top of the distribution from falling sharply, contrary to what occurs among the less-skilled. Estimating the model by indirect inference on data from the U.S. from 1951-2019, I show that it can reproduce key features of the labor market and generate a varying distribution of wages consistent with the cyclical patterns observed in the data. I further assess a range of policy interventions and find that, while certain policies, such as increased unemployment benefits, can fix productive inefficiencies generated by the private behavior of firms, they are less effective in reducing wage inequality in economic downturns.

JEL Codes: D31, E27, E32, J23, J31, J63, J64

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"*While people are finding jobs, employers are finding people to fill them, and their behaviors, strategies, and purposes play a central but often neglected role in the process of matching people to jobs.*"

Mark Granovetter, *Getting a Job: A Study of Contacts and Careers*

1 Introduction

Wage inequality in the U.S. has risen steadily over the last fifty years (Gottschalk, 1997; Katz and Autor, 1999; Eckstein and Nagypál, 2004; Autor et al., 2008). For many years, economists interpreted this upward trend as reflecting secular growth in the demand for highly educated workers stemming from skilled-biased changes in production technologies (Aghion, 2002; Acemoglu, 2003; Krusell et al., 2000). Later work finds that this pattern is more salient in recessions (Hoover et al., 2009; Heathcote et al., 2010), and the common opinion is that wage inequality increases in recessions are driven by sharp wage falls at the bottom of the distribution (Heathcote et al., 2020; Huckfeldt, 2022). In this paper, I offer a different view by arguing that recession-fueled growth in wage inequality originates at the top of the distribution and is propagated by a counter-cyclical selective recruiting behavior of firms.

Understanding the cyclical fluctuations in the wage distribution is of utmost importance for numerous reasons. First, wages and salaries represent around 65-70 percent of personal income in the U.S., so labor market performance can have serious repercussions on income inequality (CRS, 2020; IRS, 2021).[1] Second, the risk of negative labor income shocks increases in recessions due to a higher probability of unemployment, putting many households in a vulnerable situation (Storesletten et al., 2001, 2004; Krebs, 2007; Guvenen et al., 2014; Heathcote et al., 2020). Third, several labor market and social protection policies (e.g., minimum wages, unemployment benefits, social security contributions, etc.) are channeled through, or financed by, labor income, and identifying their welfare effects over the business cycle is of first-order concern for the public debate.

I motivate my argument by presenting two stylized facts about the wage distribution around recession periods in the U.S. over 1980-2019. Relative to pre-recessions, the wage distribution observed in recessions and sub-sequent recoveries: (i) is more positively skewed and (ii) contracts at the bottom but expands at the top. Together, these facts suggest that the wage distribution displays a higher fraction of overall dispersion concentrated at the top tail in recessions. Even more, these cyclical fluctuations persist up to five years from the starting date of the recession. These findings are, to the best of my knowledge, new to the literature, and provide prima-facie evidence of the importance of dispersion at the top of the wage distribution.

[1] In OECD countries, wages and labor earnings account for roughly 65 percent of total personal income (OECD, 2022).

To understand these stylized facts from a theoretical standpoint, we need a model where productivity shocks propagate into wages differently across distinct segments of the wage distribution. The fact that the wage distribution contracts at the bottom likely results from an interplay between the *cleansing* and *sullying* effects of recessions. While the former pushes wages at the bottom of the wage distribution up by eliminating unproductive matches (Davis and Haltiwanger, 1992; Caballero and Hammour, 1994; Mortensen and Pissarides, 1994), the later halts productive re-allocations at the middle of the wage distribution by lowering the quality of jobs that are created in recessions (Barlevy, 2002; Barnichon and Zylberberg, 2019). More challenging, though, is explaining why the wage distribution expands at the top. Conventional hypotheses that link to skilled-biased technical change lack empirical support — in recessions, investment in productive-enhancing activities decays (Geroski and Walters, 1995; Rafferty, 2003; Wälde and Woitek, 2004; Comin and Gertler, 2006; Barlevy, 2007) and the demand for low-skill workers usually recovers over time (Faberman and Mazumder, 2012; Şahin et al., 2014). Instead, I hypothesize that the higher dispersion at the top of the wage distribution results from better employment prospects that high-skill workers experience relative to low-skill workers in recessions which transmitted to wages via contract renegotiation.

I elaborate on this idea by constructing a bargaining model that builds off the Lise and Robin (2017) stochastic framework of random job search. In this setting, there are ex-ante heterogeneous workers and firms and aggregate productivity shocks determine the state of the economy. Further, workers are allowed to search for new jobs while employed and firms make state-contingent offers and counter-offers to workers. Equilibrium in this setting depends on the joint surplus of a worker-firm match which governs match separations and formations in the economy. I extend this setting in two important dimensions. First, firms engage in targeted recruitment behavior. Second, I am able to recover wages resulting from contract renegotiation in a Bertrand competition setting, which was left implicit in the model of Lise and Robin (2017). Each of these elements is important for explaining the previously described empirical facts.

On the one hand, targeted recruiting by firms implies that firms are able to direct their advertised vacancies to different worker types at different points in the cycle.[2] As firms target worker types, the dependency of the meeting probability on the representativeness of the desired worker type among the pool of job seekers disappears (Duffie et al., 2018; Merkl and van Rens, 2019; Cheremukhin et al., 2020). This gives rise to a varying joint distribution

[2]This, naturally, requires that the labor market is perfectly segmented across the support of worker types (Jacquet and Tan, 2007).

of advertised vacancies across the supports of worker and firm attributes that determines the level of job opportunities available to different worker types over the business cycle. This firm behavior is consistent with recent empirical evidence on cyclical selective recruiting and pre-screening strategies of firms (Choi et al., 2022; Forsythe, 2022).[3]

On the other hand, Bertrand competition implies that wages are established according to a sharing rule that splits the joint surplus of the worker-firm match between the contracting parties.[4] Once agreed upon, the sharing rule is maintained throughout the employment relationship until a new job offer triggers renegotiation.[5] The wage value then consists of a weighted average of market and non-market production flows, where the weight corresponds to the sharing rule, and a discount factor that captures the expected gains from future contract revisions to the worker.

Aggregate productivity shocks propagate to wages through two broad channels: (i) changes in the value of the joint surplus of the worker-firm match, and (ii) changes in employment prospects. A higher match-specific surplus implies a bigger amount that is split among the parties which also increases wages for any given sharing rule. Better employment prospects translate into more and better outside job offers which induce contract renegotiation and increase wages. By targeting specific worker types, firms affect the job offer arrival rate of workers found at different points in the wage distribution, hence the frequency with which contract negotiations occur and the pace at which workers move up the productivity and wage ladder. Both wage propagation of aggregate productivity shock and heterogeneous wage volatility are implications of the model.

After laying out the properties of the model, I study its quantitative implications. I estimate the structural parameters by indirect inference, matching a set of model-simulated moments to their empirical counterparts derived from standard U.S. data over 1951q1-2019q4. The model does a good job in reproducing the dynamics of key measures of employment activity (Shimer, 2005; Costain and Reiter, 2008). In addition, the model replicates salient characteristics of compensation such as the relatively mild cyclicality of real wages (Bils,

[3]Though it has been well documented that firms behave differently when searching for adequate workers, less work has been done in understanding how different firms approach and determine their strategies in recruiting and hiring processes (Oyer and Schaefer, 2011). Some studies highlight the importance of firms' hiring standards in the presence of firing costs (Sedláček, 2014), imperfect information (Baydur, 2017; Wolthoff, 2018; Acharya and Wee, 2020), firm restructuring (Berger, 2018; Huckfeldt, 2022), and other settings.

[4]Wage determination *á la* Bertrand also features in wage bargaining models such as Postel-Vinay and Robin (2002), Dey and Flinn (2005), Cahuc et al. (2006), Postel-Vinay and Turon (2010), Robin (2011), and Lise et al. (2016).

[5]This is similar to the wage determination mechanism of Bagger and Lentz (2019) with the difference that the wage distribution in my model also varies with aggregate productivity shocks.

1985; Beaudry and DiNardo, 1991; Christiano and Eichenbaum, 1992; Abraham and Haltiwanger, 1995). Together, these results support the validity of the model's ability to replicate important features of the U.S. labor market.

The set of feasible matches across the supports of worker and firm attributes changes across the business cycle, widening in expansions and narrowing in contractions. This fluctuation, however, is uneven across the support of firm attributes as the range of acceptable worker skills for firms is more volatile than the range of acceptable technologies for workers. Regarding sorting in the labor market, the model implies a correlation between worker and firm types of about 0.30, consistent with the findings of applied studies reporting rank correlations between worker and firm effects in the range of 0.10 and 0.40 in the U.S. economy (Sorkin, 2018; Song et al., 2019; Bonhomme et al., 2022; Crane et al., 2022; Lamadon et al., 2022). Sorting in the U.S. labor market is positive yet imperfect.

Aggregate productivity shocks change the value of the joint surplus of worker-firm matches, rendering some of them to negative and therefore causing them to (efficiently) dissolve. Job separations concentrate principally among low-skill workers; yet, certain high-skill workers employed by low-technology firms also lose their jobs. This process gives rise to a compositional change of matches, and is reminiscent to the *cleansing* effect of recessions whereby less productive allocation of resources are scraped away from the economy in contractions (Davis and Haltiwanger, 1992; Caballero and Hammour, 1994; Mortensen and Pissarides, 1994).

As the match-feasibility set shifts away from the less-skilled, firms target high-skill workers when advertising vacancies. The average skill level demanded by firms in contraction periods increases by 6 percent. This result is consistent with the fact that firms recruit and hire more skilled workers during tough economic times (Hershbein and Kahn, 2018; Burke et al., 2020; Modestino et al., 2020; Forsythe, 2022). The model suggests that this "upskilling" process stems from the combination of a high production complementarity between worker and firms attributes and an increased bargaining power of firms, both of which increase firms' gains from hiring high-skill workers.[6] But despite the hike in skill requirements by firms, jobs created in recessions are precarious, of short duration and low pay. This is because it is profitable for low-technology firms to advertise vacancies in recessions. This result resonates with the *sullying* effect of recessions whereby the quality of new jobs declines markedly in

[6]In practice, firms may become more stringent in their recruiting and hiring processes in economic downturns as a way of increasing productivity, restructuring their workforce, hoarding skilled labor, or skimming job applicants.

contractions (Barlevy, 2002; Barnichon and Zylberberg, 2019).[7]

With regards to the wage distribution, the model renders a cyclical variation in dispersion at different points of the wage distribution that conforms with the documented facts. The skewness of the wage distribution increases after the realization of negative productivity shocks in the economy, induced by a contraction of the 50th-to-10th percentile gap and an expansion of the 90th-to-50th percentile gap. This is because, despite the fact that both the upper and lower ends of the wage distribution falls in recessions, the median wage falls faster than either tail.

In explaining the cyclical fluctuations of wage dispersion, contract renegotiation under pressure from outside job opportunities available to workers plays a central role. In fact, roughly 60 percent of dispersion in the wage distribution observed after the realization of negative productivity shocks can be explained by contract renegotiation alone. During economic contractions, low-skill workers experience slacker employment conditions relative to their high-skill counterparts, as the unemployment rate grows while the vacancy rate collapses in their respective sub-markets. This increases the heterogeneity in job opportunities between low- and high-skill workers, favoring the latter group in terms of contract renegotiation. In turn, once the value of joint surplus between worker-firm matches declines, wages at the bottom of the distribution fall swiftly while those at the top do it less rapidly as high-skill workers face better bargaining positions.

Relatedly, most of the cyclical variation in the share of the match surplus that is kept by the worker is concentrated among medium-skill workers. While the workers' share of the match surplus is, respectively, 20 and 15 percent lower in contractions relative to expansions among workers in the first and third terciles, this figure amounts to 30 percent for workers in the second tercile of the worker skill distribution. This result, in turn, can also explain the fact that the median wage is more volatile than wages at the bottom (i.e., 10th percentile) and top (i.e., 90th percentile) ends of the distribution.[8]

Having presented the mechanics of the model, I next analyze the inefficiencies generated by the private behavior of firms. To that end, I compare the outcomes of the decentralized economy where firms can target different worker skills over the cycle with those of a centralized economy where a social planner makes all relevant decisions with the objective of maximizing aggregate production net of vacancy advertising costs, taking into account the

[7]Recent work documents that the rate at which workers move up the productivity ladder is, in turn, pro-cyclical (Bertheau et al., 2020; Haltiwanger et al., 2021; Baley et al., 2022).

[8]In a 2018 article of The Brookings Institution, the economist Brad Hershbein argues that middle-class workers were the most affected during the Great Recession and real wages at the middle grew slower than those at the tails of the distribution during the recovery period.

matching frictions that are inherent in the labor market. During economic contractions, net production under the centralized economy is 10 percent higher than that attained under the decentralized economy, with most of this gap being explained by excessive costs of vacancy advertisement and (ex-post) sub-optimal job creation. The centralized economy also renders a higher level of workers' welfare and a less unequal wage distribution compared to the decentralized economy.

In the last part of the paper I assess the extent to which labor market regulation can reduce these inefficiencies by examining the effects of different policy interventions. Specifically, I examine the welfare effects of two policy simulations mirroring vacancy advertising subsidies to firms and extended unemployment benefits. Among these policies, raising the flow value of home production leads to an increase in net aggregate production and workers' welfare, consistent with previous empirical findings (Kroft and Notowidigdo 2016; Landais et al., 2018b). On the flip side, this policy increases short-run unemployment and has no significant impact in reducing wage inequality.

Related Literature. My work contributes to several strands of the literature on the cyclical dynamics of job search and wage dispersion.

First, my paper relates to the literature on cyclical selective hiring of firms. In this line of work, recent empirical studies that analyze the text content of online job postings around the 2007-09 recession in the U.S. report an increase in employer skill requirements in the form of higher education or working experience (Hershbein and Kahn, 2018; Burke et al., 2020; Modestino et al., 2020; Forsythe, 2022). Based on these findings, they posit that firms raise their hiring standards in recessions.[9] I add to this literature by providing, to the best of my knowledge, the first theoretical approach to the cyclicality of hiring standards of firms, and offering a rational explanation to why is it optimal for firms to become more stringent when recruiting workers in periods of low aggregate productivity.[10]

A second strand of the literature to which my paper contributes studies wage dispersion over the business cycle. Grounding on theories of human capital depreciation (Barlevy and

[9]This idea can be traced back at least to 1950 when Reder (1955) noticed that the "skill margin" — the ratio of the average hourly earnings between high- and low-educated workers — declines in periods of labor shortage, and posited that employers tend to raise the hiring standards when job applicants become plentiful.

[10]Targeted recruiting by firms can also rationalize the empirical observations of an increased mismatch between firms' skill requirements and job seekers' skill attributes (Daly et al., 2012; Şahin et al., 2014) and a decline in firms' recruiting intensity (Davis et al., 2012, 2013; Gavazza et al., 2018; Mongey and Violante, 2020) in contractions. This becomes possible due to a shift in the distribution of skill requirements by firms away from that of skill attributes of job seekers and a decline in the number of firms advertising vacancies in the labor market. This mechanism can also explain the observed decline in matching efficiency in contractions (Barnichon and Figura, 2015; Sedláček, 2016; Hall and Schulhofer-Wohl, 2018).

Tsiddon, 2006; Davis and von Wachter, 2011; Burdett et al., 2020), a number of studies argue that most of the cyclical variation in wage dispersion concentrates at the bottom of the distribution and can be explained by a higher risk of unemployment and a decline in hours worked that low-skill workers experience in recessions (Heathcote et al., 2010; Alessandrini et al., 2016; Morin, 2019; Heathcote et al., 2020). I complement this literature by offering a comprehensive view that further examines dispersion at top segments of the wage distribution. In doing so, I find that the cross-sectional dispersion is lower at the bottom but higher at the top of the wage distribution, and this is mainly caused by tighter labor market conditions that high-skill workers experience in recessions.

Third, my paper relates to the literature on wage propagation of aggregate productivity shocks. Broadly speaking, there are two approaches in this literature. The first embeds (random or competitive) job search in a setting with wage posting by firms (Moscarini and Postel-Vinay, 2013, 2016; Kaas and Kircher, 2015). The second, which is closer to the modelling I adopt, incorporates job search in a wage bargaining framework (Robin, 2011). Common among these studies is to focus on the job search behavior of workers.[11] I take a different angle and advance on this literature by studying the recruiting behavior of firms. By allowing firms to target different worker skills over the business cycle, my paper bridges the gap between purely random and purely competitive dynamic search in the labor market (Duffie et al., 2018; Cheremukhin et al., 2020) and highlights the importance of selective recruitment in spreading aggregate productivity shocks across the wage distribution.

Fourth, my paper also contributes to the literature on the business cycle variation of individual earnings risk. Ample work on this topic finds that earnings risk is strongly countercyclical as earnings increases become less likely while earnings declines become more likely in recessions (Storesletten et al., 2001, 2004; Krebs, 2007; Guvenen et al., 2014; Busch et al., 2022). Less studied, though, is the heterogeneity in the cyclical variation of individual earnings risk between low- and high-earners. By examining how aggregate productivity shocks propagate differentially across worker types, I am capable of analyzing the effects these shocks have on wages along different segments of the distribution and am able to complement this literature by explaining why certain individuals may be more or less exposed to negative earnings risk over the business cycle. My findings indicate that high-wage workers present

[11] Studies featuring competitive search, such as Kaas and Kircher (2015), assume that workers target their search from a menu of wages posted by firms (Menzio and Shi, 2011; Schaal, 2017; Baley et al., *forthcoming*). In this type of models, firms determine and commit to pay wages based on a trade-off between increased profits from posting a lower wage and increased vacancy filling rates from posting a higher wage. Though firms choose the wages they pay and thereby define the profile of workers that will direct their search towards their vacant positions, they do not explicitly target the skills of job applicants.

less volatility of earnings as outside job offers act as an insurance mechanism that shield these workers from the risk of experiencing large earning drops in recessions.

Lastly, by examining the cyclical evolution of wage bargaining, my paper touches on the literature on monopsony power in the labor market. A widespread belief is that employers take a leading position when negotiating wages yet the sources of this power are unclear (Ashenfelter et al., 2010; Manning, 2021a; Ashenfelter et al., 2022; Berger et al., 2022a; Card, 2022). My paper has important implications in terms of the bargaining power of employers over the business cycle. Particularly, I find a large imbalance in terms of bargaining power as employers are estimated to retain around 90-95 percent of the worker-firm surplus. Even more, the bargaining power of employers increases in recessions when markets become slacker. This high bargaining power of employers stems, to a large extent, from the relatively low fluidity of workers across the productivity ladder in the labor market.[12]

Layout. The rest of the paper proceeds as follows. In section 2, I present stylized facts on cyclical changes in the wage distribution and analyze its implications. In section 3, I describe the model. In section 4, I explain the methodology utilized for estimating the structural parameters of the model and show the results. In sections 5 and 6, I discuss the model's implications in terms of labor market equilibrium and distributional dynamics of wages over the business cycle. In sections 7 and 8, I analyze the welfare implications of firms' targeted recruiting and assess the extent to which labor market regulation can increase welfare. I present the conclusions in section 9.

2 Distributional Dynamics of Wages

2.1 Data and Measures

I briefly describe the data sources and measures utilized in the analysis of the distributional dynamics of wages and provide a detailed description of the data construction procedure in Appendix A.

Wages. I utilize monthly data from the Current Population Survey Outgoing Rotation Group (CPS-ORG) over 1980-2019.[13] I restrict my analysis to prime-age, full-time employees

[12]Past work highlights the role of on-the-job search in propagating aggregate productivity shocks thereby affecting the wage distribution (Moscarini and Postel-Vinay, 2018; Eckhout and Lindenlaub, 2019).

[13]The CPS features a rotational monthly panel structure where individuals are tracked for 8 months over a total period of 16 months, in two separate blocks of 4 consecutive months. Initially, individuals are surveyed for 4 consecutive months, then left alone for 8 months, and finally surveyed again for another 4 consecutive months. Each calendar month, employed individuals at months 4 and 8 into the survey (i.e., the

working in private, non-farming industries.[14]

Along the analysis, I inspect cyclical changes in the distribution of real hourly wages. For workers earning by the hour, I use their reported hourly rate, and for salaried workers I define the hourly rate to be their usual weekly earnings divided by the usual hours worked per week. For consistency, I only retain workers earning at or above 90 percent of the federal minimum wage rate of the running year. To compute real wages, I deflate nominal hourly rates using the Personal Consumption Expenditure (PCE) deflator.[15]

Business Cycle Dating. I collect monthly information on business cycle dates — peak and trough months — from the National Bureau of Economic Research (NBER).[16] The NBER defines a recession period as the continuum of months spanning the time interval between peak and trough dates of economic activity. All remaining months are regarded as an expansion period.

Measures. Along the descriptive analysis, I aim at inspecting cyclical changes in wage dispersion at different points of the distribution. This naturally calls for the analysis of measures of skewness of the wage distribution.

I opt for quantile-based measures of skewness as they have important advantages over those derived from standardized moments. Specifically, and as pointed out by Busch et al. (2022), quantile-based measures of skewness: (i) are more robust to extreme values; (ii) allow for analyzing dispersion at different parts of the distribution; (iii) allow for decomposing the contribution of dispersion at different parts to the overall dispersion of the distribution; and (iv) are easy to interpret.[17]

My primary measure is the Kelley coefficient of skewness, $\mathcal{S}_{\mathrm{K}}$, which quantifies the contribution of dispersion at the top and at the bottom to the overall dispersion observed in the wage distribution. This measure ranges between -1 (i.e., negative skewness) and 1 (i.e.,

outgoing rotation group) report their labor earnings.

[14]More precisely, I focus on employed individuals ages 25-54, who are salaried or hourly-wage workers, and who work 35 or more hours per week. Although the information comprised in the CPS refers to earnings, my focus on full-time workers makes variations in hours worked per week very limited, so information on earnings can be interpreted as a plausibly good measure of wages.

[15]I have also checked that the figures obtained in the analysis are robust to the use of the Consumer Price Index (CPI) deflator.

[16]The NBER's Business Cycle Dating Committee keeps record of the chronology of U.S. business cycles. In essence, the committee identifies peaks and trough dates based on a series of measures of economic activity.

[17]Analyzing different measures of skewness, Kim and White (2004) conclude that quantile-based measures are more robust than conventional measures of skewness based on standardized moments as the former are less sensitive to extreme values in the data.

positive skewness), and obtains from the formula:

$$\mathcal{S}_{\mathrm{K}} = \frac{(\mathrm{P90} - \mathrm{P50}) \; - \; (\mathrm{P50} - \mathrm{P10})}{(\mathrm{P90} - \mathrm{P10})} \, ,$$

where P10, P50, and P90 are, respectively, the 10th, 50th, and 90th percentiles of the wage distribution. The fraction of the overall dispersion that is in the left and right tail of the distribution is measured, respectively, by $(\mathrm{P50} - \mathrm{P10})$ and $(\mathrm{P90} - \mathrm{P50})$. A positive (negative) coefficient implies that dispersion at the top (bottom) is greater than that at the bottom (top) so the distribution has a long right (left) tail thus a positive (negative) skewness.

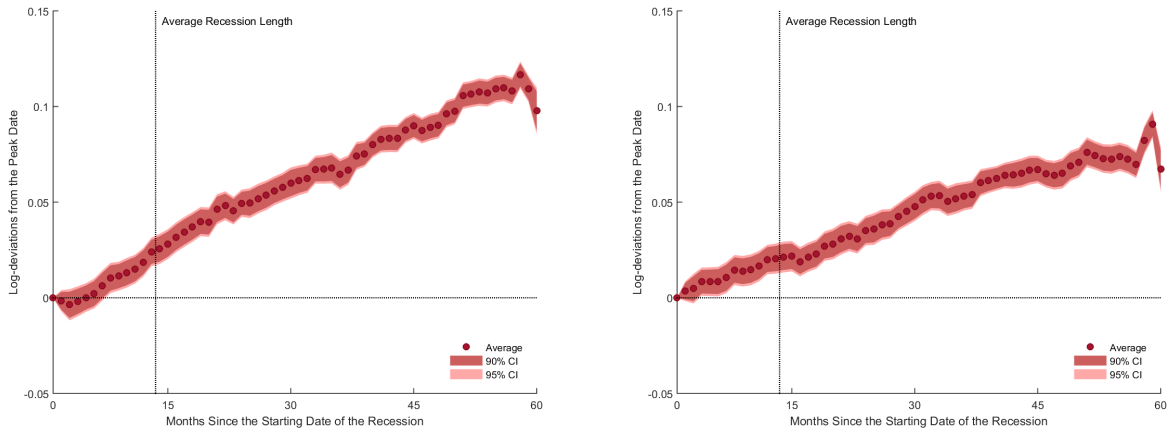
2.2 Cyclical Skewness of the Wage Distribution

In Figure 1, I plot the evolution of the average Kelley coefficient of skewness — in log-deviations from the peak date — of the wage distribution at months 1 through 60 since the starting date of recessions occurring in the U.S. over 1980-2019.[18] Respectively, Panel A and Panel B show the log-deviations in Kelley skewness using PCE and CPI deflators for computing real wages. The figure shows two interesting patterns.

[18]Chronologically, this includes the 1981m7-1982m11 recession (17 months), 1990m7-1991m3 recession (9 months), the 2001m3-2001m11 recession (9 months), and the 2007m12-2009m6 recession (19 months). I excluded the 1980m1-1980m7 recession from the analysis given its shorter duration. The average length of all four recessions included in the analysis is 13.5 months.

Figure 1: Cyclical Variation in the Skewness of the Wage Distribution

(A) Kelley Skewness (PCE-based) (B) Kelley Skewness (CPI-based)



Note: The figure shows the average Kelley skewness, in log-deviations from the peak date, of the distribution of real wages at months 1 through 60 since the starting date of recessions occurring in the U.S. over 1980-2019. Real wages are computed by deflating nominal hourly rates by the PCE (Panel A) or CPI (Panel B). Linear trends, estimated with data from months -24 through 84 from/since the starting date of each recession, have been removed from all series. Dark and light shaded areas correspond to the 90% and 95% confidence intervals, respectively, constructed from 1,000 bootstrap samples for each month. Vertical lines, at month 13.5, mark the average length of recessions according to the NBER's business cycle chronology.
Source: Author's calculations based on data from the CPS-ORG and NBER.

The first pattern relates to the fact that the wage distribution becomes more positively skewed during recessions and sub-sequent recoveries relative to the peak date. On average, the Kelley skewness increases by between 1-2 percent in the midst of the recession and between 7-8 percent during the recovery period relative to the peak date.[19] These figures imply that the spread at the top becomes larger than that at the bottom of the wage distribution during economic downturns. The second pattern relates to the slow restoration in the skewness of the wage distribution over time. In particular, both graphs show that, on average, the slope of the curve becomes negative only after almost five years of the starting date of recessions. This observation implies that recessions could, in turn, be periods prompting persistent increases in wage inequality (Heathcote et al., 2010; Heathcote et al., 2020).

In Appendix B, I further check that these cyclical patterns hold across all the four implied recessions. In addition, I check the robustness of these patterns to the use of alternate price indexes for deflating nominal wages.

[19]For exposition, the recession period spans the months 1 through 20 and the recovery period spans the months 21 through 60 after the peak date.

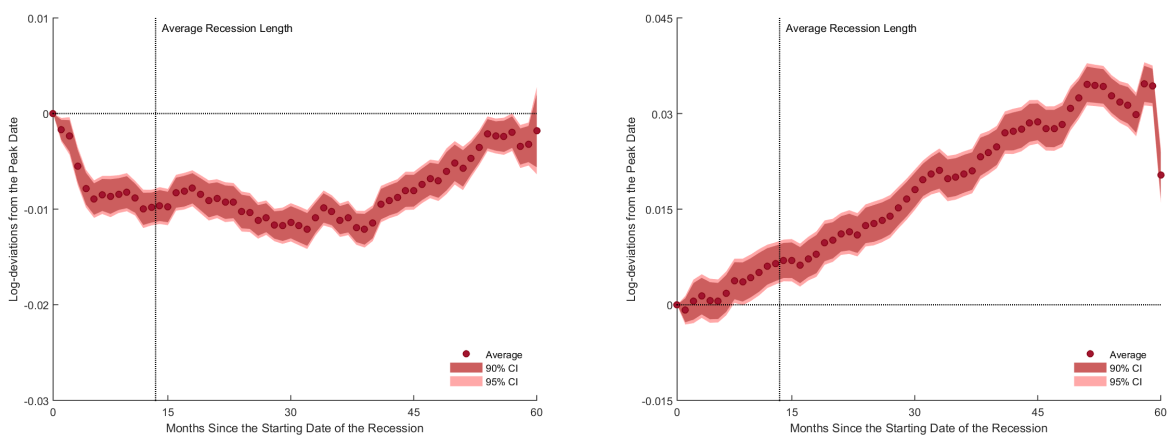
2.3 Heterogeneity in Wage Dispersion

Better understanding the empirical facts documented in the previous sub-section is the main objective of my work. In thus sub-section, I further examine the cyclical fluctuations in dispersion occurring at different segments of the wage distribution.

A Story of Two Tails. To get a clearer picture of why the wage distribution becomes more positively skewed during economic downturns, in Figure 2 I plot the average log-deviations in the P5010 (Panel A) and P9050 (Panel B) ratios from the peak date preceding recessions. Respectively, these graphs illustrate the dynamics of the 50th/10th and 90th/50th percentiles ratios and are informative about the cyclical fluctuations in dispersion at the bottom and top halves of the wage distribution. These percentile ratios constitute the principal components of the Kelley coefficient of skewness.

Figure 2: Cyclical Variation at Different Segments of the Wage Distribution

(A) P5010 Ratio (B) P9050 Ratio



Note: The figure shows the average P5010 ratio (Panel A) and average P9050 ratio (Panel B), in log-deviations from the peak date, of the distribution of real wages at months 1 through 60 since the starting date of recessions occurring in the U.S. over 1980-2019. Real wages are computed by deflating nominal hourly rates by the PCE. Linear trends, estimated with data from months -24 through 84 from/since the starting date of each recession, have been removed from all series. Dark and light shaded areas correspond to the 90% and 95% confidence intervals, respectively, constructed from 1,000 bootstrap samples for each month. Vertical lines, at month 13.5, mark the average length of recessions according to the NBER's business cycle chronology.
Source: Author's calculations based on data from the CPS-ORG and NBER.

The figure shows opposite fluctuations in dispersion at the bottom and top of the wage distribution. While the P5010 ratio decreases, the P9050 ratio increases over the course of recession and recovery periods. In turn, the mean log-deviation of the P5010 ratio is -0.008 and is not statistically different from zero (p-value = 0.010). By contrast, the mean

log-deviation of the P9050 ratio is 0.020 and is statistically different from zero (p-value = 0.001). Thus, while the gap between wages at the bottom half contracts, the gap between wages at the top half of the distribution expands during recession and recovery periods. Put simply, wage dispersion decreases at the bottom and increases at the top of the wage distribution during economic downturns.

Quantifying the Contribution of Wage Dispersion at Different Segments. In Table 1, I show the fraction of the P90-P10 gap explained by the P50-P10 and P90-P50 gaps at different points over the cycle. While the P50-P10 gap explains the contribution of dispersion at the bottom half, the P90-P50 gap explains the contribution of dispersion at the top half to overall dispersion in the wage distribution. This decomposition allows for quantifying which segment of the distribution contributes more to the cross-sectional dispersion of wages in the midst and aftermath of recessions.

Table 1: Relative Dispersion in the Wage Distribution

	Peak Date	Recession (months 1-20)	Recovery (months 21-60)
$(P50 - P10)/(P90 - P10)$	0.314	0.311	0.303
$(P90 - P50)/(P90 - P10)$	0.686	0.689	0.697

Note: The table shows the faction of the P90-P10 gap explained by the P50-P10 gap (i.e., bottom half) and the P90-P50 gap (i.e., top half) of the wage distribution during the peak date, recession, and recovery periods. The peak date is defined as the month preceding the starting date of the recession. Respectively, recession and recovery periods are defined the time span between months 1 through 20 and months 21 through 60 after the peak date.
Source: Author's calculations based on data from the CPS-ORG and NBER.

The table shows an increasing importance of dispersion at the top half of the distribution. On average, the share of the overall wage dispersion that is explained by the top half of the distribution goes from 68.6 percent to 68.9 percent (an increase of 0.5 percent) during recessions and to 69.7 percent (an increase of 1.5 percent) during recoveries, relative to the peak date. In relative terms, the ratio of the P9050 to P5010 goes from 1.09 during the peak date to roughly 1.10-1.15 during recession and recovery periods. These figures show that dispersion at the top becomes higher than that at the bottom half and thereby contributes more to the overall dispersion of the wage distribution during economic downturns.

2.4 Potential Explanations

I argue that the contraction at the bottom half of the wage distribution can be explained by a interplay between *cleansing* and *sullying* effects that arise during economic downturns. Interpreting the expansion at the top half of the wage distribution, though, is more complex. I claim that this pattern is consistent with a cyclical selective hiring behavior of firms.

Lower Dispersion at the Bottom of the Distribution. The *cleansing* effect relates to the fact that recessions are times when less productive resources are removed leading to a more productive use of available resources in the economy (Davis and Haltiwanger, 1992; Caballero and Hammour, 1994; Mortensen and Pissarides, 1994). By contrast, the *sullying* effect refers to the fact that recessions are times when a slower pace of productivity-enhancing re-allocations are observed in the economy (Barlevy, 2002; Barnichon and Zylberberg, 2019). Haltiwanger et al. (2021) document that these effects occur sequentially, with the *cleansing* effect appearing earlier in downturns.

Both effects can impact wages differently. By wiping out bad, usually low-paying, jobs, the *cleansing* effect moves wages at the bottom of the distribution closer to the median wage.[20] By slowing down the pace at which workers move up the wage ladder, the *sullying* effect halts wage growth at the middle of the distribution.[21] Combined, they may explain the contraction at the bottom half of the wage distribution.

Higher Dispersion at the Top of the Distribution. Three likely causes may account for the expansion at the top half of the wage distribution during recessions: (i) skill-biased technical change; (ii) wage bargaining; and (iii) cyclical selective hiring of firms.

Violante (2008) defines skill-biased technical change as "(...) a shift in the production technology that favors skilled (e.g., more educated, more able, more experienced) labor over unskilled labor by increasing its relative productivity and, therefore, its relative demand."[22]

[20] Ample work documents that job displacements befell predominantly among low-skill, typically low-wage workers during the Great Recession (Aaronson et al., 2010; Autor, 2010; Couch and Placzek, 2010; Elsby et al., 2010; Farber, 2011; Hoynes et al., 2012). Evidence from matched employer-employee data from Denmark (Christensen et al., 2005) and France (Chéron and Rouland, 2011) indicates that job destruction is more salient among low-earners after the economy experiences negative productivity shocks. Furthermore, a recent report from the Economic Policy Institute finds that wages during the COVID-19 pandemic grew largely because more than 80 percent of net job lost in 2020 were jobs held by wage earners below the 25 percent of the wage distribution.

[21] Evidence indicates that job mobility plays an important role in earnings growth (Topel and Ward, 1992; Keith and McWilliams, 1999; Bjelland et al., 2011; Fallick et al., 2012) and that high-paying firms are also more productive firms (Abowd et al., 1999; Dunne et al., 2004; Abowd et al., 2005). In terms of wages, Haltiwanger et al. (2018) finds strong evidence that the pace at which workers scale the wage ladder — that is, higher paying firms — declines during recessions.

[22] Implicit in this idea is the fact that the relative marginal product of skilled over unskilled labor increases

Jaimovich and Siu (2020) argue that this occurs predominantly during recessions. From this perspective, skill-biased technical change would generate a persisting expansion at the top of the wage distribution so long as the demand for high-skill workers remains high. Yet, it has been documented that firm investment in productivity-enhancing activities declines in recessions (Geroski and Walters, 1995; Rafferty, 2003; Wälde and Woitek, 2004; Comin and Gertler, 2006; Barlevy, 2007) and skills mismatch — the misallocation between job seekers' and firms' required attributes — decreases in recoveries (Faberman and Mazumder, 2012; Şahin et al., 2014). Therefore, neither a shift in the production technology nor an persisting demand for high-skill workers seem to occur in economic downturns.

Wage bargaining models that incorporate productivity shocks and on-the-job search could also explain this cyclical pattern (Robin, 2011; Lise et al., 2016).[23] In this setting, outside employment opportunities constitute an important element of wage determination as workers can use them as a threatening point in negotiation.[24] Thus, wages depend positively on the job offer arrival rate. To match the empirical facts, high-skill workers, who are usually scarce in the economy, would need to exhibit a higher job offer arrival rate compared to their low-skill counterparts. But in a single, integrated labor market, the job offer arrival rate is proportional to a worker's representation in the pool of job seekers (Merkl and van Rens, 2019) and it would take a high number of vacancies to explain the expansion at the top of the wage distribution which hardly happens in economic downturns.

A more plausible explanation is that firms may select which workers to hire in recessions, an idea referred to as "cyclical selective hiring" (Forsythe, 2022). Recent studies that scrutinize the text content of online job postings support this idea by reporting an increase in the skill requirements of recruiting firms during the Great Recession (Hershbein and Kahn, 2018; Burke et al., 2020; Modestino et al., 2020). If firms target the set of workers they want to meet through pre-screening, then the job offer arrival rate no longer depends on the representativeness of worker types in the economy. Therefore, a combination between cyclical selective hiring and wage bargaining could potentially explain the higher dispersion observed at the top of the wage distribution during economic downturns. This notion re-

as the production technology varies, pushing up the demand for high-skill workers and their wages (Acemoglu, 2002). This hypothesis was first developed by Griliches (1969) and Welch (1970), and was revised later on by Machin (2001) and Acemoglu (2002). Later work have introduced the term "routine-based technical change" to refer to a technological change in production that is biased towards replacing labor in routine tasks (Autor et al., 2003; Goos and Manning, 2007; Acemoglu and Autor, 2011; Autor and Dorn, 2013; Goos et al., 2014).

[23] See Moscarini and Postel-Vinay (2013) for a model with wage posting by firms.

[24] Naturally, wages depend also on productivity and the bargaining power of workers. Yet, as pointed out by Cahuc et al. (2006), between-firm competition for workers can explain at least 50 percent of workers' rents. This result highlights the importance of outside job offers available to workers in wage determination.

quires a certain degree of labor market segmentation such that firms can effectively narrow their search for workers, especially when the set of targeted worker types is relatively small.

2.5 Roadmap

Having presented the empirical facts and discussed the plausible explanations, I now turn to summarize the findings and formulate the hypothesis that will guide the study.

Summary of Findings. Analyzing changes in the skewness of the wage distribution during recessions in the U.S. over 1980-2019, I document three empirical facts. First, the wage distribution becomes more positively skewed. Second, this higher skewness is explained by a contraction at the bottom and an expansion at the top of the distribution. Third, dispersion at the top is relatively more important in explaining the cyclical variations in the skewness of the distribution. These facts, to the best f my knowledge, are new to the literature.

I claim that the contraction at the bottom could result from a combination of the *cleansing* and *sullying* effects of recessions but accounting for the expansion at the top of the wage distribution seems more complex. Models of skilled-biased technical change or wage bargaining can hardly match the empirical facts. A promising explanation may come from the notion of changing hiring standards of firms over the business cycle. In what follows, I aim at formalizing this notion.

Working Hypothesis. The stepping stone of my work is the idea of cyclical selective hiring of firms. Based on the existing empirical evidence (Hershbein and Kahn, 2018; Burke et al., 2020; Modestino et al., 2020), I formulate that firms target high-skill workers when advertising vacancies during recessions. This targeting mechanism introduces heterogeneity in the job offer arrival rate (Merkl and van Rens, 2019), making job offers befall more saliently among high-skill workers during recessions. When the wage bargaining scheme depends on outside offers available to workers, as in Cahuc et al. (2006), a higher job offer arrival rate implies better negotiated wages. In sum, I hypothesize that the expansion at the top of the wage distribution observed during recessions owes, to a large extent, to a better bargaining position of high-skill workers due to a more stringent hiring standard of firms.

3 Theoretical Framework

In this section, I outline the theoretical framework linking job opportunities to wages over the business cycle. The model delivers an equilibrium distribution of wages that varies according

to the aggregate state of the economy.

3.1 Economic Environment

The economy is set in an infinite-period horizon where time is discrete and indexed by the subscript t. The length of a period is one month. Productivity shocks are revealed at the end of each period and determines the aggregate state of the economy of the next period.

State of the Economy. Each period is characterized by a random variable z_t that defines the aggregate state of the economy. Variations in z_t reflect aggregate productivity shocks and are governed by a Markov transition probability $\pi(z_{t-1}, z_t)$. Given the intrinsic link between the time period and the aggregate state of the economy, for clarity of exposition, I henceforth utilize the subscript t to indicate that a variable is conditional on z_t.

Agents. The economy is populated by a continuum of two types of measure-one, infinitely-lived agents: workers and firms. Workers are ex-ante heterogeneous and characterized by their skills x. Firms are ex-ante heterogeneous and characterized by their technologies y. The distributions of skills across workers and technologies across firms are exogenous and constant over time, with PDFs denoted by $l(x)$ and $f(y)$, respectively. Both agents are risk neutral and discount per-period utility at a common subjective factor $\beta \in (0, 1)$.

Actions. Workers can be either unemployed or employed by a firm. Firms can be vacant or employing a worker. Unemployed workers dedicate to home production and search for a job with effort equal to 1. Employed workers dedicate to joint production, search for a job with a fixed effort equal to $e \in (0, 1]$, and re-negotiate their employment contracts whenever they receive outside job offers.[25] Vacant firms advertise vacancies and make job offers to workers. Occupied firms dedicate to joint production, decide whether to layoff workers or continue with their employment relationships, and re-negotiate employment contracts whenever their employees receive outside job offers.

Labor Market Interactions. Labor markets are segmented according to workers' skills. In each sub-market, there is a measure $\mathcal{L}_t(x)$ of job seekers composed of x-type unemployed and employed workers and a measure $v_t(x, y)$ of vacancies advertised by y-type firms that determine the aggregate measure of advertised vacancies $\mathcal{V}_t(x)$. Job meetings occur at random in each sub-market and its measure is determined by a meeting technology $m\big(\mathcal{L}_t(x), \mathcal{V}_t(x)\big)$. Only one-firm-one-worker matches are allowed in the economy.

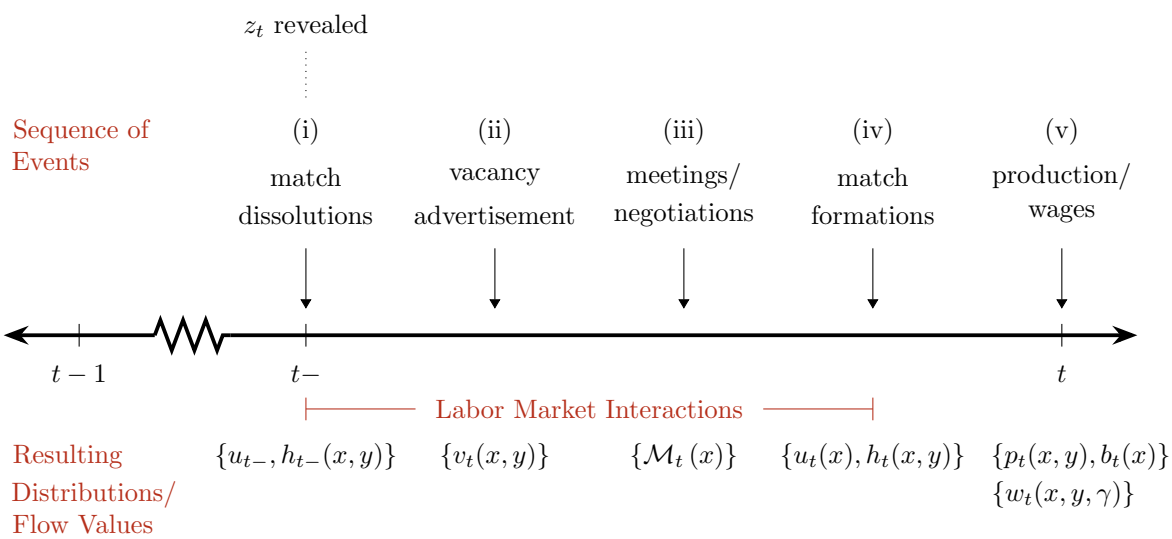
Payoffs. The utility generated from flow values is linear in the amounts received or paid by

[25] I assume that job search is costless for both unemployed and employed workers.

agents. An x-type unemployed worker receives a flow value from home production (which can be also comprised of unemployment benefits) equal to $b_t(x)$. An x-type employed worker matched with a y-type firm receives a wage flow value equal to $w_t(x, y, \gamma)$, where γ is the share of the match surplus that is kept by the worker as specified in her contract. When advertising vacancies, a recruiting firm can buy v job advertisements targeted at x-type workers from employment agencies at a cost $c(v, x)$, with $c(0, x) = 0$. A y-type firm employing an x-type worker under a contract of size γ produces value added $p_t(x, y)$, and receives a flow value equal to $p_t(x, y) - w_t(x, y, \gamma)$ after paying the worker her corresponding wage.

Timing. Figure 3 depicts the unfolding of the events between periods $t-1$ and t. The aggregate state of the economy of period t, z_t, is revealed at the end of period $t-1$. Once z_t is revealed, the timing of the events goes as follows: (i) dissolutions of matches occur instantaneously; (ii) firms observe the resulting distributions of unemployed and employed workers and advertise vacancies in each sub-market x; (iii) unemployed and employed job seekers meet recruiting firms; (iv) contract negotiations occur, matches are formed, and the new distributions of unemployed and employed workers in each sub-market x are carried onto period t; (v) production takes place and wages are paid.

Figure 3: Timing of Events



Note: The figure shows the unfolding of the events between periods $t-1$ and t in the model, after the realization of the aggregate productivity shock, z_t, at the end of period $t-1$.

3.2 Match Dissolutions, Job Search, and Meetings

In this sub-section, I explain how matches are dissolved, how workers search for jobs, how firms advertise vacancies, and how meetings occur in the labor market. This sequence of events corresponds to stages (i) through (iii) in Figure 3.

Match Dissolutions. Let $B_t(x)$ denote the present value of unemployment to an x-type worker given z_t, and $P_t(x, y)$ denote the present value of joint production between an x-type worker and a y-type firm given z_t. The match surplus, $S_t(x, y)$, obtains by subtracting the present value of unemployment from the present values of joint production given z_t: $S_t(x, y) = P_t(x, y) - B_t(x)$. Two-sided limited commitment implies that any (x, y)-type match prevails so long as $S_t(x, y) \geq 0$.

After the realization of z_t, match dissolutions occur. Matches are dissolved for two reasons: either because of exogenous reasons, at a constant rate δ, or because of endogenous reasons that resemble situations where the match surplus is negative. Let $\mathbb{1}\{S_t(x, y) \geq 0\}$ be the indicator for a non-negative surplus of an (x, y)-type match given z_t. Then, the overall probability with which an (x, y)-type match is dissolved after the realization of z_t equals $\delta_t(x, y) = \big(1 - (1 - \delta)\, \mathbb{1}\{S_t(x, y) \geq 0\}\big)$.

Let $u_{t-1}(x)$ denote the measure of x-type unemployed workers and $h_{t-1}(x, y)$ denote the measure of x-type employed workers matched with a y-type firm observed at the beginning of period $t-1$, respectively. Then, the new measures of x-type unemployed workers and x-type employed workers matched with a y-type firm after the realization of z_t, $u_{t-}(x)$ and $h_{t-}(x, y)$, respectively, become:

$$u_{t-}(x) = u_{t-1}(x) + \int \delta_t(x, y)\, h_{t-1}(x, y)\, \mathrm{d}y \tag{1}$$

and

$$h_{t-}(x, y) = \big(1 - \delta_t(x, y)\big)\, h_{t-1}(x, y)\,, \tag{2}$$

and result from adding to $u_{t-1}(x)$ or subtracting from $h_{t-1}(x, y)$ the measure of (x, y)-type matches whose surpluses turned negative after the realization of z_t.

Job Search. The measure of x-type job seekers after the realization of z_t, $\mathcal{L}_t(x)$, is:

$$\mathcal{L}_t(x) = u_{t-}(x) + \int e\, h_{t-}(x, y)\, \mathrm{d}y\,, \tag{3}$$

and results from adding to the measure of x-type unemployed workers the measure of x-type employed workers matched with a y-type firm who are effectively searching for jobs.

The total measure of vacancies targeted at x-type workers, $\mathcal{V}_t(x)$, is:

$$\mathcal{V}_t(x) = \int v_t(x, y)\, f(y)\, \mathrm{d}y\,, \tag{4}$$

and results from integrating the measure of vacancies advertised by y-type firms that are targeted at x-type workers. The recruitment effort of y-type firms in sub-market x is then given by $\kappa(x, y) = v_t(x, y) f(y)/\mathcal{V}_t(x)$.

Meetings. The measure of meetings in sub-market x, $\mathcal{M}_t(x)$, is determined by a function $m(.) : \mathbb{R}_+^2 \to \mathbb{R}_+$:

$$\mathcal{M}_t(x) = m\big(\mathcal{L}_t(x), \mathcal{V}_t(x)\big)\,,$$

such that $m(.)$ exhibits constant returns to scale. In sub-market x, the probability with which each job seeker meets a recruiting firm per unit of search effort equals $\lambda_t(x) = \mathcal{M}_t(x)/\mathcal{L}_t(x)$. Similarly, the probability with which a recruiting firm meets a job seeker per unit of recruiting effort equals $q_t(x) = \mathcal{M}_t(x)/\mathcal{V}_t(x)$.

3.3 Contract Negotiation, Workers, Firms, and Joint Production

In this sub-section, I explain the contract negotiation setting, corresponding to stage (iv) in Figure 3. This negotiation process allows me to derive the employment contract which defines the worker's and firm's value functions, and the value of joint production between an x-type worker and a y-type firm. Next, I define the (x, y)-type match surplus, a value that is key for the numerical solution of the model.

Contract Negotiation. For a given (x, y)-type match, an employment contract specifies how the match surplus is shared between the worker and the firm. In particular, a share $\gamma \in [0, 1]$ of the match surplus accrues to the worker and the rest is kept by the firm. Employment contracts are updated according to an initial share agreed upon the most recent contract revision and the offers that firms make to the worker, in a Bertrand competition setting. Importantly, this share is maintained over the duration of the employment relationship unless a new job opportunity available to the worker induces contract re-negotiation. Employment contracts are subject to two-sided limited commitment, and are re-negotiated by mutual agreement only. The wage that a worker receives as a result of contract negotiation, though, varies according to the aggregate state of the economy and other factors.

An employment contract is written as a function of the share of the match surplus that

accrues to the worker in her current employment relationship, γ, and a triple $(y, \hat{y}, z_t)$ defined by the technology of her employer, the technology of the firm making the outside job offer, and the aggregate state of the economy, respectively. Whenever a worker and a firm meet, contract negotiation follows a Bertrand competition where the worker receives the smallest offer among the two competing firms. Offers are made in terms of the share of the (x, y)-type match surplus. For convenience, denote $\hat{\gamma}$ as the share of the match surplus that would accrue to the worker in case she receives an outside job offer from a $\hat{y}$-type firm at the end of period $t-1$.

Consider first a meeting between an x-type unemployed worker and a y-type firm. By construction, an unemployed worker receives a share $\gamma = 0$ as there is no match surplus in the unemployment state, so the y-type firm can hire the worker by offering the same share $\hat{\gamma} = 0$. As a result, whenever an unemployed x-type worker meets a firm, she is just offered her present value of unemployment regardless of the technology of the firm she meets.

Consider next the case of an x-type worker matched with a y-type firm who meets a $\hat{y}$-type firm. Two possibilities are involved: either $S_t(x, \hat{y}) > S_t(x, y)$ or $S_t(x, \hat{y}) \leq S_t(x, y)$. The first possibility implies that the $\hat{y}$-type firm can offer the worker at least the entirety of the (x, y)-type match surplus. Thus, the $\hat{y}$-type firm poaches the worker from the y-type firm by offering a share $\hat{\gamma} = 1$ of the (x, y)-type match surplus.[26] The second possibility implies that the $\hat{y}$-type firm cannot poach the worker from the y-type firm. Yet, the $\hat{y}$-type firm may be able to make a sufficiently high offer to the worker such that it induces a contract revision with her current employer. This occurs whenever $\gamma < S_t(x, \hat{y})/S_t(x, y)$. In this case, the y-type firm retains the worker by countering the $\hat{y}$-type firm's offer and giving the worker a share $\hat{\gamma} = S_t(x, \hat{y})/S_t(x, y)$ of the (x, y)-type match surplus. In any other case, the contract is not revised and the worker maintains her share $\hat{\gamma} = \gamma$ of the (x, y)-type match surplus.

To recap, contract negotiation arising after meetings occur in the labor market yields the following results:

$$\hat{\gamma} = \begin{cases} 1 & \text{if } S_t(x, y) < S_t(x, \hat{y}) \\ S_t(x, \hat{y})/S_t(x, y) & \text{if } S_t(x, y) \geq S_t(x, \hat{y}) \text{ and } \gamma < S_t(x, \hat{y})/S_t(x, y) \\ \gamma & \text{if } S_t(x, y) \geq S_t(x, \hat{y}) \text{ and } \gamma \geq S_t(x, \hat{y})/S_t(x, y) \\ 0 & \text{if hired from the unemployment pool} \end{cases},$$

where the first line mirrors the case when the worker makes a job-to-job transition from a

[26] Notice that $\hat{\gamma} = 1$ implies that the worker keeps a share $S_t(x, y)/S_t(x, \hat{y})$ of the $(x, \hat{y})$-type match surplus (i.e., the match surplus attained with the poaching firm).

y-type to a $\hat{y}$-type firm, the second line implies that the worker did not change jobs but re-negotiated her contract with the y-type firm, the third line implies that the worker did not change jobs nor did she re-negotiated her contract with the y-type firm, and the fourth line resembles the case of a worker making an unemployment-to-employment transition.

This negotiation setting is similar to that from Postel-Vinay and Robin (2002), with the slight difference that it is the shares of match surpluses and not the values of joint production that are offered to the worker. A result from this negotiation process is that γ increases with tenure: the longer a worker stays in a job, the more job offers she will receive, and thus the higher the share of the match surplus that she keeps.

Value Functions of Workers. The present value of unemployment for an x-type worker given z_t, $B_t(x)$, is comprised of a flow value of home production, $b_t(x)$, and a continuation value that will depend on the probability of future transitions across employment states:

$$\begin{aligned} B_t(x) &= b_t(x) + \beta\, \mathbb{E}_{z_{t+1}} \left[B_{t+1}(x) + \lambda_{t+1}(x) \int \kappa_{t+1}(x,\hat{y}) \Big(\hat{\gamma}\, S_{t+1}(x,\hat{y}) \Big) \mathrm{d}\hat{y} \right] \\ &= b_t(x) + \beta\, \mathbb{E}_{z_{t+1}}\, B_{t+1}(x)\,, \end{aligned} \tag{5}$$

where $\mathbb{E}_{z_{t+1}}$ is the expectations operator over future values of z_{t+1} conditional on z_t. The worker gets her continuation value of unemployment plus the share of the surplus that is offered by a firm in case of a meeting. With probability $\lambda_t(x)\, \kappa_{t+1}(x,y)$, the worker meets a y-type firm who will offer the worker a share $\hat{\gamma} = 0$ of $S_t(x,y)$. Thus, the continuation value of unemployment will always be $B_{t+1}(x)$, regardless of whether the worker meets a firm or not.

The present value of employment for an x-type worker matched with a y-type firm who holds an employment contract γ given z_t, $W_t(x,y,\gamma)$, is comprised of a wage flow value $w_t(x,y,\gamma)$ and a continuation value that will depend on the probability of future movements across firms and/or employment states:

$$\begin{aligned} W_t(x,y,\gamma) = {} & w_t(x,y,\gamma) \\ & + \beta\, \mathbb{E}_{z_{t+1}} \Bigg[B_{t+1}(x) + \big(1 - \delta_{t+1}(x,y)\big) \Bigg(\big(1 - e\, \lambda_{t+1}(x)\big) \Big(\gamma\, S_{t+1}(x,y) \Big) \\ & \qquad + e\, \lambda_{t+1}(x) \int \kappa_{t+1}(x,\hat{y}) \Big(\hat{\gamma}\, S_{t+1}(x,y) \Big)\, \mathrm{d}\hat{y} \Bigg) \Bigg] \end{aligned}$$

The worker gets her continuation value of unemployment plus the expected share of the surplus that accrues to her in case the match is not dissolved. Upon continuation of the em-

ployment relationship, with probability $\big(1 - e\,\lambda_{t+1}(x)\big)$, the worker does not draw an outside job offer and receives $\gamma\, S_{t+1}(x,y)$. With probability $e\,\lambda_{t+1}(x)\,\kappa_{t+1}(x,\hat{y})$, the worker draws an outside job offer from a $\hat{y}$-type firm and receives $\hat{\gamma}\, S_{t+1}(x,y)$.

Value Functions of Firms. When advertising vacancies, any firm can buy v job advertisements targeted at x-type workers from employment agencies at a cost $c(v,x)$. I assume that there are no fixed costs of vacancy advertisement (i.e., $c(0,x) = 0$).

Let $V_t(x,y,v)$ denote the present value for a y-type firm of advertising v vacancies targeted at x-type workers given z_t. This is composed of the cost of opening this number of vacancies plus the expected gains of filling those vacancies (i.e., hiring):

$$\begin{aligned} V_t(x,y,v) = &-c(v,x) \\ &+ v\, q_t(x) \left[\frac{u_{t-}(x)}{\mathcal{L}_t(x)} + \left(\int \frac{e\, h_{t-}(x,\hat{y})}{\mathcal{L}_t(x)} \mathbb{1}\big\{ \Delta^{S_t(x,y)}_{S_t(x,\hat{y})} \geq 0 \big\} \big(1 - \hat{\gamma}\big) \mathrm{d}\hat{y} \right) \right] S_t(x,y)\,, \end{aligned}$$

where Δ^a_b denotes $a - b$. Each vacancy gives the firm a probability of meeting a worker equal to $q_t(x)$, so the measure of expected meetings equals $v\, q_t(x)$. A y-type firm's expected gain from filling a vacancy depends on the employment state of the worker she meets. With probability $u_{t-}(x)/\mathcal{L}_t(x)$, the firm meets an unemployed worker and gets $S_t(x,y)$. With probability $e\, h_{t-}(x,\hat{y})/\mathcal{L}_t(x)$, the firm meets an x-type employed worker matched with a $\hat{y}$-type firm, so she can only poach that worker if $S_t(x,y) \geq S_t(x,\hat{y})$ and gets $\big(1 - \hat{\gamma}\big)\, S_t(x,y)$ in such a case. The firm gets a value of zero for any meeting that does not result in a hire.

Firms do not advertise vacancies targeted at workers types that make the match surplus negative conditional on z_t. For all other worker types, optimality requires that the marginal expected gain from advertising v vacancies equals its marginal cost:

$$c_v(v,x) = q_t(x) \left[\frac{u_{t-}(x)}{\mathcal{L}_t(x)} + \left(\int \frac{e\, h_{t-}(x,\hat{y})}{\mathcal{L}_t(x)} \mathbb{1}\big\{ \Delta^{S_t(x,y)}_{S_t(x,\hat{y})} \geq 0 \big\} \big(1 - \hat{\gamma}\big) \mathrm{d}\hat{y} \right) \right] S_t(x,y)\,, \tag{6}$$

where $c_v\big(v,x\big)) = \partial c\big(v,x\big)/\partial v$. This condition uniquely determines the measure of vacancies advertised by a y-type firm in sub-market x, $v_t(x,y)$, and resembles the free entry condition of firms: in expectations, it is the case that $V_t(x,y,v(x,y)) = 0$.

Let $J_t(x,y,\gamma)$ be the present value of a filled job position for a y-type firm who employs an x-type worker under an employment contract γ given z_t. Together, the worker and the firm produce value added $p_t(x,y)$ and the firm pays the worker a wage $w_t(x,y,\gamma)$. Thus, the net flow value to the firm of a filled job position equals $p_t(x,y) - w_t(x,y,\gamma)$. The continuation

value will depend on the worker's future movements across firms and/or employment states:

$$
\begin{aligned}
J_t(x,y,\gamma) = p_t(x,y) - w_t(x,y,\gamma) \\
+ \beta\, \mathbb{E}_{z_{t+1}} \Bigg[\big((1-\delta_{t+1}(x,y)\big) \Bigg(\big(1 - e\,\lambda_{t+1}(x)\big)\big(1-\gamma\big)\, S_{t+1}(x,y) \\
+ e\,\lambda_{t+1}(x) \int \kappa_{t+1}(x,\hat{y}) \Big(\big(1-\hat{\gamma}\big)\, S_{t+1}(x,y) \Big) \mathrm{d}\hat{y} \Bigg) \Bigg]
\end{aligned}
$$

The firm knows that, in case the match is not dissolved, the worker draws an outside job offer from a $\hat{y}$-type firm with probability $e\,\lambda_{t+1}(x)\,\kappa_{t+1}(x,\hat{y})$. If the worker does not draw an outside job offer, then the firm receives $\big(1-\gamma\big)\, S_{t+1}(x,y)$. If the worker draws an outside job offer, then the firm receives $\big(1-\hat{\gamma}\big)\, S_{t+1}(x,y)$. In case of match dissolution, the continuation value equals zero.

Joint Production. The present value of joint production between an x-type worker and a y-type firm equals:

$$
P_t(x,y) = p_t(x,y) + \beta\, \mathbb{E}_{z_{t+1}} \Big[B_{t+1}(x) + \big(1-\delta_{t+1}(x,y)\big)\, S_{t+1}(x,y) \Big], \tag{7}
$$

and results from adding up the present value of employment to an x-type worker matched with a y-type firm and the present value of a filled job position by an x-type worker to a y-type firm: $P_t(x,y) = W_t(x,y,\gamma) + J_t(x,y,\gamma)$.

Match Surplus. The (x,y)-type match surplus results from subtracting equation (5) from equation (7):

$$
S_t(x,y) = p_t(x,y) - b_t(x) + \beta\, \mathbb{E}_{z_{t+1}} \Big[\big(1-\delta_{t+1}(x,y)\big)\, S_{t+1}(x,y) \Big], \tag{8}
$$

Equation (8) implies that match-specific surpluses do not depend on any (stationary) distribution of employment states or wages and thus can be solved for externally. Limited commitment implies that any employment relationship that yields $S_t(x,y) < 0$ results in match dissolution. Firm competition *à la* Bertrand ensures that new job opportunities available to the worker do not change the match surplus but only how it is shared between the worker and the firm.

3.4 Labor Market Flows

After contract negotiation occurs, new matches are formed and are carried onto period t. This corresponds to stage (iv) in Figure 3.

The period t measure of x-type unemployed workers that results after job placements have been realized in each sub-market x is:

$$u_t(x) = u_{t-}(x)\big(1 - \lambda_t(x)\big) \tag{9}$$

and results from subtracting the share of unemployed workers who met a recruiting firm, given that all meetings end up in hires.

Correspondingly, the period t measure of x-type employed workers matched with a y-type firm is:

$$\begin{aligned} h_t(x,y) = &\left[1 - e\,\lambda_t(x)\int \kappa_t(x,\hat{y})\,\mathbb{1}\big\{\Delta^{S_t(x,y)}_{S_t(x,\hat{y})} < 0\big\}\,\mathrm{d}\hat{y}\right] h_{t-}(x,y) \\ &+ e\,\lambda_t(x)\,\kappa_t(x,y)\int \mathbb{1}\big\{\Delta^{S_t(x,y)}_{S_t(x,\hat{y})} \geq 0\big\}\,h_{t-}(x,\hat{y})\,\mathrm{d}\hat{y} \\ &+ \lambda_t(x)\,\kappa_t(x,y)\,u_{t-}(x)\,, \end{aligned} \tag{10}$$

and results from subtracting the share of workers who were poached from a y-type firm, adding the measure of workers who were poached by a y-type firm, and adding the measure of workers who were hired from the unemployment pool by a y-type firm.

3.5 Wages

Wages are paid at the beginning of period t, once matches are formed and production has taken place. This corresponds to stage (v) in Figure 3. Wages within (x,y)-type matches are determined according to γ.

Distribution of Employment Contracts. Let $g_{t-1}(x,y,\gamma)$ denote the measure of employment contracts of size γ for (x,y)-type matches inherited from period $t-1$. Also, define the measure of employment contracts of size γ for (x,y)-type matches remaining after match dissolutions, $g_{t-}(x,y,\gamma)$, as:

$$g_{t-}(x,y,\gamma) = \big(1 - \delta_t(x,y)\big)g_{t-1}(x,y,\gamma) \tag{11}$$

The measure of employment contracts of size $\gamma > 0$ for (x,y)-type matches observed at

the beginning of period t, $g_t(x,y,\gamma)$, then becomes:

$$g_t(x,y,\gamma) = \left(1 - e\lambda_t(x)\int \kappa_t(x,\hat{y})\mathbb{1}\left\{\tfrac{S_t(x,\hat{y})}{S_t(x,y)} > \gamma\right\}\mathrm{d}\hat{y}\right) g_{t-}(x,y,\gamma)$$
$$+ e\lambda_t(x)\left(\int_0^{\gamma}\int \kappa_t(x,\hat{y})\mathbb{1}\left\{\tfrac{S_t(x,\hat{y})}{S_t(x,y)} = \gamma\right\} g_{t-}(x,y,\gamma)\,\mathrm{d}\hat{y}\,\mathrm{d}\tilde{\gamma}\right.$$
$$\left. + \kappa_t(x,y)\int \mathbb{1}\left\{\tfrac{S_t(x,\hat{y})}{S_t(x,y)} = \gamma\right\} h_{t-}(x,\hat{y})\,\mathrm{d}\hat{y}\right) \tag{12}$$

and results from subtracting the share of workers who were poached from a y-type firm or who stayed matched with a y-type firm but whose contracts were revised upwardly from γ, adding the measure of workers matched with a y-type firm whose contract sizes were raised to γ, and adding the measure of workers who were poached by a y-type firm and offered an employment contract of size γ.

Likewise, the measure of contracts of size $\gamma = 0$ for (x,y)-type matches observed at the beginning of period t, $g_t(x,y,0)$, can be written as:

$$g_t(x,y,0) = \big(1 - e\lambda_t(x)\big)\, g_{t-}(x,y,0) + \lambda_t(x)\,\kappa_t(x,y)\,u_{t-}(x) \tag{13}$$

and results from subtracting the share of x-type workers matched with a y-type firm who met a recruiting firm, regardless of whether they were hired by that firm or not, and adding the measure of workers who were hired from the unemployment pool by a y-type firm.

Future Contract Revisions. The wage level of an x-type worker matched with a y-type firm under an employment contract of size γ given z_t, $w_t(x,y,\gamma)$, can be derived from the identity: $W_t\,(x,y,\gamma) = B_t\,(x) + \gamma\, S_t\,(x,y)$. This, however, requires that agents form expectations on the aggregate state of the economy and its associated labor market distributions in period t+1 conditional on the set of state variables observed in period t, $\{z_t, h_t(x,y)\}$. In particular, agents need to form expectations (i.e., make forecasts) on:

$$\Omega_{z_{t+1}}(x,y,\gamma) = \mathbb{E}_{z_{t+1}}\left[\big(1 - \delta_{t+1}(x,y)\big)\left(e\,\lambda_{t+1}(x)\int \kappa_{t+1}(x,\hat{y})\big(\hat{\gamma} - \gamma\big)\, S_{t+1}(x,y)\,\mathrm{d}\hat{y}\right)\right], \tag{14}$$

which corresponds to the change in the share of the surplus that accrues to the worker from future contract re-negotiations, given the continuation of the employment relationship.

Wage Levels. The wage of an x-type worker matched with a y-type firm who holds an

employment contract of size γ given z_t, $w_t(x, y, \gamma)$, can be expressed as:

$$w_t(x, y, \gamma) = (1 - \gamma)\, b_t(x) + \gamma\, p_t(x, y) - \beta\, \Omega_{z_{t+1}}(x, y, \gamma)\,, \tag{15}$$

which is a weighted average of production flows $p_t(x, y)$ and $b_t(x)$, where the weight corresponds to γ, discounted by the expected future contract revisions that will grant the worker a bigger share of the match surplus conditional on the continuation of the employment relationship.

4 Quantitative Analysis

In this section, I provide details on the computation of the stochastic equilibrium and the estimation methodology used to recover structural parameters from the model presented in the previous section. I next present the estimation results and comment the model fit to observed trends in U.S. labor market indicators over 1951q1-2019q4.

4.1 Computation of the Stochastic Equilibrium

I compute the stochastic equilibrium of labor market transitions and wage levels in two stages. While the first stage returns the sequences of sub-market distributions of vacancies, transition rates, and employment states, the last stage utilizes these elements to compute the sub-market distributions of shares of surpluses (i.e., employment contracts) and wages.

Stochastic Equilibrium of Labor Market Distributions. The following procedure describes the computation of the stochastic equilibrium of labor market distributions:

1. For given functional forms $b_t(x)$ and $p_t(x, y)$, exogenous parameters β and δ, and a stochastic process $\pi(z_{t-1}, z_t)$, the value of the match surplus, $S_t(x, y)$, is sufficient to determine workers' transitions across employment states and is uniquely determined by equation (8).

2. For given PDFs of worker skills and firm productivities, $l(x)$ and $f(y)$, respectively, functional form $c(v, x)$, functional form $m\big(\mathcal{L}_t(x), \mathcal{V}_t(x)\big)$, and a set of initial distributions $\{u_0(x), h_0(x, y)\}$, a sequence of aggregate states of the economy $\{z_t\}_{t=1}^{T}$ determines a sequence:

$$\big\{v_t(x, y), u_t(x), h_t(x, y)\big\}_{t=1}^{T}$$

   calculated from $S_t(x, y)$ by iterating over equations (1)-(10).

The fact that $S_t(x, y)$ does not depend on any distribution of employment states and/or wages allows me to compute the match surplus of any (x, y)-type match for every z_t externally. Given a distribution of initial employment/unemployment states, and a sequence of aggregate shocks, $S_t(x, y$ suffices to compute the equilibrium distributions of vacancies, unemployment, employment, and thereby meeting and transition rates in the labor market.

Stochastic Equilibrium of Employment Contracts and Wage Levels. I compute the stochastic equilibrium of employment contract and wages in two stages:

1. For an initial distribution $g_0(x, y, \gamma)$ and a functional form $m\big(\mathcal{L}_t(x), \mathcal{V}_t(x)\big)$, a sequence of a set of distributions $\{v_t(x, y), u_t(x), h_t(x, y)\}_{t=1}^T$ determines a sequence:

$$\{g_t(x, y, \gamma)\}_{t=1}^T$$

   calculated from $S_t(x, y)$ by iterating over equations (11)-(13).

2. Wages are computed according to the size of the employment contract, γ, as follows:

   (a) For a sequence of aggregate states of the economy $\{z_t\}_{t=1}^T$ and a sequence of employment distributions $\{h_t(x, y)\}_{t=1}^T$, a stochastic process $\pi(z_{t-1}, z_t)$ determines a sequence of forecasts:

$$\big\{\Omega_{z_{t+1}}(x, y, \gamma)\big\}_{t=1}^T$$

   as specified in equation (14).

   (b) For given functional forms $b_t(x)$ and $p_t(x, y)$, a sequence $\big\{\Omega_{z_{t+1}}(x, y, \gamma)\big\}_{t=1}^T$, and an exogenous parameter β, a sequence:

$$\{w_t(x, y, \gamma)\}_{t=1}^T$$

   can be computed from equation (15).

This procedure will result in a time-varying joint distribution of wages over x, y, and γ. To compute the aggregate distribution of wages in each period, I stack $w_t(x, y, \gamma)$ on grids of equally spaced points over a fixed support $[0, \bar{w}]$. The density is determined by the sum of $g_t(x, y, \gamma)$ among the set of wages that fall in each grid.

4.2 Parameterization

Below, I describe the functional forms as well as the externally and internally calibrated model's structural parameters.

Time Discount. The length of a period equals one month. I set the per-period discount rate β equal to 0.99, consistent with an annual interest rate of 5 percent.

Distribution of Skills and Technologies. I assume that the distribution of skills across workers is a Beta distribution with shape parameters η_1^W and η_2^W to be estimated. Also, I assume that the distribution of technologies across firms is uniform. I approximate the distributions of workers and firms across the supports of x and y by grids of equally spaced points $\{x_1, \ldots, x_{N_x}\}$ on $[0, 1]$ and $\{y_1, \ldots, y_{N_y}\}$ on $[0, 1]$, respectively, with $N_x = N_y = 21$.

Aggregate Productivity Shocks. I specify the distribution of aggregate productivity shocks to be log-normal, consistent with the AR(1) process: $\log z_t = \rho \log z_{t-1} + \varepsilon_t$. I assume that $\varepsilon_t \sim \mathcal{N}(0, \sigma)$, with ρ and σ being parameters to be estimated. I approximate this distribution by grids of equally spaced points $\{\epsilon_1, \ldots, \epsilon_{N_z}\}$ on $[\underline{z}, \overline{z}]$ such that $z_i = \exp(\epsilon_i)$, with $N_z = 51$. I map the transition probability $\pi(z_i, z_j)$ from a Gaussian copula density $G(\epsilon_i, \epsilon_j)$ and normalize $\pi(z_i, z_j)$ such that $\sum_j \pi(z_i, z_j) = 1$.

Home and Joint Production. Following Lise and Robin (2017), I set the flow values of joint and home production, respectively, to have the following functional forms:

$$p_t(x, y) = z_t(p_1 + p_2 x + p_3 y + p_4 x^2 + p_5 y^2 + p_6 xy)$$

$$b_t(x) = 0.70 \times p_{[z_t=1]}(x, y^*(x, 1))$$

where the parameters p_1 through p_6 are to be estimated and $y^*(x, 1) = \arg\max_y P_{[z_t=1]}(x, y)$ is the firm's technology that maximizes the present value of joint production for an x-type worker when $z_t = 1$. The 0.70 scale of the flow value of home production stems from the calibration of Hagedorn and Manovskii (2008).[27].

Meeting Technology. The measure of meetings in each sub-market is determined by the Cobb-Douglas matching function:

$$\mathcal{M}\big(\mathcal{L}_t(x), \mathcal{V}_t(x)\big) = \psi\big(\mathcal{L}_t(x)^{\alpha} \mathcal{V}_t(x)^{1-\alpha}\big)$$

[27]This value lies within the range of calibrated flow values of unemployment, going from 0.40 to 0.90 (Shimer, 2005; Mortensen and Nagypál, 2007; Baydur, 2017)

where the matching efficiency parameter ψ is to be estimated. Based on the survey by Petrongolo and Pissarides (2001), I set the parameter α equal to 0.50.[28]

Vacancy Advertisement Costs. I set the following functional form for the vacancy advertisement costs:

$$c(v,x) = \frac{c_1}{1+c_2}\, x\, v^{1+c_2}$$

where c_1 and c_2 are parameters to be estimated.

The functional form assumptions on the vacancy advertisement costs and the meeting technology imply that the optimality condition for equilibrium vacancy creation for a y-type firm advertising vacancies in sub-market x is:

$$v_t(x,y) = \left(\frac{\psi\, \mathbb{E}_{\hat{y}}\big[J_t\big(x,y,\hat{\gamma}\big)\big]}{\theta_t\,(x)^{\alpha}\, c_1\, x} \right)^{\frac{1}{c_2}}$$

where $\theta_t(x) = \mathcal{V}_t(x)/\mathcal{L}_t(x)$ is the measure of advertised vacancies per job seeker (i.e., the tightness ratio) in sub-market x and

$$\mathbb{E}_{\hat{y}}\big[J_t\big(x,y,\hat{\gamma}\big)\big] = \left[\frac{u_{t-}(x)}{\mathcal{L}_t(x)} + \left(\int \frac{e\, h_{t-}(x,\hat{y})}{\mathcal{L}_t(x)} \mathbb{1}\big\{\Delta_{S_t(x,\hat{y})}^{S_t(x,y)} \geq 0\big\}\big(1-\hat{\gamma}\big)\mathrm{d}\hat{y} \right) \right] S_t(x,y)$$

denotes the expected gains from filling a vacancy in sub-market x. Integrating $v_t(x,y)$ over y and dividing by $\mathcal{L}_t(x)$ yields:

$$\theta_t\,(x) = \left(\frac{1}{\mathcal{L}_t\,(x)} \left(\frac{\psi}{c_1\, x} \int \mathbb{E}_{\hat{y}}\big[J_t\,(x,y,\hat{\gamma})\,\big]\, f(y)\,\mathrm{d}y \right)^{\frac{1}{c_2}} \right)^{\frac{c_2}{\alpha+c_2}},$$

which gives the equilibrium condition for vacancy and unemployment rates in sub-market x.

Distribution of Employment Contracts. I approximate the distribution of employment contracts of size γ, for each (x,y)-type match, by grids of equally spaced points $\big\{\gamma_1, \gamma_2, \ldots, \gamma_{N_\gamma}\big\}$ on $[0,1)$ with $N_\gamma = 11$. Each period, the distribution of employment contracts across γ within each (x,y)-type match changes according to the employment transitions induced by the aggregate state of the economy and the job prospects of workers.

Future Contract Revisions and Wage Levels. The expectations on future contract revisions component of wages can be computed by backward recursion using the Markov transition process. However, this method is computationally burdensome as it requires to

[28] I set the upper boundary of the measure of meetings to: $\min\big\{\mathcal{L}_t(x), \mathcal{V}_t(x)\big\}$.

compute $21 \times 21 \times 11 \times 21 \times 51$ different elements (i.e., the share of match surplus that would accrue to the worker in case she meets any of the 21 firm types in each of the 51 possible states of the economy) given the parameterization that I adopt. Instead, I opt for a less computationally demanding forecasting method that assumes that agents make heuristic forecasts of $\Omega_{z_{t+1}}(x, y, \gamma)$ conditional on the state of the economy in period t and the realized distributions up to period $t-1$.[29] This method yields a consistent estimate $\hat{\Omega}_{z_{t+1}}(x, y, \gamma)$ of $\Omega_{z_{t+1}}(x, y, \gamma)$. Given $\hat{\Omega}_{z_{t+1}}(x, y, \gamma)$, $w_t(x, y, \gamma)$ can be computed from equation (15). In Appendix C, I provide further details on the computation of $\hat{\Omega}_{z_{t+1}}(x, y, \gamma)$ together with a series of robustness checks for the computation of $w_t(x, y, \gamma)$.

4.3 Estimation Methodology

Fifteen parameters are to be estimated: $\left\{\delta, e, \psi, c_1, c_2, p_1, p_2, p_3, p_4, p_5, p_6, \rho, \sigma, \eta_1^W, \eta_2^W\right\}$. In estimation, I fit the model-simulated series to moments of standard U.S. quarterly time series data over the period 1951q1-2019q4. In particular, I estimate these parameters by indirect inference, targeting a set of empirical moments through the Method of Simulated Moments (MSM) introduced by McFadden (1989).

Let $\hat{\omega} = \{\hat{\omega}_1, \ldots, \hat{\omega}_N\}$ denote the $N \times 1$ vector of empirical moments derived from the data and $\tilde{\omega}_T(\varphi) = \{\tilde{\omega}_1(\varphi), \ldots, \tilde{\omega}_N(\varphi)\}$ denote its model-simulated surrogate derived from a $K \times 1$ vector of parameters φ defined over a compact space Θ (with $K \leq N$) over T simulation periods. The MSM estimate of φ, $\hat{\varphi}(A_T)$, is the vector of parameter values that solves:

$$\hat{\varphi}\big(A_T\big) = \arg\min_{\varphi \in \Theta} Q(\varphi) \equiv \left\| A_T\big(\hat{\omega} - \tilde{\omega}(\varphi)\big) \right\|^2$$

where A_T is a weighting matrix such that $A_T \to^p A$, with A being a non-random matrix with full rank N. Assuming that, for a large number of periods T, $\sqrt{T}\left(\hat{\omega} - \omega(\varphi_0)\right) \to^d \mathcal{N}\big(0, C\big)$, where C is the variance-covariance matrix of the vector of empirical moments, the asymptotic distribution of the vector of parameter estimates is:

$$\sqrt{T}\left(\hat{\varphi}\big(A_T\big) - \varphi_0\right) \to^d \mathcal{N}\big(0, \Sigma\big),$$

where Σ is the variance-covariance matrix of the vector of parameter estimates. In Ap-

[29] Different methods have been proposed for solving stochastic general equilibrium models featuring a continuum of heterogeneous agents. The main challenge is that the vector of state variables typically contains the distribution of agents in the economy which tends to be infinite-dimensional. The proposed solutions are based on parametric (Den Haan, 1997; Algan et al., 2008; Winberry, 2018), discretization (Reiter, 2002), perturbation (Reiter, 2009), and linearization (Boppart et al., 2018; Auclert et al., 2021) methods.

pendices D and E, respectively, I provide additional details on the construction of model-simulated moments and the computation of the vector of estimated parameters, $\hat{\varphi}(A_T)$, and of the heteroskedasticity-and-autocorrelation consistent (HAC) estimate of the variance-covariance matrix of the vector of parameter estimates, $\hat{\Sigma}\big(\hat{\varphi}(A_T)\big)$, based on Newey and West (1987).

4.4 Identification

Having explained the estimation methodology, I next turn to discuss how I identify the model's structural parameters from observed empirical moments.

Targeted Moments. In estimating $\varphi(A_T)$, I principally target the following moments: mean unemployment rate; mean unemployment rate of 5+ weeks; mean unemployment rate of 15+ weeks; mean unemployment rate of 27+ weeks; mean employment-to-unemployment transition rate; mean unemployment-to-employment transition rate; mean job-to-job transition rate; mean vacancy rate; mean dispersion of labor productivity; mean dispersion of real weekly wages; mean labor share of output; standard deviation of value added; autocorrelation of value added; correlation between unemployment and vacancy rates; correlation between value added and unemployment rate; correlation between value added and vacancy rate; correlation between value added and unemployment-to-employment transition rate; correlation between value added and employment-to-unemployment transition rate; correlation between unemployment-to-employment and job-to-job transition rates; correlation between value added and dispersion of labor productivity; correlation between value added and real weekly wages; correlation between value added and dispersion of real weekly wages; and correlation between value added and labor share of output. This adds up to a total of 23 targeted moments.

Identification. The structural parameters are intuitively identified from empirical moments as follows. The parameters governing the AR(1) process of aggregate productivity shocks, σ and ρ, are identified from the standard deviation and autocorrelation of value added. The exogenous rate at which matches are dissolved, δ, is identified from the mean employment-to-unemployment transition rate. The relative job search effort of employed workers, e, is identified from the mean job-to-job transition rate. The parameters governing the vacancy advertisement costs, c_1 and c_2, are identified from the mean unemployment rate and the mean vacancy rate. The parameter determining the efficiency of the matching technology, ψ, is identified from the mean unemployment-to-employment transition rate. The mean un-

employment rates of 5+, 15+, and 27+ weeks serve to identify the shape parameters of the Beta distribution of skills across workers, η_1^W and η_2^W. Lastly, the parameters governing the joint production function, $\{p_1, p_2, p_3, p_4, p_5, p_6\}$, are identified from the dispersion of labor productivity, the dispersion of real weekly wages, and all the remaining correlations.

Data Sources. I utilize 13 quarterly series to compute the empirical moments used for identification of the structural parameters. I gather quarterly series real gross value added in the business, non-farming sector over 1951q1-2019q4 from the Bureau of Economic Analysis (BEA). This series correspond to value added (VA_t) in the quantitative analysis.

I obtain monthly series of the unemployment rate, unemployment rates of 5+, 15+, or 27+ weeks, employment-to-unemployment rate, and unemployment-to-employment rate over the period 1951m1-2019m12 from the Bureau of Labor Statistics (BLS). I compute the monthly job-to-job transition rate over the period 1995m1-2019m12 by using information on job mobility across individuals who were surveyed in contiguous months by the CPS. I bring together two sources of information — the updated version of the composite Help Wanted Index (Barnichon, 2010; Cajner and Ratner, 2016) and the Job Openings and Labor Turnover Survey (JOLTS) — to construct a monthly series of the vacancy rate over 1951m1-2019m12. I construct monthly series of (log.) real wages and dispersion of (log.) real wages over 1985m1-2019m19 using data from the CPS-ORG. I transform all these monthly series into quarterly series by taking averages within quarters.

I extract annual series of dispersion of (log.) labor productivity (DLP_t) over 1975-2009 from Bloom et al., (2018). I transform the annual data to quarterly series by interpolation using a cubic polynomial (the mean remains unchanged to the use of linear or spline methods for interpolation). The resulting series span the period 1975q1-2009q4.

Lastly, I obtain quarterly series of the labor share of output (i.e., the amount of GDP paid out in wages, salaries, and benefits) for the non-farm business sector over 1951q1-2019q4 from the BLS.

Computation of Model-simulated Moments. I simulate a series of aggregate productivity shocks derived from the initial value z_0 and the estimated Markov transition process over 9,600 periods (i.e., 800 years), using the first 1,200 periods as a burning phase. To compute model-simulated moments, I first transform monthly series into quarterly series by averaging (or adding, in the case of value added) across months within a quarter. Next, I compute the moments by taking averages, standard deviations, or correlations — whichever the case may be — from the transformed quarterly series.

4.5 Parameter Estimates and Model Fit

I begin the presentation of the results of the quantitative analysis by describing the structural parameter estimates. Next, I comment on the model fit and its capability to match observed moments and fluctuations of different series.

Parameter Estimates. In Table 2, I present estimates of the model's structural parameters, along with their standard errors (reported in parentheses), resulting from matching model-simulated moments with moments observed for the U.S. economy over the period 1951q1-2019q4. Judging by the size of the estimated standard errors, all structural parameters are precisely estimated. This speaks of the ability of the empirical moments to pin down underlying structural parameters accurately.

The estimated exogenous separation rate δ equals 0.021, consistent with previous estimates ranging from 0.01 to 0.04 (Shimer, 2005; Hagedorn and Manovskii, 2008; Robin, 2011). The estimated relative on-the-job search effort e equals 0.026, significantly lower than typical estimates of between 0.10 and 0.20 (Robin, 2011; Moscarini and Postel-Vinay, 2018; Faberman et al., 2022). This discrepancy stems from the fact that I treat workers transiting from employment to unemployment and then back to employment between contiguous months as having made an unemployment-to-employment transition. Lack of higher frequency data, though, does not permit to distinguish whether workers transiting across jobs between contiguous months, as reported by the CPS, indeed spent some time unemployed. This would imply that search effort increases during the unemployment spell if not properly accounted.

The estimated matching efficiency ψ equals 0.59. This estimate lies within the range of 0.50-0.80, estimated for the U.S. over the period 1967-2018 by Crawley et al. (2021). As for the vacancy advertisement costs, the estimated parameters of the cost function are $c_1 = 0.09$ and $c_2 = 0.02$. Vacancy advertisement costs are therefore slightly convex on the number of vacancies advertised in a given sub-market. Further, vacancy advertisement costs represents, on average, nearly 10 percent of a firm's total labor costs (i.e., payroll), which is higher than the average figure of 5 percent reported by Manning (2011).

I obtain an estimate of the persistence parameter of aggregate productivity shocks ρ equal to 0.99 and an estimate of the standard deviation σ of the stochastic term of the AR(1) process equal to 0.07. At a quarterly frequency, these estimates are consistent with those calibrated in previous work (Hornstein et al., 2005; Hagedorn and Manovskii, 2008). Further, OLS estimates of $\log z_t$ on $\log z_{t-1}$ from the observed HP-filtered quarterly series imply a persistence parameter equal to 0.93 and a standard deviation of the estimated residual equal to 0.01. In my simulations, these figures amount to 0.96 and 0.01, respectively.

Table 2: Structural Parameter Estimates

Description	Parameter	Value	Description	Parameter	Value
Job Destruction			Value Added		
	δ	0.021	$p_t(x,y) = z_t(p_1 + p_2 x$	p_1	0.003
		(0.001)	$+ p_3 y + p_4 x^2$		(0.001)
On-the-job Search Effort			$+ p_5 y^2 + p_6 xy)$	p_2	1.536
	e	0.026			(0.030)
		(0.002)		p_3	-0.063
Matching Efficiency					(0.015)
$\psi\big(\mathcal{L}_t(x)\mathcal{V}_t(x)\big)^{\frac{1}{2}}$	ψ	0.591		p_4	6.616
		(0.082)			(0.166)
Vacancy Advertisement				p_5	-2.407
$c(v,x) = \frac{c_1}{1+c_2}\, x\, v^{1+c_2}$	c_1	0.091			(0.026)
		(0.013)		p_6	7.189
	c_2	0.019			(0.019)
		(0.001)	Distribution of Worker Skills		
Aggregate Shocks			Beta(η_1, η_2)	η_1	3.250
$\log z_t = \rho \log z_{t-1} + \varepsilon_t$	ρ	0.996			(0.050)
$\varepsilon_t \sim \mathcal{N}(0, \sigma)$		(0.001)		η_2	12.944
	σ	0.070			(0.066)
		(0.001)			

Note: The table shows structural parameter estimates, along with their corresponding standard errors, obtained by matching model-simulated moments to empirical moments from U.S. quarterly series over the period 1951q1-2019q4. Standard errors are computed by correcting for heteroskedasticity and autocorrelation in the variance-covariance matrix of empirical moments (HAC-robust). The number of periods utilized for the simulations are 8,400 at a monthly frequency (2,800 at a quarterly frequency). Additional details of the estimation results are described within the table. The data utilized to compute empirical moments come from BEA, BLS, JOLTS, the updated composite HWI (Barnichon, 2010; Cajner and Radner, 2016), the data archive from Bloom et al. (2018), and the CPS-ORG.

In the model, the shape parameters of the underlying Beta distribution of worker skills measure the degree of heterogeneity in the labor market. Estimates of these parameters correspond to $\eta_1 = 3.25$ and $\eta_2 = 12.95$. The production function is monotonically increasing in worker skills for a given firm type and aggregate state of the economy but non-monotonically increasing in firm technology for a given worker type and aggregate state of the economy.

Model Fit. In Table 3, I present the empirical and surrogate moments obtained from U.S. quarterly series and model simulations.

Table 3: Data and Model-simulated Moments

Fitted Moment	Data	Model	Fitted Moment	Data	Model
$\mathbb{E}[U_t]$	0.056	0.057	corr. $[VA_t, VA_{t-1}]$	0.931	0.955
	(0.007)			(0.006)	
$\mathbb{E}\left[U_t^{5+}\right]$	0.033	0.034	corr. $[U_t, V_t]$	-0.899	-0.876
	(0.007)			(0.002)	
$\mathbb{E}\left[U_t^{15+}\right]$	0.016	0.016	corr. $[VA_t, U_t]$	-0.850	-0.809
	(0.006)			(0.007)	
$\mathbb{E}\left[U_t^{27+}\right]$	0.009	0.008	corr. $[VA_t, V_t]$	0.816	0.820
	(0.004)			(0.007)	
$\mathbb{E}[UE_t]$	0.404	0.455	corr. $[VA_t, UE_t]$	0.829	0.794
	(0.066)			(0.003)	
$\mathbb{E}[EU_t]$	0.024	0.028	corr. $[VA_t, EU_t]$	-0.751	-0.695
	(0.001)			(0.008)	
$\mathbb{E}[J2J_t]$	0.016	0.018	corr. $[UE_t, J2J_t]$	0.648	0.683
	(0.004)			(0.015)	
$\mathbb{E}[V_t]$	0.031	0.022	corr. $[VA_t, DLP_t]$	-0.090	-0.090
	(0.008)			(0.020)	
$\mathbb{E}[DLP_t]$	0.494	0.486	corr. $[VA_t, w_t]$	0.080	0.045
	(0.040)			(0.015)	
$\mathbb{E}[Dw_t]$	0.582	0.513	corr. $[VA_t, Dw_t]$	-0.163	-0.203
	(0.020)			(0.014)	
$\mathbb{E}[LSO_t]$	0.617	0.650	corr. $[VA_t, LSO_t]$	-0.015	-0.009
	(0.016)			(0.010)	
sd. $[VA_t]$	0.031	0.025			
	(0.003)				

Note: The table shows empirical and model-simulated moments obtained from U.S. quarterly series over 1951q1-2019q4 and from simulated series derived by evaluating the model at parameter values reported in Table 2, respectively. Empirical moments include means ($\mathbb{E}$), standard deviations (sd.), and correlations (corr.) of the unemployment rate (U_t), unemployment rates of 5+, 15+, and 27+ weeks (U_t^{5+}, U_t^{15+}, U_t^{27+}), unemployment-to-employment transition rate (UE_t), employment-to-unemployment transition rate (EU_t), job-to-job transition rate ($J2J_t$), vacancy rate (V_t), cross-sectional dispersion of labor productivity DLP_t, (log.) real wages (w_t), cross-sectional dispersion of (log.) real wages (Dw_t), labor share of output (LSO_t), and value added (VA_t). Standard errors corrected for heteroskedasticity and autocorrelation of empirical moments (HAC-robust) are shown in parentheses. Additional details of the estimation results are described within the table. The data utilized to compute empirical moments come from BEA, BLS, JOLTS, the updated composite HWI (Barnichon, 2010; Cajner and Radner, 2016), the data archive from Bloom et al. (2018), and the CPS-ORG.

In terms of labor market distributions, the model reproduces well the unemployment

rates and the employment-to-unemployment and job-to-job transition rates but overstates the unemployment-to-employment transition rate and understates the vacancy rate. These two last points likely result from the fact that all meetings with unemployed workers end up in hires. Thus, as the pool of job seekers is mainly composed of unemployed workers, firms do not need to create many vacancies to fill their vacant positions as in models where meetings do not necessarily end up in hires (Lise and Robin, 2017).

The model also recreates well the dispersion in labor productivity in the economy. Though it understates the dispersion of wages in the economy, it does a good job in reproducing the labor share of output which lies between 60 and 65 percent.[30] With respect to output, the model reproduces fairly well the volatility and persistence of aggregate production shocks in the economy. Lastly, the model replicates well the size and direction of the correlation between value added and key labor market variables.

Validation. To further show the ability of the model to reproduce labor market responses to aggregate productivity shocks, in Figure 4, I depict the realized and model-predicted fluctuations in the unemployment rate, vacancy rate, employment-to-unemployment transition rate, unemployment-to-employment transition rate, and job-to-job transition rate over 1951q1-2019q4.

To derive model-predicted fluctuations, I first obtain the series of z_t shocks that exactly mimic the drifts in output over this period (Panel A). Next, I feed the model with these shocks, one at a time, and recover the one-period-ahead prediction that obtains from the Markov transition process. Though not strictly the same, this exercise is in the spirit of testing the model's capability to perform out-of-sample predictions conditional on state variables and distributions.

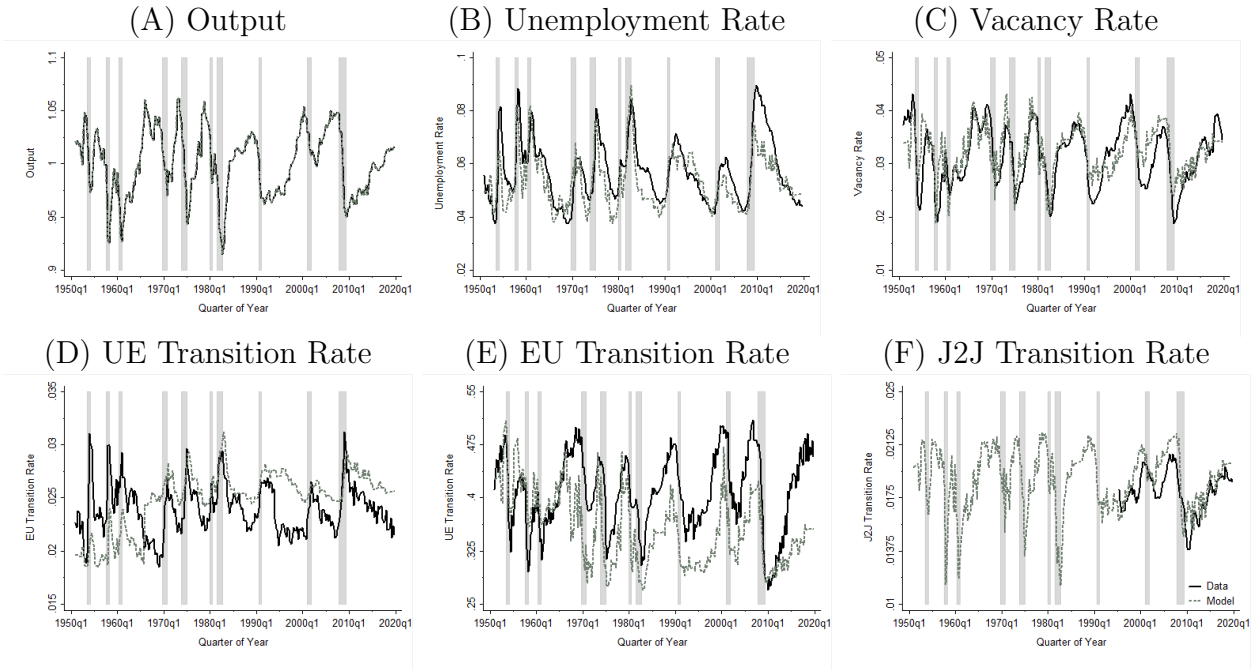
The model's predictions replicate quite well the drifts in labor market variables observed in the U.S. economy. In turn, the predictions for unemployment (Panel B) and vacancy (Panel C) rates coincide almost one-on-one with what is observed in the data. Naturally, it is only the propagation of sudden drops or rises in aggregate productivity to the employment-to-unemployment (Panel D) and unemployment-to-employment (Panel E) transition rates that make the realized and model-predicted trends diverge as this is not fully captured by the Markov transition process. Yet, for the years when data is available, the model seems to predict well the drifts in job-to-job transition rates (Panel F).

All in all, the model's ability to gauge future conditions in the labor market, conditional

[30]The lower dispersion of wages implied by the model may be a result of the relatively small number of grids of employment contract sizes. In turn, increasing the grids of γ increases the wage dispersion in the economy at the cost of decreasing tractability.

on state variables and distributions, is quite remarkable.

Figure 4: Realized and Predicted Fluctuations



Note: The figure shows realized and predicted quarterly fluctuations in output (Panel A), unemployment rate (Panel B), vacancy rate (Panel C), unemployment-to-employment transition rate (Panel D), employment-to-unemployment transition rate (Panel E), and job-to-job transition rate (Panel F) over 1951q1-2019q4. Predicted fluctuations are derived from the one-period-ahead realizations derived from the Markov transition process after feeding the model with the series of z_t shocks that reproduce the drifts in output observed over the period of analysis. The gray bars correspond to the NBER recession periods.
Source: Author's calculations based on model simulations and data from BLS, JOLTS, the updated composite HWI (Barnichon, 2010; Cajner and Radner, 2016), and CPS.

5 Model Implications

Having presented the model's ability to genuinely propagate aggregate productivity shocks, I now turn to discuss how match feasibility, job separations, vacancy advertisement, hiring, and sorting vary across expansions and contractions. I define an expansion as the set of quarters with $z_t \in [0.95, 1.05]$ and a contraction period as the set of quarters with $z_t \in [0.70, 0.75]$. The set of aggregate shocks of contraction periods correspond to a decay of between 3 and 3.5 standard deviations from the mean of the distribution of aggregate shocks across the simulations, and implies a 5-6 percent decrease in output level which is consistent with what is observed in the U.S. economy.

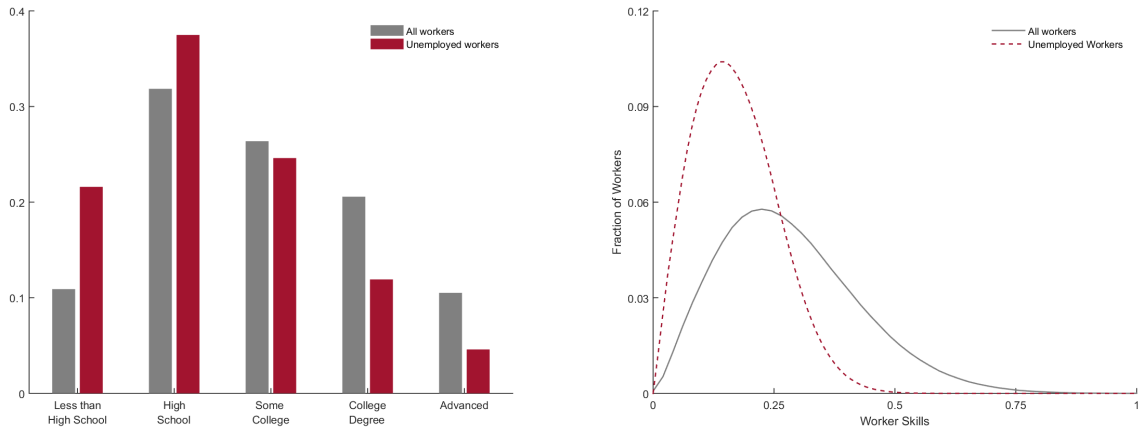
5.1 Distribution of Worker Skills

I begin the analysis by presenting estimates of the distribution of worker skills in the economy. In Figure 5, I show the distribution of the workforce across different educational categories in the U.S. (Panel A) and the distribution of worker skills derived from the model structural parameters (Panel B). In the observational data, educational attainment is taken as a proxy for worker skills. In each graph, I depict the distributions of all (i.e., employed and unemployed) workers and unemployed workers separately.

The model estimate of the implied distribution of worker skills seems to conform well with its observational counterpart. The mean skill level from the estimated distribution of worker skills is roughly 0.20. Furthermore, the distribution of worker skills among the pool of unemployed workers displays a higher mass at low skill levels, implying a positive skewness relative to the overall distribution of worker skills as it is also certain in the observational data. Certainly, the economy exhibits a concentration of worker types among the low- and medium-skill.

Figure 5: Distribution of Worker Skills

(A) Data (B) Model



Note: The figure shows the distribution of the workforce and unemployed individuals across different educational levels in the U.S. economy (Panel A) and the model's implied distribution of the workforce and unemployed workers across worker skills (Panel B). The distributions displayed in Panel A are obtained by averaging across the entire period of analysis over 1980m1-2019m12. The distributions displayed in Panel B are obtained by averaging across the entire 2,800 simulated quarterly series.
Source: Author's calculations based on CPI-ORG and model simulations.

5.2 Match Feasibility

In Figure 6, I plot the set of feasible matches (Panel A) and the firm type that would maximize the present value of joint production (i.e., the efficient firm type) for each worker type (Panel B) during expansions and contractions. The set of feasible matches comprise all matches with non-negative surpluses. The efficient firm type for each worker type, $y^*(x, z_t)$, is such that $y^*(x, z_t) = \arg\max_y P_t(x, y)$.

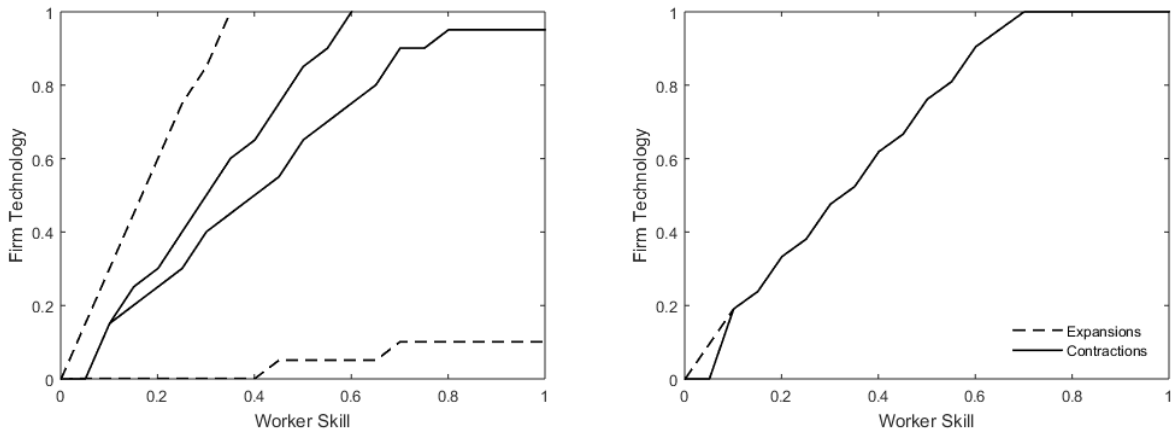
The dashed and solid lines in Panel A represent the set of feasible matches during expansions and contractions, respectively. If the aggregate state of the economy moved from an expansion to a contraction, all matches in between the dashed and solid lines would dissolve immediately, and the set of jobs that are feasible for unemployed workers would shrink. The left boundary of the matching sets is the minimum worker type that is acceptable for a particular firm type. Correspondingly, the right boundary of the matching sets is the minimum firm type that is acceptable for a particular worker type.

Interestingly, the reservation worker type for a firm is less volatile than the reservation firm type for a worker. Even more, the decline in the reservation worker type for high-technology firms is greater than that for low-technology firms, which implies that high-technology firms are more prone to shift the demand for high-skill workers relative to their low-technology counterparts during contractions.

The line delimiting the efficient firm type lies away from the 45 degree line marking perfect assortative matching in the labor market, especially at the top of the set of feasible matches. Much of the the gains in terms of production efficiency during expansions comes from the bottom of this set. However, the implied gain in production efficiency is not negligible given that a substantial share of worker-firm matches concentrate on this part of the set during expansions.

Figure 6: Match Feasibility Over the Business Cycle

(A) Feasible Matches (B) Efficient Matches



Note: The figure shows the set of feasible matches (Panel A) and efficient matches (Panel B) during expansions and contractions. Feasible matches correspond to the minimum worker skill for firms and minimum firm technology for workers that results in a non-negative match surplus. Efficient matches for each worker type correspond to the firm technology $y^*(x, z_t) = \arg\max_y P_t(x, y)$.
Source: Author's calculations based on model simulations.

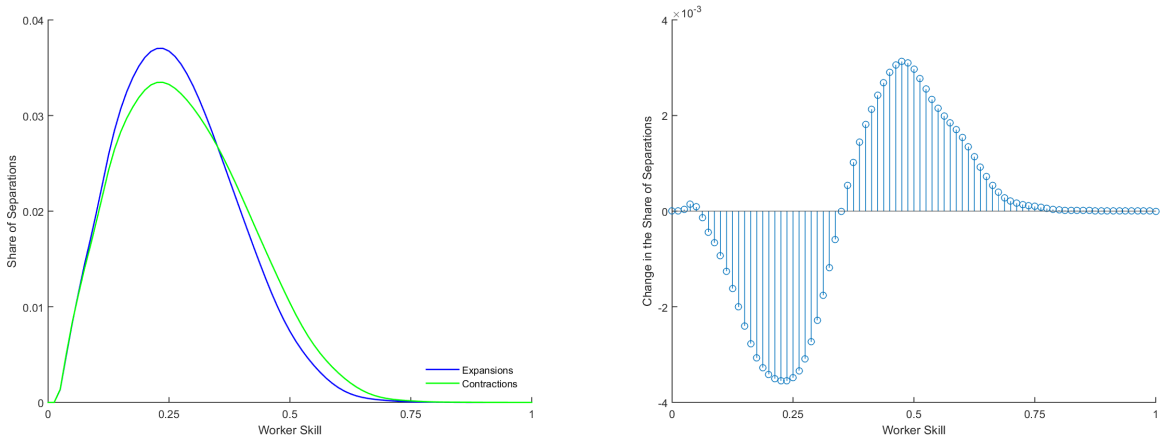
5.3 Match Dissolutions

Match dissolutions occur immediately after the realization of z_t. All matches whose surpluses are negative (i.e., infeasible matches) are scraped away from the economy. In Figure 7, I plot the share of separations during expansions and contractions (Panel A) and the change in the share of separations across the support of worker skills during contractions relative to expansions (Panel B). During expansions, roughly 90 percent of all match dissolutions occur among worker skills below 0.50. This figure is smaller during contractions, and a higher share of medium- and high-skill workers also experience a job loss.

In Appendix F.1, I further examine the share of separations across the wage support. Consistent with observational data, job loss befalls predominantly among low-wage workers during contractions. In turn, over 60 percent of separations during economic downturns occur among workers earning below the 25th percentile of the pre-shock wage distribution. These figures are also compatible with empirical studies finding that low-earners are among the most affected by job displacements during recessions, both in the U.S. (Aaronson et al., 2010; Autor, 2010; Couch and Placzek, 2010; Elsby et al., 2010; Farber, 2011) and Europe (Christensen et al., 2005; Chéron and Rouland, 2011).

Figure 7: Job Separations Over the Business Cycle

(A) Distribution of Separations (B) Change in the Distribution



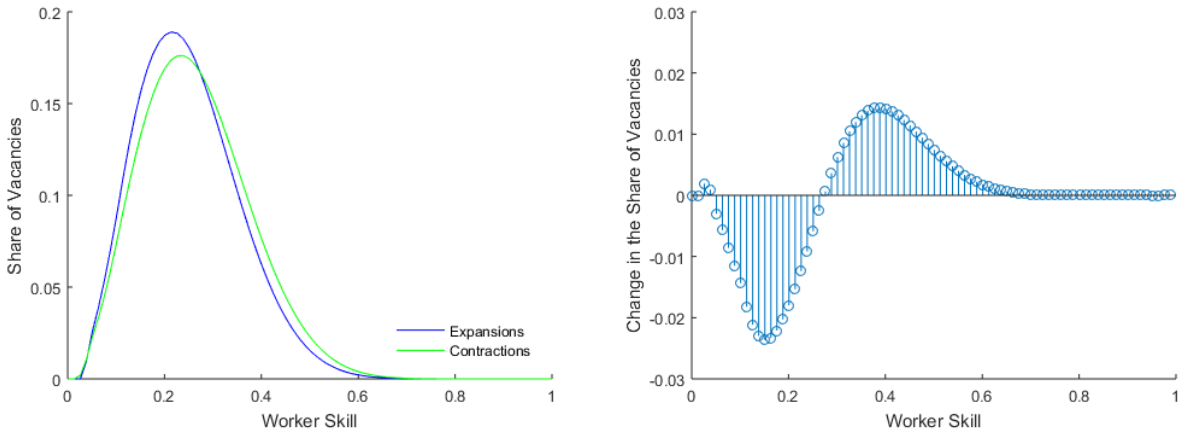
Note: The figure shows the share of job separations across the support of worker skills in expansions and contractions (Panel A) and the change in the share of job separations across different worker types in contractions relative to expansions (Panel B).
Source: Author's calculations based on model simulations.

5.4 Vacancy Advertisement

In Figure 8, I plot the share of vacancies advertised across different sub-markets during expansions and contractions (Panel A) and the change in the share of vacancies advertised in different sub-markets during contractions relative to expansions (Panel B). A direct implication of the targeted recruiting mechanism is that a bigger share of advertised vacancies is targeted to high-skill workers during contractions. During this period, a significant proportion of mass loss occurs at the bottom of the support of worker skills and the average targeted worker skill is 0.263 vis-à-vis 0.248 during expansions, implying an upskilling effect of 6 percent during recessions. This figure speaks to the sizable magnitude of upskilling during contractions.

Figure 8: Vacancy Advertisement Over the Business Cycle

(A) Distribution of Vacancies (B) Change in the Distribution



Note: The figure shows the share of advertised vacancies across the support of worker skills in expansions and contractions (Panel A) and the change in the share of advertised vacancies across different worker skills in contractions relative to expansions (Panel B).
Source: Author's calculations based on model simulations.

In Appendix F.2, I further delve on the characteristics of advertised vacancies in expansions and contractions. The average firm technology among recruiting firms declines from 0.287 in expansions to 0.278 during contractions. The probability of hiring per vacancy is fivefold higher during contractions (18.6 percent) relative to expansions (3.6 percent), in line with past work documenting a counter-cyclical job filling rate (Davis et al., 2012, 2013; Şahin et al., 2014). Also consistent with previous studies (Barlevy, 2002; Mustre-del-Río, 2014), the model implies that the expected duration of vacancies advertised during recessions is significantly lower during contractions (24 months) compared to expansions (69 months). Lastly, average entry wages are about 8.6 percent lower during contractions.

The observed counter-cyclical upskilling pattern is directly supported by recent empirical studies that document increases in skill requirements during and after the 2007-09 U.S. recession (Hershbein and Kahn, 2018; Burke et al., 2020; Modestino et al., 2020). By analyzing the text content of firm-level online job postings, these studies report that employers searched for workers with higher educational attainment and higher expertise in the occupation associated with the job position in the aftermath of the Great Recession. This pattern relates to the cyclically selective hiring of firms — the fact that less-experienced workers are less likely to be hired during recessions (Forsythe, 2022).

Diverse studies have incorporated, in a way or another, a component related to varying hiring standards of firms (Sedláček, 2014; Baydur, 2017; Merkl and van Rens, 2019). Recent developments have embedded this notion in the context of business cycle fluctuations and

conclude that firms hiring standards in terms of worker skills tend to increase during recessions, either because of firms' are risk averse with respect to unsuitable matches (Acharya and Wee, 2020) or because of their need to compensate for fixed job posting costs with a higher productivity in the presence of strong production complementarity (Huckfeldt, 2022).[31] By considering perfect labor market segmentation, my work is closer in spirit to the latter.

In the model, three different factors explain the observed shift in the distribution of advertised vacancies during contractions: worker heterogeneity, complementarity in joint production, and bargaining power. To better understand how each of these mechanisms affect vacancy advertising, in Figure 9 I plot the share of vacancies advertised across the support of worker types under the following counter-factual simulations: (i) reducing by 25, 50, and 75 percent the standard deviation of the distribution of worker skills σ^W (Panel A); (ii) reducing by 25, 50, and 75 percent the production complementarity parameter p_6 (Panel B); and (iii) fixing at 10, 15, and 20 percent the workers' bargaining power (i.e., contract size) parameter γ (Panel C). All these factors are present in the firm's optimal vacancy advertising condition for each sub-market described by equation (6).

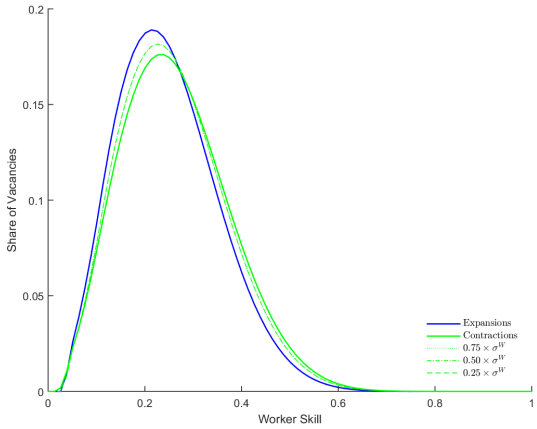
The most obvious determinant of the rightwards shift in the distribution of advertised vacancies in contractions is the diversity of worker skills. As shown in the graph in Panel A, reducing the dispersion in the distribution of worker skills attenuates the shift in the distribution of advertised vacancies. Less obvious, though, is the way how production complementarity and workers' bargaining power determine the cyclical variation in advertised vacancies. As can be seen from the graphs in Panels B and C, both a decrease in production complementarity and an increase in workers' bargaining power halt the upskilling effect observed during contractions through two different channels: a lower marginal gain in production — thereby, match-specific surplus — over the domain of x conditional on y, and a lower monopsony power from firms. Otherwise stated, while a decrease in p_6 implies that the expected marginal gain in terms of match surplus from hiring high-skill workers conditional on y becomes flatter, an increase in γ implies a reduction in the share of $S_t(x, y)$ that is kept by the firm. Combined with increasing vacancy advertising costs over x, a decrease in p_6 and an increase in γ deters firms' willingness to hire high-skill workers.

All in all, leaving worker type heterogeneity aside, the strong production complementarity between worker skills and firm technologies together with the high monopsony power of firms may be the two most important factors that generate the observed upskilling in the labor market during recessions.

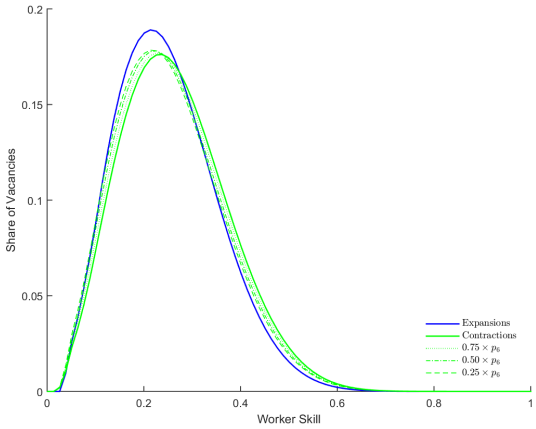
[31] In a related study, Berger (2018) builds a model where firms' restructuring during recessions increase the demand for high-skill workers.

Figure 9: Determinants of Targeted Recruitment by Firms

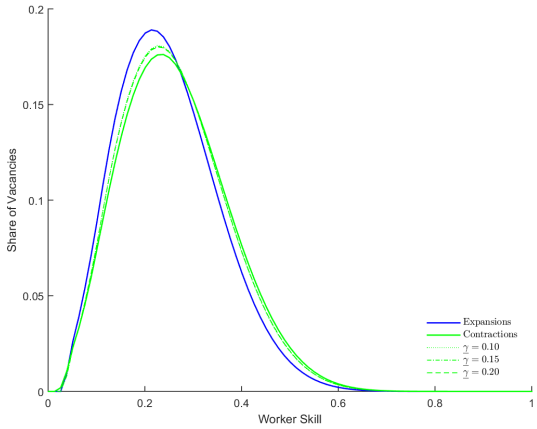
(A) Worker Heterogeneity



(B) Production Complementarity



(C) Bargaining Power



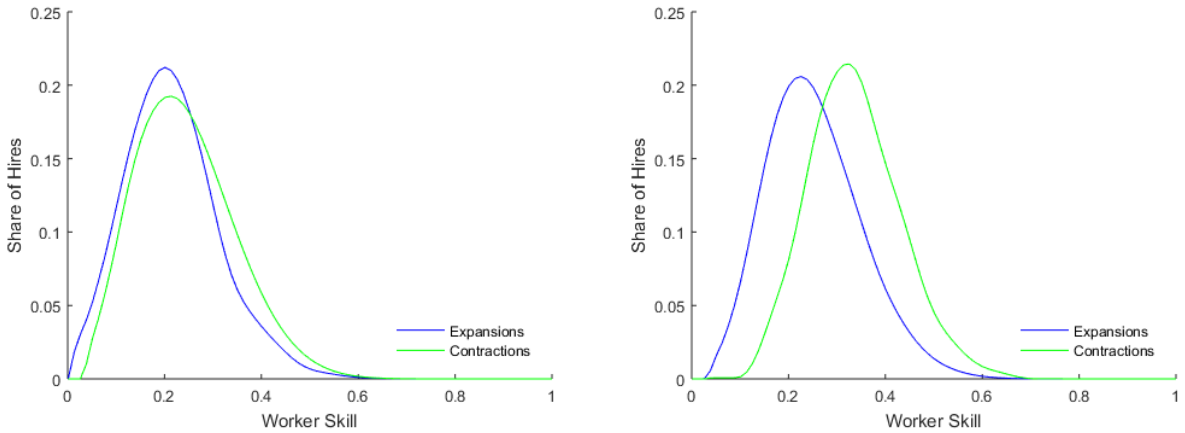
Note: The figure shows the share of advertised vacancies during expansions and contractions (blue and green solid lines, respectively) together with counter-factual simulations.
Source: Author's calculations based on model simulations.

5.5 Match Formations and Sorting

I close this section by examining the model's cyclical implications in terms of match formations and the degree of sorting in the economy. In Figure 10, I plot the share of hires from unemployment (Panel A) and hires from employment (Panel B) across the support of worker skills during expansions and contractions. The share of hires from both the unemployment (i.e., unemployment-to-employment transitions) and employment (i.e., job-to-job transitions) pools shift towards high-skill workers during contractions. This, naturally, is a direct consequence of targeted recruiting in the economy.

Figure 10: Distribution of Hires Over the Business Cycle

(A) Hires from Unemployment (B) Hires from Employment



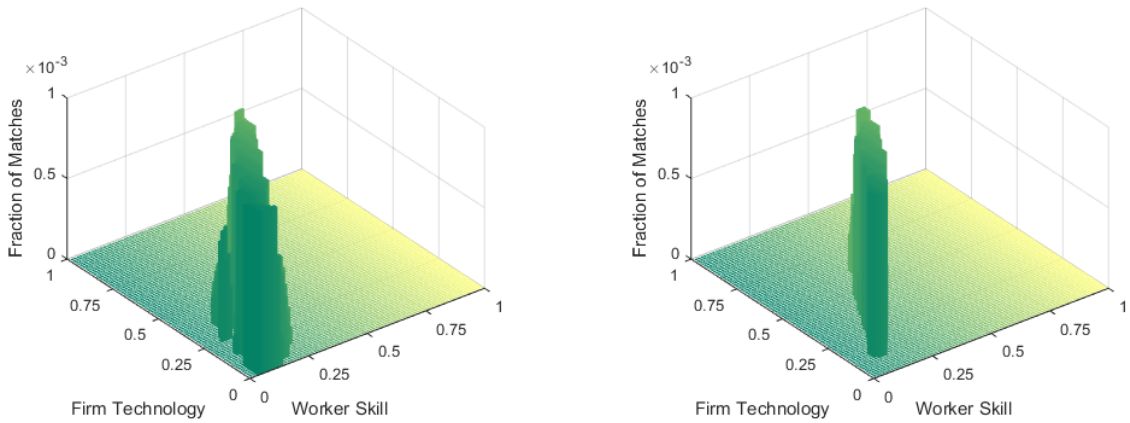
Note: The figure shows the share of hires from unemployment (Panel A) and the share of hires from employment (Panel B) across different sub-markets in expansions and contractions.
Source: Author's calculations based on model simulations.

Turning to the inspection of the degree of sorting in the labor market, in Figure 11, I plot the joint distribution of worker-firm matches during expansions (Panel A) and contractions (Panel B). From this figure, it is clear that there is substantial mass along the line corresponding to the boundary of reservation worker types for firms. However, the share of matches near the boundary is substantially lower during expansions. This occurs because job-to-job transitions are more common during expansions, implying that there is a significant re-allocation of workers towards high-technology firms (i.e., along the production efficiency line). This notion is supported by new empirical work documenting that the pace at which workers move up the productivity ladder increases during expansions (Bertheau et al., 2020; Haltiwanger et al., 2021).

In spite of the random nature of meetings between workers and firms, the equilibrium distribution of worker-firm matches is characterized by some degree of positive sorting. While the correlation between worker and firm types is roughly 0.30 during contractions, this figure amounts to 0.33 during expansions. In line with these figures, previous studies that utilize employer-employee administrative data in the U.S. report a rank correlation between worker and firm effects ranging between 0.10 and 0.40 (Sorkin, 2018; Song et al., 2019; Bonhomme et al., 2022; Crane et al., 2022; Lamadon et al., 2022).

Figure 11: Match Formations Over the Business Cycle

(A) Expansions (B) Contractions



Note: The figure shows the joint distribution of matches across worker skills and firm technologies during expansions (Panel A) and contractions (Panel B).
Source: Author's calculations based on model simulations.

6 Distributional Dynamics of Wages

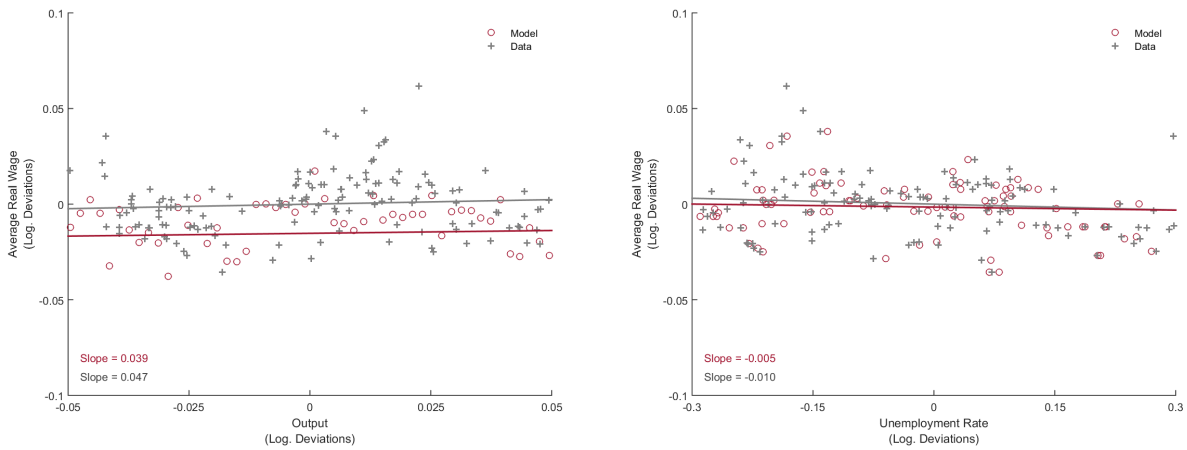
In this section, I present the model's predictions on the cyclicality of wages and its distributional dynamics. I further discuss the key mechanisms behind the cyclical changes in wage dispersion; namely, outside job offers and contract negotiation. Lastly, I reconvene the discussion on the change in the skewness of the wage distribution over the business cycle and present the model's ability to qualitatively reproduce the empirical facts from Section 2.

6.1 Wage Cyclicality

As a first step, I assess the model's ability to reproduce the cyclical trend of real wages. In Figure 12, I show model- and data-implied correlations between wages and output (Panel A) and between wages and unemployment (Panel B). The modest correlation between wages and output observed in the data is quite closely reproduced by the model. Respectively, these figures amount to 0.039 and 0.047. Qualitatively, the model reproduces fairly well the mild negative correlation between wages and unemployment. In particular, the model generates a correlation between the average wage and the unemployment rate of -0.005, half of that observed in the data.

Figure 12: Cyclicality of Wages

(A) Output (B) Unemployment



Note: The figure shows the model- and data-implied correlations between wages and output (Panel A) and between wages and unemployment (Panel B). Model-implied correlations are constructed by averaging wages across 100 equally-spaced bins of output/unemployment rate.
Source: Author's calculations based on CPS-ORG, BEA, BLS, and model simulations.

The figures derived from the model also conform with past accounts on the modest cyclicality of real wages (Bils, 1985; Beaudry and DiNardo, 1991; Christiano and Eichenbaum, 1992; Abraham and Haltiwanger, 1995).[32] This observation also relates to the "unemployment volatility puzzle" — the fact that the standard DMP model hardly matches the observed mild cyclicality of wages and large unemployment and vacancy fluctuations (Shimer, 2005; Costain and Reiter, 2008). Recent work argues that this puzzle can be at least partially solved by incorporating wage rigidity (Shimer, 2004; Hall, 2005; Costain and Reiter, 2008; Hall and Milgrom, 2008; Christiano et al., 2016), limited wage negotiation (Pissarides, 2009; Yamaguchi, 2010; Haefke et al., 2013), backward-looking components in wage negotiation (Gertler and Trigari, 2009; Michaillat, 2012; Koenig et al., 2022), or informational frictions (Kennan, 2010; Morales-Jiménez, 2022). In my model, wage rigidity obtains from infrequent contract negotiations among low- and medium-skill workers who account for a high share of the workforce, but, unlike the DMP model, labor market fluctuations are independent of equilibrium wages.

6.2 Cyclical Wage Dispersion

I next analyze how wage dispersion varies over the business cycle.

[32] Solon et al., (1994) argue that the mild cyclicality of real wages documented in the literatures largely owes to a composition bias that overweights the importance of wages from low-skill workers during expansions.

Wage Distribution During Expansions and Contractions. In Figure 13, I plot the probability distribution (Panel A) and the swarm scatter chart (Panel B) from the wage distribution during expansions and contractions. The figure shows interesting patterns pointing towards an increased skewness of the wage distribution during contractions relative to expansions.

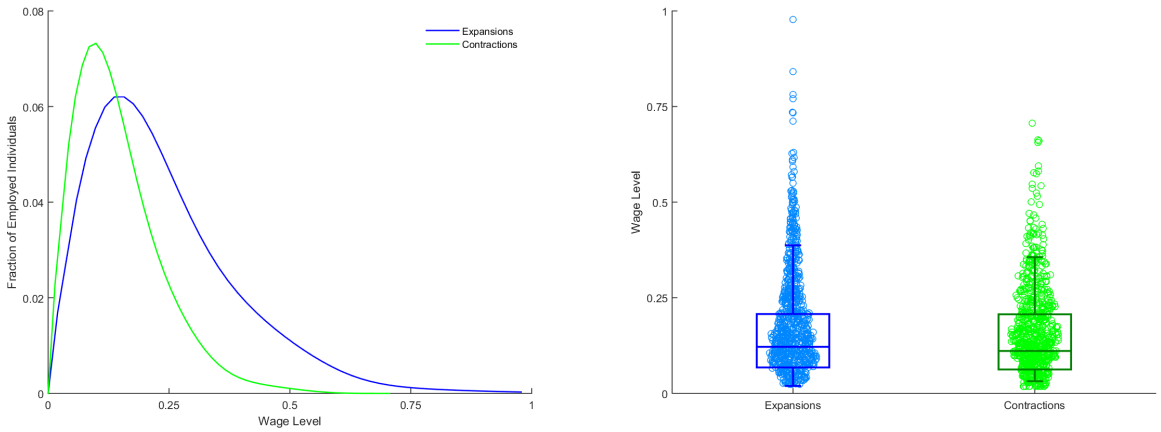
First, the mean and median wages during expansions are, respectively, 0.154 and 0.122. During contractions, these figures are 0.124 and 0.0964. Thus, while the ratio of median to mean is 0.789 during expansions, the corresponding figure is 0.775 during contractions, so the median is much more lower than the mean in contractions relative to expansions. This implies that wages at the top do not decrease as much as wages at the bottom of the distribution, pulling the mean wage up and farther away from the median wage.

Second, the 10th, 50th, and 90th percentiles are, respectively, 0.035, 0.122, and 0.313 during expansions. These same figures amount to 0.027, 0.096, and 0.259 during contractions. Thus, the 10th, 50th, and 90th percentiles are 25, 23, and 17 percent lower during contractions relative to expansions. This implies that wages at the bottom and middle tend to fall faster than wages at the top of the distribution during contractions.

Third, the Kelley skewness during expansions is 0.380 whereas that during contractions is 0.399. Thus, the Kelley skewness is 5 percent higher during contractions relative to expansions. This number is similar to what is recounted in Section 2 and implies that the skewness of the wage distribution is higher during contractions relative to expansions, as observed in the data.

Figure 13: Wage Distribution Over the Business Cycle

(A) Probability Distribution (B) Swarm Scatter Chart



Note: The figure shows the probability distribution (Panel A) and the swarm scatter chart (Panel B) of the wage distribution during expansions and contractions. Swarm scatter charts contain box plots, where the central boxes mark the 25th, 50th, and 75th percentiles, and the bars mark the 10th and 90th percentiles of the corresponding wage distributions. The Kelley coefficients of skewness during expansions and contractions are, respectively, 0.380 and 0.399.
Source: Author's calculations based on model simulations.

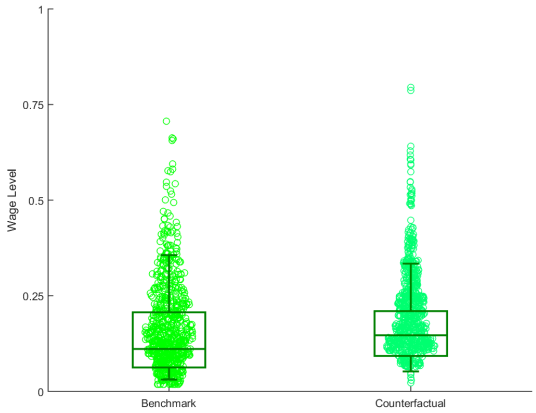
Cyclical and Frictional Components of Wages. A closer inspection of equations (14) and (15) reveals that cyclical changes in wage levels are essentially determined by changes in the employment contract size and changes in the match surplus. Which of these two components, γ or $S_t(x, y)$, is the leading cause of the observed cyclical change in the wage distribution is, thus far, unclear. To assess how each of these components affect the wage distribution during contractions, I perform two counterfactual simulations: one in which I maintain the match surplus fixed at its value observed during expansions but allow for changes in employment contract sizes and other in which I keep the employment contract size fixed at its value observed during expansions but allow for changes in the match surplus. While the first simulation teases out the contribution of γ, the second simulation tracks down the contribution of $S_t(x, y)$ to the wage distribution during contractions.

In Panels A and B of Figure 14, I present swarm scatter charts of the wage distribution observed in contractions along with the wage distributions that result from the two counterfactual simulations. In Panels C and D, I plot the corresponding Q-Q plots. While the graphs at the top show the dispersion across different wage values, the graphs at the bottom plot the quantiles of the benchmark distribution against the quantiles of the counterfactual distributions. The smaller the gap between the linear fit line and the 45 degree line, the better the simulated distribution mimics the shape of the wage distribution during

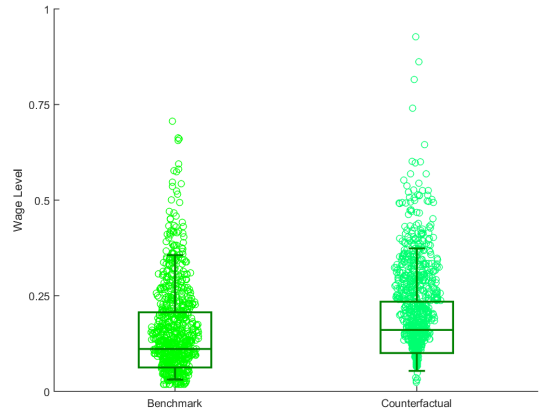
contractions.

Figure 14: Counterfactual Wage Distributions During Contractions

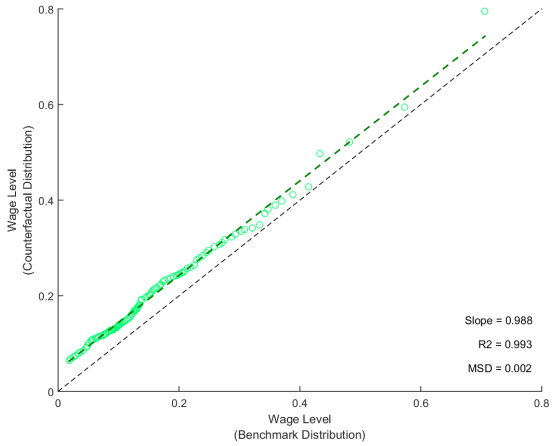
(A) Fixed $S_t(x,t)$ (Swarm Scatter Chart)



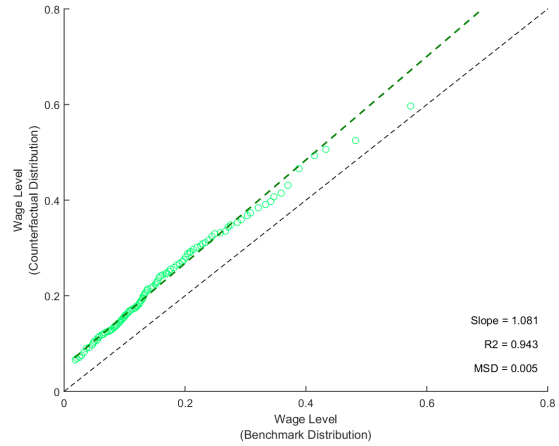
(B) Fixed γ (Swarm Scatter Chart)



(C) Fixed $S_t(x,t)$ (Q-Q Plot)



(D) Fixed γ (Q-Q Plot)



Note: The figure shows swarm scatter charts (Panels A and B) and Q-Q plots (Panels C and D) of the model-implied wage distribution observed during contractions along with wage distributions that result from two counterfactual simulations. The first simulation keeps $S_t(x,y)$ fixed at the value observed during expansions and allows for changes in γ only. The second simulation keeps γ fixed at the value observed during expansions and allows for changes in $S_t(x,y)$ only.
Source: Author's calculations based on model simulations.

A visual inspection of the swarm scatter charts reveals that changes in the employment contract size yield a wage distribution more similar to what is observed in contractions. However, changes in γ alone do not suffice to explain wage dispersion at the bottom of the distribution. By contrast, allowing for changes in the match surplus yields a distribution with a low mass at the bottom end of the wage support, opposite to what is observed in the benchmark distribution. This also becomes evident when comparing the Q-Q plots, where the mean squared deviation for the fixed $S_t(x,y)$ and fixed γ simulations are 0.002

($R^2 = 0.993$) and 0.005 ($R^2 = 0.948$) respectively. The results from these simulations are indicative of the importance of contract negotiation in determining cyclical changes in the wage distribution.

6.3 Contract Negotiation and Job Offer Arrival Rate

I now turn to inspect the theoretical underpinnings of the distributional dynamics of wages. As described before, contract negotiation is central in explaining the cyclical dynamics of the wage distribution in the model. Yet, behind contract negotiation, is the heterogeneity in available job opportunities and how it changes over the business cycle.

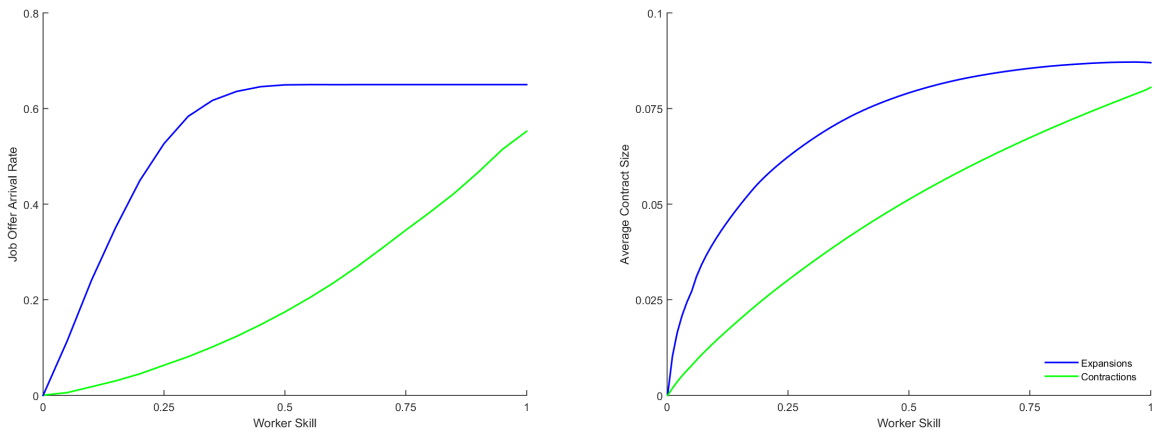
To see how these two elements relate, in Figure 15, I plot the job offer arrival rate (Panel A) and the average contract size (Panel B) across the support of worker skills during expansions and contractions. A significant decline in the job offer arrival rate occurs at the middle and bottom of the support of worker skills. For instance, the job offer arrival rate of workers with skill levels between 0.35 and 0.35 in contractions is roughly 65 percent lower than that in expansions while this same figure sums up to 75 percent for workers with skill levels below 0.35. This does not occur with workers at the top end of the support of worker skills whose job offer arrival rates are between 15 and 20 percent lower in contractions relative to expansions. These numbers reveal that the extent to which job offers differ across worker types is large and that low-skill workers are the ones experiencing substantially lower employment opportunities during contractions. Past work documents similar cyclical patterns when analyzing the heterogeneity of the job finding rate across workers in the U.S. economy (Sedláček, 2014; Barnichon and Figura, 2015).

With regards to the average contract size, the results are striking. The average contract size in the economy is 0.081, reaching 0.089 during expansions and 0.041 during contractions.[33] These figures are indicative of a high bargaining power that employers exhibit, consistent with ample empirical evidence (Boal and Ransom, 1997; Ashenfelter et al., 2010; Webber, 2015; Manning, 2021a; Ashenfelter et al., 2022; Berger et al., 2022a; Card, 2022). Analyzing the dynamics of the cross-sectional variation in contract sizes, it can be observed that much of the reduction in the average contract size between expansions and contractions occur at the middle of the support of worker skills. This, in turn, may explain why wages at the middle of the wage distribution decline at a higher pace during recessions as discussed previously.

[33] Lise and Robin (2017) report an average contract size of around 0.115 for newly hired workers in the economy. In my model, this adds up to roughly 0.045, being the heterogeneity in the job offer arrival rate the main cause of discrepancy between these two figures.

Figure 15: Job Offer Arrival Rate and Contract Size Over the Business Cycle

(A) Job Offer Arrival Rate (B) Contract Size



Note: The figure shows job offer arrival rates (Panel A) and average contract sizes (Panel B) across the support of worker skills during expansions and contractions. The job offer arrival rate corresponds to $\lambda_t(x)$ and the average contract size corresponds to $\iint \gamma\, g_t(x, y, \gamma)\, \mathrm{d}\gamma\, \mathrm{d}y$.
Source: Author's calculations based on model simulations.

6.4 Impulse Response Functions

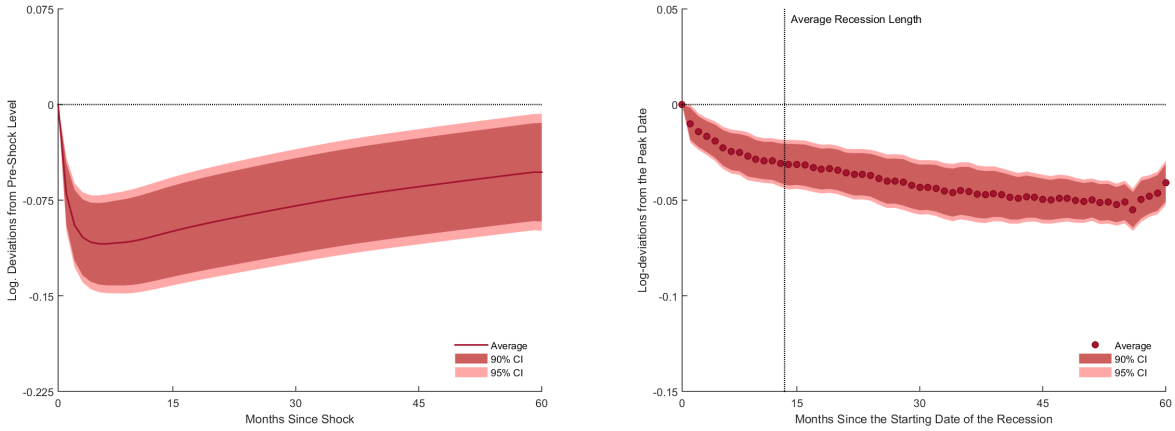
I next present impulse response functions (IRFs) of the median wage, skewness of the wage distribution, and P5010 and P9050 ratios to a 6 percent decrease in output. To construct the IRFs, I depart from a steady-state equilibrium $z_0 = 1$ and disturb the economy with a one-period-shock of size -3.5σ in the innovation parameter of the AR(1) process of the aggregate productivity shock, ε_t, targeting the desired decrease in output.

Median Wage. In Figure 16, I plot the resulting IRF of the median wage to a 6 percent decrease in output (Panel A) and its observational counterpart derived from individual-level data from the CPS (Panel B). The negative shock generates a sizable and persistent decline in the economy's median wage. Specifically, the median wage declines by around 10 percent in the months following the shock, with no signs of full recovery even 60 months after the shock. The median wage from the data resembles a similar cyclical pattern, decaying by around 6 percent in the months following the starting date of recessions.[34]

[34]These figures are similar to the documented 6 percent decline in median real hourly earnings and 8 percent decline in median real weekly earnings in the years following the starting date of the Great Recession in the U.K. (Cribb and Johnson, 2019).

Figure 16: Impulse Response Function of the Median Wage

(A) Model IRF (B) Data Counterpart



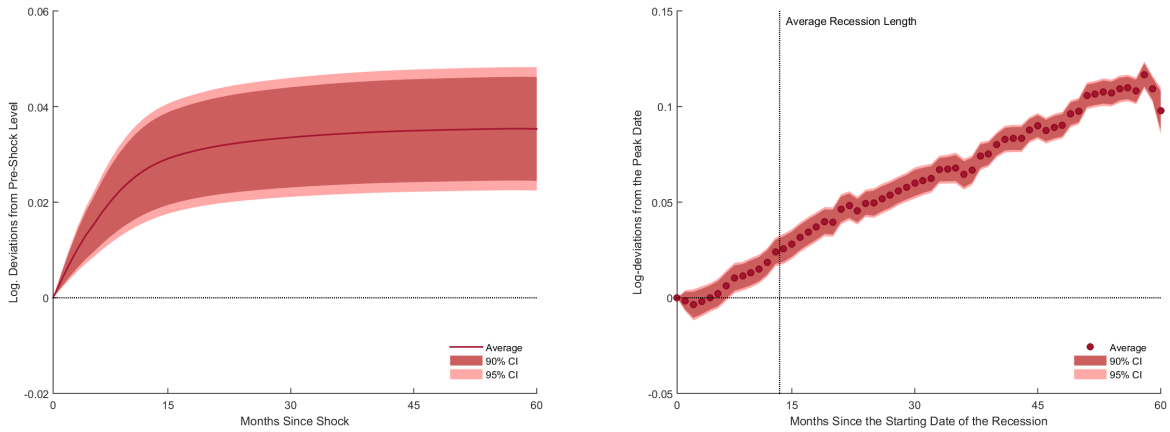
Note: The figure shows the impulse response function of the median wage to a 6% decrease in output (Panel A) and the median wage of the distribution of real wages, in log-deviations from the peak date, at months 1 through 60 since the starting date of recessions occurring in the U.S. over 1980-2019 (Panel B). Real wages in the data are computed by deflating nominal hourly rates by the PCE. Linear trends, estimated with data from months -24 through 84 from/since the starting date of recessions, have been removed from data series. Dark and light shaded areas correspond to the 90% and 95% confidence intervals, respectively, constructed from 1,000 bootstrap samples for each month.
Source: Author's calculations based on CPS-ORG, NBER, and model simulations.

Skewness. In Panel A of Figure 17, I present the impulse response function of the Kelley skewness of the wage distribution to a 6 percent decrease in output. In Panel B, I reproduce its observational counterpart corresponding to the graph in Panel A of Figure 1. The model captures the observed increase in the skewness of the wage distribution in recessions.

In the model, the Kelley skewness increases, on average, by 3.5 percent in the months following the negative aggregate productivity shock. This figure represents nearly 60 percent of the observed average increase in the skewness of the wage distribution (6.25 percent) between months 1 through 60 after the starting date of recessions observed in the U.S. over 1980-2019. Even more, the increase in the skewness of the wage distributions persists after 60 months from the shock, consistent with what is observed in the data. Yet, the increase in Kelley skewness in the model reaches a plateau around the month 30 after the shock and remains stable thereafter, a pattern that is not observed in the data. In turn, the skewness of the wage distribution in the data only shows a negative slope after month 55 from the starting date of the recession. A possible explanation for this divergence is the faster recovery of the labor market after economic downturns that is implied by the model.

Figure 17: Impulse Response Function of the Skewness of the Wage Distribution

(A) Model IRF (B) Data Counterpart

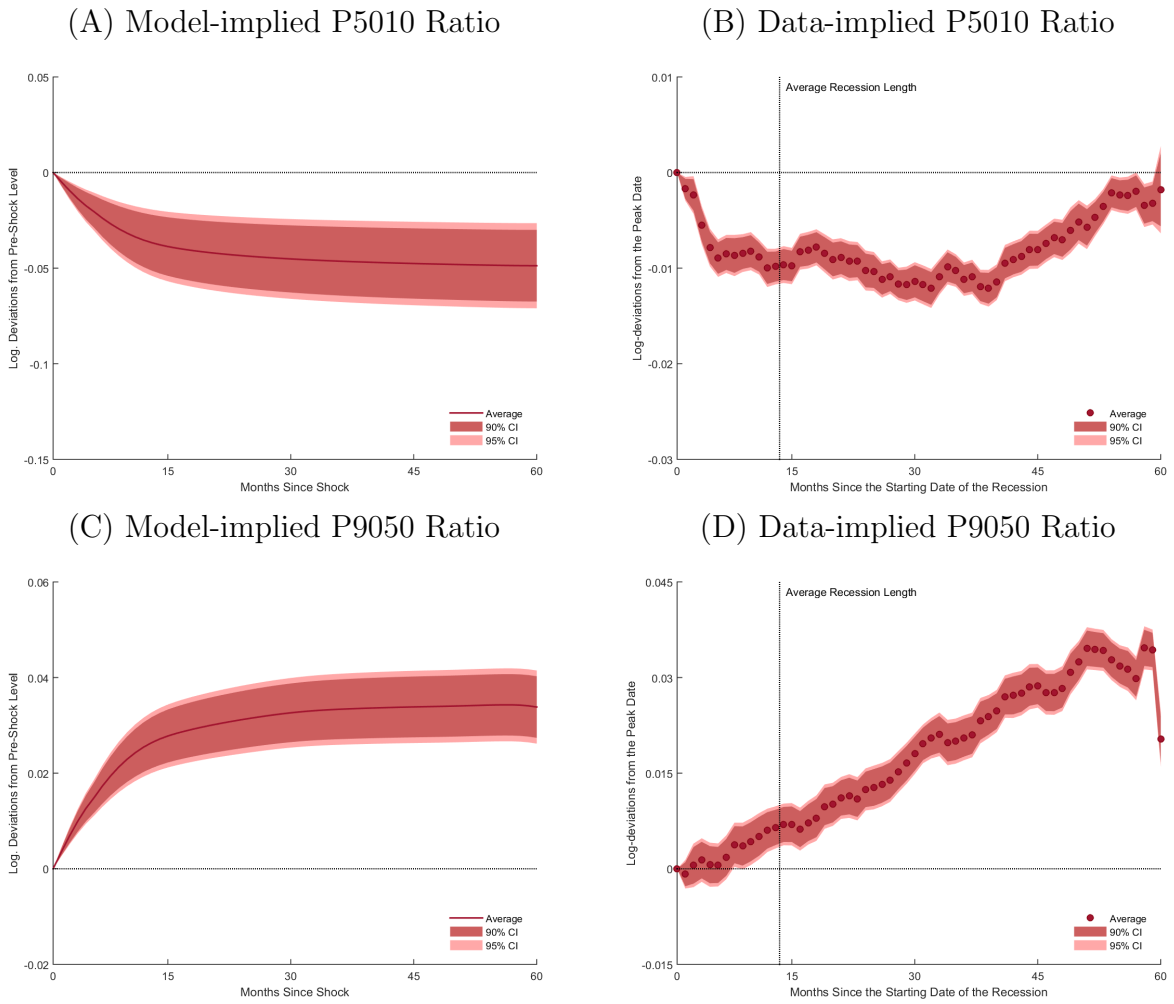


Note: The figure shows the impulse response function of the Kelley skewness to a 6% decrease in output (Panel A) and the average Kelley skewness of the distribution of real wages, in log-deviations from the peak date, at months 1 through 60 since the starting date of recessions occurring in the U.S. over 1980-2019 (Panel B). Real wages in the data are computed by deflating nominal hourly rates by the PCE. Linear trends, estimated with data from months -24 through 84 from/since the starting date of recessions, have been removed from data series. Dark and light shaded areas correspond to the 90% and 95% confidence intervals, respectively, constructed from 1,000 bootstrap samples for each month.
Source: Author's calculations based on CPS-ORG, NBER, and model simulations.

P5010 and P9050 Percentile Ratios. In Panel A of Figure 18, I present the impulse response functions of the P5010 and P9050 ratios (Panels A and C) to a 6 percent decrease in output. In Panels B and D, I reproduce their corresponding observational counterparts taken from Figure 2.

The model replicates the downward trend in the P5010 ratio observed in the data. Yet, the decrease in the P5010 ratio in the model is almost fivefold higher than that observed in the data. Turning to the upper half of the distribution, again, the model replicates quite well the observed increase in the P9050 ratio with only a relatively small upward bias relative to what is observed in the data. All in all, the model is capable of reproducing the contraction at the bottom half and the expansion at the top half of the wage distribution observed during economic downturns and subsequent recovery periods, as documented in Section 2.

Figure 18: Impulse Response Functions of the P5010 and P9050 Ratios



Note: The figure shows the impulse response function of the P5010 and P9050 ratios (Panels A and B) to a 6 percent decrease in output and the average P5010 and P9050 ratios, in log-deviations from the peak date, of the distribution of real wages at months 1 through 60 since the starting date of recessions occurring in the U.S. over 1980-2019 (Panels C and D). Real wages in the data are computed by deflating nominal hourly rates by the PCE. Linear trends, estimated with data from months -24 through 84 from/since the starting date of recessions, have been removed from data series. Dark and light shaded areas correspond to the 90% and 95% confidence intervals, respectively, constructed from 1,000 bootstrap samples for each month.
Source: Author's calculations based on CPS-ORG, NBER, and model simulations.

Contribution of Wage Dispersion at Different Segments. I next quantify the contribution of dispersion at the bottom and top of the wage distribution. In Table 4, I show the fraction of the P90-P10 gap explained by the P50-P10 and the P90-P50 gaps at different points over the cycle. The observational counterparts for these figures are those reported in Table 1, which I also reproduce in the table for ease of reading.

Table 4: Relative Dispersion in the Wage Distribution

	Peak Date	Recession (months 1-20)	Recovery (months 21-60)
(P50 − P10)/(P90 − P10)			
Model	0.315	0.276	0.300
Data	0.314	0.311	0.303
(P90 − P50)/(P90 − P10)			
Model	0.685	0.724	0.700
Data	0.686	0.689	0.697

Note: The table shows the model- and data-implied factions of the P90-P10 gap explained by the P50-P10 gap (i.e., bottom half) and the P90-P50 gap (i.e., top half) of the wage distribution during the peak date, recession, and recovery periods. The peak date is defined as the month preceding the starting date of the recession. Respectively, recession and recovery periods are defined the time span between months 1 through 20 and months 21 through 60 after the peak date. Source: Author's calculations based on data from the CPS-ORG, NBER, and model simulations.

The model results indicate that dispersion at the top becomes more important in explaining the overall increase in dispersion of the wage distribution observed in recession and recovery periods. In particular, dispersion at the bottom half declines by between 5-12 percent whereas dispersion at the top half of the wage distribution increases by between 2-6 percent during recessions and subsequent recoveries. These figures conform with the cyclical patterns observed in the data and are indicative of the capability of the model to reproduce changes in the wage distribution over the business cycle.

6.5 Discussion

I close the analysis by summarizing and discussing the model's results on the distributional dynamics of wages.

First, the model is capable of reproducing the mild cyclicality of real wages that is observed in the data. While past studies have incorporated wage rigidities into the standard DMP model to match the data (Shimer, 2004; Hall, 2005; Costain and Reiter, 2008; Hall and Milgrom, 2008), my model replicates this pattern, as well as the high response of unemployment and vacancy rates to changes in aggregate productivity, in a totally flexible wage bargaining framework. In this regard, ample labor market fluctuations together with a relatively mild cyclicality of wages arise in the model from a combination of aggregate productivity shocks that act as match-specific shocks by changing the value of the match surplus

(Robin, 2011; Lise and Robin, 2017) and limited wage negotiation from heterogeneous job opportunities across worker types (Pissarides, 2009; Haefke et al., 2013).

Second, employers exhibit a seemingly high bargaining power, which is empirically supported by several studies (Boal and Ransom, 1997; Ashenfelter et al., 2010; Webber, 2015; Manning, 2021a; Ashenfelter et al., 2022; Berger et al., 2022a; Card, 2022). In this context, the relatively mild cyclicality of wages that displays both in the model and data may result from a high degree of monopsony in the labor market that impedes that a higher productivity manifest into higher wages in the economy, yielding the low observed correlation between aggregate output and wages. In the model, the high employer bargaining power, especially during contractions, arises from the relatively low job offer arrival rate and the low number of competitors for labor services (Azar et al., 2020, Benmelech et al., 2022; Rinz, 2022).[35]

Third, contract negotiation through outside employment opportunities available to workers is of utmost importance in explaining cyclical variations in the wage distribution. In the model, contract negotiation (i.e., changes in the employment contract size) on its own can explain 60 percent of the observed increase in the skewness of the wage distribution (and 85 percent of the increase in the P9050 ratio) during recessions. This result is consonant with previous studies that highlight the role of outside job offers as a mean of increasing workers' bargaining positions (Bontemps et al., 1999; Postel-Vinay and Robin, 2002; Cahuc et al., 2006; Yamaguchi, 2010; Hall and Krueger, 2012; Bagger and Lentz, 2019).

Fourth, most of the variation in employment contract sizes over the business cycle concentrates among medium-skill workers who have a substantive representation in the workforce. This result may accommodate the fact that both the contraction at the bottom half and the expansion at the top half of the wage distribution arise from a significant drop of the median wage. By contrast, employment contract sizes show a lower volatility at the extremes of the support of worker skills as low-skill workers tend to receive lower while high-skill workers tend to receive higher outside job offers irrespective of the point in the cycle.

Lastly, the model performs surprisingly well in reproducing the decline in the median wage, the increase in the skewness, the decline in the P5010 ratio, and the increase in the P9050 ratio of the wage distribution during recessions relative to pre-recession periods that are observed in the U.S. economy over the last forty years. Key to explain these patterns is the targeted recruiting mechanism by firms that prevents wages at the top of the distribution from falling swiftly. This is achieved by shifting the distribution of advertised vacancies

[35] In a recent compendium of studies on monopsony in the labor market, Ashenfelter et al. (2022) conclude that "(...) renewed public interest in employer market power and monopsony attest the broader issues related to wage stagnation that currently confront public policy."

towards high-skill workers which increases the employment prospects of high-skill workers relatively more than their low-skill counterparts, generating the higher cross-sectional dispersion at the top of the wage distribution that is observed during recessions.

7 Welfare Implications

Up to this point I have analyzed the decentralized economy where firms make recruiting decisions based on state variables. In this section, I compare the decentralized equilibrium allocation with those arising from a centralized mechanism where a social planner makes all relevant decisions conditional on the state variables. This comparison enables me to quantify the aggregate output and workers' welfare losses arising from allocative inefficiencies in the economy. Further, I examine the implications in terms of cyclical wage dispersion and examine potential policy interventions that may bring the decentralized equilibrium allocation closer to the social optima.

7.1 Sources of Net Output Loss

In a decentralized setting, frictions that are inherent to the process of matching workers to firms can generate productive inefficiencies thereby output losses to society. A commonly held view is that these inefficiencies lead to a socially sub-optimal unemployment rate as the externalities generated by the search behavior of agents are not considered (Mortensen, 1982; Hosios, 1990; Moen, 1997). In my model, these inefficiencies can be exacerbated by the presence of heterogeneous job opportunities across sub-markets that could generate more or less welfare losses at different points over the cycle. I revise three different sources of productive inefficiencies: unfilled jobs, ex-post sub-optimal jobs, and mismatch. In Appendix F.3, I provide details on the accounting of each of these sources of productive inefficiencies.

Unfilled Jobs. A first source of net output loss arises from unfilled vacant jobs that make firms incur in excessive costs related to job creation. Unfilled vacant jobs abound in sub-markets with high employment levels and where matches are highly productive. For one thing, a high employment rate means that the pool of job seekers is mainly composed of employed workers whose search efficiency is low. For another, a high productivity among existing matches implies that recruiting firms find it more difficult to poach workers out of incumbent ones. While the first case implies that the rate at which workers meet firms decay, the second case implies that the rate at which job offers get turned down by employed workers increase. Overall, these two cases involve a lower job filling rate and therefore high

costs associated with job creation.

Ex-post Sub-optimal Job Creation. A second source of net output loss owes to the presence of ex-post sub-optimal job creation. This encompasses newly filled jobs whose gains in terms of production enhancement are lower than the costs of creating them. Formally, these are jobs such that: $p_t(x, y) - b_t(x) < c(1, x)$ or $p_t(x, y) - p_t(x, \hat{y}) < c(1, x)$. Respectively, they mirror situations where the cost of advertising a vacancy exceeds the gains of joint production with workers hired from unemployment or poached from another firm. Privately, firms are ex-ante willing to advertise these vacancies given the expected future gains of employing such workers. Ex-post, and from a social perspective, it would have been better that such workers remained unemployed or matched with their previous employers.

Mismatch. A third source of net output loss comes from mismatch in the labor market. Given $y_t^+(x) = \arg\max_y p_t(x, y(x, z_t))$, and provided that $p_t(x, y_t^+(x)) - b_t(x) \geq c(1, x)$, any match between an x-type worker and a y-type firm such that $y \neq y_t^+(x)$ generates a productive inefficiency in the sense that it involves forgone output. This inefficiency arises because low-technology firms are encouraged to advertise vacancies among high-skill workers given the possibility of extracting high rents from those matches. Besides, workers are also willing to accept such job offers in their search for a better bargaining position and/or job prospect.

7.2 Social Optima

Social optima can be achieved through a centralized allocation mechanism where a social planner makes all relevant decisions in the economy. The social planner takes the information contained in the state variables and provides an optimal distribution of advertised vacancies that maximize output net of vacancy advertisement costs, taking into account the implied matching frictions in each sub-market. I defer the analysis of the unconstrained social planner who is not conditioned by matching frictions to Appendix F.4.[36]

The constrained social planner brings into consideration matching frictions in her optimization problem and cannot move workers across employment states and/or firms at will. Instead, she chooses the number of vacancies advertised by each y-type firm in each sub-market to maximize output net of vacancy advertisement costs. This distribution of vacancies then yields an allocation $h_t^{\text{SP-C}}(x, y)$ via the matching function. Specifically, the

[36] By comparing the equilibrium allocations of the constrained and unconstrained social planners, I am able to quantify the costs of both matching frictions and inefficient assignments in the economy.

allocation $h_t^{\text{SP-C}}(x,y)$ obtains from solving:

$$
\begin{aligned}
h_t^{\text{SP-C}}(x,y) = \arg\max_{v_t(x,y)} \; \mathcal{Y}_t(x) &\equiv \int p_t(x,y)\, h_t(x,y)\, \mathrm{d}y \; + \; b_t(x)\, u_t(x) - \int c\big(x, v(x,y)\big)\, \mathrm{d}y \\
\text{s.t.:} \quad \mathcal{V}_t(x) &= \int v_t(x,y)\, f(y)\, \mathrm{d}y \\
\mathcal{M}_t(x) &= m\big(\mathcal{L}_t(x), \mathcal{V}_t(x)\big) \\
&\text{(9) and (10)}\,,
\end{aligned}
$$

given the aggregate state z_t, the initial conditions (1) and (2), and the set of feasible matches implied by (8). Since vacancy advertisement costs are homogeneous across firm types, the social planner chooses to advertise vacancies only from the $y_t^+(x)$-type firm in each submarket, provided that the gains in terms of output exceed the costs of advertising the implied measure of vacancies. Vacancies advertised by any other firm type would generate mismatch and thereby productive inefficiencies.

7.3 Net Production and Labor Market Equilibrium

In Table 5, I present the net production and its components (Panel A), the equilibrium labor market distributions (Panel B), and the sources of productive inefficiencies (Panel C) for the decentralized and centralized economies during expansions and contractions. For brevity purposes, I focus on principally in contraction periods when commenting the results.

Net Production. In contractions, the net production under the decentralized equilibrium is 84.6; almost 4 percent less that what is observed during expansions. Roughly 90 percent of aggregate production is composed of market or joint production between workers and firms and vacancy advertising costs amount for near 10 percent of aggregate production in the economy.

Interestingly, the social planner increases the level of aggregate production by decreasing market or joint production in the economy. In this line, joint production under the centralized equilibrium amounts for 79.5 percent of aggregate production. The social planner further reduces vacancy advertising costs, which amount to 2.6 percent of aggregate production and are four times less of that implied by the decentralized equilibrium. Overall, the value of net production under the centralized economy is 94, 10 percent higher than that of the decentralized economy.

Labor Market Distributions. Directly tied to the reduction in joint production is the

fact that the social planner assigns a higher fraction of workers to home production. In this aspect, the unemployment rate under the centralized equilibrium is 10 percent whereas that under the decentralized equilibrium is 6.6 percent. Even more, the vacancy rate under the centralized equilibrium is significantly lower than that of the decentralized equilibrium. Together with the fact that the social planner cannot induce separations at will, this implies that the higher unemployment rate under the centralized equilibrium results predominantly from a lower job finding rate. This also becomes apparent in the lower tightness ratio which is more than 50 percent lower than that of the decentralized equilibrium and implies that there are substantially less vacant jobs for each job seeker in the economy. In sum, the social planner increases net output by creating a lower number of jobs in the economy.

Quantifying Productive Inefficiencies. Socially sub-optimal jobs account for 94.5 percent of productive inefficiencies under the decentralized equilibrium in contractions. Unfilled jobs and mismatch account only for 5.5 and 0.1 percent of productive inefficiencies, respectively. Thus, most of the net output loss under the decentralized equilibrium comes from sub-optimal job creation.

These figures are in sharp contrast to those observed under the centralized equilibrium where almost the totality of unproductive inefficiencies come from mismatch. Importantly, this misallocation of productive resources in the economy arises from already existing jobs as job creation is relatively low under the centralized equilibrium. If allowed, the social planner would terminate those matches and re-allocate those workers to a more productive state with the aim of increasing net production in the economy.

The Role of Vacancy Advertising Costs and Matching Frictions. In Appendix F.4, I present the results implied by the unconstrained social planner's allocation. The net output under this scenario mount up to 97.8, representing 13 percent more than that of the decentralized equilibrium. Furthermore, the costs generated solely by frictions and vacancy advertisement in the labor market add up to about 3 percent of the net output of the constrained social planner. Of particular interest is the fact that the unconstrained social planner allocates more workers into home production, giving rise to an astonishing 16 percent unemployment rate.

Table 5: Net Production under Different Economies

	Expansions		Contractions	
	Decentralized	Constrained Social Planner	Decentralized	Constrained Social Planner
	Panel A: Components of Net Production			
Net Production	87.985	93.773	84.551	93.976
Aggregate Production	100.000	98.014	94.139	96.458
Joint Production	96.320	96.951	83.874	76.662
Home Production	3.680	1.063	10.265	19.796
Vacancy Advertisement	-12.015	-4.237	-9.588	-2.482
	Panel B: Labor Market Distributions			
Unemployment Rate (U_t)	0.039	0.051	0.066	0.099
Vacancy Rate (V_t)	0.035	0.014	0.017	0.007
Tightness Ratio (θ_t)	0.739	0.487	0.532	0.238
	Panel C: Productive Inefficiencies			
Unfilled Jobs	45.409 %	1.004 %	5.466 %	0.412 %
Socially Sub-optimal Jobs	54.562 %	0.000 %	94.526 %	0.000 %
Mismatch	0.029 %	98.996 %	0.008 %	99.588 %

Note: The table shows the components of net aggregate production (Panel A), the labor market distributions (Panel B), and the sources of productive inefficiencies (Panel C) resulting from the equilibrium allocations of the decentralized and the constrained social planner economies during expansion and contraction periods. Expansion periods are defined as $z_t = [0.95; 1.05]$ and contraction periods are defined as $z_t = [0.70; 0.75]$ (6 percent decrease in output relative to expansion periods). The figures in Panel A are normalized relative to the aggregate production level of the decentralized equilibrium allocation during expansion periods. The tightness ratio is calculated as $\theta_t = \int \theta_t(x)\, l(x)\, \mathrm{d}x$. Unfilled jobs refer to the measure of advertised vacancies that did not meet a job seeker or were turned down by employed workers. Socially sub-optimal jobs refers to the measure of newly created jobs whose productivity gains are lower than the costs of vacancy advertisement. Mismatch refers to the measure of prevailing or newly created jobs between x-type workers and y-type firms for $y \neq y_t^+(x)$, where $y_t^+(x) = \arg\max_y p_t(x, y(x, z_t))$. Additional details are described within the table.
Source: Author's calculations based on model simulations.

7.4 Workers' Welfare

I next compare workers' welfare under the two scenarios. Given the assumption of linear utility, workers' welfare, denoted by $\mathcal{W}_t$, results from adding up labor income and home production. Formally, $\mathcal{W}_t$ is calculated as:

$$\mathcal{W}_t^j = \int \Bigg[\underbrace{\int \Bigg(\int w_t(x,y,\gamma)\, g_t^j(x,y,\gamma)\, \mathrm{d}\gamma \Bigg) f(y)\, \mathrm{d}y}_{\substack{\text{labor}\\ \text{income}}} + \underbrace{b_t(x)\, u_t^j(x)}_{\substack{\text{home}\\ \text{production}}} \Bigg] l(x)\, \mathrm{d}x\,,$$

where the superscript j indicates the decentralized (D) or constrained social planner (SP-C) equilibrium allocations.

I present the components of workers' welfare from the decentralized and the constrained social planner equilibrium allocations during expansions and contractions in Table 6. The decentralized equilibrium yields a workers' welfare level of 82.7, 17 percent lower than that observed in expansions. By contrast, the constrained social planner allocation attains a workers' welfare level of 91.1, 10 percent higher than the decentralized allocation. Most of the gain in workers' welfare under the centralized economy comes from home production, as implied by the higher unemployment rate. In this respect, labor income during contractions under the decentralized equilibrium does not translate into high utility gains for workers.

Table 6: Workers' Welfare under Different Economies

	Expansions		Contractions	
	Decentralized	Constrained Social Planner	Decentralized	Constrained Social Planner
Workers' Welfare	100.000	100.053	82.650	91.112
Labor Income	98.356	98.834	82.005	74.500
Home Production	1.644	1.219	0.645	16.612

Note: The table shows components of workers' welfare resulting from the equilibrium allocations of the decentralized and the constrained social planner economies during expansion and contraction periods. Expansion periods are defined as $z_t = [0.95; 1.05]$ and contraction periods are defined as $z_t = [0.70; 0.75]$ (6 percent decrease in output relative to expansion periods). The figures are normalized relative to the workers' welfare level of the decentralized equilibrium allocation during expansion periods. Additional details are described within the table.
Source: Author's calculations based on model simulations.

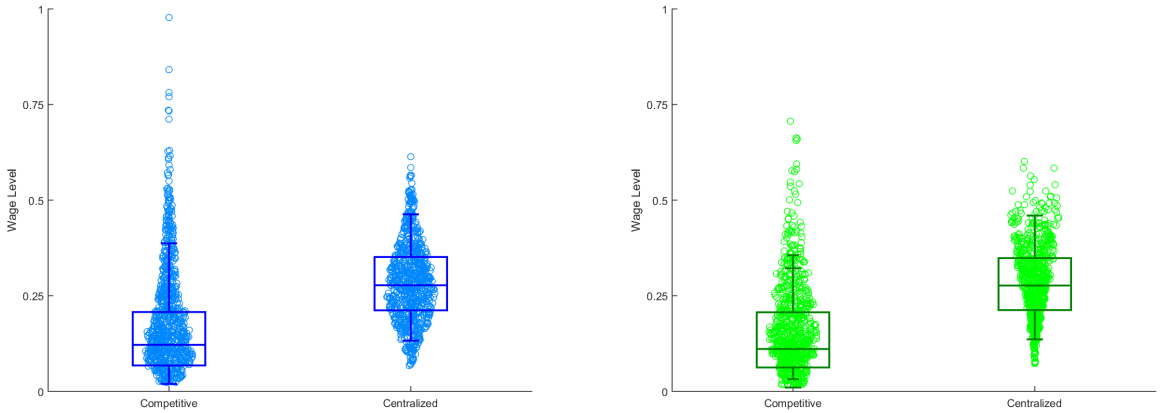
7.5 Wage Distribution

In Figure 19, I present the wage distribution arising from the decentralized and the constrained social planner equilibrium allocations during contractions and expansions. Table

7 presents the corresponding summary statistics from the wage distributions. Visibly, the centralized economy renders a wage distribution displaying a higher mean both in expansions and contractions. Moreover, the wage distribution under the centralized economy tends to be more normal. This manifests in the Kelley skewness coefficients that amount to 0.09 during expansions and 0.11 during contractions, both significantly lower that what is observed in the decentralized economy. Thus, not only does the social planner increases net output and workers' welfare but also reduces wage inequality during contractions.

Figure 19: Wage Distributions under Different Economies

(A) Expansions (B) Contractions



Note: The figure shows swarm scatter charts of the wage distributions resulting from the equilibrium allocations of the decentralized and the constrained social planner economies during expansions (Panel A) and contractions (Panel B).
Source: Author's calculations based model simulations.

Table 7: Statistics of the Wage Distribution under Different Economies

	Expansions		Contractions	
	Decentralized	Constrained Social Planner	Decentralized	Constrained Social Planner
Mean	0.154	0.285	0.124	0.285
(P50 − P10)/(P90 − P10)	0.315	0.454	0.304	0.445
(P90 − P50)/(P90 − P10)	0.685	0.546	0.696	0.554
Kelley Skewness	0.370	0.093	0.393	0.109

Note: The table shows summary statistics of the wages distributions resulting from the equilibrium allocations of the decentralized and the constrained social planner economies during expansions. Expansion periods are defined as $z_t = [0.95; 1.05]$ and contraction periods are defined as $z_t = [0.70; 0.75]$ (6 percent decrease in output relative to expansion periods). Additional details are described within the table.
Source: Author's calculations based on model simulations.

8 Policy Simulations

In this last section, I analyze different policy interventions seeking to amend imperfections in the labor market and to reduce productive inefficiencies in the economy. I compare the effectiveness of different policies in terms of net production, workers' welfare, and wage distribution relative to what is observed in the decentralized economy. I consider a policy intervention to be effective if it brings the aggregate welfare state closer to that attained under the centralized economy.

8.1 What Needs to be Amended in the Labor Market?

Upon closer examination, it becomes clearer that sub-optimal job creation generates most of the net output loss in the decentralized economy. Put simply, jobs created during contractions tend to be precarious and rarely do they generate sizable increases in value added. This becomes evident when examining the characteristics of vacancies that are advertised in recessions, usually offering a lower expected employment duration and a lower pay. Even more, this problem originates in both sides of the market as low-technology firms are willing to advertise vacancies given the higher expected gains from hiring and workers are willing to accept mediocre jobs in their search for better employment profiles in contractions. In such context, policies aiming at deterring job creation by low-technology firms or increasing

the reservation value of workers would lead to an increase in net production by reducing the losses from ex-post sub-optimal match formations and unfilled jobs.

Net output loss from mismatch, albeit to a lesser extent, is still present in the labor market during contractions. This can be mostly explained by the fact that, during recessions, a great deal of low-productive matches are wiped away from the economy, as implied by the *cleansing* effect of recessions. Yet, an even higher net output level can be achieved with policies aiming at re-allocating low-skill workers whose matches prevailed after the negative shock into more productive employment states or halting vacancy advertising from low-technology firms.

To recount, policy interventions that seek to reduce labor market imperfections and productive inefficiencies during contractions would produce a high impact by focusing on: (i) deterring job creation by low-technology firms; (ii) increasing the reservation value of workers; and (iii) spurring productive-enhancing re-allocations in the labor market.

8.2 Policy Simulations

Having discussed the type of policy interventions that are required for reducing productive inefficiencies in the economy, I now turn to evaluate different labor market policies.

I perform simulations by varying certain structural parameters of the model that directly map to each of the policy interventions to recover policy-implied labor market distributions during contractions. On this matter, it is worth pointing out that, in the process of computing these alternate distributions, I use as inputs the streams of period t aggregate productivity shocks, $\{z_t\}_{t=0}^{T}$, and period $t-1$ employment distributions, $\{u_{t-1}, h_{t-1}(x,y)\}_{t=0}^{T}$, observed in the competitive economy. This manner, the simulations can be interpreted as a counterfactual scenario with a policy inception at a particular point over the cycle.[37]

Policy Interventions. I assess the performance of two different policy interventions in the economy: (i) a vacancy advertising subsidy; and (ii) an increase in unemployment benefits. Respectively, they are simulated as a 10 percent decrease in vacancy advertisement costs and a 10 percent increase in the flow value of home production. I present the results from the policy simulations in Table 8. For ease of reference, I report the figures obtained during expansions and contractions derived from the decentralized economy (i.e., no-policy scenario) in the first two columns of the table.

Net Production and Labor Market Equilibrium. Relative to the decentralized econ-

[37]In evaluating these policies, it is also important to mention that I do not calculate the corresponding fiscal costs but only focus on the gains in terms of net production and welfare. For the same token, I do not examine the cost-benefit analysis of the policy interventions.

omy (i.e., no-policy scenario), both policy interventions perform better in terms of net production during contractions. A vacancy advertising subsidy generates net production that is 2 percent higher than that observed under the decentralized economy. The corresponding figure for increased unemployment benefits is 7 percent.

Turning to labor market distributions, the vacancy advertisement subsidy produce unemployment rates that are smaller and vacancy rates that are larger than those observed in the decentralized economy. As expected, this policy aims to increase job creation by firms thereby reducing unemployment. By contrast, increased unemployment benefits increases the unemployment rate by a factor of 2.3 and reduces the vacancy rate by nearly one half relative to the decentralized economy. By increasing workers' value of unemployment, this policy discourages job creation by firms.

Productive Inefficiencies. A vacancy advertisement subsidy leads to an increase in the fraction of productive inefficiencies explained by unfilled jobs as it naturally increase job postings by firms. However, this policy also increases mismatch in the labor market by increasing the incentives of job creation by low-technology firms. Higher unemployment benefits increases the fraction of productive inefficiencies explained by mismatch from previous existing jobs. Yet, the fraction of socially sub-optimal jobs is still the leading contributor to productive inefficiencies as it requires higher flows of value added to make $p_t(x, y)$ greater than $b_t(x)$.

Workers' Welfare. In Table 9, I present the workers' welfare level attained under different policy interventions. A vacancy advertisement subsidy would generate almost no difference in the workers' welfare level relative to the decentralized economy. By contrast, increased unemployment benefits would generate a workers' welfare level that is roughly 3 percent higher than the decentralized economy.

Table 8: Policy Simulations

		Contractions		
	Expansions	No Policy	Vacancy Advertising Subsidy	Extended Unemployment Benefits
	Panel A: Components of Net Production			
Net Production	87.985	84.551	86.274	90.661
Aggregate Production	100.000	94.139	95.109	91.167
Joint Production	96.320	83.874	94.494	75.947
Home Production	3.680	10.265	0.615	15.220
Vacancy Advertisement	-12.015	-9.588	-8.835	-0.506
	Panel B: Labor Market Distributions			
Unemployment Rate (U_t)	0.039	0.066	0.064	0.152
Vacancy Rate (V_t)	0.035	0.017	0.021	0.009
Tightness Ratio (θ_t)	0.739	0.532	0.596	0.355
	Panel C: Productive Inefficiencies			
Unfilled Jobs	45.409 %	5.466 %	6.367 %	0.215 %
Socially Sub-optimal Jobs	54.562 %	94.526 %	92.625 %	81.626 %
Mismatch	0.029 %	0.008 %	1.008 %	18.159 %

Note: The table shows the components of net aggregate production (Panel A), the labor market distributions (Panel B), and the sources of productive inefficiencies (Panel C) resulting from different equilibrium allocations based on policy simulations during contraction periods. The policy simulations include: the no-policy scenario (i.e., status quo), a 10% decrease in vacancy advertising costs, and a 10% increase in the flow value of home production. Expansion periods are defined as $z_t = [0.95; 1.05]$ and contraction periods are defined as $z_t = [0.70; 0.75]$ (6 percent decrease in output relative to expansion periods). The figures in Panel A are normalized relative to the aggregate production level of the competitive equilibrium allocation during expansion periods. See the notes on Table 5 for further information. Additional details are described within the table.
Source: Author's calculations based on model simulations.

Table 9: Workers' Welfare from Policy Simulations

		Contractions		
	Expansions	No Policy	Vacancy Advertising Subsidy	Extended Unemployment Benefits
Workers' Welfare	100.000	82.650	82.624	85.295
Labor Income	98.356	82.005	82.110	72.960
Home Production	1.664	0.645	0.515	12.335

Note: The table shows components of workers' welfare resulting from different equilibrium allocations based on policy simulations during contraction periods. The policy simulations include: the no-policy scenario (i.e., status quo), a 10% decrease in vacancy advertising costs, and a 10% increase in the flow value of home production. Expansion periods are defined as $z_t = [0.95; 1.05]$ and contraction periods are defined as $z_t = [0.70; 0.75]$ (6 percent decrease in output relative to expansion periods). The figures in Panel A are normalized relative to the aggregate production level of the competitive equilibrium allocation during expansion periods. Additional details are described within the table.
Source: Author's calculations based on model simulations.

Other Policy Interventions. In Appendix F.5, I analyze two other policy interventions: an expansionary monetary policy that lowers the interest rate and leads to an increase in the time-discount factor β, and a more restrictive employment termination procedure that generates a decrease in the exogenous separation rate δ. Both these policies are frequently observed in recessions as a measure to stimulate aggregate demand and avoid employment fallout.

Respectively, reducing the interest rate and increasing the layoff costs bring about net production levels of 86.1 and 84.3, implying a 2 percent higher and a 0.3 percent lower net production during recessions relative to the decentralized economy. Vacancy costs produced by the expansionary monetary policy are greater as this policy increases the continuation value of the match formation thereby the gains from hiring. However, as firms weigh more the present value of future gains from joint production, they also search for high-skill workers as they render a lower risk of future match dissolution. Under this policy, the vacancy rate increases slightly and the unemployment rate falls moderately compared to those observed in the decentralized economy, and productive inefficiencies are almost entirely explained by unfilled jobs and sub-optimal job creation as the targeted group of workers are likely employed by high-technology firms.

8.3 Effects on the Wage Distribution

In Table 10, I present summary statistics of the wage distribution from different policy interventions. Both policy interventions have a positive and similar effect on the mean wage. On average, each policy intervention yields an average wage that is around 15 percent higher than that attained under the decentralized economy during contractions. Concerning the skewness of the wage distribution, only increased unemployment benefits yields a wage distribution with a Kelley skewness that is 6 percent lower than that from the decentralized economy during contractions. This lower skewness owes mainly to a higher median wage, which also increases the fraction of the P90-P10 gap explained by the bottom half of the wage distribution.

Table 10: Statistics of the Wage Distribution from Policy Simulations

		Contractions		
	Expansions	No Policy	Vacancy Advertising Subsidy	Extended Unemployment Benefits
Mean	0.154	0.124	0.144	0.144
$(P50 - P10)/(P90 - P10)$	0.315	0.304	0.300	0.331
$(P90 - P50)/(P90 - P10)$	0.685	0.696	0.700	0.699
Kelley Skewness	0.370	0.393	0.400	0.368

Note: The table shows summary statistics of the wage distributions resulting from different equilibrium allocations based on policy simulations during contraction periods. The policy simulations include: the no-policy scenario (i.e., status quo), a 10% decrease in vacancy advertising costs, and a 10% increase in the flow value of home production. Expansion periods are defined as $z_t = [0.95; 1.05]$ and contraction periods are defined as $z_t = [0.70; 0.75]$ (6 percent decrease in output relative to expansion periods). The figures in Panel A are normalized relative to the aggregate production level of the competitive equilibrium allocation during expansion periods. Additional details are described within the table.
Source: Author's calculations based on model simulations.

8.4 Evidence on the Effectiveness of Policy Interventions

I next discuss the results of the policy simulations in light of past empirical evidence on related policy interventions.

Vacancy Advertisement Subsidy. Because only a few number of countries have incorporated hiring firms in their plans for boosting job creation during recessions, evidence on vacancy advertisement subsidies is scarce. A conceptually different intervention is the hiring subsidy, which essentially subsidizes the payroll of new hires in the form of credits or tax

relieves. In my model, a hiring subsidy operates on the $(1-\gamma)$ share of the surplus that is kept by the firm, as the firm does not pay the total wage amount to the worker but only part of it. However, it does not reduce vacancy advertising or associated recruiting costs.

Effectively, a hiring subsidy acts as an employment subsidy that focuses on the supply- instead of the demand-side of the labor market. Critics of this measure argue that such interventions are ineffective because low employment during recessions is rather a consequence of an insufficient labor demand (Galí, 2013). Yet, Cahuc et al. (2019), who assess a hiring credit program in France targeted at small firms in the midst of the Great Recession, finds that the program had a rapid and sizable increase in employment and posed a virtually zero net cost per job created for the government. In a survey of the literature on the effects of hiring subsidies, Neumark and Grijalva (2017) concludes that hiring subsidies may have a significant employment effect if they do not target specific demographic groups composed mostly of disadvantaged job seekers. In my model, this idea becomes evident as firms would not hire low-skill workers during recessions even in the presence of hiring or payroll subsidies as the surplus of matching these workers is likely to be negative.

A notable exception in this literature is Algan et al. (2022) who evaluate a free recruitment service from the French Public Employment Service targeted at small- and medium-size firms. Compared to a hiring subsidy, this centralized recruitment service directly affects vacancy advertisement costs. In my model, this is reflected in a reduction of the parameter c_1. Among the free services provided, the intervention covered: on-line vacancy posting and editing, access to a CV bank, information on vacancy performance, pre-selection/pre-screening, interview support, amid others. The findings reveal that the program was successful in increasing vacancy posting by firms through the centralized website as well as increasing the quality of newly hired workers.

Increased Unemployment Benefits. In my model, increased unemployment benefits is reflected by an increment in the flow value $b_t(x)$, and it produces to two distinct effects: one in terms of employment and the other in terms of wages. With respect to employment, a rise in $b_t(x)$ reduces the match surplus which increases job separations and reduces vacancy advertisement by firms thereby increasing unemployment. As for wages, it generates two positive effects: first, by directly increasing the weighted average of production flows and, second, by indirectly reducing the wage penalty associated to the expected future contract revisions through a lower future match surplus.

Previous work also identifies the dual effect unemployment insurance has as it may reduce employment but help workers find suitable jobs (Marimon and Zilibotti, 1999). Ultimately,

whether unemployment insurance increases or not unemployment depends on the way it affects the labor market tightness. On this matter, Landais et al. (2018a) point to two opposing mechanisms through which unemployment insurance affects the labor market tightness: a positive one whereby the competition for jobs among workers diminishes, and a negative one whereby the increase in wages through bargaining boosts job search. Empirical evidence indicates that extended unemployment benefits have modest effects on the job finding rate yet increases participation in the labor force by bolstering individuals' incentives to engage in active job search (Farber et al., 2015).[38] However, these effects only consider the supply side of the market and evidence indicates that job creation by firms is negatively affected by the increased wage mechanism (Hagedorn et al., 2013). All things considered, unemployment benefits seem to have positive marginal welfare gains especially during economic downturns (Kroft and Notowidigdo, 2016; Landais et al., 2018b).

8.5 Summary of Findings and Discussion

Targeted recruiting by firms can exacerbate productive inefficiencies in the labor market by introducing additional dimensions of market imperfections — namely, unfilled jobs, suboptimal job creation, and mismatch. These imperfections abound in markets where job opportunities befall predominantly among high-skill workers as they tend to be usually employed thereby searching for jobs with a lower intensity or turning down outside offers more often. Figures reveal that the societal losses in terms of forgone production and workers' utility are substantial, which justifies the scope for welfare-improving policy interventions in the labor market.

Together, unfilled jobs and social-suboptimal job creation account for almost the entirety of productive inefficiencies during contractions in the economy. This finding is consistent with the hypothesis of the *sullying* effect of recessions establishing that jobs created during contractions tend to be of lower quality thus slowing down the pace at which productive reallocations occur in the economy (Barlevy, 2002; Barnichon and Zylberberg, 2019; Mustre-del-Río, 2014). In such context, policies aiming to increase net production and workers' welfare in the face of economic downturns should turn their focus on stimulating the creation of high-quality jobs that would generate sizable rises in value added in the economy and increase rate at which workers transit towards more productive jobs.

[38] Arbogast and Dupor (2022), however, document that the early cessation of federal emergency unemployment benefits plan (that was included in the 2020 CARES Act in the U.S.) in some states lead to a rapid increase in employment levels.

Policy simulations reveal that increased unemployment benefits (as well as longer unemployment compensation periods or higher welfare stipends) in recessions could lead to a substantial welfare improvement. This effect is supported by similar findings from ample work on unemployment insurance. But despite the positive aggregate effects on the economy, this policy is less effective in reducing wage inequality during contractions. Even more, this policy intervention does not come without societal costs. On the one hand, this policy yields high short-term unemployment rates as plenty of workers are displaced from their jobs and not many new job positions are created by firms. On the other hand, this policy can be burdensome in terms of public finances as it may bring about elevated running costs that would need to be covered by taxes or public debt. Therefore, policy-makers would need to weigh the costs and benefits of this policy intervention, also reckoning that it may induce changes in the search behavior of both workers and firms thereby introducing additional distortions and frictions that could affect equilibrium in the labor market.

9 Conclusion

Can recessions prompt increases in wage inequality? Conventional wisdom suggests that this can indeed be the case as negative aggregate productivity shocks cause sharp falls in wages at the bottom tail of the distribution which increases the gap between middle and bottom wages. In this paper I argue that, while recessions can increase wage inequality, negative aggregate productivity shocks lead, in turn, to a higher dispersion at top segments of the distribution. Observational evidence around the time of recessions in the U.S. over 1980-2019 corroborates this view. In recessions, the wage distribution: (i) becomes more positively skewed, and (ii) shrinks at the bottom but widens at the top. These stylized facts indicate that the cross-sectional distribution of wages displays a higher fraction of overall dispersion concentrated at the top tail.

To understand how aggregate productivity shocks spread in wages at top segments of the distribution, I build a wage bargaining model of random job search that incorporates targeted recruiting by firms. Aggregate productivity shocks affect the value of the joint surplus of worker-firm matches. In times of low aggregate productivity, some worker-firm matches, especially those involving low-skill workers, become infeasible due to their limited productivity. Firms then shift the target of their vacancies towards high-skill workers, making them more likely to receive outside job offers relative to low-skill ones. The higher pace at which job offers arrive prevents wages of high-skill workers from plummeting as they can

use outside job offers as a bargaining instrument wage setting. Wages at the top then move apart from wages at the bottom of the distribution thus increasing wage inequality.

Understanding that wage inequality rises in recessions originate at the top of the wage distribution has important implications for labor market regulation. While macro-stabilization policies usually focus in reducing unemployment by boosting labor demand, most of the jobs created in recessions are precarious and rarely do they help in reducing wage gaps. As wages account for nearly 70 percent of individual income in the U.S. (and high-income countries in general), these policies can have significant welfare consequences in the short- and long-run. Policies aiming at protecting workers while unemployed and incentivizing the creation of better-quality jobs over time, on the contrary, may boost productivity and reduce wage inequality at the expense of increasing unemployment in the short-run.

References

Aaronson, Daniel, Bhashkar Mazumder, and Shani Schechter. 2010. "What is behind the rise in long-term unemployment?." Federal Reserve Bank of Chicago – Economic Perspectives, 34(2): 28-51.

Abel, Martin, Rulof Burger, Eliana Carranza, and Patrizio Piraino. 2019. "Bridging the Intention-behavior Gap? The Effect of Plan-making Prompts on Job Search and Employment." American Economic Journal: Applied Economics, 11(2): 284-301.

Abowd, John M., Francis Kramarz, and David N. Margolis. 1999. "High Wage Workers and High Wage Firms." Econometrica, 67(2): 251-333.

_____**, and** _____. 2005. "Human Capital and Worker Productivity: Direct Evidence from Linked Employer-employee Data." Annales d'Economie et de Statistique, 323-338.

Abraham, Katharine G., and John C. Haltiwanger. 1995. "Real Wages and the Business Cycle." Journal of Economic Literature, 33(3): 1215-1264.

Acemoglu, Daron. 2002. "Technical Change, Inequality, and the Labor Market." Journal of Economic Literature, 40(1): 7-72.

_____. 2003. "Labor- and Capital-augmenting Technical Change." Journal of the European Economic Association, 1(1): 1-37.

_____**, and David H. Autor**. 2011. "Skills, Tasks and Technologies: Implications for Employment and Earnings." In *Handbook of Labor Economics*, Vol. 4: 1043-1171.

Acharya, Sushant, and Shu Lin Wee. 2020. "Rational Inattention in Hiring Decisions." American Economic Journal: Macroeconomics, 12(1): 1-40.

Addison, John T., McKinley L. Blackburn, and Chad D. Cotti. 2013. "Minimum Wage Increases in a Recessionary Environment." Labor Economics, 23: 30-39.

Aghion, Philippe. 2002. "Schumpeterian Growth Theory and the Dynamics of Income Inequality." Econometrica, 70(3): 855-882.

Alessandrini, Diana, Stephen Kosempel, Alessandra Pelloni, and Thanasis Stengos. 2016. "Earnings Inequality, the Business Cycle, and the Life Cycle." Mimeo. Available at: link (Accessed: 15 September 2022).

Algan, Yann, Olivier Allais, and Wouter J. Den Haan. 2008. "Solving Heterogeneous-agent Models with Parameterized Cross-sectional Distributions." Journal of Economic Dynamics and Control, 32(3): 875-908.

_____**, Bruno Crépon, and Dylan Glover**. 2022. "Are Active Labor Market Policies Directed at Firms Effective? Evidence from a Randomized Evaluation with Local Employment." Mimeo. Available at: link (Accessed: 15 September 2022).

Altmann, Steffen, Armin Falk, Simon Jäger, and Florian Zimmermann. 2018. "Learning About Job Search: A Field Experiment with Job Seekers in Germany." Journal of Public Economics, 164: 33-49.

Arbogast, Iris, and Bill Dupor. 2022. "Increasing Employment by Halting Pandemic Unemployment Benefits." Federal Reserve Bank of St. Louis Review. Available at: link (Accessed: 15 September 2022).

Ashenfelter, Orley C., Henry Farber, and Michael R. Ransom. 2010. "Labor Market Monopsony." Journal of Labor Economics, 28(2): 203-210.

_____, **David Card, Henry Farber, and Michael R. Ransom**. 2022. "Monopsony in the Labor Market: New Empirical Results and New Public Policies." Journal of Human Resources, 57(S): S1-S10.

Autor, David H.. 2010. "The Polarization of Job Opportunities in the US Labor Market: Implications for Employment and Earnings." Center for American Progress and The Hamilton Project, 6: 11-19.

_____, **and David Dorn**. 2013. "The Growth of Low-skill Service Jobs and the Polarization of the US Labor Market." American Economic Review, 103(5): 1553-97.

_____, **Frank Levy, and Richard J. Murnane**. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." The Quarterly Journal of Economics, 118(4): 1279-1333.

_____, **Lawrence F. Katz, and Melissa S, Kearney**. 2008. "Trends in US Wage Inequality: Revising the Revisionists." The Review of Economics and Statistics, 90(2): 300-323.

Auclert, Adrien, Bence Bardóczy, Matthew Rognlie, and Ludwig Straub. 2021. "Using the Sequence-space Jacobian to Solve and Estimate Heterogeneous-agent Models." Econometrica, 89(5): 2375-2408.

Azar, José, Ioana Marinescu, Marshall Steinbaum, and Bledi Taska. 2020. "Concentration in US Labor Markets: Evidence from Online Vacancy Data." Labour Economics, 66: 101886.

Bagger, Jesper, and Rasmus Lentz. 2019. "An Empirical Model of Wage Dispersion with Sorting." The Review of Economic Studies, 86(1): 153-190.

Baley, Isaac, Ana Figueiredo, and Robert Ulbricht. forthcoming. "Mismatch Cycles." Journal of Political Economy.

Barlevy, Gadi. 2002. "The Sullying Effect of Recessions." The Review of Economic Studies, 69(1): 65-96.

_____. 2007. "On the Cyclicality of Research and Development." American Economic Review, 97(4): 1131-1164.

_____, **and Daniel Tsiddon**. 2006. "Earnings Inequality and the Business Cycle." European Economic Review, 50(1): 55-89.

Barnichon, Regis. 2010. "Building a Composite Help-wanted Index." Economics Letters, 109(3): 175-178.

_____, **and Andrew Figura**. 2015. "Labor Market Heterogeneity and the Aggregate Matching Function." American Economic Journal: Macroeconomics, 7(4): 222-249.

_____, **and Yanos Zylberberg**. 2019. "Underemployment and the Trickle-down of Unemployment." American Economic Journal: Macroeconomics, 11(2): 40-78.

Baydur, Ismail. 2017. "Working Selection, Hiring, and Vacancies." American Economic Journal: Macroeconomics, 9(1): 88-127.

Beaudry, Paul, and John DiNardo. 1997. "The Effect of Implicit Contracts on the Movement of Wages Over the Business Cycle: Evidence from Micro Data." Journal of Political Economy, 99(4): 665-688.

Belot, Michele, Philipp Kircher, and Paul Muller. 2019. "Providing Advice to Job-seekers at Low Cost: An Experimental Study on Online Advice." The Review of Economic Studies, 86(4): 1411-1447.

Benmelech, Efraim, Nittai K. Bergman, and Hyunseob Kim. 2022. "Strong Employers and Weak Employees How Does Employer Concentration Affect Wages?." Journal of Human Resources, 57(S): S200-S250.

Berger, David. 2018. "Countercyclical Restructuring and Jobless Recoveries." Mimeo. Available at: link (Accessed: 15 September 2022).

_____, **Kyle F. Herkenhoff, and Simon Mongey**. 2022a. "Labor Market Power." American Economic Review, 112(4): 1147-93.

_____, _____, **and** _____. 2022b. "Minimum Wages, Efficiency and Welfare." NBER WP 29662. Available at: link (Accessed: 15 September 2022).

Bertheau, Antoine, Henning Bunzel, and Rune Vejlin. 2020. "Employment Reallocation over the Business Cycle: Evidence from Danish Data." IZA DP No. 13681. Available at: link (Accessed: 15 September 2022).

Bils, Mark J.. 1985. "Real Wages Over the Business Cycle: Evidence from Panel Data." Journal of Political Economy, 93(4): 666-689.

Bjelland, Melissa, Bruce Fallick, John C. Haltiwanger, and Erika McEntarfer. 2011. "Employer-to-employer Flows in the United States: Estimates Using Linked Employer-employee Data." Journal of Business & Economic Statistics, 29(4): 493-505.

Bloom, Nicholas, Max Floetotto, Nir Jaimovich, Itay Saporta-Eksten, and Stephen J. Terry. 2018. "Really Uncertain Business Cycles." Econometrica, 86(3): 1031-1065.

Boal, William M., and Michael R. Ransom. 1997. "Monopsony in the Labor Market." Journal of Economic Literature, 35(1): 86-112.

Bonhomme, Stephane, Kerstin Holzheu, Thibaut Lamadon, Elena Manresa, Magne Mogstad, and Bradley Setzler. 2022. "How Much Should we Trust Estimates of Firm Effects and Worker Sorting?." Journal of Labor Economics, In Press.

Bontemps, Christian, Jean-Marc Robin, and Gerard J. Van Den Berg. 1999. "An Empirical Equilibrium Job Search Model with Search on the Job and Heterogeneous Workers and Firms." International Economic Review, 40(4): 1039-1074.

Boppart, Timo, Per Krusell, and Kurt Mitman. 2018. "Exploiting MIT Shocks in Heterogeneous-agent Economies: The Impulse Response as a Numerical Derivative." ournal of Economic Dynamics and Control, 89: 68-92.

Burdett, Kenneth, Carlos Carrillo-Tudela, and Melvyn Coles. 2020. "The Cost of Job Loss." The Review of Economic Studies, 87(4): 1757-1798.

Burke, Mary A., Alicia Sasser Modestino, Shahriar Sadighi, Rachel B. Sederberg, and Bledi Taska. 2020. "No Longer Qualified? Changes in the Supply and Demand for Skills within Occupations." Federal Reserve Bank of Boston Research Department Working Papers No. 20-3. Available at: link (Accessed: 15 September 2022).

Busch, Christopher, David Domeij, Fatih Guvenen, Rocio Madera. 2022. "Skewed Idiosyncratic Income Risk over the Business Cycle: Sources and Insurance." American Economic Journal: Macroeconomics, 14(2): 207-242.

Caballero, Ricardo J., and Mohamad L. Hammour. 1994. "The Cleansing Effect of Recessions." American Economic Review, 84(5): 1350-1368.

Cajner, Tomaz, and David Ratner. 2016. "A Cautionary Note on the Help Wanted Online Data." FEDS Notes 2016-06-23, Board of Governors of the Federal Reserve System. Available at: link (Accessed: 15 September 2022).

Cahuc, Pierre, Stéphane Carcillo, and Thomas Le Barbanchon. 2019. "The Effectiveness of Hiring Credits." The Review of Economic Studies, 86(2): 593-626.

_____, **Fabien Postel-Vinay, and Jean-Marc Robin**. 2006. "Wage Bargaining with On-the-job Search: Theory and Evidence." Econometrica, 74(2): 323-364.

Card, David. 2022. "Who Set Your Wage?." American Economic Review, 112(4): 1075-90.

_____, **Jochen Kluve, and Andrea Weber**. 2010. "Active Labour Market Policy Evaluations: A Meta-analysis." The Economic Journal, 120(548): F452-F477.

_____, _____, **and** _____. 2018. "What Works? A Meta Analysis of Recent Active Labor Market Program Evaluations." Journal of the European Economic Association, 16(3): 894-931.

Cheremukhin, Anton, Paulina Restrepo-Echevarria, and Antonella Tutino. 2020. "Targeted Search in Matching Markets." Journal of Economic Theory, 185: 104956.

Chéron, Arnaud, and Bénédicte Rouland. 2011. "Endogenous Job Destructions and the Distribution of Wages." Labour Economics, 18(6): 845-852.

Choi, Sekyu, Nincen Figueroa, and Benjamin Villena-Roldán. 2022. "Wage Cyclicality Revisited: The Role of Hiring Standards." Mimeo. Available at: link (Accessed: 15 September 2022).

Christensen, Bent Jesper, Rasmus Lentz, Dale T. Mortensen, George R. Neumann, and Axel Werwatz. 2005. "On-the-job Search and the Wage Distribution." Journal of Labor Economics, 23(1): 31-58.

Christiano, Lawrence J., and Martin Eichenbaum. 1992. "Current Real-business-cycle Theories and Aggregate Labor-market Fluctuations." American Economic Review, 82(3): 430-450.

_____, _____, **and Mathias Trabandt**. 2016. "Unemployment and Business Cycles." Econometrica, 84(4): 1523-1569.

Clemens, Jeffrey, Lisa B. Kahn, and Jonathan Meer. 2021. “”Dropouts Need Not Apply? The Minimum Wage and Skill Upgrading.” Journal of Labor Economics 39(S1): S107-S149.

_____, **and Michael Wither**. 2019. “The Minimum Wage and the Great Recession: Evidence of Effects on the Employment and Income Trajectories of Low-skilled Workers.” Journal of Public Economics, 170: 53-67.

Comin, Diego, and Mark Gertler. 2006. “Medium-term Business Cycles.” American Economic Review, 96(3): 523-551.

Costain, James S., and Michael Reiter. 2008. “Business Cycles, Unemployment Insurance, and the Calibration of Matching Models.” Journal of Economic Dynamics and Control, 32(4): 1120-1155.

Couch, Kenneth A., and Dana W. Placzek. 2010. “Earnings Losses of Displaced Workers Revisited.” American Economic Review, 100(1): 572-89.

Crane, Leland D., Henry R. Hyatt, and Seth M. Murray. 2022. “Cyclical Labor Market Sorting.” Journal of Econometrics, In Press.

Crawley, Andrew, Sarah Welch, and Julieta Yung. 2021. “Improving Estimates of Job Matching Efficiency with Different Measures of Unemployment.” Journal of Macroeconomics, 67: 103282.

Cribb, Jonathan, and Paul Johnson. 2019. “Employees’ Earnings Since the Great Recession: The Latest Picture.” IFS Briefing Note BN256. Available at: link (Accessed: 15 September 2022).

CRS. 2020. “Introduction to U.S. Economy: Personal Income.” Congressional Research Service. Washington D.C. Available at: link (Accessed: 15 September 2022).

Daly, Mary; Bart Hobijn, Ayşegül Şahin, and Robert G. Valletta. 2012. “A Search and Matching Approach to Labor Markets: Did the Natural Rate of Unemployment Rise?.” Journal of Economic Perspectives, 26(3): 3-26.

Davis, Steven J., R. Jason Faberman, and John C. Haltiwanger. 2012. “Labor Market Flows in the Cross-section and over Time.” Journal of Monetary Economics, 59(1): 1-18.

_____, **and** _____, _____. 2013. “The Establishment-level Behavior of Vacancies and Hiring.” The Quarterly Journal of Economics, 128(2): 581-622.

_____, **and John C. Haltiwanger**. 1992. “Gross Job Creation, Gross Job Destruction, and Employment Reallocation.” The Quarterly Journal of Economics, 107(3): 819-863.

_____, **and Till von Wachter**. 2011. “Recessions and the Costs of Job Loss.” Brookings Papers on Economic Activity, 2011(2): 1-72.

Den Haan, Wouter J.. 1997. “Solving Dynamic Models with Aggregate Shocks and Heterogeneous Agents.” Macroeconomic Dynamics, 1(2): 355-386.

Dey, Matthew S., and Christopher J. Flinn. 2005. “An Equilibrium Model of Health Insurance Provision and Wage Determination.” Econometrica, 73(2): 571-627.

Dhia, Aïcha Ben, Bruno Crépon, Esther Mbih, Louise Paul-Delvaux, Bertille Picard, and Vincent Pons. 2022. "Can a Website Bring Unemployment Down? Experimental Evidence from France." NBER WP 29914. Available at: link (Accessed: 15 September 2022).

Duffie, Darrell, Lei Qiao, and Yeneng Sun. 2018. "Dynamic Directed Random Matching." Journal of Economic Theory, 174: 124-183.

Dunne, Timothy, Lucia Foster, John C. Haltiwanger, and Kenneth R. Troske. 2004. "Wage and Productivity Dispersion in United States Manufacturing: The Role of Computer Investment." Journal of Labor Economics, 22(2): 397-429.

Eckstein, Zvi, and Eva Nagypál. 2004. "The Evolution of US Earnings Inequality: 1961-2002." Federal Reserve Bank of Minneapolis Quarterly Review, 28(2): 10-29.

Eeckhout, Jan, and Ilse Lindenlaub. 2019. "Unemployment Cycles." American Economic Journal: Macroeconomics, 11(4): 175-234.

Elsby, Michael W.L., Bart Hobijn, and Ayşegül Şahin. 2010. "The Labor Market in the Great Recession." Brookings Papers on Economic Activity, 2010(1): 1-48.

Faberman, R. Jason, and Bhashkar Mazumder. 2012. "Is there a Skills Mismatch in the Labor Market?." Chicago Fed Letter, Federal Reserva Bank of Chicago. Available at: link (Accessed: 15 September 2022).

_____, **Andreas I. Mueller, Ayşegül Şahin, and Giorgio Topa**. 2022. "Job Search Behavior Among the Employed and Non-employed." Econometrica, 90(4): 1743-1779.

Fallick, Bruce, John C. Haltiwanger, and Erika McEntarfer. 2012. "Job-to-job Flows and the Consequences of Job Separations." Finance and Economics Discussion Series 2012-73, Board of Governors of the Federal Reserve System. Available at: link (Accessed: 15 September 2022).

Farber, Henry S. 2011. "Job Loss in the Great Recession: Historical Perspective from the Displaced Workers Survey, 1984-2010." NBER WP 17040. Available at: link (Accessed: 15 September 2022).

_____, **Jesse Rothstein, and Robert G. Valletta**. 2015. "The Effect of Extended Unemployment Insurance Benefits: Evidence from the 2012-2013 Phase-out." American Economic Review, 105(5): 171-76.

Forsythe, Eliza. 2022. "Why Don't Firms Hire Young Workers During Recessions?." The Economic Journal, 132(645): 1765-1789.

Galí, Jordi. 2013. "Notes for a New Guide to Keynes (I): Wages, Aggregate Demand, and Employment." Journal of the European Economic Association, 11(5): 973-1003.

Gavazza, Alessandro, Simon Mongey, and Giovanni L. Violante. 2018. "Aggregate Recruiting Intensity." American Economic Review, 108(8): 2088-2127.

Geroski, Paul A., and Chris F. Walters. 1995. "Innovative Activity Over the Business Cycle." The Economic Journal, 105(431): 916-928.

Gertler, Mark, and Antonella Trigari. 2009. "Unemployment Fluctuations with Staggered Nash Wage Bargaining." Journal of political Economy, 117(1): 38-86.

Goos, Maarten, and Alan Manning. 2007. "Lousy and Lovely Jobs: The Rising Polarization of Work in Britain." The Review of Economics and Statistics, 89(1): 118-133.

_____, _____, **and Anna Salomons**. 2014. "Explaining Job Polarization: Routine-biased Technological Change and Offshoring." American Economic Review, 104(8): 2509-26.

Gottschalk, Peter. 1997. "Inequality, Income Growth, and Mobility: The Basic Facts." Journal of Economic Perspectives, 11(2): 21-40.

Griliches, Zvi. 1969. "Capital-skill Complementarity." The Review of Economics and Statistics, 51(1): 465-468.

Guvenen, Fatih, Serdar Ozkan, and Jae Song. 2014. "The Nature of Countercyclical Income Risk." Journal of Political Economy, 122(3): 621-660.

Haefke, Christian, Marcus Sonntag, and Thijs Van Rens. 2013. "Wage Rigidity and Job Creation." Journal of Monetary Economics, 60(8): 887-889.

Hagedorn, Marcus, Fatih Karahan, Iourii Manovskii, and Kurt Mitman. 2013. "Unemployment Benefits and Unemployment in the Great Recession: The Role of Macro Effects." NBER WP 19499. Available at: link (Accessed: 15 September 2022).

_____, **and Iourii Manovskii**. 2008. "The Cyclical Behavior of Equilibrium Unemployment and Vacancies Revisited." American Economic Review, 98(4): 1692-1706.

Hall, Robert E.. 2005. "Employment Fluctuations with Equilibrium Wage Stickiness." American Economic Review, 95(1): 50-65.

_____, **and Alan B. Krueger**. 2012. "Evidence on the Incidence of Wage Posting, Wage Bargaining, and On-the-job Search." American Economic Journal: Macroeconomics, 4(4): 56-67.

_____, **and Paul R. Milgrom**. 2008. "The Limited Influence of Unemployment on the Wage Bargain." American Economic Review, 98(4): 1653-74.

_____, **and Sam Schulhofer-Wohl**. 2018. "Measuring Job-Finding Rates and Matching Efficiency with Heterogeneous Job-Seekers." American Economic Journal: Macroeconomics, 10(1): 1-32.

Haltiwanger, John C., Henry R. Hyatt, Lisa B. Kahn, and Erika McEntarfer. 2018. "Cyclical Job Ladders by Firm Size and Firm Wage." American Economic Journal: Macroeconomics, 10(2): 52-85.

_____, _____, **Erika McEntarfer, and Matthew Staiger**. 2021. "Cyclical Worker Flows: Cleansing vs. Sullying." NBER WP 28802. Available at: link (Accessed: 15 September 2022).

Heathcote, Jonathan, Fabrizio Perri, and Giovanni L. Violante. 2020. "The Rise of US Earnings Inequality: Does the Cycle Drive the Trend?." Review of Economic Dynamics, 37: S181-S204.

_____, **Kjetil Storesletten, and Giovanni L. Violante**. 2010. "The Macroeconomic Implications of Rising Wage Inequality in the United States." Journal of Political Economy, 118(4): 681-722.

Hershbein, Brad, and Lisa B. Kahn. 2018. "Do Recessions Accelerate Routine-biased Technological Change? Evidence from Vacancy Postings." American Economic Review, 108(7): 1737-72.

Hoover, Gary A., Daniel C. Giedeman, and Sel Dibooglu. 2009. "Income Inequality and the Business Cycle: A Threshold Cointegration Approach." Economic Systems, 33(3): 278-292.

Hornstein, Andreas, Per Krusell, and Giovanni L. Violante. 2005. "Unemployment and Vacancy Fluctuations in the Matching Model: Inspecting the Mechanism." FRB Richmond Economic Quarterly 91(3): 19-51.

Hosios, Arthur J. 1990. "On the Efficiency of Matching and Related Models of Search and Unemployment." The Review of Economic Studies, 57(2): 279-298.

Hoynes, Hilary, Douglas L. Miller, and Jessamyn Schaller. 2012. "Who suffers during recessions?." Journal of Economic Perspectives, 26(3): 27-48.

Huckfeldt, Christopher. 2022. "Understanding the Scarring Effect of Recessions." American Economic Review, 112(4): 1273-1310.

IRS. 2021. "Statistics of Income 2019: Individual Income Tax Returns." Internal Revenue Service. Washington D.C. Available at: link (Accessed: 15 September 2022).

Jacquet, Nicolas L., and Serene S. Tan. 2007. "On the Segmentation of Markets." Journal of Political Economy, 115(4): 639-664.

Jaimovich, Nir, and Henry E. Siu. 2020. "Job Polarization and Jobless Recoveries." Review of Economics and Statistics, 102(1): 129-147.

Kaas, Leo, and Philipp Kircher. 2015. "Efficient Firm Dynamics in a Frictional Labor Market." American Economic Review, 105(10): 3030-60.

Kaplan, Greg, Benjamin Moll, and Giovanni L. Violante. 2018. "Monetary Policy According to HANK." American Economic Review, 108(3): 697-743.

Katz, Lawrence F., and David H. Autor. 1999. "Changes in the Wage Structure and Earnings Inequality." In *Handbook of Labor Economics*. Vol. 3: 1463-1555.

Keith, Kristen, and Abagail McWilliams. 1999. "The Returns to Mobility and Job Search by Gender." ILR Review, 52(3): 460-477.

Kennan, John. 2010. "Private Information, Wage Bargaining and Employment Fluctuations." The Review of Economic Studies, 77(2): 633-664.

Kim, Tae-Hwan, and Halbert White. 2004. "On More Robust Estimation of Skewness and Kurtosis." Finance Research Letters, 1(1): 56-73.

Koenig, Feliz, Alan Manning, and Barbara Petrongolo. 2022. "Reservation Wages and the Wage Flexibility Puzzle." Mimeo. Available at: link (Accessed: 15 September 2022).

Krebs, Tom. 2007. "Job Displacement Risk and the Costs of Business Cycles." American Economic Review, 97(3): 664-686.

Kroft, Kory, and Matthew J. Notowidigdo. 2016. "Should Unemployment Insurance Vary with the Unemployment Rate?." The Review of Economic Studies, 83(3): 1092-1124.

Krusell, Per, Lee E. Ohanian, José-Víctor Ríos-Rull, and Giovanni L. Violante. 2000. "Capital-skill Complementarity and Inequality: A Macroeconomic Analysis." Econometrica, 68(5): 1029-1053.

Kuhn, Peter, and Mikal Skuterud. 2004. "Internet Job Search and Unemployment Durations." American Economic Review, 94(1), 218-232.

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

Landais, Camille, Pascal Michaillat, and Emmanuel Saez. 2018a. "A Macroeconomic Approach to Optimal Unemployment Insurance: Theory." American Economic Journal: Economic Policy, 10(2): 152-181.

_____, _____, **and** _____. 2018b. "A Macroeconomic Approach to Optimal Unemployment Insurance: Applications." American Economic Journal: Economic Policy, 10(2): 182-216.

Lise, Jeremy, Costas Meghir, and Jean-Marc Robin. 2016. "Matching, Sorting and Wages." Review of Economic Dynamics, 19: 63-87.

_____, **and Jean-Marc Robin**. 2017. "The Macrodynamics of Sorting between Workers and Firms." American Economic Review, 107(4): 1104-35.

Ljungqvist, Lars. 2002. "How Do Lay-off Costs Affect Employment?."The Economic Journal, 112(482): 829-853.

Machin, Stephen. 2001. "The Changing Nature of Labour Demand in the New Economy and Skill-biased Technology Change." Oxford Bulletin of economics and Statistics, 63(s1): 753-776.

Manning, Alan. 2011. "Imperfect Competition in the Labor Market." In *Handbook of Labor Economics*, Vol. 4: 973-1041.

_____. 2021a. "Monopsony in Labor Markets: A Review." ILR Review, 74(1): 3-26.

_____. 2021b. "The Elusive Employment Effect of the Minimum Wage." Journal of Economic Perspectives, 35(1): 3-26.

Marimon, Ramon, and Fabrizio Zilibotti. 1999. "Unemployment vs. Mismatch of Talents: Reconsidering Unemployment Benefits." The Economic Journal, 109(455): 266-291.

Marinescu, Ioana E.. 2017. "Job Search Monitoring and Assistance for the Unemployed." IZA World of Labor.

McFadden, Daniel. 1989. "A Method of Simulated Moments for Estimation of Discrete Response Models Without Numerical Integration." Econometrica, 57(5): 995-1026.

Menzio, Guido, and Shouyong Shi. 2011. "Efficient Search On the Job and the Business Cycle." Journal of Political Economy, 119(3): 468-510.

Merkl, Christian, and Thijs van Rens. 2019. "Selective Hiring and Welfare Analysis in Labor Market Models." Labour Economics, 57: 117-130.

Michaillat, Pascal. 2012. "Do Matching Frictions Explain Unemployment? Not in Bad Times." American Economic Review, 102(4): 1721-50.

Modestino, Alicia Sasser, Daniel Shoag, and Joshua Ballance. 2020. "Upskilling: Do Employers Demand Greater Skill When Workers are Plentiful?." Review of Economics and Statistics, 102(4): 793-805.

Moen, Espen R. 1997. "Competitive Search Equilibrium." Journal of Political Economy, 105(2): 385-411.

Mongey, Simon, and Giovanni L. Violante. 2020. "Macro Recruiting Intensity from Micro Data." Mimeo. Available at: link (Accessed: 15 September 2022).

Morales-Jiménez, Camilo. 2022. "The Cyclical Behavior of Unemployment and Wages under Information Frictions." American Economic Journal: Macroeconomics, 14(1): 301-31.

Morin, Annaïg. 2019. "Wage Dispersion over the Business Cycle." Economic Letters, 181: 17-21.

Mortensen, Dale T.. 1982. "Property Rights and Efficiency in Mating, Racing, and Related Games." American Economic Review, 72(5): 968-979.

_____, and Christopher A. Pissarides. 1994. "Job Creation and Job Destruction in the Theory of Unemployment." The Review of Economic Studies, 61(3): 397-415.

_____, and Eva Nagypál. 2007. "More on Unemployment and Vacancy Fluctuations." Review of Economic Dynamics, 10(3): 327-347.

Moscarini, Giuseppe, and Fabien Postel-Vinay. 2013. "Stochastic Search Equilibrium." The Review of Economic Studies, 80(4): 1545-1581.

_____, and _____. 2016. "Wage Posting and Business Cycles." American Economic Review, 106(5): 208-13.

_____, and _____. 2018. "The Cyclical Job Ladder." Annual Review of Economics, 10: 165-188.

Mustre-del-Río, José. 2014. "Job Duration, Wages, and the Cleansing and Sullying Effects of Recessions." Federal Reserve Bank of Kansas City RWP 12-08. Available at: link (Accessed: 15 September 2022).

Näf, Armando, Yannic Stucki, and Jacqueline Thomet. 2022. "The Effects of Firing Costs on Labour Market Dynamics." Economica, 89(354): 461-488.

Neumark, David, and Diego Grijalva. 2017. "The Employment Effects of State Hiring Credits." ILR Review, 70(5): 1111-1145.

Newey, Whitney K., and Kenneth D. West. 1987. "A Simple Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." Econometrica, 55(3): 703-708.

OECD. 2022. "National Accounts of OECD Countries." OECD Publishing. Paris. Available at: link (Accessed: 15 September 2022).

Oyer, Paul, and Scott Schaefer. 2011. "Personnel Economics: Hiring and Incentives." In *Handbook of Labor Economics*, Vol. 4: 1769-1823.

Petrongolo, Barbara, and Christopher A. Pissarides. 2001. "Looking into the Black Box: A Survey of the Matching Function." Journal of Economic Literature, 39(2): 390-431.

Pissarides, Christopher A.. 2009. "The Unemployment Volatility Puzzle: Is Wage Stickiness the Answer?." Econometrica, 77(5): 1339-1369.

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

_____**, and Hélène Turon**. 2010. "On-the-job Search, Productivity Shocks, and the Individual Earnings Process." International Economic Review, 51(3): 599-629.

Rafferty, Matthew C.. 2003. "Do Business Cycles Influence Long-run Growth? The Effect of Aggregate Demand on Firm-financed R&D Expenditures." Eastern Economic Journal, 29(4): 607-618.

Reder, Melvin W.. 1955. "The Theory of Occupational Wage Differentials." The American Economic Review, 45(5): 833-852.

Reiter, Michael. 2002. "Recursive Computation of Heterogeneous Agent Models." Mimeo. Available at: link (Accessed: 15 September 2022).

_____. 2009. "Solving Heterogeneous-agent Models by Projection and Perturbation." Journal of Economic Dynamics and Control, 33(3): 649-665.

Rinz, Kevin. 2022. "Labor Market Concentration, Earnings, and Inequality." Journal of Human Resources, 57(S): S251-S283.

Robin, Jean-Marc. 2011. "On the Dynamics of Unemployment and Wage Distributions." Econometrica, 79(5): 1327-1355.

Şahin, Ayşegül, Joseph Song, Giorgio Topa, and Giovanni L. Violante. 2014. "Mismatch Unemployment." American Economic Review, 104(11): 3529-64.

Schaal, Edouard. 2017. "Uncertainty and Unemployment." Econometrica, 85(6): 1675-1721.

Sedláček, Petr. 2014. "Match Efficiency and Firms' Hiring Standards." Journal of Monetary Economics, 62: 123-133.

_____. 2016. "The Aggregate Matching Function and Job Search from Employment and Out of the Labor Force." Review of Economic Dynamics, 21: 16-28.

Shimer, Robert. 2004. "The Consequences of Rigid Wages in Search Models." Journal of the European Economic Association, 2(2-3): 469-479.

_____. 2005. "The Cyclical Behavior of Equilibrium Unemployment and Vacancies." American Economic Review, 95(1): 25-49.

Solon, Gary, Robert Barsky, and Jonathan A. Parker. 1994. "Measuring the cyclicality of real wages: how important is composition bias?." The Quarterly Journal of Economics, 109(1): 1-25.

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

Sorkin, Isaac. 2018. "Ranking Firms using Revealed Preferences." The Quarterly Journal of Economics, 133(3): 1331-1393.

Storesletten, Kjetil, Chris I. Telmer, and Amir Yaron. 2001. "The Welfare Costs of Business Cycles Revisited: Finite Lives and Cyclical Variation in Idiosyncratic Risk." European Economic Review, 45(7): 1311-1339.

_____, _____, and _____. 2004. "Cyclical Dynamics in Idiosyncratic Labor Market Risk." Journal of Political Economy, 112(3): 695-717.

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

Veracierto, Marcelo. 2008. "Firing Costs and Business Cycle Fluctuations." International Economic Review, 49(1): 1-39.

Violante, Giovanni L.. 2008. "Skill-biased Technical Change." The New Palgrave Dictionary of Economics, 2: 1-6.

Wälde, Klaus, and Ulrich Woitek. 2004. "R&D Expenditure in G7 Countries and the Implications for Endogenous Fluctuations and Growth." Economic Letters, 82(1): 91-97.

Webber, Douglas A.. 2015. "Firm Market Power and the Earnings Distribution." Labour Economics, 35: 123-134.

Welch, Finis. 1970. "Education in Production." Journal of Political Economy, 78(1): 35-59.

Winberry, Thomas. 2018. "A Method for Solving and Estimating Heterogeneous Agent Macro Models." Quantitative Economics, 9(3): 1123-1151.

Wolthoff, Ronald. 2018. "Applications and Interviews: Firms' Recruiting Decisions in a Frictional Labour Market." The Review of Economic Studies, 85(2): 1314-1351.

Yamaguchi, Shintaro. 2010. "Job Search, Bargaining, and Wage Dynamics." Journal of Labor Economics, 28(3): 595-631.

Appendix Material for:
The Distributional Dynamics of Wages over the Business Cycle

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October 2022

A. Data Construction

A.1. Data Assembling Procedure

In this section I provide details of the data assembling procedure. For ease of exposition, I use lower case for referring to individual-level and upper cases for referring to aggregate-level data.

A.1.1. Stylized Facts

In this sub-section I provide details on the data handling procedure followed for recounting the stylized facts discussed in section 2 of the main text.

Business Cycle Dating. I gather information on contraction dates for the U.S. economy over 1980m1-2019m4 from the NBER data repository.[1] The NBER's Business Cycle Dating Committee keeps track of the chronology of U.S. business cycles. In essence, the committee identifies peaks and trough dates based on a series of measures of economic activity. According to the NBER, a contraction is a period between a peak of economic activity and its subsequent trough or lowest point. Between a trough and a peak, the economy is in an expansion.

Real Hourly Wages. I use data from the Outgoing Rotation Group extract of the Current Population Survey (CPS-ORG) for computing moments of the real wage distribution in the U.S. economy over 1980m1-2019m12. These data are made available to the public by the National Bureau of Economic Research (NBER).[2]

In the analysis, I focus on cyclical variations of the real hourly wage distribution among hourly-wage and salaried workers. To compute nominal hourly wages from CPS-ORG data, I follow the same procedure utilized by previous studies (Hirsch and Schumacher, 2004; Cengiz et al., 2019). For workers earning by the hour, I compute nominal hourly wages directly from their reported hourly rate (variable `hourwage`). For salaried workers, I divide their reported weekly earnings (variable `earnweek`) by the number of hours usually worked per week (variable `uhrswork1` for the period 1980-1993 and `uhrsworkt` for the period 1994-2019). To obtain real hourly wages, I deflate nominal hourly wages by the Personal Consumption Expenditure (PCE) deflator. I have also checked that the figures arising from this analysis are very similar if I use the Consumer Price Index of Urban Consumers (CPI-U) deflator. To avoid potential biases from extreme values, I top code real hourly wages at the 99th percentile of the real wage distribution of each year.[3]

I restrict my analysis to prime-age (ages 25-54) individuals working full-time (35+ hours

[1] For accessing these data, follow this link.

[2] For accessing these data, follow this link.

[3] The CPS-ORG top-codes weekly earnings at US$ 999 between 1980 and 1988, at US$ 1,923 between 1989 and 1997, and at US$ 2,885 from 1998 onwards. All these upper limits correspond, at least, to the 95th percentile of the distribution of nominal weekly wages of each month. In my analysis, I focus on percentiles below the 90th, inclusive. As a robustness check, I have also confirmed that the percentiles that I obtain are similar to the ones resulting from fitting a log-normal distribution to the data through Maximum Likelihood.

per week) in private, non-farming industries. For consistency, I only keep in my empirical sample individuals earning at or above 90% of the statutory federal hourly minimum wage of the running year.[4] Though the information comprised in the CPS-ORG strictly refers to labor earnings, my focus on full-time workers makes variations in hours of work very limited; thus, labor earnings in this context are a plausibly good measure of wages. Given these sample restrictions, I compute sample moments for each month by collapsing the data using CPS-ORG sampling weights (variable `earnwt`).

A.1.2. Quantitative Analysis

In this sub-section I describe the construction of the time series that I use for computing the moments utilized in the quantitative analysis presented in section 4 of the main text. All the series are seasonally adjusted, either as provided by the Bureau of Labor Statistics (BLS) or the Bureau of Economic Analysis (BEA), or by using a ratio-to-moving average adjustment method.

Unemployment Rate. I construct monthly series of the unemployment rate (U_m) by dividing the number of unemployed individuals (series LNS13000000) by the civilian labor force (series LNS11000000), both of them provided by the BLS. These series span the period 1951m1-2019m12.

Unemployment Rates of 5+/15+/27+ Weeks. I construct monthly series of the unemployment rate of 5+, 15+, and 27+ weeks (U_m^{5+}, U_m^{15+}, U_m^{27+}) by dividing the number of individuals unemployed for 5/15/27 or more weeks (series LNS13008756, LNS13008516, and LNS13008636, respectively) by the civilian labor force (series LNS11000000), all of them provided by the BLS. These series span the period 1951m1-2019m12.

Vacancy Rate. I bring together two sources of information to create monthly series of the vacancy rate (V_m) spanning the period 1951m1-2019m12. I obtain data over 1951m1-2000m12 from the updated version of the composite Help-Wanted Index (Barnichon, 2010; Cajner and Radner, 2016) and complete the series by gathering data on job openings from non-farming industries (series JTS000000000000000JOR) over 2001m1-2019m12 from the BEA's Job Openings and Labor Turnover Survey (JOLTS).[5]

Unemployment-to-employment Transition Rate. I construct monthly series of unemployment-to-employment (UE_m) transition rate over 1951m1-2019m12 using data from the BLS as follows:

$$UE_m = 1 - \frac{U_m^{5+}}{U_{m-1}} \ ,$$

[4] I gather the annual time series of the statutory federal minimum wage from Vaghul and Zipperer (2016), available at the following link.

[5] The Federal Reserve Bank of San Francisco (FRBSF) provides readily available data on monthly vacancy rates over 1951m1-2014m12. These series are constructed by combining information from the Help-Wanted Index and the JOLTS, correcting for discontinuities around the transition months, and can be downloaded from the following link. In my analysis, I use these series and complement them with information from the BEA's JOLTS for the remaining months (i.e., 2015m1-2019m12).

where U_m^{5+} is unemployment of 5 or more weeks (series LNS13008756) and U_{m-1} unemployment in the previous month (series LNS13000000).

Employment-to-unemployment Transition Rate. I construct monthly series of employment-to-unemployment (EU_m) transition rate over 1951m1-2019m12 using data from the BLS as follows:

$$EU_m = \frac{U_m^{<5}}{E_{m-1}} ,$$

where $U_m^{<5}$ is unemployment of less than 5 weeks (series LNS13008396) and E_{m-1} employment in the previous month (series LNS12000000).

Job-to-job Transition Rate. To construct the series of job-to-job transition rates, I first construct indicators for a hire from employment for each month m following the gross-flow method utilized by Fujita and Ramey (2009). Starting in the year 1994, the CPS included a question enquiring whether a currently employed respondent was employed by the same employer (and at the same job) in the previous month (variable `empsame`). Let $ee_{i,m}$ be the indicator for individual i's month-over-month change between jobs as reported in the basic monthly CPS. This indicator takes the value of 1 if the individual is employed in consecutive months $m-1$ and m and, additionally, there is a change in her employer relative to month $m-1$. Based on this information, I construct monthly series of the job-to-job transition rate ($J2J_m$) over 1995m1-2019m12 as follows:

$$J2J_m = \frac{\sum_i ee_{i,m}}{\sum_i e_{i,m-1}} ,$$

where $e_{i,m-1}$ is an indicator that takes the value of 1 if individual i was employed in month $m-1$. In computing this rate, I utilize CPS-implied weights (variable `wtfinl`).

Value Added. I gather quarterly series of real gross value added in the business, non farming sector from the BEA (series A358RX1Q020SBEA). These data span the period 1951q1-2019q4.

Dispersion of Labor Productivity. I gather annual series of the cross-sectional dispersion of (log.) labor productivity over 1975-2009 from Bloom et al. (2018).[6] To harmonize the periodicity of the data, I recover quarterly series by interpolation, using a cubic polynomial.[7] The resulting series span the period 1975q1-2009q4.

Real Wages. I construct monthly series of (log.) real weekly wages and their cross-sectional dispersion (standard deviation) over 1985m1-2019m12 using data from the CPS-ORG. As with the data utilized for building the stylized facts, I construct these series by restricting the

[6]These data can be downloaded from the following link. In particular, I utilize information on the standard deviation of (log.) total factor productivity shocks among establishments from firms surveyed by the Census of Manufacturers and the Annual Survey of Manufacturers, both of them elaborated by the U.S. Census Bureau.

[7]I have checked that the moments obtained from these series are similar if I use alternate specifications for interpolation, such as a spline method or higher-order polynomials.

sample to include prime-age employees working full-time in private, non-farming industries, and who earn at least 90% of the statutory federal minimum wage of the running year. I convert nominal to real values using the PCE deflator. To obtain weekly wages, I multiply the hourly rates by the number of hours usually worked per week (variable `uhrswork1` for the period 1980-1993 and `uhrsworkt` for the period 1994-2019).

Labor Share of Output. I obtain quarterly series of the labor share of output (i.e., the amount of GDP paid out in wages, salaries, and benefits) for the non-farm business sector over 1951q1-2019q4 from the BLS's press release of June 2021.[8]

A.2. Aggregation

I aggregate all monthly series to a quarterly periodicity by averaging the data across months within a given quarter. The resulting quarterly series span the period 1951q1-2019q4 for the unemployment rate, the unemployment rate of 5+/15+/27+ weeks, the vacancy rate, the unemployment-to-employment transition rate, and the employment-to-unemployment transition rate; 1995q1-2019q4 for the job-to-job transition rate; and 1985q1-2019q4 for (log.) real wages and their cross-sectional dispersion. All remaining series are already aggregated at a quarterly periodicity and span the period 1951q1-2019q4 for the value added and the labor share of output, and 1975q1-2009q4 for the dispersion of labor productivity.

A.3. Extraction of Cyclical Components of the Series

Once constructed, I apply a logarithmic transformation to all quarterly series. Next, I extract their cyclical component by re-expressing them as deviations from their Hodrick-Prescott (HP) trend using a smoothing parameter value to 10^5, as in Shimer (2005). All the moments utilized in the quantitative analysis are computed from the series' HP-filtered cyclical components.

B. Stylized Facts: Additional Analyses

B.1. Robustness

I provide additional robustness analyses in support of the counter-cyclical fluctuation of the positive skewness of the distribution of real wages.

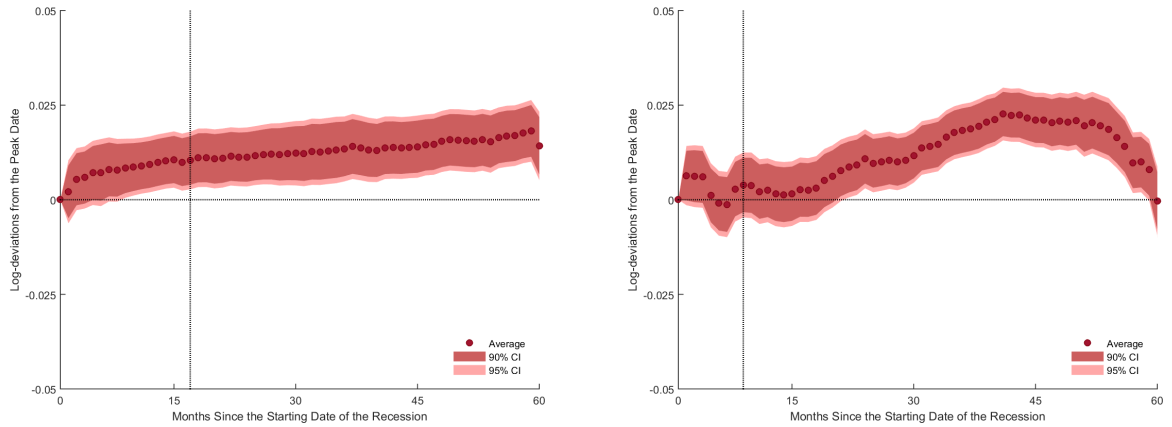
Recessions Between 1980-2019. In Appendix Figure B.1, I show the average Kelley skewness, in log-deviations from the peak date, of the distribution of real wages at months 1 through 60 for different recession periods occurring in the U.S. over 1980-2019. Though different in magnitudes, all graphs show that the wage distribution becomes more positively

[8]For further information, visit the following website.

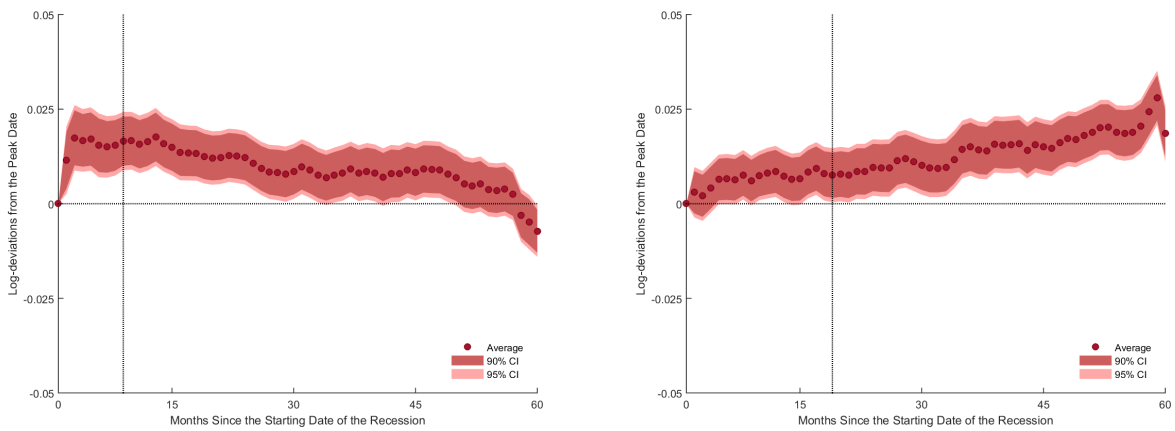
skewed during recession periods and sub-sequent recoveries. This provides further support for the figures presented in section 2 of the main text.

Appendix Figure B.1: Robustness to each Recession Between 1980-2019

(A) July 1981 – December 1982 (B) July 1990 – March 1991



(C) March 2001 – November 2001 (D) December 2007 – June 2009



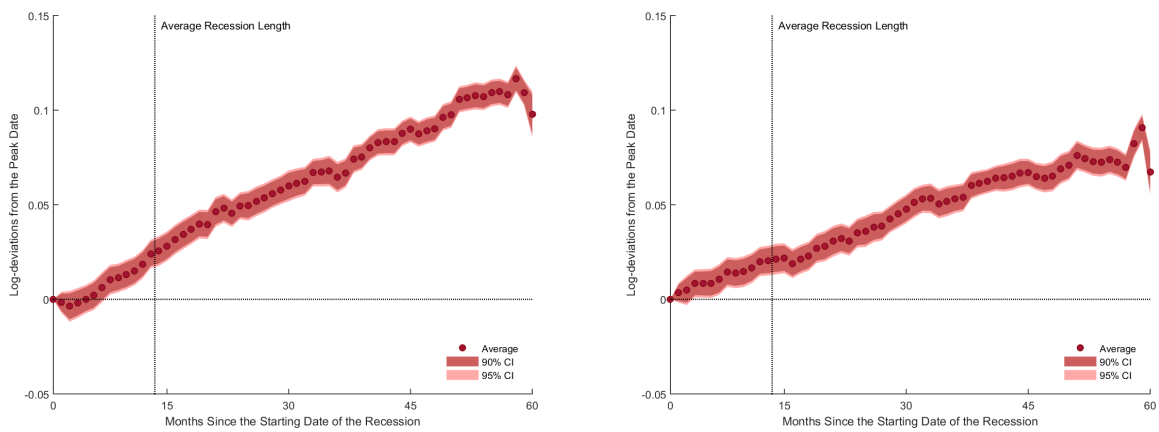
Note: The figure shows the average Kelley skewness, in log-deviations from the peak date, of the distribution of real wages in the U.S. at months 1 through 60 since the starting date of the 1981m7-1982m12 recession (Panel A), the 1990m7-1991m3 recession (Panel B), the 2001m3-2001m11 recession (Panel C), and the 2007m12-2009m6 recession (Panel A). Real wages are computed by deflating nominal hourly rates by the PCE. Linear trends, estimated with data from months -24 through 84 from/since the starting date of each recession, have been removed from all series. Dark and light shaded areas correspond to the 90% and 95% confidence intervals, respectively, constructed from 1,000 bootstrap samples for each month. Vertical lines mark the length of each recession according to the NBER's business cycle chronology.
Source: Author's calculations based on data from the CPS-ORG and NBER.

Alternate Price Indexes. I further test for the robustness of the stylized facts to the use of alternate price deflator indexes. In Appendix Figure B.2, I plot the analogue of Figure 1 in section 2 of the main text using two alternate deflators: the Producer Price Index (Panel A) and the Implicit Price Deflator (Panel B). I obtain monthly series of these price indexes

from the BLS and BEA websites. Both deflators index prices using the year 2012 as the base year. The graphs show the same cyclical pattern as the one depicted in Figure 1 of the main text.

Appendix Figure B.2: Robustness to Alternate Inflation Indexes

(A) Producer Price Index (B) Implicit Price Deflator



Note: The figure shows the average Kelley skewness, in log-deviations from the peak date, of the distribution of real wages at months 1 through 60 since the starting date of recessions occurring in the U.S. over 1980-2019. Real wages are computed by deflating nominal hourly rates by the Producer Price Index (Panel A) or Implicit Price Deflator (Panel B). Linear trends, estimated with data from months -24 through 84 from/since the starting date of each recession, have been removed from all series. Dark and light shaded areas correspond to the 90% and 95% confidence intervals, respectively, constructed from 1,000 bootstrap samples for each month. Vertical lines, at month 13.5, mark the average length of recessions according to the NBER's business cycle chronology. Source: Author's calculations based on data from the CPS-ORG, BEA, BLS, and NBER.

C. Computation of Model-simulated Wages

C.1. Forecasting Rule

Wage Equation. In the model, the wage flow value of a (x, y)-type match is a function of the size of the employment contract, γ, the flow value of joint production, $p_t(x, y)$, the flow value of home production, $b_t(x)$, and the expected gains from future employment contract revisions, $\Omega_{z_{t+1}}(x, y, \gamma)$:

$$w_t(x, y, \gamma) = \gamma\, p_t(x, y) + (1 - \gamma)\, b_t(x) - \beta\, \Omega_{z_{t+1}}(x, y, \gamma)\,, \tag{C.1}$$

as implied by equation (15) in the main text.

The last component of (C.1), $\Omega_{z_{t+1}}(x, y, \gamma)$, requires agents to form expectations based on the set of state variables and distributions. Formally, let:

$$
\begin{aligned}
&\Omega_{z_{t+1}}(x,y,\gamma) \\
&= \mathbb{E}_{z_{t+1}}\left[\big((1-\delta_{t+1}(x,y)\big)\left(e\,\lambda_{t+1}(x)\int\kappa_{t+1}(x,\hat{y})\big(\hat{\gamma}-\gamma\big)\,S_{t+1}(x,y)\,\mathrm{d}\hat{y}\right)\right] \\
&= \sum_{z_{t+1}}\pi(z_t,z_{t+1})\left[\big((1-\delta_{[z_{t+1}]}(x,y)\big)\left(e\,\lambda_{[z_{t+1}]}(x)\int\kappa_{[z_{t+1}]}(x,\hat{y})\big(\hat{\gamma}_{[z_{t+1}]}-\gamma\big)\,S_{[z_{t+1}]}(x,y)\,\mathrm{d}\hat{y}\right)\right],
\end{aligned}
$$

be the expectations component of the wage level for a (x,y)-type match with an employment contract of size γ, given z_t and $h_t(x,y)$. In the second equality, $\pi(z_t,z_{t+1})$ is the transition probability between z_t and z_{t+1} derived from the Markov process and the subscript $[z_{t+1}]$ denotes that a variable is conditional on a particular realization of z_{t+1}. The value of $\Omega_{z_{t+1}}(x,y,\gamma)$ can be numerically approximated by computing the change in the share of the match-specific surplus that accrues to the worker given z_t, $h_t(x,y)$, a particular realization of z_{t+1}, and the Markov transition probabilities. This procedure, however, is computationally expensive given the high dimensionality of the model. Specifically, it would require computing a different value for each (x,y,γ) triplet meeting a $\hat{y}$-type firm in each possible future state of the economy — a total of $21\times21\times11\times21\times51$ values.

Forecasting Rule. To reduce computational complexity, I adopt an heuristic numerical solution method that utilizes historical series generated by the model. To this end, I make three important assumptions. First, I assume that all agents have perfect information with respect to the present value of the (x,y)-type match surplus in every possible state of the economy. Second, I assume that the forecasting rule is common to all agents.[9] Third, I assume that all agents keep a perfect record of distributions generated over time. While the first and second assumptions are important for guaranteeing that expectations are symmetric across workers and firms, the third assumption is important for computing expectations based on past realizations of z_t.

This forecasting rule takes advantage of the possibility to estimate labor market distributions, given z_t and $h_t(x,y)$, without the necessity of solving for equilibrium wages each period. Put differently, the ability of the model to generate time series independent of wages allows me to compute wage levels after I have solved for equilibrium distributions in the labor market.[10] Further, this recursive formulation of the model enables me to use the actual realizations (i.e., once z_{t+1} has been revealed) for numerically approximating the expectations component of wage levels.

To fix ideas, let $\ddot{\Omega}_{z_{t+1}}(x,y,\gamma)$ be the *actual* realization of $\Omega_{z_{t+1}}(x,y,\gamma)$ that is observed

[9] Of course, one can envision a more interesting scenario where workers and/or firms have imperfect information with respect to the surplus of the match or even different forecasting rules. This would generate an asymmetry in the formation of expectations (and thereby the wage level) between workers and firms that would have to be solved through bargaining.

[10] This is somewhat similar to the Block Recursive Equilibrium of Menzio and Shi (2010).

in a given period t. Specifically, for every (past) period $\tau \in [0, t-1]$, it is possible to observe a sequence $\{\ddot{\Omega}_{z_{\tau+1}}(x, y, \gamma)\}_{\tau=0}^{t-1}$ constructed from the one-period-ahead realizations of $\lambda_{\tau+1}(x)$ and $\kappa_{\tau+1}(x, y)$, taking $S_{\tau+1}(x, y)$ and γ as inputs. For instance, for the period $\tau = t-1$, $\ddot{\Omega}_{z_{\tau+1}}(x, y, \gamma)$ can be computed for every γ from the period t observed distributions $\lambda_t(x)$ and $\kappa_t(x, y)$, and using $S_t(x, y)$.

Let $\ddot{\mathcal{O}}_{[z_{\tau+1}=z_t]}(x, y, \gamma) = \{\ddot{\Omega}_{z_{\tau+1}}(x, y, \gamma)\}_{[z_{\tau+1}=z_t]}$ denote the collection of $\ddot{\Omega}_{z_{\tau+1}}(x, y, \gamma)$s observed whenever $z_{\tau+1}$ takes the period t's realized value z_t, and $\ddot{o}^j_{[z_{\tau+1}=z_t]}(x, y, \gamma)$ be the j-th element of this array. Further, define $\ddot{H}_{[z_{\tau+1}=z_t]}(x, y)$ as the associated collection of historical measures of (x, y)-type matched in the economy, and take $\ddot{h}^j_{[z_{\tau+1}=z_t]}(x, y)$ to be the j-th element of this array. Given these two arrays, I compute an estimate of $\Omega_{z_{t+1}}(x, y, \gamma)$, $\hat{\Omega}_{z_{t+1}}(x, y, \gamma)$, as follows:

$$\hat{\Omega}_{z_{t+1}}(x, y, \gamma) = \sum_j K_j\big(h_t(x, y), \ddot{h}^j_{[z_{\tau+1}=z_t]}(x, y)\big)\, \ddot{o}^j_{[z_{\tau+1}=z_t]}(x, y, \gamma)\,, \tag{C.2}$$

where $K_j(.)$ is a distance-based kernel weighting function and $h_t(x, y)$ is the measure of (x, y)-type matches observed in period t. In words, $\hat{\Omega}_{z_{t+1}}(x, y, \gamma)$ is a weighted average of historical expectations components of wages, where weights are proportional to the proximity between current and historical state variables.

The rationale behind this formulation is that agents can make use of the full extent of information on the history of the economy in order to form expectations on period $t+1$, based on the state variables observed in period t. Past periods that mirror a closer situation to the current state of the economy convey more information in the process of forming these expectations. Even more, as the economy evolves and the realized transition pairs (z_t, z_{t+1}) adjust to their Markov process, it is the case that $\hat{\Omega}_{z_{t+1}}(x, y, \gamma)$ converges to $\Omega_{t+1}(x, y, \gamma)$. This is just another way of stating that forecasts become more accurate as time elapses given an improvement in the information set.

Kernel Weighting Function. To compute the Kernel-based forecast of the expectations component of wages, I allow $K_j(.)$ to take the form of a Gaussian weighting function. I choose a bandwidth ϑ equal to:

$$\vartheta = 0.9 \min\left\{\hat{\sigma}_n, \frac{\text{IQR}}{1.340}\right\} n^{-\frac{1}{5}}\,,$$

where n is the number of elements in $\ddot{\mathcal{O}}_{[z_{\tau+1}=z_t]}(x, y, \gamma)$, IQR is the inter-quantile range, and $\hat{\sigma}_n$ is the empirical standard error. This bandwidth is chosen to minimize the mean integrated square error. Given ϑ, I construct the distance-based kernel weights, $K_j(.)$, as follows:

$$K_j\big(h_t(x, y), \ddot{h}^j_{[z_{\tau+1}=z_t]}(x, y)\big) = \begin{cases} (2\pi\vartheta^2)^{-\frac{1}{2}} \exp\left(\frac{d^2}{2\vartheta^2}\right) & \text{if } |\, d \,| \leq \vartheta \\ 0 & \text{if } |\, d \,| > \vartheta \end{cases}\,,$$

where $d = \big(\ddot{h}^j_{[z_{\tau+1}=z_t]}(x, y) - h_t(x, y)\big)$.

C.2. Algorithm

The algorithm for computing $\hat{\Omega}_{z_{t+1}}(x, y, \gamma)$ consists of 5 steps:

1. In period t, compute $\ddot{\Omega}_{z_t}(x, y, \gamma)$ from the realizations of $\lambda_t(x)$, $\kappa_t(x, y)$, and $S_t(x, y)$, for every value of γ. This corresponds to the *realized* value of $\Omega_{z_{\tau+1}}(x, y, \gamma)$ for $\tau = t - 1$.
2. From the sequence $\{\ddot{\Omega}_{z_{\tau+1}}(x, y, \gamma)\}_{\tau=0}^{t-1}$, keep all $\ddot{\Omega}_{z_{\tau+1}}(x, y, \gamma)$s such that $z_{\tau+1} = z_t$ (i.e., those for which the aggregate state of the economy in the next period equals z_t). Call this array $\ddot{\mathcal{O}}_{[z_{\tau+1}=z_t]}(x, y, \gamma)$ and let $\ddot{o}^j_{[z_{\tau+1}=z_t]}(x, y, \gamma)$ be the j-th element of this array.
3. Keep the corresponding employment distributions. Call this array $\ddot{H}_{[z_{\tau+1}=z_t]}(x, y)$ and let $\ddot{h}^j_{[z_{\tau+1}=z_t]}(x, y)$ be the j-th element of this array.
4. Given $h_t(x, y)$ and $\ddot{h}^j_{[z_{\tau+1}=z_t]}(x, y)$, compute the optimal bandwidth ϑ and the Kernel weighting function $K_j(.)$.
5. Compute $\hat{\Omega}_{z_{t+1}}(x, y, \gamma)$ from equation (C.2).

Since the solution of the model does not require the computation of wage values, this algorithm should be executed at the end of all the simulations.

C.3. Accuracy of Forecasts

In Figure C.1, I show the comovement between the Kernel-based forecast and the realized value of the expectations component of wages (Panel A) along with the mean error (Panel B) across the last 2,400 simulated periods which I use to compute model-simulated wage moments (see the next section). I compute the period t mean error, e_t, as follows:

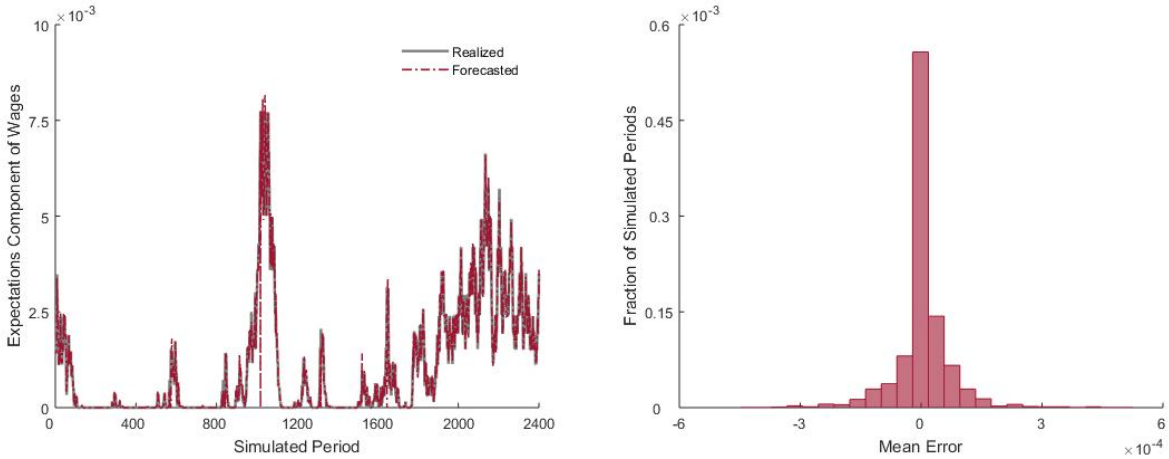
$$e_t = \iiint \left(\hat{\Omega}_{z_{t+1}}(x, y, \gamma) - \ddot{\Omega}_{[z_t]}(x, y, \gamma)\right) g_t(x, y, \gamma)\, \mathrm{d}\gamma\, f(y)\, \mathrm{d}y\, l(x)\, \mathrm{d}x\,,$$

where $g_t(x, y,)$ is the period t measure of contracts of size γ for (x, y)-type matches, from equations (12) and (13) in the main text.

The Kernel-based forecast of the expectations component of wages does a very good job in predicting the realized value. The correlation between these two series is 0.991 and the R^2 from a linear regression of Kernel-based forecasts on realized values is 0.998. Moreover, the mean error is $4.289\mathrm{e}^{-6}$, which speaks to the high precision of the forecasts.

Appendix Figure C.1: Accuracy of Forecasts

(A) Comovement (B) Mean Error



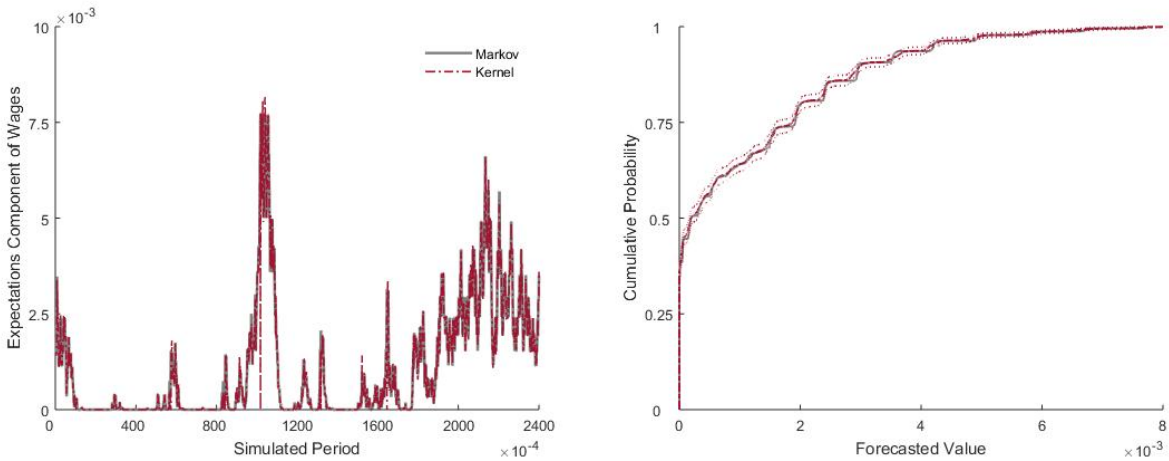
Note: The figure shows the comovement (Panel A) and the mean error (Panel B) between the Kernel-based forecast of the expectations component of wages and its realized value across 2,400 simulated periods.
Source: Author's calculations based on model simulations.

C.4. Comparison with Alternate Forecasting Rules

I next analyze the extent to which the Kernel-based estimate of the expectations component of wages differ from that based on the Markov process, conditional on the model's estimated structural parameters. In Panel A of Figure C.2, I plot the Markov- and Kernel-based estimates of the expectations component of wages and, in Panel B, I plot their corresponding Kaplan-Meier estimates of the empirical CDFs across the last 2,400 simulated periods. The Kernel-based tracks accurately the Markov-based forecast of the expectations component of wages. Based on the Kolmogorov-Smirnov test with a KS-statistic equal to 0.029 (p-value = 0.549), I cannot reject the null hypothesis that the implied series are drawn from a common underlying distribution. From these figures, I conjecture that forecasts based on one or another method yield very similar results.

Appendix Figure C.2: Markov- and Kernel-based Forecasting Methods

(A) Comovement (B) Empirical CDFs



Note: The figure shows the comovement between Markov- and Kernel-based estimates of the expectations component of wages (Panel A) and their corresponding Kaplan-Meier estimates of the empirical CDFs (Panel B). Dotted lines on the graph shown in Panel B correspond to the 95% confidence bands of the empirical CDF of the Kernel-based estimate of of the expectations component of wages.
Source: Author's calculations based on model simulations.

C.5. Computation of Wage Levels

From equations (C.1) and (C.2), I compute the wage level of an x-type worker employed by a y-type firm under an employment contract of size γ in period t as follows:

$$w_t(x, y, \gamma) = \gamma\, p_t(x, y) + (1 - \gamma)\, b_t(x) - \beta\, \hat{\Omega}_{z_{t+1}}(x, y, \gamma)\,,$$

which is obtained by swapping $\Omega_{z_{t+1}}(x, y, \gamma)$ and $\hat{\Omega}_{z_{t+1}}(x, y, \gamma)$.

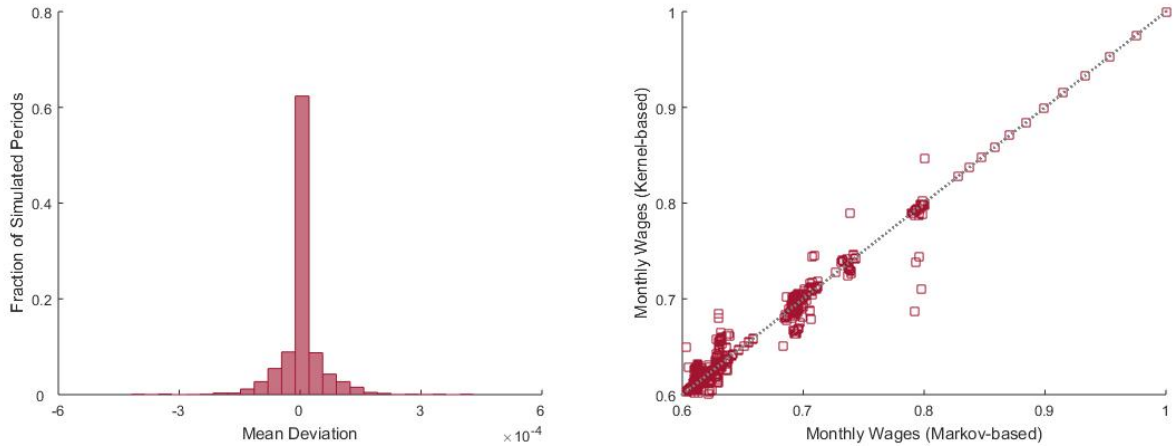
In Appendix Figure C.3, I depict the mean deviation (Panel A) and correlation (Panel B) between wage levels computed from Markov- and Kernel-based expectations component of wages resulting from the last 2,400 simulated periods.[11] The mean deviation between the two methods for computing wage levels is 1.754e^{-6}, with a correlation of 0.998.[12] Further, the t-statistic from a two-sample t-test equals -0.012 (p-value = 0.957), which implies that I cannot reject the null hypothesis that mean wages computed from Markov- or Kernel-based forecasting methods are the same. I take these findings as supporting evidence the validity of the Kernel-based forecasting rule.

[11] I compute the mean deviation in the same manner I compute the mean error between forecasted and realized values.

[12] The R^2 from a linear regression of the Kernel-based estimates on the Markov-bases estimates of the expectations component of wages equals 0.999.

Appendix Figure C.3: Markov- and Kernel-based Wage Computation

(A) Mean Deviation (B) Correlation



Note: The figure shows the distribution of mean deviations (Panel A) and the correlation (Panel B) between wage levels computed from Markov- and Kernel-based expectations component of wages. Wage levels are computed across 2,400 simulated periods.
Source: Author's calculations based on model simulations.

D. Model-simulated Moments

D.1. Simulations

I set each period to have a length of 1 month. To obtain the model-simulated moments, I first simulate the model for 9,600 periods (i.e., 800 years) and discard the first 1,200 periods (i.e., 100 years) as I consider it to be a burning/adjusting phase of the model. Importantly, I compute model-simulated moments that link to labor market transitions and/or distributions from the last 8,400 simulations but only consider the last 2,400 simulations to compute moments that link to wage levels with the aim of reducing computing time.

D.2. Construction of Quarterly Time Series

I utilize 23 moments to estimate the structural parameters of the model. In computing these moments, I try to follow as close as possible the methods utilized for constructing the data moments presented in Appendix A.

Unemployment Rate. I compute monthly time series of the unemployment rate, U_t, as follows:

$$U_t = \int u_t(x)\, l(x) \mathrm{d}x \,,$$

and aggregate these series at a quarterly frequency by averaging across months within a quarter.

Unemployment Rates of 5+/15+/27+ Weeks. Provided that 4 weeks account for approximately 1 month, I compute monthly time series of the unemployment rate of 5+, 15+, or 27+ weeks, U_t^{5+}, U_t^{15+}, U_t^{27+}, respectively, as follows:

$$U_t^{5+} = \int u_{t-1}(x) \left(1-\lambda_t(x)\right) l(x) \, \mathrm{d}x$$

$$U_t^{15+} = \int u_{t-4}(x) \prod_{k=0}^{3} \left(1 - \lambda_{t-k}(x)\right) l(x) \, \mathrm{d}x$$

$$U_t^{27+} = \int u_{t-6}(x) \prod_{k=0}^{5} \left(1 - \lambda_{t-k}(x)\right) l(x) \, \mathrm{d}x \,,$$

and aggregate these series at a quarterly frequency by averaging across months within a quarter.

Vacancy Rate. I compute monthly time series of the vacancy rate, V_t, as:

$$V_t = \int\int v_t(x, y) f(y) \, \mathrm{d}y \, l(x) \, \mathrm{d}x \,,$$

and aggregate these series at a quarterly frequency by averaging across months within a quarter.

Unemployment-to-employment Transition Rate. I construct monthly time series of the unemployment-to-employment transition rate, UE_t, by combining the unemployment rate of the previous month, U_{t-1}, with the job finding rate of the current month, U_t^{5+}, as follows:

$$UE_t = 1 - \frac{U_t^{5+}}{U_{t-1}} \,,$$

and aggregate these series at a quarterly frequency by averaging across months within a quarter.

Employment-to-unemployment Transition Rate. Let

$$E_{t-1} = 1 - U_{t-1}$$

and

$$U_t^{<5} = U_t - U_t^{5+}$$

be the measure of employed workers observed in period $t-1$ and the measure of workers who are unemployed for less than 5 weeks in period t, respectively. I combine these two measures in order to compute monthly time series of the employment-to-unemployment transition rate, EU_t, as follows:

$$EU_t = \frac{U_t^{<5}}{E_{t-1}}\,,$$

and aggregate these series at a quarterly frequency by averaging across months within a quarter.

Job-to-job Transition Rate. Let

$$EE_t = \iint h_{t-}(x,y)\Big(\int\Big(\lambda_t(x)\,\kappa_t(x,\hat{y})\,\mathbb{1}\big\{\Delta_{S_t(x,\hat{y})}^{S_t(x,y)} < 0\big\}\Big)\,\mathrm{d}\hat{y}\Big) f(y)\,\mathrm{d}y\,l(x)\,\mathrm{d}x$$

be the measure of employed workers who changed jobs between periods $t-1$ and t. I compute monthly time series of the job-to-job transition rate, $J2J_t$, as follows:

$$J2J_t = \frac{EE_t}{E_{t-1}}\,,$$

and aggregate these series at a quarterly frequency by averaging across months within a quarter.

Value Added. I compute monthly time series of the aggregate real value added, VA_t, as follows:

$$VA_t = \iint p_t(x,y)\,h_t(x,y)\,f(y)\,\mathrm{d}y\,l(x)\,\mathrm{d}x\,,$$

and aggregate these series at a quarterly frequency by adding across months within a quarter.

Dispersion of Labor Productivity. I approximate the cross-sectional dispersion of labor productivity, DLP_t, by the standard deviation of the firm-level (log.) value added per worker. Let:

$$VA_t(y) = \int p_t(x,y)\,h_t(x,y)\,l(x)\,\mathrm{d}x$$

and

$$E_t(y) = \int h_t(x,y)\,l(x)\,\mathrm{d}x$$

be the the real value added and the measure of employed workers in a y-type firm in period t, respectively. Further, define

$$VAW_t(y) = \frac{VA_t(y)}{E_t(y)}$$

and

$$\overline{VAW}_t = \int VAW_t(y)\, f(y)\, \mathrm{d}y$$

as the value added per worker of a y-type firm and the mean value added per worker across firms in month t, respectively. I compute monthly time series of the dispersion of (log.) labor productivity as follows:

$$DLP_t = \left[\int \left(\left(\log\left(VAW_t(y)\right) - \log(\overline{VAW}_t) \right)^2 \right) f(y)\, \mathrm{d}y \right]^{\frac{1}{2}},$$

where the log-transformation stems from the scale used in Bloom et al. (2018). I aggregate these series at a quarterly frequency by averaging across months within a quarter.

Real Wages. I compute monthly time series of (log.) real wages, w_t, as follows:

$$\log(w_t) = \iint \left(\int \log\left(w_t^{\mathrm{w}}(x,y,\gamma)\right) g_t(x,y,\gamma)\, \mathrm{d}\gamma \right) f(y)\, \mathrm{d}y\, l(x)\, \mathrm{d}x\,,$$

where $w_t^{\mathrm{w}}(x,y,\gamma) = 0.25 \times w_t(x,y,\gamma)$ resembles real weekly wages, and the 0.25 scale stems from the fact that 4 weeks account for approximately 1 month. I aggregate these series at a quarterly frequency by averaging across months within a quarter.

Dispersion of Real Wages. I compute monthly time series of the cross-sectional dispersion of (log.) real wages, Dw_t, as follows:

$$\log\left(w_t\right) = \left[\iint \left(\int \left(\log\left(w_t^{\mathrm{w}}(x,y,\gamma)\right) - \log\left(w_t\right) \right)^2 g_t(x,y,\gamma)\, \mathrm{d}\gamma \right) f(y)\, \mathrm{d}y\, l(x)\, \mathrm{d}x \right]^{\frac{1}{2}},$$

and aggregate these series at a quarterly frequency by averaging across months within a quarter.

Labor Share of Output. Let

$$I_t(y) = \iint w_t(x,y,\gamma)\, g_t(x,y,\gamma)\, \mathrm{d}\gamma\, l(x)\, \mathrm{d}x$$

denote the payroll (i.e., the sum of wages that are paid to workers) of a y-type firm in period t. Further, define

$$LSO_t(y) = \frac{I_t(y)}{VA_t(y)}$$

as the labor share of output of a y-type firm in period t. I compute monthly time series of the labor share of output, LSO_t, as follows:

$$LSO_t = \int LSO_t(y)\, f(y)\, \mathrm{d}y\,,$$

and aggregate these series at a quarterly frequency by averaging across months within a quarter.

D.3. Computation of Model-simulated Moments

To compute model-simulated moments, I follow the same procedure I did with the observational data. Specifically, I first apply a logarithmic transformation to all quarterly series. Next, I compute moments such as means, standard deviations, and correlations from the log-transformed quarterly series.

E. Parameter Estimation

E.1. Estimation Method

I estimate the 15 structural parameters of the model by indirect inference (Gouriéroux et al., 1993), targeting a set of empirical moments derived from U.S. quarterly data over the period 1951q1-2019q4 through the Method of Simulated Moments (MSM). In practice, the MSM can be thought of as a Generalized Method of Moments (GMM) estimator that does not need close form moment conditions to hold. Instead, the MSM chooses the model parameters to make simulated model moments match data moments.

Let $\hat{\omega} = \{\hat{\omega}_1, \hat{\omega}_2, \ldots, \hat{\omega}_N\}$ denote the $N \times 1$ vector of empirical moments derived from the data and $\omega(\varphi) = \{\omega_{1,T}(\varphi), \omega_{2,T}(\varphi), \ldots, \omega_{N,T}(\varphi)\}$ denote the model-simulated moments derived from T simulation periods and a $K \times 1$ vector of parameters φ defined over a compact space $\Theta \subseteq \mathbb{R}^K$, with $K \leq N$. Then, the MSM estimate of φ, $\hat{\varphi}(A_T)$, is the vector of parameter values that solves:

$$\hat{\varphi}(A_T) = \arg\min_{\varphi \in \Theta} Q(\varphi) \equiv \left\| A_T \left(\hat{\omega} - \tilde{\omega}(\varphi)\right) \right\|^2,$$

where $\tilde{\omega}(\varphi)$ is an affine transformation (see section E.5) of $\omega(\varphi)$, and A_T is a weighting matrix that converges in probability to a nonrandom matrix A with full rank N (i.e., $A_T \to^p A$ as

$T \to \infty$).[13] Notice that the vector of parameter estimates will be a function of A_T.

E.2. Asymptotic Properties

Standard first-order conditions imply:

$$\begin{aligned} \left.\frac{\partial\, Q(\varphi)}{\partial\, \varphi}\right|_{\varphi=\hat{\varphi}(A_T)} &= 0 &= \nabla'_{\tilde{\omega}}\, \Lambda \left[\hat{\omega} - \tilde{\omega}\big(\hat{\varphi}(A_T)\big)\right] \\ &&= \nabla'_{\tilde{\omega}}\, \Lambda \left[\hat{\omega} - \Big(\tilde{\omega}\big(\varphi_0\big) + \nabla_{\tilde{\omega}}\, \big(\hat{\varphi}(A_T) - \varphi_0\big)\Big)\right] + o_p(1)\,, \end{aligned}$$

where $\nabla_{\tilde{\omega}}$ is the gradient of $\tilde{\omega}\big(\varphi_0\big)$ (i.e., the matrix of first-derivatives of the vector of model-simulated moments with respect to the parameters) and $\Lambda = A'_T A_T$. The second equality follows from an expansion around φ_0, the unique minimizer of $Q(\varphi)$ over Θ (i.e., $Q(\varphi_0) = 0$). From the Central Limit Theorem, we know that $\sqrt{T}\,\big(\hat{\omega} - \omega(\varphi_0)\big) \to^d \mathcal{N}\big(0, C\big)$ as $T \to \infty$, where C is the variance-covariance matrix of the vector of data moments. Then, together with the first-order conditions outlined above, the asymptotic distribution of the vector of parameter estimates is:

$$\sqrt{T}\,\big(\hat{\varphi}(A_T) - \varphi_0\big) \to^d \mathcal{N}\big(0, \Sigma\big)\,,$$

where the variance-covariance matrix of the vector of parameter estimates, Σ, is given by:

$$\Sigma = \big(\nabla'_{\tilde{\omega}}\, \Lambda\, \nabla_{\tilde{\omega}}\big)^{-1}\, \nabla'_{\tilde{\omega}}\, \Lambda\, C\, \Lambda\, \nabla_{\tilde{\omega}}\, \big(\nabla'_{\tilde{\omega}}\, \Lambda\, \nabla_{\tilde{\omega}}\big)^{-1}$$

Given a consistent estimate $\hat{\varphi}(A_T)$ of the vector of structural parameters, it is possible to construct the empirical counterparts $\hat{\nabla}_{\tilde{\omega}}$ and $\hat{\Lambda}$, and compute a consistent estimate $\hat{\Sigma}\big(\hat{\varphi}(A_T)\big)$ of the variance-covariance matrix of the vector of parameter estimates. This, however, would also require to compute $\hat{C}$, a consistent estimate of the asymptotic variance-covariance (or limiting spectral density at frequency zero) matrix of the vector of data moments.

E.3. Asymptotic Distribution of Data Moments

Estimation of Data Moments. In estimation, I utilize moments such as sample averages, standard deviations, and correlations, derived from an array $a_t = (a_{1,t}, \ldots, a_{L,t})$ of variables. Let

$$\begin{aligned} \ell_{1i}(a_t, \omega) &= a_{i,t} - \mu_i \\ \ell_{2ij}(a_t, \omega) &= (a_{i,t} - \mu_i)(a_{j,t} - \mu_j) - \rho_{ij}\, \sigma_i\, \sigma_j\,, \end{aligned}$$

[13] In practice, I normalize $\big(\hat{\omega} - \tilde{\omega}(\varphi)\big)$ by pre-multiplying by the inverse of $\mathrm{diag}\,(\hat{\omega})$. This normalization allows me to obtain a standard metric across the different moments used for estimation of the structural parameters.

be transformed arrays, where $\omega = [\mu, \sigma, \rho]'$ is the vector of population moments that are to be estimated, such that $\mu = (\mu_1, \ldots, \mu_L)$ is the vector of means, $\sigma = (\sigma_1, \ldots, \sigma_L)$ is the vector of standard deviations, and $\rho = (\rho_{ij})_{i \neq j\,;\, i,j=1,\ldots,L}$ is the vector of correlations. I estimate the vector of data moments, $\hat{\omega}$, by solving simultaneously:

$$\frac{1}{T_\omega} \sum_{t=1}^{T_\omega} \ell_{1i}(a_t, \hat{\omega}) = 0 \quad \text{and} \quad \frac{1}{T_\omega} \sum_{t=1}^{T_\omega} \ell_{2ij}(a_t, \hat{\omega}) = 0 \;\; \forall\; i, j\,,$$

where T_ω is the size of the data series.

Estimation of the Variance-covariance Matrix of Data Moments. Given that ℓ_{1i} and ℓ_{2ij} are functions of the data moments, I estimate the asymptotic variance-covariance matrix of the vector of data moments by the Delta method. Further, given dynamic nature of the model and the high persistence of aggregate productivity shocks, I allow for a certain degree of serial correlation in the estimation. To proceed, let $\hat{\ell}_{1i}(a_t, \hat{\omega}) = a_{it} - \hat{\mu}_i$ and $\hat{\ell}_{2ij}(a_t, \hat{\omega}) = (a_{it} - \hat{\mu}_i)(a_{jt} - \hat{\mu}_j) - \hat{\rho}_{ij}\hat{\sigma}_i\hat{\sigma}_j$. Also, define $\hat{\ell}_1(a_t, \hat{\omega}) = (\hat{\ell}_{11}, \ldots, \hat{\ell}_{1L})$ and $\hat{\ell}_2(a_t, \hat{\omega}) = (\hat{\ell}_{2(1,1)}, \ldots, \hat{\ell}_{2(i,j)}, \ldots\, \hat{\ell}_{2(L,L)})_{i \geq j\,;\, i,j=1,\ldots,L}$, and let $\hat{\ell}(a_t, \hat{\omega}) = [\hat{\ell}_1(a_t, \hat{\omega}), \hat{\ell}_2(a_t, \hat{\omega})]'$.

First, I estimate the Jacobian matrix of first-derivatives of $\mathbb{E}\,\ell(a_t, \omega)$ with respect to the vector of data moments ω, $\hat{C}_0$. For each element $\ell_p(a_t, \omega) \in \ell(a_t, \omega)$, I estimate the partial derivative with respect to ω_n, the n-th element in the vector of estimated data moments, as follows:

$$\left.\frac{\partial\, \mathbb{E}\,\ell_p(a_t, \omega)}{\partial\, \omega_n}\right|_{\omega=\hat{\omega}} \equiv \hat{C}_{0,(p,n)} \;=\; \frac{1}{T_\omega} \sum_{t=0}^{T_\omega} \frac{\hat{\ell}_p(a_t, \ddot{\omega}) - \hat{\ell}_p(a_t, \hat{\omega})}{h}\,,$$

where $\ddot{\omega}$ is constructed by swapping the estimated data moment $\hat{\omega}_n$ by $\hat{\omega}_n + h$, with $h = 0.001$, and keeping all remaining estimated data moments fixed at their corresponding values. Then, I construct the estimated Jacobian matrix, $\hat{C}_0$, as follows:

$$\hat{C}_0 = \begin{bmatrix} \hat{C}_{0,(1,1)} & \hat{C}_{0,(1,2)} & \cdots & \hat{C}_{0,(1,N)} \\ \hat{C}_{0,(2,1)} & \hat{C}_{0,(2,2)} & \cdots & \hat{C}_{0,(2,N)} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{C}_{0,(P,1)} & \hat{C}_{0,(P,2)} & \cdots & \hat{C}_{0,(P,N)} \end{bmatrix},$$

where P and N are the number of different series in $\hat{\ell}(a_t, \hat{\omega})$ and the number of data moments utilized for estimating the model's structural parameters, respectively.

Second, I compute the estimate of the variance-covariance matrix of $\ell(a_t, \omega)$, $\hat{C}_1$, as follows:

$$\hat{C}_1 = \frac{1}{T_\omega - 2m} \left(\sum_{t=m+1}^{T_\omega - m} \sum_{s=-m}^{m} \phi_s\, \hat{\ell}(a_t, \hat{\omega})\, \hat{\ell}(a_{t-s}, \hat{\omega})' \right),$$

where $m \leq T_\omega - 1$ is the maximum number of leads/lags allowed for the serial correlation and ϕ_s is the weight ascribed to the m-th lead/lag, given by the formula:

$$\phi_s = 1 - \frac{|\, m \,|}{m+1}$$

such that $\phi_s \in (0, 1]$. This non-parametric approach for computing $\hat{C}_1$, postulated by Newey and West (1987), assumes that the serial correlation decays linearly with increasing leads/lags. The rationale behind this formulation is that the serial correlation attenuates as one moves farther away in time.[14]

Given $\hat{C}_0$ and $\hat{C}_1$, I compute an heteroskedasticity-and-autocorrelation-robust (HAC-robust) estimate of the asymptotic variance-covariance matrix of the vector of data moments as follows:

$$\hat{C} = \left(\hat{C}_0' \, \hat{C}_1^{-1} \, \hat{C}_0 \right)^{-1} ,$$

which is an $N \times N$ matrix.

Estimation Details. A particular caveat in estimating the variance-covariance matrix of the vector of data moments is that not all data series have the same lengths. For instance, while the series of the unemployment rate have a length of 276 quarters, the series of the cross-sectional dispersion of labor productivity have a length of 140 quarters. Thus, T_ω is not constant across the series. I deal with this caveat by performing the computation on the subset of quarters for which I observe information across all data series; a total of 140 quarters. Further, in estimating $\hat{C}$, I follow the rule of thumb by setting the bandwidth for leads/lags $m = 0.75\, T_\omega^{\frac{1}{3}}$ (Den Haan and Levin, 1997). Since $T_\omega = 140$, this results in a bandwidth $m = 4$.

Alternate Estimation Method. As a robustness check, I also estimate the variance-covariance matrix of the vector of data moments by block bootstrap. To that end, I follow Berkowitz and Kilian (2000) and divide the matrix containing the data series $[a_1; \ldots; a_{T_\omega}]$ into B non-overlapping blocks of length r, such that $T_\omega = r\, B$.[15,16] This yields blocks $\{z_1, \ldots, z_B\}$, where $z_b = \left[\left(a_{1,(b-1)r+1}, \ldots, a_{1,(b-1)r+r} \right); \ldots; \left(a_{L,(b-1)r+1}, \ldots, a_{L,(b-1)r+r} \right) \right]$ for $b = 1, \ldots, B$. I randomly sample B blocks from $\{z_1, \ldots, z_B\}$, with replacement, such that each block has an equal probability $1/B$ from being drawn. I pool these blocks end-to-end to form a new data series, and repeat this procedure S times to form different bootstrapped samples $\left[a_1^s; \ldots; a_{T_\omega}^s \right]$ for $s = 1, \ldots, S$.

[14] Note that only the central $T_\omega - 2m$ periods are considered for estimating $\hat{C}_1$ since, by construction, the leads/lags are impossible to calculate for the first/last m periods.

[15] I adopt the conventional notation that refers to $[a_t; a_{t+1}]$ as the vertical stacking of $a_t = (a_{1,t}, \ldots, a_{L,t})$ across dimension t.

[16] In practice, I set $r = 10$ such that it approximates the $2m + 1$ bandwidth of leads/lags utilized in the computation of the HAC-robust variance-covariance matrix of the vector of data moments at the same time of ensuring that $(T_\omega / r) \in \mathbb{N}$.

For each sample s, I estimate the vector of moments, $\hat{\omega}^s$, by solving simultaneously:

$$\frac{1}{T_\omega}\sum_{t=1}^{T_\omega} \ell_{1i}^s(a_t^s, \hat{\omega}^s) = 0 \quad \text{and} \quad \frac{1}{T_\omega}\sum_{t=1}^{T_\omega} \ell_{2ij}^s(a_t^s, \hat{\omega}^s) = 0 \;\; \forall\; i, j\,,$$

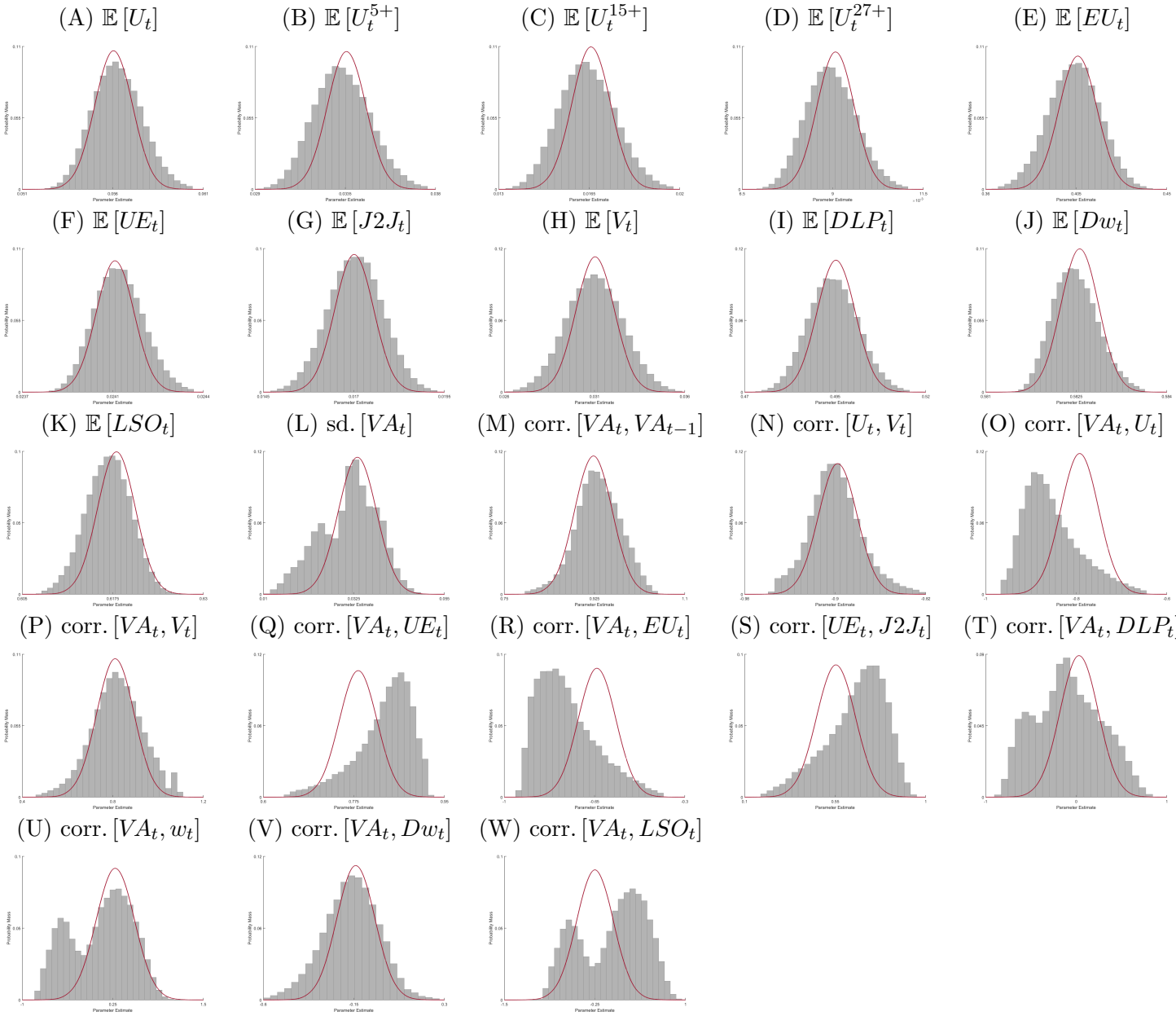
where $\ell_{1i}^s(a_t^s, \hat{\omega}^s)$ and $\ell_{2ij}^s(a_t^s, \hat{\omega}^s)$ are analogues to $\ell_{1i}(a_t, \hat{\omega})$ and $\ell_{2ij}(a_t, \hat{\omega})$, constructed from the bootstrapped sample. Given $\hat{\omega}^s$, for $s = 1, \ldots, S$, I compute the the $n_1 n_2$-th element of the bootstrap estimate of the variance-covariance matrix of the vector of data moments, $\hat{C}^b$, as follows:

$$\hat{C}^b_{n_1 n_2} = \frac{1}{S-1}\left[\sum_{s=1}^{S}\left(\hat{\omega}^s_{n_1} - \bar{\hat{\omega}}_{n_1}\right)\,\left(\hat{\omega}^s_{n_2} - \bar{\hat{\omega}}_{n_2}\right)\right]\,,$$

where $\bar{\hat{\omega}}_{n_q}$ is the average across the S bootstrap estimates of the n_q-th estimated moment, for $n_q = 1, \ldots, N$.

In Appendix Figure E.1, I depict the probability distributions of the vector of data moments derived from the asymptotic properties and the bootstrapped samples. Both methods yield very similar distribution in terms of expectations (i.e., first moments). The distribution of some correlations, however, differ across methods. This is particularly the case for corr.$[VA_t, U_t]$, corr.$[VA_t, UE_t]$, corr.$[VA_t, EU_t]$, corr.$[UE_t, J2J_t]$, corr.$[VA_t, w_t]$, and corr.$[VA_t, LSO_t]$, for which the bootstrapped samples yield either skewed or bimodal distributions.

Appendix Figure E.1: Estimated Distributions of Data Moments



Note: The figure shows probability distributions of data moments derived from the estimator's asymptotic properties (maroon) and from block bootstrap (gray). The asymptotic distributions are constructed from a sample of 10,000 draws from a Gaussian distribution with moments means and standard deviations equal to those reported in Table 3 of the main text. The block-bootstrap distributions are constructed from 10,001 bootstrapped samples.
Source: Author's calculations based on data series.

E.4. Variance-Covariance Matrix of Parameter Estimates

Estimation of the Variance-Covariance Matrix of Parameter Estimates. The efficient GMM estimator is obtained by setting $A_T = \hat{C}^{-\frac{1}{2}}$.

Given this choice, I compute the variance-covariance matrix of the vector of parameter estimates as follows:

$$\hat{\Sigma}\big(\hat{\varphi}(\hat{C}^{-1/2})\big) = \big(\hat{\nabla}'_{\tilde{\omega}}\,\hat{C}^{-1}\,\hat{\nabla}_{\tilde{\omega}}\big)^{-1},$$

where $\hat{\nabla}_{\tilde{\omega}}$ is a consistent estimate of the gradient of $\tilde{\omega}\big(\varphi_0\big)$.

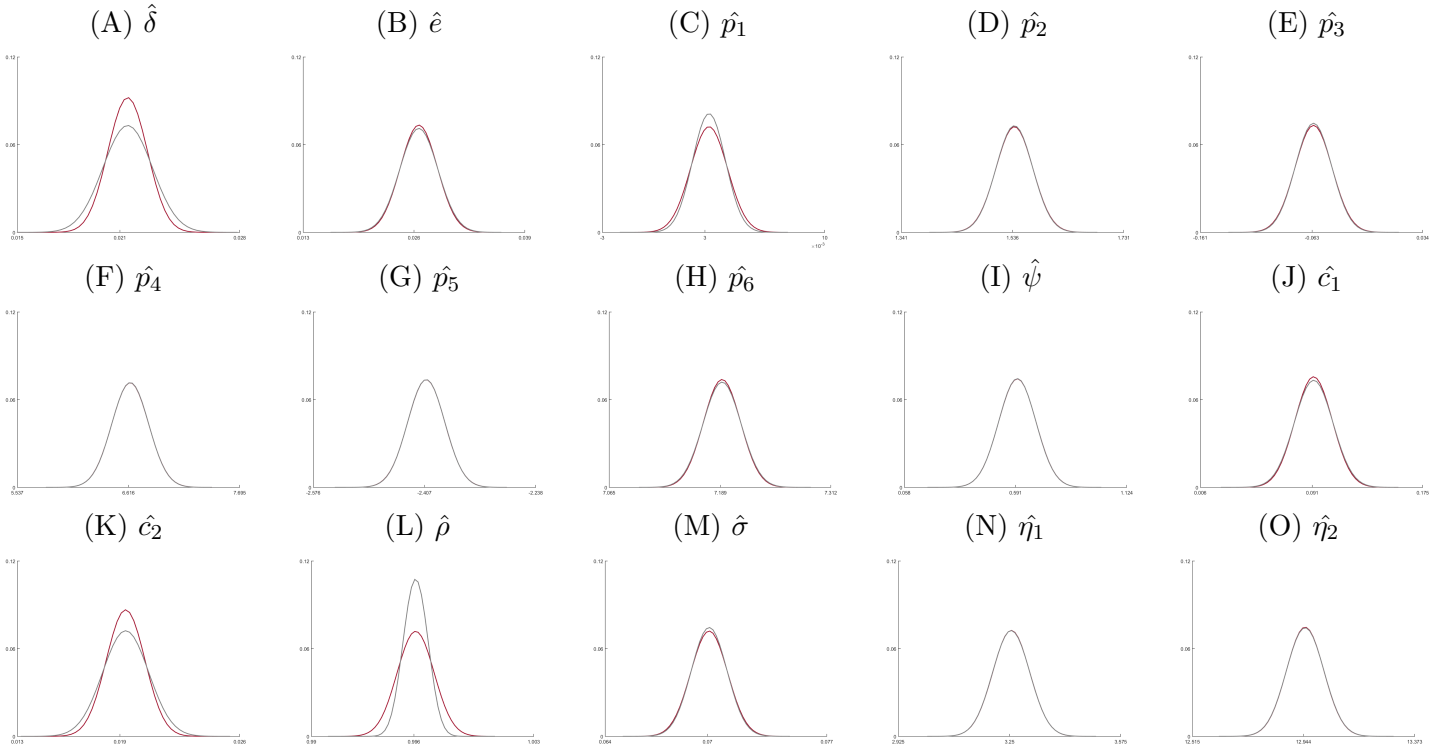
Computation of $\hat{\nabla}_{\hat{\omega}}$. I estimate $\hat{\nabla}_{\hat{\omega}}$ by numerical approximation around a vicinity of $\hat{\varphi}(A_T)$. In particular, for each estimated parameter $\hat{\varphi}_k(A_T)$, I simulate the model by evaluating at $\ddot{\varphi}_k(A_T) = \hat{\varphi}_k(A_T) + h$, with $h = 0.001$, while holding all other parameters fixed at their estimated values. Let $\tilde{\omega}_n(\hat{\varphi}_k)$ and $\tilde{\omega}_n(\ddot{\varphi}_k)$ denote the resulting model-simulated n-th moment, for $n = 1, \ldots, N$, when evaluating at the estimated, $\hat{\varphi}_k$, and altered, $\ddot{\varphi}_k$, k-th parameter values, respectively. I compute the approximate partial derivative with respect to φ_k as follows:

$$\frac{\partial\,\tilde{\omega}(\varphi)'}{\partial\,\varphi_k} \approx \left[\frac{(\tilde{\omega}_1(\ddot{\varphi}_k)-\tilde{\omega}_1(\hat{\varphi}_k))}{h}, \ldots, \frac{(\tilde{\omega}_N(\ddot{\varphi}_k)-\tilde{\omega}_N(\hat{\varphi}_k))}{h}\right],$$

such that $\hat{\nabla}_{\hat{\omega}}$ can be constructed from stacking the vector of partial derivatives across k.

Distribution of Estimated Parameters. In Appendix Figure E.2, I present the estimated distributions of the structural parameters of the model, where the variances are obtained from the asymptotic (maroon) or bootstrapped (gray) distributions. The estimated distributions are similar across both methods employed for computing the variance-covariance matrix of the vector of model parameters.

Appendix Figure E.2: Estimated Distributions of Structural Parameters



Note: The figure shows estimated probability distributions of structural parameters of the model from the estimator's asymptotic properties (maroon) and from block bootstrap (gray).
Source: Author's calculations based on data series.

E.5. Implementation Details

Transformation of the Vector of Model-implied Moments. As I mentioned in section D.1, I utilize a rescaled vector of the model-simulated moments for estimating the structural parameters. In particular, I construct rescaled moments as $\tilde{\omega}(\varphi) = \upsilon' \omega(\varphi)$, where υ is a column vector containing scales of the order 0.10, 1, or 10. As a general rule, I assign a fixed rescaling parameter of 1 to all expectations and standard deviations (except for the expected value of the job-to-job transition rate whose ascribed rescaling parameter equals 10). For all remaining moments (all of them correlations), I set the rescaling parameter as the one which brings the model-simulated moment closer to its observational counterpart.

Formally, for the i-th moment, I pick the rescaling parameter υ_i that solves:

$$\upsilon_i = \arg \min_{\mu \in \Upsilon} \left| \hat{\omega}_i - \mu \, \omega_i(\varphi) \right| ,$$

where $\Upsilon = \{0.10, 1, 10\}$. This rescaling method does not affect the computation of the variance-covariance matrix of the vector of parameter estimates. This transformation is also similar to that used by Lise and Robin (2017). The final vector υ assigns rescaling parameters of 0.10 to $\{\text{corr.}[VA_t, DLP_t]; \text{corr.}[VA_t, w_t]; \text{corr.}[VA_t, LSO_t]\}$, of 10 to $\{\mathbb{E}[J2J_t]; \text{corr.}[VA_t, EI_t]\}$,

and of 1 to all remaining moments.

Parameters Associated with the Hiring Costs. In practice, with very limited information on additional moments related to the hiring costs of firms, it is not possible to identify separately the parameters associated with the hiring costs c_1 and c_2. To amend this problem, I first run the GA by fixing c_1 to a specified value. Then, I perform a local search for c_1 by targeting the average labor market tightness ratio (i.e., the ratio of the vacancy to the unemployment rate) of 0.634 for the U.S. economy (Hagedorn and Manovskii, 2008) and keeping all other parameters fixed at their optimum.

Optimization Algorithm. I opt for the Genetic Algorithm (GA) as the main optimization algorithm for estimating the structural parameters of the model. This algorithm, utilized for finding global maxima in constrained and unconstrained optimization problems, is based on a natural selection that mimics biological evolution. In short, the GA selects genotypes — parameters — from an initial population (called the parents) to form a second population (called the children) evolving each time towards a better solution to the optimization problem. This second population is formed by cloning (i.e., retaining the strongest genotypes), mutating (i.e., altering the genotypes), or mixing (i.e., combining the genotypes), all of this performed on the basis a fitness level derived from the objective function. Across the different iterations, the GA reduces the search space by the process of evolution. I start the search with an ample population of 50 different genotypes to guarantee sufficient variety in the search for the global minima. The algorithm halts either when a maximum number of generations has been produced or a satisfactory fitness level has been attained. Once the GA finds a solution, I perform a final local search along a reduced parameter space near the solution. This final search not only refines the optimization process but also ensures that there are no other local minima around the solution point.

F. Additional Analysis

F.1. Job Loss

In Appendix Figure F.1, I depict the model- (Panel A) and data-implied (Panel B) distributions of job separations across the support of wages. The data-implied distribution is constructed based on information on employment stocks and flows from the CPS-ORG. In particular, I approximate the number of individuals who lost their jobs in each wage bin of size US$1.00 as the difference between the employment levels in months t and $t+1$ minus the number of workers who found a job paying that bin's wage level.[17] I then normalize the wage level by dividing each bin's wage level by the maximum value across all wage bins.

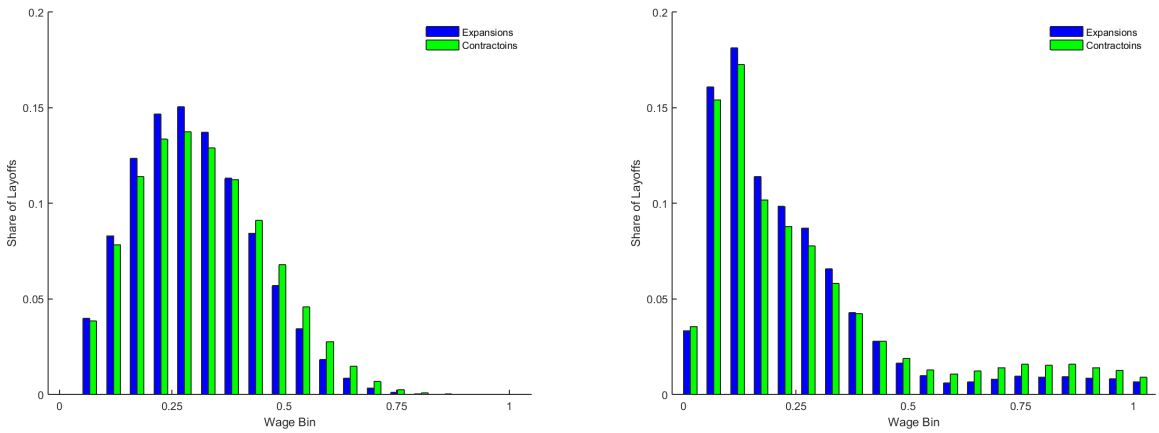
The model-implied distribution of job separations across the support of wages is similar to the observed in the data. Even more, the model generates the observed shift in the distribution that includes more high-earners among all workers who lose their jobs in recessions.

[17] In this computation, I consider workers hired from both the unemployment and employment pools.

Still, job loss is more prevalent among low-earners during recessions in the U.S. economy, consistent with previous empirical findings (Aaronson et al., 2010; Autor, 2010; Couch and Placzek, 2010; Elsby et al., 2010; Farber, 2011).

Appendix Figure F.1: Distribution of Job Separations by Wage Level

(A) Model (B) Data



Note: The figure shows the model- (Panel A) and data-implied (Panel B) distributions of job separations across the support of wages during expansions and contractions.
Source: Author's calculations based on model simulations and CPS-ORG.

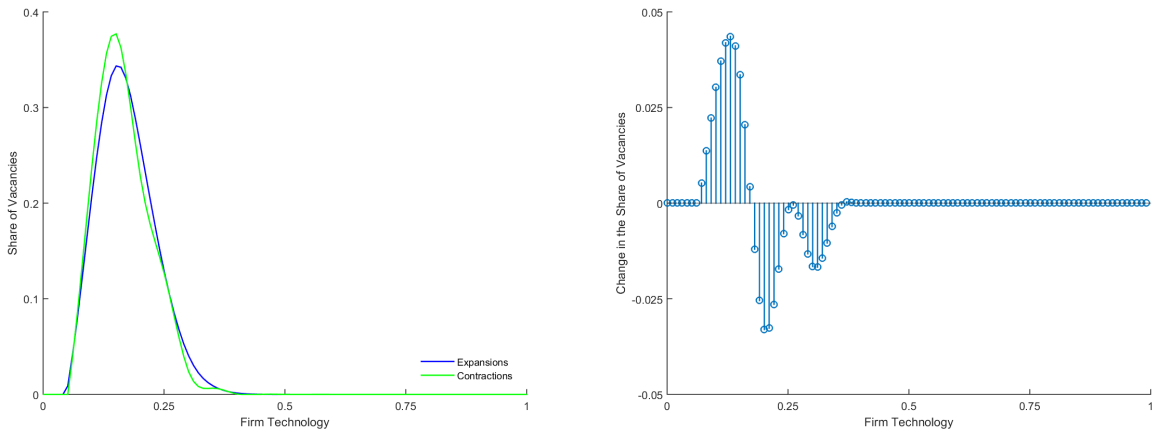
F.2. Job Creation

What Type of Firms Advertise Vacancies in Recessions? In Appendix Figure F.2, I plot the share of vacancies advertised by different firm types during expansions and contractions (Panel A) and the change in the share of vacancies advertised by different type of firms during contractions relative to expansions (Panel B).

The graphs depict two interesting patterns. First, low-technology firms tend to advertise more vacancies during contractions relative to expansions. The technology of the average firm advertising vacancies during expansions is 0.287 whereas that in contractions is 0.278. Second, the variance of the distribution of advertised vacancies across firm technologies decrease during contractions relative to expansions. This lower variance results from the smaller range of firm technologies in the match feasibility set during contractions. Also related to this point is the fact that the variance in the distribution of advertised vacancies across the support firm types is smaller than that across the support of worker types, as the range of reservation worker types for firms is more volatile over the cycle (see Figures 6 and 8 in the main text).

Appendix Figure F.2: Distribution of Advertised Vacancies by Firm Type

(A) Distribution of Vacancies (B) Change in the Distribution



Note: The figure shows the share of advertised vacancies across the support of firm technologies in expansions and contractions (Panel A) and the change in the share of advertised vacancies across different firm technologies in contractions relative to expansions (Panel B).
Source: Author's calculations based on model simulations.

Characterization of Advertised Vacancies. In Appendix Table F.1, I present the characteristics of vacancies advertised in expansions and contractions across all and different sub-markets. Consistent with past empirical work, the job filling rate increases in contractions as markets become slacker (Davis et al., 2012, 2013). This is reflected in the higher probability of hiring per vacancy during periods of low aggregate productivity.

However, the table also shows that jobs advertised in contractions tend to be more precarious. In particular, the average technology of firms advertising vacancies in contractions decay and the expected duration of a job is reduced by about 2.85 times from an average duration of 68 months in expansions. In terms of wages, the average entry wage during contractions is about 8.5 percent lower in contractions relative to expansions and most of this reduction is explained by the lower wages offered to low-skill workers during these periods. These findings are consistent with the *sullying* effect of recessions (Barlevy, 2002; Mustre-del-Río, 2014; Barnichon and Zylberberg, 2019).

Appendix Table F.1: Characterization of Advertised Vacancies

		Worker Skill		
	Overall	Low-skill $[x \in T_1(x)]$	Medium-skill $[x \in T_2(x)]$	High-skill $[x \in T_3(x)]$
Expansions				
Type of Firm	0.287	0.119	0.247	0.446
Probability of Hiring (per vacancy)	0.036	0.031	0.048	0.026
Expected Duration (months)	68.800	65.584	69.789	69.835
Entry Wage	0.058	0.016	0.042	0.103
Contractions				
Type of Firm	0.278	0.112	0.244	0.444
Probability of Hiring (per vacancy)	0.186	0.154	0.258	0.125
Expected Duration (months)	23.937	18.274	25.767	25.657
Entry Wage	0.053	0.013	0.038	0.098

Note: The table shows characteristics of advertised vacancies during expansion and contraction periods by workers' skill level. Workers' skills include: low-skill, medium-skill, and high-skill. Respectively, these categories group workers according to the firs, second, and third terciles of the Beta distribution of worker skills. Expansion periods are defined as $z_t = [0.95; 1.05]$ and contraction periods are defined as $z_t = [0.70; 0.75]$ (6% below the value of aggregate productivity during expansion periods). Additional details are described within the table.
Source: Author's calculations based on model simulations.

F.3. Welfare Implications: Quantifying Productive Inefficiencies

Unfilled Jobs. Let $\ulcorner \mathcal{V}_t(x)$ denote the measure of advertised vacancies in sub-market x that did not result in a hire. In particular, $\ulcorner \mathcal{V}_t(x)$ can be expressed as:

$$\ulcorner \mathcal{V}_t(x) = \mathcal{V}_t(x)\left(1 - q_t(x)\right) + \iint v_t(x,y)\left(q_t(x)\,\frac{eh_{t-}(x,\hat{y})}{\mathcal{L}_t(x)}\,\mathbb{1}\{\Delta^{S_t(x,y)}_{S_t(x,\hat{y})} < 0\}\,\mathrm{d}\hat{y}\right) f(y)\,\mathrm{d}y\,,$$

where the first term is the measure of advertised vacancies that passed unnoticed among job seekers and the second term is the measure of job offers made by recruiting firms that were turned down by employed workers. To quantify net output losses from unfilled jobs, I evaluate $\ulcorner \mathcal{V}_t(x)$ in the vacancy advertisement costs function.

Ex-post Sub-optimal Job Creation. I quantify productive inefficiencies owing to ex-post sub-optimal job creation as follows. Let $\mathbb{1}\{\Delta^{p_t(x,y)}_{b_t(x)} < c(1,x)\}$ and $\mathbb{1}\{\Delta^{p_t(x,y)}_{p_t(x,\hat{y})} < c(1,x)\}$ be the indicators for ex-post sub-optimal jobs created from unemployment and employment, respectively. Then, I compute net output losses from ex-post sub-optimal jobs in sub-market x, denoted by $\ulcorner \mathcal{J}_t(x)$, as:

$$\begin{aligned}\ulcorner \mathcal{J}_t(x) = u_{t-}(x)&\left[\int \lambda_t(x)\,\kappa_t(x,y)\,\mathbb{1}\{\Delta^{p_t(x,y)}_{b_t(x)} < c(1,x)\}\,\ulcorner \mathcal{J}_{1,t}(x)\,\mathrm{d}y\right]\\ &+ \int h_{t-}(x,y)\left(\int e\,\lambda_t(x)\,\kappa_t(x,\hat{y})\,\mathbb{1}\{\Delta^{p_t(x,y)}_{p_t(x,\hat{y})} < c(1,x)\}\,\ulcorner \mathcal{J}_{2,t}(x)\,\mathrm{d}\hat{y}\right)\mathrm{d}y\,,\end{aligned}$$

where $\ulcorner\mathcal{J}_{1,t}(x) = \big(b_t(x) + c(1,x)\big) - p_t(x,y)$ and $\ulcorner\mathcal{J}_{2,t}(x) = \big(p_t(x,\hat{y}) + c(1,x)\big) - p_t(x,y)$. The first term accounts for sub-optimal jobs for workers hired from unemployment and the second term accounts for sub-optimal jobs for workers hired from another firm.

Mismatch. Lastly, I quantify productive inefficiencies arising from mismatch, which I denote by $\ulcorner\mathcal{X}_t(x)$, as:

$$\ulcorner\mathcal{X}_t(x) = \int h_t(x)\, \mathbb{1}\big\{\Delta_{b_t(x)}^{p_t(x,y)} \geq c(1,x)\big\}\big(p_t(x,y) - p_t(x, y_t^+(x))\big)\, \mathrm{d}y\,,$$

where $y_t^+(x,y) = \arg\max_y p_t(x, y(x, z_t))$. Any match between an x-type worker and a y-type firm such that $y \neq y_t^+(x)$ generates an inefficiency in terms of forgone production.

F.4. Welfare Implications: Unconstrained Social Planner

Unconstrained Social Planner's Problem. The unconstrained social planner can reallocate workers across employment states and/or jobs at will, without any frictions or costs involved, to maximize output in each sub-market. Under this assumption, the unconstrained social planner's allocation, $h_t^{\text{SP-U}}(x,y)$, results from solving:

$$h_t^{\text{SP-U}}(x,y) = \arg\max_{h_t(x,y)} \mathcal{Y}_t(x) \equiv \int p_t(x,y)\, h_t(x,y)\, \mathrm{d}y \;+\; b_t(x)\, u_t(x)$$
$$\text{s.t.: } u_t(x) = 1 - \int h_t(x,y)\, \mathrm{d}y\,,$$

given the aggregate state z_t, the initial conditions (1) and (2), and the set of feasible matches subsumed in (8).

A solution to this problem is one such that all x-type workers are either unemployed if $p_t(x, y_t^+(x)) < b_t(x)$ or employed by a $y_t^+(x)$-type firm if $p_t(x, y_t^+(x)) \geq b_t(x)$. This equilibrium resembles the Beckerian allocation where the social planner chooses the maximum sum of the outputs over all matches in the labor market (Becker, 1973). Thus, by comparing equilibrium allocations $h_t^{\text{SP-U}}(x,y)$ and $h_t^{\text{SP-C}}(x,y)$, it is possible to determine the productive costs of matching frictions in the economy.

Net Production. In Appendix Table F.2, I present the components of net production, labor market distributions, and sources of productive inefficiencies under the decentralized, unconstrained social planner, and constrained social planner during expansions and contractions. The unconstrained social planner attains a level of net production of 97.8 during contractions. Interestingly, the unconstrained social planner allocates more workers into the unemployment state, thus increasing the contribution of home production to aggregate production in the economy. This is reflected in the higher unemployment rate: while the unemployment rate under the unconstrained social planner allocation is 16%, that of the constrained social planner allocation is 10%. The unconstrained social planner would take more people out of the employment state to reduce productive inefficiencies in the economy.

Appendix Table F.2: Net Production under Different Economies

	Expansions			Contractions		
	Decentralized	SP-U	SP-C	Decentralized	SP-U	SP-C
	Panel A: Components of Net Production					
Net Production	87.985	98.649	93.773	85.551	97.814	93.976
Aggregate Production	100.000	98.649	98.014	95.139	97.814	96.458
Joint Production	96.320	84.669	96.951	84.374	70.380	76.662
Home Production	3.680	13.980	1.063	10.765	27.435	19.796
Vacancy Advertisement	-12.015	—	-4.237	-9.588	—	-2.482
	Panel B: Labor Market Distributions					
Unemployment Rate (U_t)	0.039	0.119	0.051	0.066	0.159	0.099
Vacancy Rate (V_t)	0.035	—	0.014	0.017	—	0.007
Tightness Ratio (θ_t)	0.739	—	0.487	0.532	—	0.238
	Panel C: Productive Inefficiencies					
Unfilled Jobs	45.409 %	—	1.004 %	5.466 %	—	0.412 %
Socially Sub-optimal Jobs	54.562 %	—	0.000 %	94.526 %	—	0.000 %
Mismatch	0.029 %	—	98.996 %	0.008 %	—	99.588 %

Note: The table shows the components of net aggregate production (Panel A), the labor market distributions (Panel B), and the sources of productive inefficiencies (Panel C) resulting from the equilibrium allocations of the decentralized, unconstrained social planner, and constrained social planner economies during expansions and contraction periods. Expansion periods are defined as $z_t = [0.95; 1.05]$ and contraction periods are defined as $z_t = [0.70; 0.75]$ (6% below the value of aggregate productivity during expansion periods). The figures in Panel A are normalized relative to the aggregate production level of the decentralized equilibrium allocation during expansion periods. The tightness ratio is calculated as $\theta_t = \int \theta_t(x)\, l(x)\, \mathrm{d}x$. Unfilled jobs refer to the measure of advertised vacancies that did not meet a job seeker or were turned down by employed workers. Socially sub-optimal jobs refers to the measure of newly created jobs whose productivity gains are lower than the costs of vacancy advertisement. Mismatch refers to the measure of prevailing or newly created jobs between x-type workers and y-type firms for $y \neq y_t^+(x)$, where $y_t^+(x) = \arg\max_y p_t(x, y(x, z_t))$. Additional details are described within the table.
Source: Author's calculations based on model simulations.

Quantifying the Costs of Matching Frictions. By comparing the net production of the unconstrained and constrained social planner economies it is possible to quantify the productive losses from matching frictions in the labor market. In particular, the net production level under the unconstrained and constrained social planners are, respectively, 97.8 and 94.0. This implies that matching frictions in the economy amount to around 3% of forgone production. To a large extent, this forgone production is explained by mismatch, presumably from low-productivity matches that are not dissolved in contractions.

F.5. Additional Policy Simulations

I present the results from additional policy interventions in Appendix Table F.3. These policy interventions consists of: (i) a 10% increase in the matching efficiency parameter ψ, (ii) a wage floor equal to 20% of the median wage observed in expansions, (iii) a 10% increase

in the time-discount factor β, and (iv) a 10% decrease in the exogenous separation rate δ. Respectively, these policies relate to enhanced matching efficiency, minimum wage, increased interest rate, and more restrictive layoff procedures.

Enhanced Matching Efficiency. A policy intervention aiming at enhancing the matching efficiency in the labor market generates a 0.8% increase in net production during contractions. This policy would increase vacancy advertising from firms and reduce unemployment. However, much of the productive inefficiency losses would concentrate on unfilled jobs and socially sub-optimal job creation. Interventions aiming at increasing matching efficiency in the labor market are mostly related to employment intermediation. In my model, these programs directly affect the matching efficiency parameter ψ thereby the meeting rates $\lambda_t(x)$ and $q_t(x)$. As $q_t(x)$ increases, the marginal gain from advertising more vacancies increases, leading to a higher vacancy rate.

Existing employment intermediation programs generally focus on the supply side of the labor market. One example of such programs is the provision of job-search assistance to unemployed workers which has been found to increase employment (Card et al., 2010, 2018). However, their efficiency depends on two key dimensions: the particular aspect of the job search process they focus in, and the demographic characteristics of the beneficiaries. Experimental evidence indicates that these programs are effective in increasing employment when the intervention focuses on motivating and broadening the search for jobs (Belot et al., 2019; Abel et al., 2019). Moreover, these programs can be particularly successful if they encourage job search among individuals at the risk of long-term unemployment (Altmann et al., 2018). Yet, evidence also points to potentially detrimental effects on job finding as the group of program beneficiaries tend to be adversely selected among the population of job seekers (Kuhn and Skuterud, 2004; Dhia et al., 2022). Nevertheless, these programs have been typically found to be a cost-effective policy for reducing unemployment duration and speeding up re-employment (Marinescu, 2017).

Minimum Wage. A minimum wage policy would reduce net production by 6.5 percent during contractions. This policy would reduce vacancy advertising from firms thereby market production in the economy. Arguably, minimum wage policies could potentially reduce efficiency losses from monopsony power in the labor market. Theoretically, minimum wage increases translate into a higher employment contract size γ thus reducing employers' expected gains from hiring thereby vacancy advertisement. In addition, minimum wage policies can increase unemployment by eliminating low-productive matches (i.e., matches whose surpluses become negative if paying workers the minimum wage) in the economy.

Empirical studies document negative effects of minimum wage rises on employment in recession periods (Addison et al., 2013; Clemens and Wither, 2019). A large extent of this effect can be explained by more selective hiring practices that firms adopt in response to minimum wage hikes (Clemens et al., 2021), which occurs on top of the "upskilling" effect of recessions. A recent study finds that most of the welfare gains of minimum wage policies stem from redistribution — that is, increasing wages via an improved bargaining position —

rather than efficiency (Berger et al., 2022). In light of this, it must be the case that large increases in the minimum wage may lead to lower welfare states and recessions seem to be periods when these welfare losses become more salient (Manning, 2021).

Increased Interest Rate. An expansionary monetary shock that increases the time-discount rate β through a reduction in the interest rate could increase net production by 1.9% during contractions. This policy would not have a significant effect on unemployment but would reduce the vacancy rate compared to the status quo. Thus, most of the unemployment would be explained by a reduction in hiring.

In particular, this policy intervention would re-direct firms preferences towards long-lasting employment relationships. This, in turn, can shift the distribution of advertised vacancies towards high-skill workers, increasing unemployment and thus home production among low-skill workers. In new Keynesian models with heterogeneous agents, interest rate cuts have been tied to increased welfare through a relaxation of borrowing constraint and a general equilibrium increase in labor demand (Kaplan et al., 2018; Smirnov, 2022).

Restrictive Layoff Procedure. As for restrictive employment termination procedures, a lower the exogenous separation rate δ would yield a lower net production in the economy. In particular, this policy would increase the expected continuation value of the surplus thereby stimulating vacancy advertisement by firms. Yet, this generates productive inefficiencies in the form of unfilled jobs and sub-optimal job creation. Research shows that firms opt to reduce job creation when facing more elevated firing or layoff costs (Veracierto, 2008; Näf et al., 2022) In the end, the effects on welfare depend on how these costs enter the bargaining process (Ljungqvist, 2002).

Appendix Table F.3: Additional Policy Simulations

		Contractions				
	Expansions	No Policy	Enhanced Matching Efficiency	Minimum Wage	Increased Interest Rate	Restrictive Layoff Procedure
		Panel A: Components of Net Production				
Net Production	87.985	84.551	85.263	78.995	86.143	84.270
Aggregate Production	100.000	94.139	95.089	88.007	96.103	93.170
Joint Production	96.320	83.874	94.572	79.647	85.418	92.730
Home Production	3.680	10.265	0.517	8.360	10.685	0.440
Vacancy Advertisement	-12.015	-9.588	-9.826	-9.012	-9.960	-8.900
		Panel B: Labor Market Distributions				
Unemployment Rate (U_t)	0.039	0.066	0.062	0.069	0.065	0.059
Vacancy Rate (V_t)	0.035	0.017	0.020	0.012	0.019	0.029
Tightness Ratio (θ_t)	0.739	0.532	0.589	0.515	0.515	0.563
		Panel C: Productive Inefficiencies				
Unfilled Jobs	45.409 %	5.466 %	6.868 %	4.537 %	6.762 %	9.652 %
Socially Sub-optimal Jobs	54.562 %	94.526 %	93.125 %	86.457 %	93.231 %	90.337 %
Mismatch	0.029 %	0.008 %	0.007 %	9.006 %	0.007 %	0.007 %

Note: The table shows the components of net aggregate production (Panel A), the labor market distributions (Panel B), and the sources of productive inefficiencies (Panel C) resulting from different equilibrium allocations based on policy simulations during contraction periods. The policy simulations include: the no-policy scenario (i.e., status quo), a 10% increase in matching efficiency, a minimum wage policy of 20% of the median wage level observed during expansions, a 10% increase in the time-discount factor, and a 10% decrease in the exogenous separation rate. Expansion periods are defined as $z_t = [0.95; 1.05]$ and contraction periods are defined as $z_t = [0.70; 0.75]$ (6% below the value of aggregate productivity during expansion periods). The figures in Panel A are normalized relative to the aggregate production level of the competitive equilibrium allocation during expansion periods. See the notes on Appendix Table F.2 for further information. Additional details are described within the table.
Source: Author's calculations based on model simulations.

References

Aaronson, Daniel, Bhashkar Mazumder, and Shani Schechter. 2010. "What is behind the rise in long-term unemployment?." *Federal Reserve Bank of Chicago – Economic Perspectives*, 34(2): 28-51.

Abel, Martin, Rulof Burger, Eliana Carranza, and Patrizio Piraino. 2019. "Bridging the Intention-behavior Gap? The Effect of Plan-making Prompts on Job Search and Employment." *American Economic Journal: Applied Economics*, 11(2): 284-301.

Addison, John T., McKinley L. Blackburn, and Chad D. Cotti. 2013. "Minimum Wage Increases in a Recessionary Environment." *Labour Economics*, 23: 30-39.

Altmann, Steffen, Armin Falk, Simon Jäger, and Florian Zimmermann. 2018. "Learning About Job Search: A Field Experiment with Job Seekers in Germany." *Journal of Public Economics*, 164: 33-49.

Autor, David H. 2010. "The Polarization of Job Opportunities in the US Labor Market: Implications for Employment and Earnings." *Center for American Progress and The Hamilton Project*, 6: 11-19.

Barlevy, Gadi. 2002. "The Sullying Effect of Recessions." *The Review of Economic Studies*, 69(1): 65-96.

Barnichon, Regis. 2010. "Building a composite Help-Wanted Index." *Economic Letters*, 109(3), 175-178.

_____, and Yanos Zylberberg. 2019. "Underemployment and the Trickle-down of Unemployment." *American Economic Journal: Macroeconomics*, 11(2): 40-78.

Becker, Gary S. 1973. "A Theory of Marriage: Part I." *Journal of Political Economy*, 81(4): 813-846.

Belot, Michele, Philipp Kircher, and Paul Muller. 2019. "Providing Advice to Jobseekers at Low Cost: An Experimental Study on Online Advice." *The Review of Economic Studies*, 86(4): 1411-1447.

Berger, David, Kyle F. Herkenhoff, and Simon Mongey. 2022. "Minimum Wages, Efficiency and Welfare." *NBER WP 29662*. Available at: link (Accessed: 15 September 2022).

Bloom, Nicholas, Max Floetotto, Nir Jaimovich, Itay Sapora-Eksten, and Stephen J. Terry. 2018. "Really Uncertain Business Cycles." *Econometrica*, 86(3), 1031-1065.

Berkowitz, Jeremy, and Lutz Kilian. 2000. "Recent Developments in Bootstrapping Time Series." *Econometrics Reviews*, 19(1), 1-48.

Cajner, Thomas, and David Ratner. 2016. "A Cautionary Note on the Help Wanted Online Data." *FEDS Notes 2016-06-23*, Board of Governors of the Federal Reserve System (U.S.).

Card, David, Jochen Kluve, and Andrea Weber. 2010. "Active Labour Market Policy Evaluations: A Meta-analysis." *The Economic Journal*, 120(548): F452-F477.

_____, _____, and _____. 2018. "What Works? A Meta Analysis of Recent Active Labor Market Program Evaluations." *Journal of the European Economic Association*, 16(3): 894-931.

Cengiz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer. 2019. "The Effect of Minimum Wages on Low-Wage Jobs." *The Quarterly Journal of Economics*, 134(3), 1405-1454.

Clemens, Jeffrey, Lisa B. Kahn, and Jonathan Meer. 2021. ""Dropouts Need Not Apply? The Minimum Wage and Skill Upgrading." *Journal of Labor Economics*, 39(S1): S107-S149.

_____, and Michael Wither. 2019. "The Minimum Wage and the Great Recession: Evidence of Effects on the Employment and Income Trajectories of Low-skilled Workers." *Journal of Public Economics*, 170: 53-67.

Couch, Kenneth A., and Dana W. Placzek. 2010. "Earnings Losses of Displaced Workers Revisited." *American Economic Review*, 100(1): 572-89.

Davis, Steven J., R. Jason Faberman, and John C. Haltiwanger. 2012. "Labor Market Flows in the Cross-section and over Time." *Journal of Monetary Economics*, 59(1): 1-18.

_____,_____, and _____. 2013. "The Establishment-level Behavior of Vacancies and Hiring." *The Quarterly Journal of Economics*, 128(2): 581-622.

Dhia, Aïcha Ben, Bruno Crépon, Esther Mbih, Louise Paul-Delvaux, Bertille Picard, and Vincent Pons. 2022. "Can a Website Bring Unemployment Down? Experimental Evidence from France." *NBER WP 29914*. Available at: link (Accessed: 15 September 2022).

Den Haan, Wouter J., and Andrew T. Levin. 1997. "A Practitioner's Guide to Robust Covariance Matrix Estimation." *Handbook of Statistics*, 15, 299-342.

Elsby, Michael W.L., Bart Hobijn, and Ayşegül Şahin. 2010. "The Labor Market in the Great Recession." Brookings Papers on Economic Activity, 2010(1): 1-48.

Farber, Henry S. 2011. "Job Loss in the Great Recession: Historical Perspective from the Displaced Workers Survey, 1984-2010." *NBER WP 17040*. Available at: link (Accessed: 15 September 2022).

Fujita, Shigeru, and Garey Ramey. 2009. "The Cyclicality of Separation and Job Finding Rates." *International Economic Review*, 50(2), 415-430.

Gouriéroux, Christian, Alain Monfort, and Eric Renault. 1993. "Indirect Inference." *Journal of Applied Econometrics*, 8(S1), S85-S118.

Hagedorn, Marcus, and Iourii Manovskii. 2008. "The Cyclical Behavior of Equilibrium Unemployment and Vacancies Revisited." *American Economic Review*, 98(4), 1692-1706.

Hirsch, Barry T., and Edward J. Schumacher. 2004. "Match Bias in Wage Gap Estimates Due To Earnings Imputation." *Journal of Labor Economics*, 22(3), 689-722.

Kaplan, Greg, Benjamin Moll, and Giovanni L. Violante. 2018. "Monetary Policy According to HANK." *American Economic Review*, 108(3): 697-743.

Krusell, Per, and Anthony A. Smith. 1998. "Income and Wealth Heterogeneity in the Macroeconomy." *Journal of Political Economy*, 106(5), 867-896.

Kuhn, Peter, and Mikal Skuterud. 2004. "Internet Job Search and Unemployment Durations." *American Economic Review*, 94(1), 218-232.

Lise, Jeremy, and Jean-Marc Robin. 2017. "The Macrodynamics of Sorting Between Workers and Firms." *American Economic Review*, 107(4), 1104-1135.

Ljungqvist, Lars. 2002. "How Do Lay-off Costs Affect Employment?." *The Economic Journal*, 112(482): 829-853.

Manning, Alan. 2021. "The Elusive Employment Effect of the Minimum Wage." *Journal of Economic Perspectives*, 35(1): 3-26.

Marinescu, Ioana E. 2017. "Job Search Monitoring and Assistance for the Unemployed." *IZA World of Labor*.

Menzio, Guido, and Shouyong Shi. 2010. "Block Recursive Equilibria for Stochastic Models of Search On The Job." *Journal of Economic Theory*, 145(4), 1453-1494.

Mustre-del-Río, José. 2014. "Job Duration, Wages, and the Cleansing and Sullying Effects of Recessions." *Federal Reserve Bank of Kansas City RWP 12-08*. Available at: link (Accessed: 15 September 2022).

Näf, Armando, Yannic Stucki, and Jacqueline Thomet. 2022. "The Effects of Firing Costs on Labour Market Dynamics." *Economica*, 89(354): 461-488.

Newey, Whitney K., and Kenneth D. West. 1987. "A Simple, Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica*, 55(3), 703-708.

Reiter, Michael. 2009. "Solving Heterogeneous-agent Models by Projection and Perturbation." *Journal of Economic Dynamics and Control*, 33(3), 649-665.

Shimer, Robert. 2005. "The Cyclical Behavior of Equilibrium Unemployment and Vacancies." *American Economic Review*, 95, 25-49.

Smirnov, Danila. 2022. "Optimal Monetary Policy in HANK." *Mimeo*. Available at: link (Accessed: 15 September 2022).

Vaghul, Kavya, and Ben Zipperer. 2016. "Historical State and Sub-State Minimum Wage Data." *Washington Center for Equitable Growth*.

Veracierto, Marcelo. 2008. "Firing Costs and Business Cycle Fluctuations." *International Economic Review*, 49(1): 1-39.