Time-varying Risk Premium and Youth Unemployment

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Abstract

We document that the sensitivity of the unemployment rate of young workers to changes in the dividend-price ratio of the stock market is twice as large as that of prime-age workers. To explain this finding, we construct a general equilibrium search model in which: (a) the expected productivity of a firm-worker match is unobservable and learned over time and (b) the risk premium varies over different macroeconomic states. We have three results. First, we show that including time variation in the risk premium is essential in capturing the dynamics of youth and prime-age unemployment rates, especially during recessions. Second, our model predicts that youth (prime-age) unemployment would have been 2.3% (1.1%) higher by June 2009, had the dividend-price ratio not declined rapidly in the post-TARP period beginning in March 2009. Third, we show that there is faster labor-market cleansing of relatively poor matches when the risk premium is high, which can result in an increase in the average output per worker during recessions. JEL Codes: D83, E24, E32, E44, J11, J63, J64.

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1 Introduction

The unemployment rate of young workers in the United States increases sharply relative to that of prime-age workers during recessions (Clark and Summers (1981) and Figure 1). Understanding what drives changes in youth unemployment over the business cycle is important for at least two reasons. First, unemployment in the early stage of an individual’s working life results in a large and long-lasting drop in lifetime earnings (Topel and Ward, 1992; Mroz and Savage, 2006). Second, young workers contribute disproportionately to the amplitude of aggregate unemployment fluctuations because they constitute a significant fraction of the total unemployed population. Over the period 1951-2017, the number of unemployed workers less than 24 years of age constituted on average about 37% of the total pool of unemployed workers. Despite its importance, a successful explanation of the business cycle dynamics of youth unemployment has proven to be challenging.\footnote{While Jaimovich, Pruitt, and Siu (2013) explain the higher volatility in hours worked by young workers compared to prime-age workers, the model in that paper does not feature unemployment.}

To the best of our knowledge, our paper is the first to provide a general equilibrium theory which explains differences in the unemployment rate of young workers relative to prime-age workers over the business cycle.

We proceed in two steps. First, we document that there is significant cross-sectional heterogeneity in the sensitivity of unemployment rates to changes in the dividend-price ratio of the stock market. Changes in the dividend-price ratio is a standard measure of changes in the aggregate risk premium (see, for example, Campbell and Shiller (1988)). In particular, we find that the sensitivity of the unemployment rate of young workers to changes in the risk premium is twice as large as that of prime-age workers. Second, we construct a general equilibrium labor search and matching model that delivers realistic cross-sectional differences in unemployment risk exposure to changes in the risk premium. Our model has two key features: (a) the expected productivity of a firm-worker match is unobservable and learned over time, and (b) the risk premium varies over macroeconomic states.
Our calibrated model matches both the level and volatility of the unemployment rates of young and prime-age workers. Beyond matching moments, our model delivers three results. First, we show that including time variation in the risk premium is essential in capturing the business cycle dynamics of the unemployment rates of young and prime-age workers, especially during deep, prolonged recessions. Second, our model predicts that the unemployment rate of young (prime-age) workers would have been 2.3% (1.1%) higher by June 2009, had the dividend-price ratio not declined rapidly in the period immediately after the Troubled Asset Relief Program (TARP) beginning in March 2009. Third, we show that there is faster labor-market cleansing of relatively poor matches when the risk premium is high. This improves the average output per worker of surviving matches. A prolonged period of such cleansing can overcome the exogenous drop in productivity towards the end of long recessions. In such scenarios, the average output per worker can increase even while the aggregate unemployment rate is simultaneously rising. We show that this pattern is exhibited by the four largest recessions in post-war US data.

We build on the model of Moscarini (2005), who shows that in an environment in which the expected productivity of a worker-firm match is unobservable and learned over time, the job separation rate is a declining function of worker tenure. Compared to prime-age workers, young workers on average have less time and also fewer attempts to be matched to firms where they are more productive. Thus, younger workers have a higher unemployment rate than prime-age workers.

Our contribution is to extend his analysis to include aggregate shocks and therefore derive implications for changes in the unemployment rates of young and prime-age workers over the business cycle. We consider two aggregate shocks in our model: (a) a shock which changes the mean productivity of all workers by the same amount, and (b) a shock which changes the risk premium. We find the combined effect of a decline in labor productivity accompanied by an increase in the risk premium to be quantitatively large. In such recessions, the value of hiring a new worker declines significantly. As a result, firms post fewer vacancies, and therefore
the probability of an unemployed worker finding a job declines. The logic is similar to Hall (2017). Recessions lower the value of current and potential matches not only because of a drop in labor productivity (a cash-flow effect), but also because future rents from the match are discounted more heavily due to the increase in the risk premium (a discount rate effect). For simplicity, we assume that this decline in job-finding probability is uniform for all workers, irrespective of age.\footnote{This assumption avoids the need to track the distribution of the experience of the unemployment pool. In Appendix A we examine the empirical validity of this simplifying assumption.} Despite this assumption, younger workers in our model experience a bigger increase in the unemployment rate during recessions and their unemployment rate is therefore more volatile over the business cycle. The reason for this is that the level of the unemployment rate for young workers is higher than that of prime-age workers. Therefore, even though the two groups experience an identical decline in the job-finding probability, the group of younger workers experience a bigger decline in the number of unemployed workers finding jobs. Consequently, this group experiences a bigger increase in the unemployment rate. Let us describe the intuition for our three results.

Our first result is that a model which includes both labor productivity and risk premium shocks better matches realized unemployment rates of young and prime-age workers in comparison to a model which incorporates only labor productivity shocks. In other words, financial markets are informative about the future labor market experience of these groups of workers. To make the models comparable, we calibrate each model to match the unconditional volatilities of unemployment rates of the two groups of workers in the data. We carry out the comparison by feeding in the realized paths of the labor productivity series reported by the Federal Reserve Economic Data (FRED) and dividend-price ratio series of the stock market during the period of the Great Recession of 2008–2009 to the two models. We find that the model which includes time-varying risk premium captures about half of the variation in the data, while the model which includes only labor productivity shocks shows almost no increase in unemployment rates. This is because over the period of the Great Recession, the
peak-trough drop in labor productivity was only 2%, which corresponds to a one unconditional standard deviation decline. In contrast, the dividend-price ratio doubled over this period, which is a three unconditional standard deviation increase. Accordingly, the model which accounts for time-varying risk premium predicts a bigger increase in unemployment rates than the model with labor productivity shocks alone.

Second, we use our model to carry out a counter-factual analysis around the Great Recession. The market risk premium (measured using the dividend-price ratio of the aggregate stock market) approximately doubled in value between the start of the recession in December 2007 and March 2009, before sharply declining. The timing of this decline coincided with the implementation of TARP through which some $300 billion worth of troubled assets were purchased. To the extent we believe that TARP was responsible for the decline in the market risk premium, our model provides estimates of the potential increase in unemployment rates of young and prime-age workers in a scenario without any such intervention. Since part of the Federal Reserve’s thinking behind TARP was to avoid a Great Depression-like outcome (see, e.g., Bernanke (2015)), the hypothetical scenario that we consider is one under which the increase in the aggregate dividend-price ratio is similar to that observed during the Great Depression. Under this scenario, our model predicts that youth (prime-age) unemployment would have been an additional 2.3% (1.1%) higher after a period of three months. To the extent that a social planner cares differentially about young versus prime-age workers, the heterogeneous response of young and prime-age unemployment to intervention policies indicates that it is important to model the differences in the sensitivities of unemployment rates for workers of different age groups when considering the potential impact of policy interventions.

Third, we show that our model predicts average output per worker to follow a U-shaped

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3Large-Scale Asset Purchase (LSAP) programs such as TARP seek to lower the risk premium. As explained in a speech by Bernanke (Bernanke, 2013), “as the Federal Reserve buys a larger share of the outstanding stock of longer-term securities, the quantity of these securities available for private-sector portfolios declines. As the securities purchased by the Fed become scarcer, they should become more valuable. Consequently, their yields should fall as investors demand a smaller term premium for holding them.”
path during deep, prolonged recessions.\textsuperscript{4} This is due to a compositional change in the pool of employed workers in which relatively poor matches dissolve as a recession unfolds. The resulting improvement in the average quality of surviving matches leads to an increase in the average output per worker. For sufficiently prolonged recessions, this endogenous increase in productivity can more than offset the drop in exogenous productivity. In other words, our model predicts deep, prolonged recessions to feature simultaneous increases in average labor productivity and unemployment rates of all workers towards the end of recessions. We show that this prediction is consistent with labor productivity and unemployment dynamics during US recessions.

The rest of this paper is organized as follows. In Section 2 we review the literature. We present our new stylized facts in Section 3 followed by our model in Section 4. We discuss our quantitative results in Section 5, illustrate the importance of accounting for time-varying risk premium in Section 6, and present results of our counter-factual exercise related to TARP in Section 7. In Section 8 we present our labor market cleansing result, before concluding in Section 9. We relegate all proofs and a discussion of our numerical implementation to the Appendix.

2 Literature Review

Our paper contributes to the literature on the business cycle dynamics of youth labor supply. For an extensive study on issues surrounding the youth labor market, see the NBER volume Freeman and Wise (1982). Clark and Summers (1981) document the much higher volatility of the cyclical component of youth unemployment rates compared to that of prime-age workers in US data. Rios-Rull (1996), Gomme, Rogerson, Rupert, and Wright (2005) and Jaimovich and Siu (2009) find similar results in the context of hours worked. More recently,

\textsuperscript{4}Our definition of average output per worker, calculated as the aggregate output divided by the total number of employed workers in the economy, coincides with the definition of aggregate labor productivity used by the Federal Reserve Economic Data (FRED) series.
Guvenen, Schulhofer-Wohl, Song, and Yogo (2017) document that for all but the top end of the income distribution, the earnings of younger workers are more exposed to aggregate risk in comparison to that of older workers. On the theoretical side, Rios-Rull (1996), Gomme, Rogerson, Rupert, and Wright (2005), Hansen and Imrohoroglu (2009), and Jaimovich, Pruitt, and Siu (2013) focus on life-cycle considerations to explain the difference in worker hours at various life-cycle stages. In contrast, our model is search-based and focuses on differences in unemployment rates for workers of different ages.

Our paper also belongs to the labor search and matching literature of McCall (1970), Mortensen (1970), Diamond (1981), Diamond (1982a), Diamond (1982b), Pissarides (1985), and Mortensen and Pissarides (1994). For a comprehensive list of references, we refer the reader to Rogerson, Shimer, and Wright (2005). While most of this literature assumes exogenous separation rates, separations are endogenous in our model and arise as a result of firms and employees learning about match-quality. We build on early work by Jovanovic (1979) and adapted to a labor-search framework by Moscarini (2005). While these papers analyze the behavior of wage dynamics and unemployment in the steady-state, we focus on business cycle dynamics in the presence of aggregate shocks. Our emphasis on modelling learning about match-quality is guided by Nagypal (2007) who finds that learning about match-quality, rather than learning by doing, dominates at tenures longer than six months. In addition, our emphasis on learning about an unobserved component of a worker-firm match takes into account Menzio and Shi (2011) who find, in the context of directed search, that instead of treating matches as an inspection good, it is more important to emphasize the experience good aspect of matches if the goal is to generate realistic fluctuations in unemployment rates across the business cycle.

We build on the analysis of Hall (2017) who shows that accounting for time-varying risk premium improves the quantitative fit of the canonical labor search model in matching the volatility of the aggregate unemployment rate. Along similar lines, Kilic and Wachter (2018) provide a disaster-risk based explanation of large variation in risk premium and therefore
high unemployment volatility. Our paper differs from these papers in one key respect: we show that there is significant cross-sectional heterogeneity in the sensitivity of unemployment risk to changes in the risk premium and we analyze the aggregate consequences of this heterogeneity. Caggese, Cunat, and Metzger (2017) find evidence for financially constrained firms firing short-tenured workers relatively more frequently compared to unconstrained firms using Swedish data.

A growing literature examines the effect of labor market frictions on the returns of the aggregate stock market and the cross-section of asset returns. For example, Petrosky-Nadeau, Zhang, and Kuehn (2018) examines the impact of labor market search frictions on aggregate asset prices. Danthine and Donaldson (2002), Uhlig (2007), and Favilukis and Lin (2015), among others, study the effect of sticky wages on the cost of capital of firms. Kilic (2017) studies the effect of the demographic composition of a firm’s workforce on its cost of capital. Belo, Lin, and Bazdresch (2014) study changes in a firm’s risk premium arising from changes in a firm’s hiring rate. In contrast to these papers, we analyze the effect of firm valuation on labor policies of the firm and the composition of the aggregate labor force.

3 New Stylized Facts

In this section, we relate the increase in the unemployment rate of young and prime-age workers to changes to changes in labor productivity (real output per hour of all persons in the non-farm business sector) and the dividend-price ratio of the US stock market. In a seminal paper, Clark and Summers (1981) examine the business cycle sensitivity of the unemployment rate of various age-groups defined by the Current Population Survey (CPS), namely 16-19, 20-24, 25-34, 35-44, 45-54, 55-64, and over 65 years old. They find that the unemployment rate of workers in buckets 16-19 and 20-24 are about twice as sensitive to business cycle variations than the corresponding rate of other workers. While these authors use the unemployment rate of workers in the age group 35-44 as a proxy for aggregate
labor demand, we relate unemployment rates to labor productivity and risk premium. More recently, Jaimovich, Pruitt, and Siu (2013) find that the cyclical volatility of hours of young workers to be twice as high as that of prime-age workers.

We choose individuals between 20-24 years as our definition of young workers since we do not focus on teen-age unemployment. We choose individuals between 35-44 years to represent prime-age workers (the unemployment rate of workers in the four buckets between 25-54 exhibit similar business cycle properties). We use non-farm business sector real output per hour series from the Federal Reserve Economic Data (FRED) series as our measure of aggregate labor productivity. Following the asset pricing literature, we use dividend yields \((D/P)\) to proxy for the risk premium. We construct this series using the aggregate value weighted returns series from CRSP. All series are first adjusted for seasonal effects using the Census Bureau’s X13 program before being HP-filtered with smoothing parameter 1600 to remove long run trends. The final sample is quarterly and spans 1951Q1 to 2015Q4. Table 1 shows the summary statistics.

We document two new stylized facts:

1. Compared to prime-age workers, the unemployment rate of young workers is more sensitivity to changes in aggregate labor productivity and the dividend-price ratio.

2. Labor productivity shocks are amplified more strongly in states with higher values of the dividend-price ratio.

Table 2 reports the results for one-quarter ahead predictive regressions. All standard errors are Newey-West with 4 lags. Columns (1) through (3) report the results for youth unemployment, columns (4) to (6) report results for prime-age workers, while the final three columns report results for the difference in unemployment rates between young and prime-age workers. Columns (1) and (4) reports the sensitivity of young and the prime-age workers unemployment rates, respectively, to changes in labor productivity \((z)\) in a univariate regression. We see that both unemployment rates are counter-cyclical, with youth
unemployment being about twice as sensitive to changes in labor productivity as that of prime-age workers. The coefficients from the univariate regressions imply that as labor productivity decreases from its 95th percentile value of 1.6% to its 5th percentile value of -2%, youth unemployment rates increase by 1.06% while unemployment rates for prime-age workers increase by 0.48%.

Next, columns (2) and (5) show that youth unemployment rates are also more sensitive to changes in the risk premium (as proxied by the dividend-price ratio) relative to prime-age workers. The coefficients from these univariate regressions indicate that youth unemployment is, on average, 1.8 times more sensitive to changes in risk premia relative to that of prime-age workers. An increase in the (cycle component) of dividend-price ratio from its 5th percentile value of -0.15% to its 95th percentile value of 0.24% is associated with a 1.29% (0.73%) increase in youth (prime-age workers) unemployment rates.

When both productivity and dividend yields are included as regressors, we see from the negative coefficient on the interaction term in columns (3) and (6) that unemployment rates are more sensitive to labor productivity shocks in periods in which the risk premium is high. Furthermore, the slope coefficient of the interaction term between labor productivity and the dividend-price ratio is larger for the young, indicating that the difference in young and prime-age worker unemployment rates becomes more sensitive to productivity shocks when the risk premium is high. The interaction term is large and economically significant. The same 95th to 5th percentile decrease in labor productivity is associated with an additional increase of 1.87% (1.13%) in youth (prime-age workers) unemployment rates when the dividend-price ratio is at its 95th percentile compared to when it is at its 5th percentile.

4 The Model

In this section, we present a labor search model with unobserved match quality and time-varying risk premium. Section 4.1 introduces the macroeconomic environment. Section 4.2
then describes the labor market choices of firms and workers. Finally, Section 4.3 characterizes aggregate outcomes.

4.1 The Economy

The economy is set in discrete time and over an infinite horizon. Operating in this economy is a representative household comprised of a unit mass of ex ante identical workers and a large number of capitalists who create and operate firms. The large number of capitalists ensures free entry for vacancy creation. In addition, there is a government that levies lump sum taxes in order to provide unemployment benefits, but does nothing else.

Production occurs after vacancies, which are posted by capitalists, become successfully matched to workers. The process of matching is subject to two labor market imperfections. First, labor markets are subject to search frictions so that it takes time to fill vacancies. In particular, a total of \( m(U, V) \) meetings take place between prospective workers and vacancies when \( U \) unemployed workers search for jobs and \( V \) vacancies are available. Following den Haan, Ramey, and Watson (2000), we parameterize the matching function to have the following form:

\[
m(U, V) = \frac{UV}{(U^\iota + V^\iota)^\iota}, \iota > 0.
\]

The contact rate between unemployed workers and vacancies depends on labor market tightness \( \Theta \equiv V/U \). In particular, the probability of an unemployed worker meeting a vacancy is given by \( f(\Theta) = m(U, V)/U = (1 + \Theta^{-\iota})^{-\frac{1}{\iota}} \), while the probability of a vacancy coming into contact with a prospective (unemployed) worker is \( g(\Theta) = m(U, V)/V = (1 + \Theta^\iota)^{-\frac{1}{\iota}} \).

The second labor market imperfection is that workers need not be matched to their ideal jobs or, equivalently, not all vacancies are filled by ideal candidates. In particular, matches can differ in their quality \( \nu_i \in \{H, L\} \), which could either be of high (\( H \)) or low (\( L \)) type. A

\[\text{This parameterization has the convenient property that the resulting meeting probabilities automatically lie between 0 and 1.}\]
match $i$ generates output:

$$y_{it} = e^{z_t + \mu(\nu_i) - \frac{1}{2}\sigma^2 + \sigma\epsilon_{it}}$$  \hspace{1cm} (2)$$

in period $t$, where aggregate productivity $z_t$ is observable and follows an AR(1) process:

$$z_t = \rho z_{t-1} + \sigma z \epsilon_{z,t},$$ \hspace{1cm} (3)$$

with autocorrelation $\rho_z$, volatility $\sigma_z$ and normally distributed innovations $\epsilon_{z,t} \sim \mathcal{N}(0,1)$. Output $y_{it}$ is also subject to a match specific component $\mu(\nu_i)$ that is higher when the match is of high quality (i.e. $\mu(H) > \mu(L)$), as well as a match-specific shock $\epsilon_{it} \sim \mathcal{N}(0,1)$.

Following Moscarini (2005), we assume that match quality $\nu_i$ is not directly observed by either party. Instead, it must be inferred from realized match output (2), which is observable. The match quality type $\nu_i$ is never known with certainty as the inference problem is subject to noise associated with the presence of idiosyncratic output shocks $\epsilon_{it}$. The initial match quality is drawn by nature with high quality matches occurring with probability

$$p_0 = \mathbb{P}(\nu_i = H).$$ \hspace{1cm} (4)$$

Subsequent inferences regarding match quality types are Bayesian in nature: time series observations for the aggregate productivity $z_t$ and output $y_{it}$ generate a filtration $\mathcal{F}_{it}$. Parties then update their beliefs from the initial common prior $p_0$ to form posterior beliefs $p_{it} = \mathbb{P}(\nu_i = H | \mathcal{F}_{it})$ regarding the quality of the match. In turn, the presence of idiosyncratic productivity shocks lead to cross-sectional differences in beliefs $p_{it}$ regarding the quality of different matches.

Our formulation of output heterogeneity among workers, (2) and (4), abstracts from observed differences across workers. The reasons for this choice are as follows. First, as our goal is to capture differences in business cycle fluctuations in unemployment rates across different groups of workers, our focus on unobserved heterogeneity is guided by findings from Menzio
and Shi (2011). They show that, in a setting with directed search, unobservable heterogeneity has a much larger effect on unemployment fluctuations than observable differences across workers. Furthermore, our emphasis on learning about match-quality is guided by Nagypal (2007) who finds that learning about match-quality, rather than learning by doing, dominates at job tenures longer than six months. Moreover, by assuming that all unemployed workers looking to be matched with firms are identical as far as future productivity is concerned, we are able to avoid tracking the cross-sectional distribution of the ability and experience of the unemployment pool. This greatly simplifies our analysis. An implication of this simplifying assumption is that job finding probabilities are identical across young and prime-age workers. In Appendix A we examine the validity of this assumption. We show in Figure A.1 that a synthetic unemployment rate series constructed using our approximation is able to capture much of the business cycle variation present in the actual data for both groups of workers.

Neither firms nor workers can commit to a wage contract. The presence of search frictions creates a surplus that is split between workers and firms according to a generalized bargaining rule in which workers have bargaining power \( \eta \in [0, 1] \). Key in the determination of wages is the valuation of the surplus from a match. For this, we assume that there is perfect risk-sharing between members of the representative household, so that idiosyncratic risks are not priced and both workers and capitalists are symmetric in their assessment of systematic risks.\(^6\) We assume that investors face complete asset markets for payoffs that depend only on aggregate outcomes. From the Fundamental Theorem of Asset Pricing (see Dybvig and Ross (1987, 2003)), the lack of arbitrage in asset markets implies the existence of a stochastic discount factor (SDF), \( \Lambda_{t,t+1} \). The SDF prices all asset returns, \( R_{t,t+1} \), according to the asset pricing relationship:

\[
1 = \mathbb{E}_t [\Lambda_{t,t+1} R_{t,t+1}].
\] (5)

Market completeness further implies that the SDF is unique and changes in the SDF are

\(^6\)This is a standard assumption in the labor search literature. For example, see Shimer (2010) for a textbook treatment.
driven purely by aggregate shocks. We model the SDF according to:

$$\Lambda_{t,t+1} = \exp \left\{ -r_f - \frac{1}{2} x_t^2 - x_t \varepsilon_{z,t+1} \right\},$$  

(6)

where the risk-free rate $r_f = -\log (\mathbb{E}_t [\Lambda_{t,t+1}])$ is taken to be constant, and $x_t$ is the market price of risk for aggregate productivity shocks $\varepsilon_{z,t+1}$. The market price of risk, $x_t$, is the compensation that investors receive for holding assets whose returns are perfectly correlated to the productivity shock $\varepsilon_{z,t+1}$ (with unit exposure). That is, for assets whose log returns are of the form $\log R_{t,t+1} = \mathbb{E}_t[\log R_{t,t+1}] + \varepsilon_{z,t+1}$, it follows from the asset pricing equation (5) that $\mathbb{E}_t[\log R_{t,t+1}] - r_f - \frac{1}{2} \text{Var}_t(\log R_{t,t+1}) = -\text{Cov}_t(\log \Lambda_{t,t+1}, \log R_{t,t+1})$. From (6), this quantity is just the market price of risk, $x_t$. We model the market price of risk as an AR(1) process in logs:

$$\log(x_t) = (1 - \rho_x) \log \overline{x} + \rho_x \log(x_{t-1}) + \sigma_x \varepsilon_{x,t},$$  

(7)

with mean $\log \overline{x}$, autocorrelation $\rho_x$ and volatility $\sigma_x$. For simplicity, we take innovations to the market price of risk $\varepsilon_{x,t} \sim \mathcal{N}(0,1)$ to be orthogonal to aggregate productivity innovations $\varepsilon_{z,t}$ (alternatively, $x_t$ can be thought of as the component of market price of risk that is orthogonal to aggregate productivity). We do not take a stance on the microfoundations behind the SDF (6), nor the drivers for a time-varying market price of risk (7).\footnote{A standard list of candidates from the asset pricing literature include habit (Campbell and Cochrane, 1999), long-run risk (Bansal and Yaron, 2004), and disaster risk (Rietz, 1988), among others. See Cochrane (2011) for a review.} Rather, we take asset prices as given and instead focus on the implications of time-varying risk premia for labor market outcomes for different groups of workers. This approach is in line with Hall (2017), who finds that movements in risk premia can have large effects on aggregate unemployment rates over the business cycle.

Finally, we complete the description of the economy by describing the timing of events within each period $t$, as follows:
(i) At the start of period $t$, there is a mass of $N_t = 1 - U_t \in [0, 1]$ previously employed workers. The distribution of match-quality beliefs for these incumbent workers is denoted by $\mathcal{P}_t$. That is, for a given set $A \subset [0, 1]$, $\mathcal{P}_t(A) \in [0, 1]$ gives the fraction of incumbent workers with match-quality belief $p_{it}$ contained in $A$.

(ii) Nature draws aggregate productivity $z_t$ and the market price of risk $x_t$ according to their respective laws of motions (3) and (7).

(iii) Capitalists post a total of $V_t$ vacancies. The mass, $U_t = 1 - N_t$, of prospective unemployed workers are then matched to vacancies according to the matching function (1). The initial match type $\nu_{i0} \in \{H, L\}$ is determined by nature and has a probability of $p_0 \in [0, 1]$ of being the high type, where $p_0$ is the initial prior. Hiring and firing decisions are then made conditional on both the aggregate state and match quality beliefs. Wages are set according to a generalized Nash bargaining rule.

(iv) Output $y_{it}$ is realized. Match quality beliefs are updated for the next period in a Bayesian manner.

(v) Wages are paid and consumption takes place. Unemployed workers receive unemployment benefits, which are financed through lump sum taxation.

(vi) Matches exogenously separate with probability $s$.

The above timing of events is summarized graphically in Figure 2.

4.2 Firms and workers’ problem

A matched firm-worker pair makes two decisions immediately after the realization of the state variables $z_t$ and $x_t$: whether or not to continue with the match, and conditional on continuing, how to split the resulting match surplus. In addition, capitalists have a choice regarding whether or not to post vacancies. These decisions depend on the present value of a
match, which is determined by the market price of risk as well as the expected productivity of a match. The latter crucially depend on learning about the (unobserved) quality of the match.

**Bayesian learning.** We define \( p_{it} \) to be the start of period belief of a high-quality match \( p_{it} = \mathbb{P}(\nu_{it} = H | \mathcal{F}_{it}) \) where, due to our timing convention, the filtration \( \mathcal{F}_{it} \) used in the learning problem is generated from all past observations of output from the match, \( \{y_{is}\}_{s < t} \), as well as all past and present observations for the aggregate states \( \{z_s, x_s\}_{s \leq t} \).

The expected output from a match, conditional on match quality belief \( p_i \) and aggregate productivity \( z \) is \( \mathbb{E}[y_i | p_i, z] = e^z [p_i e^{\mu(H)} + (1 - p_i) e^{\mu(L)}] \). Clearly, matches with higher match quality beliefs are expected to be more productive. Bayesian updating for the posterior match quality belief involves comparing realized output against expected output and making upward (downward) adjustments in beliefs in the event of a positive (negative) performance surprise. More specifically, the match quality belief for the next period is given by \( p_{i,t+1} = \mathbb{P}(\nu_i = H | \mathcal{F}_{it}, y_{it}) = p'_{it}(y_{it}, p_{it}, z_{it}) \), where the posterior is given by the following expression:

\[
p'_{it}(y, p, z) = \frac{pe^{-\frac{1}{2\sigma^2}[\log y - (z + \mu(H) - \frac{1}{2}\sigma^2)]^2}}{pe^{-\frac{1}{2\sigma^2}[\log y - (z + \mu(H) - \frac{1}{2}\sigma^2)]^2} + (1 - p)e^{-\frac{1}{2\sigma^2}[\log y - (z + \mu(L) - \frac{1}{2}\sigma^2)]^2}}.
\] (8)

**Firms’ problem.** The value of a matched firm at the start of the period, \( F(p, z, x) \), after observing the aggregate states \( z_t = z \) and \( x_t = x \) but before observing the current period’s output, is given by:

\[
F(p, z, x) = \max \left\{ 0, d(p, z, x) + (1 - s) \mathbb{E} [\Lambda(x, \varepsilon'_z) F(p', z', x') | p, z, x] \right\}, \quad (9)
\]

where \( p \) denotes the start of period match-quality belief. Firm value (9) reflects the option for the capitalist to dissolve the match, in which case the value will be worth zero.
Should the capitalist continue with the match, he obtains expected dividends \( d(p, z, x) = e^z \left[ pe^{\mu(H)} + (1 - p)e^{\mu(L)} \right] - w(p, z, x) \), which is just the difference between expected output and wages. In addition, the firm is kept as a going concern as long as the firm does not exogenously separate at the end of the period (this occurs with probability \( 1 - s \)). The future cashflows of the firm are discounted according to the SDF (6), and cashflow forecasts naturally take into account Bayesian updating of match quality beliefs (8).

It can be shown that the continuation value of the firm is increasing in \( p \) (see Proposition 1 in Appendix B). This implies that firms follow a threshold strategy when deciding whether or not to continue with the match. In particular, matches with match quality belief below a cutoff \( p(z, x) \) are dissolved, where the firing threshold \( p(z, x) \) is characterized as the solution to the following indifference condition:

\[
0 = d(p(z, x), z, x) + (1 - s)\mathbb{E} \left[ \Lambda(x, \varepsilon'_z)F(p', z', x') \mid p(\omega), \omega \right],
\]

while matches with match quality belief at or above \( p(z, x) \) are continued. The threshold \( p(z, x) \) is symmetric between firms and workers, meaning that workers will also find it more favorable to stick with the match (walk away) whenever \( p \) is greater (less than) the threshold \( p(z, x) \).

**Vacancy creation.** Capitalists can freely post vacancies subject to a per unit vacancy creation cost of \( \kappa > 0 \). The value of a vacancy in state \( (z, x) \) is:

\[
F_{V}(z, x) = g(\Theta(z, x))F(p_0, z, x)\mathbb{1} \left( p_0 \geq p(z, x) \right)
\]

and takes into account the probability \( g(\Theta(z, x)) \) of meeting a potential employee when the aggregate state is \( (z, x) \). The vacancy is worthless ex post if either it fails to get matched to a potential worker, or if a matched worker’s initial match quality \( p_0 \) is too low to clear the threshold \( p(z, x) \).
A capitalist’s decision to post a vacancy depends on the value of a vacancy relative to the unit cost of posting a vacancy, and vacancies will be posted as long as the former remain greater. Since there is free entry, the equilibrium amount of vacancies posted, $V$, is determined as the solution to the following complementary slackness problem:

$$\kappa \geq F_V(z, x),$$  \hspace{1cm} (12)

with equality if and only if equilibrium vacancies $V$ is strictly positive, where the left-hand side of (12) is the unit cost of posting a vacancy, while the right-hand side is the expected value of a vacancy (11).

**Workers’ problem.** The value function for an incumbent worker that is employed at the start of the period, $J_e(p, z, x)$, is given by:

$$J_e(p, z, x) = \max \left\{ J_{eu}(z, x), w(p, z, x) + \mathbb{E} \left[ \Lambda(x, \varepsilon'_z) \left[ sJ_u(z', x') + (1 - s)J_e(p', z', x') \right] \big| p, z, x \right] \right\}.$$  \hspace{1cm} (13)

An already-matched worker can either quit or stay with the match. In the latter case, the worker obtains wages $w(p, z, x)$, and the match continues so long as the exogenous separation shock (which occurs with probability $s$) does not materialize.

Recall that an incumbent match with match-quality belief $p$ below cutoff $p(z, x)$ is dissolved. In this case, the worker becomes newly unemployed and has value function:

$$J_{eu}(z, x) = b + \mathbb{E} \left[ \Lambda(x, \varepsilon'_z)J_u(z', x') \big| z, x \right].$$  \hspace{1cm} (14)

That is, such a worker obtains unemployment benefit $b$ in the current period and searches for new jobs starting from the next period. Note that our timing convention does not allow for a newly unemployed worker to immediately search for a new job.
The value for an already unemployed worker who is searching for a new job is given by:

\[ J_u(z, x) = f(\Theta(z, x)) J_e(p_0, z, x) \mathbb{1}(p_0 \geq p(z, x)) + [1 - f(\Theta(z, x))] J_{eu}(z, x). \] (15)

With probability \( f(\Theta(z, x)) \), the unemployed worker is matched to a vacancy, and the worker becomes employed so long as \( p_0 \) clears the threshold \( p(z, x) \). Otherwise, the worker remains unemployed in which case he obtains unemployment benefits \( b \) and continues searching for a job next period.

**Wages.** Wages are determined by standard Nash bargaining in which case the total match surplus \( S(p, z, x) \equiv J_e(p, z, x) - J_{eu}(z, x) + F(p, z, x) \) is split between the worker and the firm, with the worker surplus accounting for a share \( \eta \in [0, 1] \) of the total match surplus. In particular, the worker obtains \( J_e(p, z, x) - J_{eu}(z, x) = \eta S(p, z, x) \), while the firm gets \( F(p, z, x) = \eta S(p, z, x) \). This characterizes wages:

\[
 w(p, z, x) = \eta \left\{ e^z \left[ p e^{\mu(H)} + (1 - p) e^{\mu(L)} \right] + (1 - s) \mathbb{E} \left[ \Lambda(x, \varepsilon'_z) F(p', z', x') | p, z, x \right] \right\} \\
- (1 - \eta) \left\{ \mathbb{E} \left[ \Lambda(x, \varepsilon'_z) [s J_u(z', x') + (1 - s) J_e(p', z', x')] | p, z, x \right] - J_u(z, x) \right\}. \] (16)

**Equilibrium.** The notion of equilibrium for the economy is standard: all value functions must satisfy their respective Bellman equations (cf equations (9), (13), (14), and (15)), wages must be set according to the Nash bargaining rule (16), and labor market tightness must be determined according to the free entry condition (12). In Appendix B, we provide the formal definitions and prove that an equilibrium exists. We also provide a scheme for the numerical verification of equilibrium uniqueness.
4.3 Aggregate Quantities

Aggregate employment. The aggregate dynamics of the economy are determined by the start of period aggregate employment $N_t \in [0, 1]$, the start of the period distribution of match quality $P_t$, which we view as a probability with support on $[0, 1]$, as well as the exogenous aggregate states $z_t$ and $x_t$. The aggregate unemployment rate is then $U_t = 1 - N_t$ at the start of period $t$.

Start of period employment $N_t$ evolves as follows:

$$N_{t+1} = (1 - s) \{(1 - N_t) f(\Theta(z_t, x_t)) \mathbb{1}(p_0 \geq \underline{p}(z_t, x_t)) + N_t P_t(\{p(z_t, x_t), 1]) \}. \quad (17)$$

The law of motion (17) reflects the following: at the start of period $t$, there are $N_t$ employed with match quality distributed according to $P_t$. Of the initially employed workers, those with match quality below $\underline{p}(z_t, x_t)$ separate from their jobs, so $N_t P_t(\{p(z_t, x_t), 1])$ is the amount of workers continuing to be employed. In addition, a fraction $f(\Theta(z_t, x_t))$ of the $1 - N_t$ unemployed workers at the start of the period are matched to vacancies. These new matches are consummated as long as the initial prior $p_0$ is above the threshold $\underline{p}(z_t, x_t)$. This gives new employment of $(1 - N_t) f(\Theta(z_t, x_t)) \mathbb{1}(p_0 \geq \underline{p}(z_t, x_t))$ workers. Finally, a fraction $s$ of employed workers separate for exogenous reasons between the end of period $t$ and the start of the next period $t + 1$.

The evolution of the distribution match quality beliefs at the start of each period is:

$$P_{t+1}(A) = \int_{\underline{p}(z_t, x_t)}^1 \Gamma_A(p, z_t) \tilde{P}_t(dp), \quad (18)$$

where $P_{t+1}(A)$ gives the fraction of workers at the start of the next period with match quality
beliefs lying within the set $A \subset [0, 1]$

$$\Gamma_A(p, z) = p \mathbb{P}\left(p'(e^{z+\mu(H)}-\frac{1}{2}\sigma^2+\sigma\varepsilon_{i}, p, z) \in A | p, z\right) \quad (19)$$

$$+(1 - p) \mathbb{P}\left(p'(e^{z+\mu(L)}-\frac{1}{2}\sigma^2+\sigma\varepsilon_{i}, p, z) \in A | p, z\right)$$

is the probability that an individual with start of period match quality belief $p$ will end up having posterior (8) in set $A$, and

$$\tilde{\mathcal{P}}_t(dp) = \frac{(1 - N_t)f(\Theta(z_t, x_t))\mathcal{P}_0(dp) + N_t\mathcal{P}_t(dp)}{(1 - N_t)f(\Theta(z_t, x_t))\mathbb{1}(p_0 \geq p(z_t, x_t)) + N_t\mathcal{P}_t([p(z_t, x_t), 1])} \quad (20)$$

is the aggregate distribution of match quality beliefs right after hiring and firing have taken place but before output has been observed, with $\mathcal{P}_0$ denoting a point mass at $p_0$. The law of motion (18) first computes the posteriors for individuals of a fixed initial match quality belief $p$ according to the function $\Gamma_A(p, z)$. Here, posteriors may differ despite individuals being ex ante identical—different idiosyncratic output shocks lead to different posteriors ex post. These posteriors are then aggregated over groups of workers with different initial match quality beliefs according to the distribution $\tilde{\mathcal{P}}_t$ in order to arrive at the final distribution of match quality beliefs for the start of the next period.

**Group-specific employment.** A key focus for our analysis is the unemployment rate and distribution of match quality beliefs for workers of different age groups. For simplicity, we take the initial working age to be the same across all workers. In particular, a group of workers who first enter the job market at time $\tau$ will have a potential experience of $e = t - \tau$ at time $t \geq \tau$. The employment rate, $N_{\tau,t}$, and match quality belief distribution, $\mathcal{P}_{\tau,t}$, for a cohort $\tau$ at the start of period $t \geq \tau$ can then be computed from the laws of motion (17) and (18) under the initial condition $N_{\tau,\tau} = 0$ (i.e. all workers begin being unemployed).
Quantities. The number of workers who end up producing at the end of the period:

\[
N_{end,t} = (1 - N_t) f(z_t, x_t) \mathbb{I} \left( p_0 \geq p(z_t, x_t) \right) + N_t \mathcal{P}_t \left( [p(z_t, x_t), 1] \right),
\]

is given by the sum of surviving incumbent workers and newly matched workers. These productive workers are paid wages, which total \( W_t = \bar{w}_t N_{end,t} \) where the average wage is \( \bar{w}_t = \int_{p(z_t, x_t)}^1 w(p, z_t, x_t) \tilde{\mathcal{P}}_t(dp) \). The remaining unemployed workers receive unemployment benefits, which total \( B_t = b(1 - N_{end,t}) \).

Aggregate output \( Y_t \) is the sum of all individual output (2) across the mass \( N_{end,t} \) of productive workers:

\[
Y_t = e^{Z_t} N_{end,t},
\]

where aggregate labor productivity, defined as log output per worker,

\[
Z_t = z_t + \log \left( \int_{p(z_t, x_t)}^1 \left[ p e^{\mu(H)} + (1 - p) e^{\mu(L)} \right] \tilde{\mathcal{P}}_t(dp) \right),
\]

(21)

takes into account both exogenous productivity \( z_t \), as well as the endogenous productivity of employed workers as determined by the distribution of match quality beliefs, \( \tilde{\mathcal{P}}_t \), which is given by (20). The Law of Large Numbers is implicit in the computation of aggregate labor productivity, so that idiosyncratic output shocks, \( \varepsilon_{it} \), are diversified away and do not directly show up in expression (21).\(^8\)

Finally, a total of \( V_t = (1 - N_t) \Theta(z_t, x_t) \) vacancies are created at the start of the period. This is determined by the unemployment rate, \( 1 - N_t \), and market tightness \( \Theta(z_t, x_t) \), all at the start of the period. The total amount of resources spent towards vacancy creation is given by \( \kappa V_t \).

\(^8\)With a continuum of workers, additional technical assumptions are required for the Law of Large Numbers to hold. See Sun (2006) and Duffie and Sun (2012) for details.
5 Quantitative Analysis

In this section we show the importance of including time-variation in the risk premium to capture the business cycle dynamics of the unemployment rate of workers of different ages. To illustrate this point, we compare two models: (1) our baseline model (Model 1) which features time-varying risk premium and aggregate labor productivity shocks, and (2) a risk-neutral model (Model 2) which features only labor productivity shocks. To make a fair comparison, we calibrate both models by targeting the standard set of labor market moments described below. We simulate both models at monthly frequency. Our solution approach is described in detail in Appendix C.

5.1 Calibration

We use the parameters shown in Table 3 for our simulation experiments. In models 1 and 2, we use the same process for labor productivity, which is modeled as an AR(1) process in logs. We choose the persistence $\rho_z = 0.9$ and volatility $\sigma_z = 0.01$ of the labor productivity process to match the persistence and volatility of the de-trended, quarterly series for non-farm business real output per person reported by the Federal Reserve Economic Data (FRED) database. We de-trend the series from 1950-2016 using an HP filter with a bandwidth of 1600. Our baseline model (Model 1) features changes in the market price of risk given by (6). We model the market price of risk, $x$, as an AR(1) process in logs and set its persistence $\rho_x = 0.985$ and volatility $\sigma_x = 0.035$ based on the persistence and volatility of the aggregate log dividend yield series. In addition, we set the mean market price of risk to be $\bar{x} = 0.22$ based on an average Sharpe ratio of 22%. This calibration for the market price of risk process is very much consistent with calibrations from leading asset pricing models (see, e.g., Campbell and Cochrane (1999)). The risk-neutral model, Model 2, does not include the shock $x$. We choose the risk-free rate $r_f = 0.0017$ (annual rate of 2%) to match the data counterpart for both models.
Both models feature four learning parameters: the match-specific productivity parameters \( \mu_H \) and \( \mu_L \), the parameter \( \sigma \), which measures the informativeness of individual output about match-quality, and \( p_0 \), which measures the prior belief about initial match-quality.\(^9\) We use the same values for these parameters for both models and choose them in the following way. We normalize \( \mu_L = -\mu_H \) and choose \( p_0 \) to be close to the expected output from a median worker. Getting an exact equality requires solving a fixed point problem since the choice of \( p_0 \) impacts the median of the distribution of workers. Therefore, for simplicity, we choose \( p_0 \) such that the expected output from a new match is 1. This implies \( p_0 = 0.295 \). We choose \( \mu_H = 0.87 \) and \( \sigma = 2.73\% \) to match the cross-sectional dispersion in plant-level total factor productivity of 1.92 measured by Syverson (2004) and the expected tenure of a new match. The latter depends on the ratio \( (\mu_H - \mu_L)/\sigma \). The expected tenure of a new match is estimated by BLS to be 52 months.\(^{10}\) The expected tenure is 54 months in Model 1, while it is 57 months in Model 2. Finally, we include the possibility of matches dissolving for reasons other than those we consider here. We set the probability of these exogenous separations so that, for each model, the model-implied mean unemployment rate of the aggregate population matches the average aggregate unemployment rate in the data. This results in choosing \( s = 0.37\% \) per month for Model 1 and \( s = 0.35\% \) for Model 2.

We follow the labor search literature and choose the values of the remaining parameters \( \kappa \), \( \iota \), \( b \), and \( \eta \) to target the first two moments of unemployment and vacancies, and the elasticity of wages to productivity. As pointed out by Shimer (2005), the standard DMP labor search model has difficulty in generating realistic volatility of labor markets. Although accounting for time-variation in the risk premium helps in increasing the volatility of labor market moments, this increase is insufficient once we restrict the volatility and persistence of the stochastic discount factor to take on realistic values. Since our focus is to provide an explanation for

\(^9\)Note that the parameter \( \sigma \) in our model is a measure of the informativeness of individual output about match-quality and not the idiosyncratic volatility of firm output. A firm employs many workers, therefore, match-level idiosyncratic shocks average out within a firm.

\(^{10}\)See http://www.bls.gov/news.release/tenure.t01.htm.
the relative volatilities of the unemployment rate of young and prime-age workers and not
the volatility of the average unemployment rate, we adopt the simplest resolution of Shimer’s
puzzle in the literature. We follow Hagedorn and Manovskii (2008) and choose a high value
for the unemployment benefits parameter: we set \( b = 1.95 \) for Model 1 and a slightly higher
value \( b = 2.0 \) for Model 2. These imply wage-replacement ratios (unemployment benefit
normalized by mean wages) of 0.95 for both models. This value is the same as Hagedorn
and Manovskii (2008), who interpret the parameter \( b \) as capturing the value of leisure, in
addition to unemployment benefit payments. We choose the curvature parameter of the
matching function \( \iota = 3.2 \) for both models, and the cost of vacancies \( \kappa = 4.0 \) and \( \kappa = 4.1 \)
for Models 1 and 2, respectively. The results from our simulations and the data counterparts
are shown in Table 4. In simulations, the average unemployment rate is 5.2% and 4.9% for
Models 1 and 2, respectively. These values are close to the data counterpart of 5.6%. The
volatility of the unemployment rate in our simulations are 0.70% per quarter for Model 1
and 0.50% for Model 2. These values are also close to the data counterpart of 0.75%.\(^{11}\)
The mean labor market tightness as reported by the FRED using JOLTS data between 2001-2017
is 0.54; it is 0.56 in Model 1 and 0.58 in Model 2. The volatility of labor market tightness in
our simulations is 8.6% for Model 1 and 7.9% for Model 2; in the data it is 9.2%. We set
the bargaining power of workers to \( \eta = 0.04 \). Our model implied wage elasticities are 0.50
and 0.45 for Models 1 and 2, respectively, which are close to the empirical estimate of 0.45
reported by Shimer (2005).

5.2 Unconditional moments

Our model does a good job in matching unconditional moments and the conditional dynamics
of unemployment rates of young and prime-age workers. The BLS reports unemployment levels
for workers in different age buckets. We choose workers between 20-24 years to correspond
\(^{11}\)We report the volatility of the cyclical component of unemployment rates without taking logs. The
volatility of the log unemployment rate is 0.16 in the data and 0.17 in our model.
to young workers, and those between 35-44 years to correspond to prime-age workers. In simulations, we define young workers as those with between 1-5 years of experience, while prime-age workers have between 15-25 years of experience. These definitions are similar to the BLS age groups under the assumption that workers enter the labor force at age 20. In the model simulations, a cohort of workers entering in period $\tau$ begin their careers being unemployed and without any work experience. When they find a job, the match quality belief is initialized to $p_0$. Thereafter, we track the unemployment rate and distribution of match quality beliefs of each cohort over time. We consider the CPS equivalent of age-specific unemployment rates so that the unemployment rate of workers with $e \geq 0$ periods of potential work experience in period $t$ corresponds to the unemployment rate of the cohort of workers that entered in period $\tau = t - e$.

Table 5 shows the unconditional model-implied moments for the unemployment rates of young and prime-age workers. In the data, the mean unemployment rate of young workers is 9.8%; our model with time-varying risk premium (Model 1) generates an average unemployment rate of 10.5%, while Model 2 generates 10.1%. This rate is much lower for prime-age workers: 4.6% in the data, and 5.3% and 4.9% in Models 1 and 2, respectively. In both models, young, inexperienced workers have a higher average unemployment rate relative to prime-age workers because newly formed matches have a higher likelihood of being dissolved. As bad matches get dissolved, the average match quality of survivors improves. In other words, matches which survive for a long time are of higher quality on average as shown in Panel A of Figure 3. In this figure, we compare the distribution of posterior beliefs for workers with one year of experience to that of workers with 15 years of experience. The match quality belief of the median young worker with one year of experience is 0.45. In comparison, this value is much higher at 0.96 for the median worker with 15 years of experience. Panel B of Figure 3 shows hazard rates as a function of tenure in the stochastic steady-state. The hazard rate declines as poor matches are dissolved early on during the tenure of employment. According to our model, the first seven or eight years of experience are critical in reducing
unemployment risk—additional experience does not make much of a difference.

Both Models 1 and 2 feature a much higher volatility of the youth unemployment rate compared to prime-age workers. In other words, the unemployment rate of the young is much more sensitive to variation in macro-economic conditions than that of prime-age workers. The intuition for this result is the following. When the economy transitions into a recession, the job-finding probability declines uniformly for all workers. This is due to our simplifying assumption that the job-finding probability for unemployed workers is independent of age. However, because the young started the period with a higher unemployment rate, the decline in the number of such workers who leave the unemployment state and find a job drops by a larger amount compared to prime-age workers. Put differently, even though job finding probabilities are symmetric across groups in the model, young workers experience more volatile flows from unemployment to employment. This is a result of match qualities being poorer on average for this group, and as a result, these workers are unemployed more often and are therefore more exposed to fluctuations in firms’ hiring incentives. In our calibration, the flow into unemployment due to separations is quite acyclic for all workers. Overall, Models 1 and 2 match the unconditional volatilities of unemployment rates quite well. In the data, the volatility of the youth unemployment rate is 1.1%. It is 1.4% in Model 1 and 1.1% in Model 2. In comparison, the volatility of the unemployment rate of prime-age workers is 0.7% both in the data and in Model 1, while in Model 2 it is 0.5%.

5.3 Conditional dynamics

In this subsection we compare the model-implied sensitivities of the unemployment rates for young and prime-age workers to \( z \) and \( x \) shocks to those in the data reported in Section 3.

In Figure 5 we show unemployment rates in more detail by plotting the conditional unemployment rates for young, \( \mathbb{E}[u_t^y | x_t = x, z_t = z] \), and prime-age workers, \( \mathbb{E}[u_t^p | x_t = x, z_t = z] \), as a function of labor productivity \( z \) and the market price of risk \( x \). All results in this
subsection refer to our baseline Model 1, which features time-varying risk premium. Panels A
and B show how the unemployment rates for young (Y) and prime-age (P) workers vary with
aggregate productivity (z), for different levels of the market price of risk (x), while Panel C
shows the difference in unemployment rates between these two groups as a function of z for
three different levels of x. These plots allow us to compare the model implied sensitivities of
the unemployment rates for each group to z and x shocks and we obtain two results which
are in line with the empirical results of Section 3.

First, as shown in Figure 5, our model is able to generate the higher sensitivity of youth
unemployment rates to both z and x shocks, compared to prime-age unemployment. From
Panel A we see that when x is at its mean value of \( x = 0.22 \), a drop in z from its 95th percentile
value to its 5th percentile value results in an increase in the young (prime-age) unemployment
rate by 4.8% (2.3%).\(^\text{12}\) For x shocks, a change from the 95th to 5th percentile value results a
1.3% (0.6%) increase in youth (prime-age) unemployment. The youth unemployment rate is,
therefore, twice as sensitive to changes in labor productivity and the market price of risk
than that of prime-age workers, which is consistent with our regression results in Section 3.
The intuition for this result is the following. When either aggregate labor productivity drops
or the market price of risk increases, the present value of cash flows from a potential match
decreases. This reduces the incentives of firms to post vacancies (shown in Panel A of Figure 4).
Fewer vacancies in turn reduce the probability of an unemployed worker meeting a vacancy.
In our model, despite this decline in job-finding probability being the same for workers of all
ages, the young suffer a bigger drop in the number of workers who are successfully matched to
a vacancy because this group started the period with a higher unemployment rate relative to
prime-age workers. Consequently, with fewer young workers successfully finding employment,
this group experiences a bigger increase in the unemployment rate.

\(^{12}\)The model-implied changes in unemployment rates are much higher than our regression-based estimates
in Section 3. This is likely due to non-linearities in the model, which are missed by a linear regression estimate.
Our model-implied slope coefficient along z around the mean \( z = 0 \) is \(-0.4\) for young workers. This number
is close to the slope coefficient of \(-0.29\) reported in column (1) of Table 2.
Second, in our model, unemployment rates are more sensitive to variation in labor productivity in states in which the risk premium is high. This is in line with our empirical analysis in Section 3, where we document the slope coefficient of the interaction between labor productivity and the dividend-price ratio to be statistically and economically significant in determining the unemployment rate of young and prime-age workers (and also the difference in the unemployment rates). In our simulations, when \( x \) is at its 95-th percentile, a decline in \( z \) from its 95th to 5th percentile results in an increase in youth (prime-age) unemployment rate of 6.1% (2.9%). In comparison, when \( x \) is at its 5th percentile, the same decline in \( z \) results in a much more muted increase: youth (prime-age) unemployment increases only by 3.9% (1.8%). The reason for a much sharper increase in unemployment rates when the risk premium is high is because in these states, the value of current and potential matches drops not only because of a drop in labor productivity (a cash-flow effect), but also because future rents from the match are discounted more due to the increase in the risk premium (a discount rate effect). The number of vacancies posted therefore decline by a bigger amount so that unemployment rates experience a sharper increase.

5.4 Impulse response

In this subsection, we examine the impulse responses of unemployment rates to labor productivity and the market price of risk shocks. We start the economy at \( t = 0 \) with both \( z \) and \( x \) at their mean levels and with the distribution of match quality beliefs at the stochastic steady-state. At \( t = 1 \), we shock the economy by either a two unconditional standard-deviation drop in labor productivity \( z \) (shown by the solid blue line in Panels A through C of Figure 6), a (log) two unconditional standard deviation increase in the market price of risk \( x \) (dashed black line), or a combination of a two standard-deviation shock to \( z \) and \( x \) simultaneously (dot-dash red line). Comparing Panels A, B, and C of Figure 6, we see that the youth unemployment rate is about twice as sensitive to both labor productivity \( z \)
and market price of risk $x$ shocks than that of prime-age workers.

Furthermore, we see that unemployment rates for both young and prime-age workers are more responsive to a pure labor productivity shock (solid blue line) in comparison to a pure market price of risk shock (dashed black line). For instance, in Panel A of Figure 6, we see that a two standard-deviation decline in labor productivity $z$ leads to a 2.5% increase in youth unemployment rates, while a two standard-deviation increase in the market price of risk $x$ leads to a smaller increase of 0.7% in youth unemployment rates. However, this does not imply that changes in the market price of risk are of less quantitative importance for unemployment rates. This is because recessions usually feature a simultaneous decrease in labor productivity accompanied by an increase in the risk premium, and there is a substantial interaction effect between labor productivity and the market price of risk shocks for unemployment outcomes. For instance, we see from the red dash-dot line in Panel A of Figure 6 that when both labor productivity and the market price of risk shocks arrive simultaneously, the magnitude of the resulting increase in youth unemployment is about 4%, which is 0.8% larger than the sum of the resulting youth unemployment rate outcomes from the two pure shocks alone. This demonstrates the importance of accounting for both labor productivity and the market price of risk shocks, along with their interactions effects, when accounting for youth unemployment dynamics during recessions.

6 Importance of Time-varying Risk Premium

The Great Recession of 2008-2009 featured large increases in unemployment rates and therefore provides us with a setting to better understand the important drivers of labor market movements. In this section, we compare the realized unemployment rates for young and prime-age workers during this period with the predictions of Models 1 and 2. As discussed above, Model 1 features both labor productivity ($z$) and market price of risk ($x$) shocks, while Model 2 features only $z$ shocks. As can be seen from Table 5, both models are calibrated to
match the unconditional volatilities of labor market tightness and unemployment rates for young and prime-age workers over the entire sample period from 1951 to 2016.

For this exercise, we feed in the realized labor productivity ($z$) and market price of risk ($x$) shocks over this period into Model 1. The series for realized labor productivity ($z$) shown in Panel A of Figure 7 is the de-trended real output per worker per hour series reported by the FRED.\footnote{Real output per worker per hour is available from the FRED at a quarterly frequency. We convert this quarterly series to a monthly frequency by assuming that labor productivity remains constant within each quarter.} Unlike labor productivity, the market price of risk is not directly observed in the data. We estimate shocks to $x$ by assuming that the log market price of risk $x$ is an affine function of the dividend-price ratio with a slope of one.\footnote{This approximation can be motivated by the Gordon growth model, under which the dividend price ratio $D/P = r - g$ is simply the difference between the expected stock return $r$ and the dividend growth rate $g$. Based on findings from Campbell and Shiller (1988), we assume that innovations in dividend yields chiefly correspond to discount rate $r$ shocks (rather than shocks to the dividend growth rate $g$). Finally, to link discount rate shocks to shocks to the market price of risk $x$, we note that in settings with a single risk factor, as is the case in our Model 1, the expected return can in turn be written as $r = r_f + \beta x$, where $r_f$ is the risk-free rate, $\beta$ is the quantity of risk, and $x$ denotes the market price of risk. Our identifying assumption for $x$ shocks is that the quantity of risk $\beta$ remains constant so that variations in expected returns correspond to fluctuations in the market price of risk (we ignore interest rate volatility as it is small in comparison in the data).} Under this assumption, changes in the log market price of risk correspond one-for-one to changes in the market price of risk. Since labor market dynamics are non-linear in $x$ in our model, we need to specify the initial value of $x$ at the start of the recession. We assume that $x$ was at its mean value of 0.22. Panel B shows the estimated path of the market price of risk ($x$). Our key result is that a model which accounts for time-variation in the risk premium better matches labor market dynamics during the Great Recession.

In Panel C of Figure 7, we compare the predicted path for labor market tightness from Models 1 and 2 with the data, while Figure 8 shows this comparison for the unemployment rates of young and prime-age workers. In these figures, there are two model-implied paths: one for Model 1 and one for Model 2. The black dash-dot line corresponds to our Model 1, while the red dotted line corresponds to Model 2. The data are indicated by a solid, blue line. Even though Models 1 and 2 are calibrated to match the volatility of labor market tightness
and unemployment rates in the data, the former comes closer to matching the data over the
period of the Great Recession.

Panel A of Figure 8 shows the increase in the unemployment rate of young workers during
the Great Recession. The line corresponding to the data shows the increase relative to the
unemployment rate in the quarter preceding the NBER start-date of the Great Recession.
Similarly, the model-implied paths plot the increase in the unemployment rate in comparison
to the stochastic steady-state. Panel B shows the corresponding plot for prime-age workers,
while Panel C shows the relative difference in the unemployment rate of young and prime-age
workers. Our baseline model (dash-dot, black line) shows a steady increase in unemployment
rates for both young and prime-age workers, peaking in the first quarter of 2009. From the
figure we see that while our baseline model (dash-dot line) is able to capture about half of
the variation in the data, the risk-neutral model (dotted red line) predicts almost no increase
in unemployment rates. This is because, the peak-trough drop in labor productivity was
2% (Panel A of Figure 7) which corresponds to only a one unconditional standard deviation
drop. In contrast, the increase in the market price of risk was much bigger. Accordingly, our
baseline model which accounts for this shock predicts a bigger increase in unemployment
rates and slacker labor markets (Panel C of Figure 7) than the risk-neutral model.

7 Unemployment Rates Absent TARP

There was a large increase in the aggregate risk premium during the Great Recession. The
dividend-price ratio of the stock market approximately doubled in value between December
2007 and March 2009, before sharply declining. The timing of this decline coincided with
the implementation of the Troubled Asset Relief Program (TARP) through which some
$300 billion worth of troubled assets were purchased between November 2008 and March
2009 by the U.S. government. Large-Scale Asset Purchase (LSAP) programs such as TARP
seek to lower risk premia by directly decreasing the quantity of risky assets that the private
sector would have to bear (Bernanke, 2013). We use our model to quantify the increase in unemployment for young and prime-age workers in a scenario without the sharp decline in risk premium, and we find that the youth (prime-age) unemployment rate would have been 2.3% (1.1%) higher. To the extent we believe that TARP was responsible for the decline in the risk premium, our model shows this intervention produced a sizeable reduction in unemployment rates, especially for young workers.

The setup for this counterfactual analysis is as follows. We feed two risk-premia scenarios into our baseline model (Model 1) in order to generate model-implied paths for youth and prime-age unemployment. The first scenario represents the realized outcome for risk-premia in the data in which TARP was implemented, while the second is a hypothetical scenario used to capture an increase in risk premia corresponding to a counterfactual outcome in which TARP had not been implemented. Our model-implied estimates for the effect of TARP on youth and prime-age unemployment rates are then based on the difference in model implied unemployment outcomes across these two scenarios.

Since part of the Federal Reserve’s thinking behind TARP was to avoid a Great Depression-like outcome (see, e.g., Bernanke (2015)), the hypothetical scenario that we consider is one under which the value for the aggregate dividend-price ratio between March and June of 2009 is set to be three times that of its level in November 2007 (right before the start of the Great Recession). This captures a Great Depression-like scenario in which the Federal Reserve did not intervene as forcefully (in comparison to 2008). We then convert this scenario for the dividend-price ratio into a corresponding series for the market price of risk following the procedure outlined in Section 6. The dotted line in Panel A of Figure 9 illustrates the implied market price of risk, which takes a value of 0.66 between March and June of 2009. The market price of risk under the scenario in which TARP was implemented is just our fitted series for the realized market price of risk series, which we first constructed in Section 6.

\textsuperscript{15}Using stock returns data from CRSP, we find that the aggregate dividend-price ratio increased by 200% between the start and the peak of the Great Depression.
Panel B (C) of Figure 9 illustrates the resulting model implied path for changes in youth (prime-age) unemployment levels since December 2008.

Our baseline model predicts that in the absence of TARP, youth (prime-age) unemployment rates would have been 2.3% (1.1%) higher by the end of the Great Recession in June 2009. We arrive at these numbers as follows. Under the realized path in which TARP was implemented, we see from Panels B and C of Figure 9 that, in comparison to December 2008, our model predicts a 1% (0.5%) decline in youth (prime-age) unemployment rates by June 2009. In comparison, absent TARP, our model predicts that youth (prime-age) unemployment rates would have increased by a further 1.3% (0.6%) by June 2009. Taking the difference in unemployment rates across the two scenarios, we see that TARP lowered youth (prime-age) unemployment rates by 2.3% (1.1%) as of the end of the Great Recession in June 2009.

While a full welfare computation would have to further take into account the potential costs of TARP, we nevertheless view our model as a useful input into any welfare assessment exercise. Our results indicate that there is substantial heterogeneity in the response of youth and prime-age unemployment rates to policy interventions such as TARP. Modeling cross-sectional heterogeneity in unemployment responses to policy innovations is important to the extent that policy-makers may care differentially about the unemployment experience of young versus prime-age workers.

8 Labor Market Cleansing

The end of the Great Recession featured an increase in labor productivity (measured as the average output per worker) simultaneous with an increase in unemployment rates of all workers. In fact, average labor productivity started increasing from the last quarter of 2008, two quarters before the end of the recession. This pattern is not unique to the Great Recession; Figure 10 shows a similar pattern for the four largest recessions in post-war US data. Our model which features heterogeneity in the quality of worker-firm matches can
generate such a pattern, namely an increase in average output per worker simultaneous with an increase in unemployment.

Panel A of Figure 11 plots the difference between average output per worker and exogenous productivity for our baseline model (Model 1). In a model with no heterogeneity in match quality, this difference would be zero. In contrast, in our model the distribution of the quality of worker-firm matches is time-varying. During recessions a decline in productivity (z) and/or an increase in the market price of risk (x) leads to matches of poor quality dissolving at a higher than average rate. This leads to an improvement in the average quality of the pool of currently employed workers and provides an offsetting force to the exogenous drop in labor productivity. We show the improvement in the composition of current matches in Panels B and C. Both of these plots compare the distribution of match quality of workers after the shock relative to the stochastic steady-state and we see that there is less mass of poor matches in states with low z (Panel B) and also when both z is low and x is high (Panel C).

For recessions in which the decline in labor productivity is simultaneous with an increase in the market price of risk, the increase in endogenous productivity as a result of cleansing can be large. As shown by the dash, dot red line in Panel A of Figure 11, although exogenous productivity declines by 4.7%, a large part of this drop is offset by a 3.2% increase in endogenous productivity. Still larger increases in the market price of risk can more than offset the exogenous drop in labor productivity.

9 Conclusion

We find that there is significant cross-sectional heterogeneity in the sensitivity of unemployment rates of young and prime-age workers to changes in the dividend-price ratio of the aggregate stock market: the sensitivity of the unemployment rate of young workers to changes in the dividend-price ratio is twice as large as that of prime-age workers. Our finding shows that the standard driver of unemployment rates over the business cycle used in the literature,
namely aggregate labor productivity (measured as the average output per worker per hour), is insufficient to capture differences in cyclical dynamics of the unemployment rates of young and prime-age workers. We analyze CPS data over the period 1951-2017 and find that over this period, the level of the dividend-price ratio of the aggregate stock market has incremental information (beyond aggregate labor productivity) about the level of future unemployment rates of young and prime-age workers. Our paper, therefore, highlights the value of using information available in financial markets in predicting the future path of unemployment rates of workers, especially younger workers.

In order to provide an explanation of the differences in sensitivities of the unemployment rates of the two groups of workers, we build a general equilibrium search model with two key ingredients. First, we assume that the expected productivity of a firm-worker match is unobservable and learned over time. This generates differences in job-separation rates across workers with different levels of experience. Second, business cycle dynamics in our model is captured by two aggregate shocks: aggregate labor productivity and time variation in the risk premium. We derive the implications for the unemployment dynamics of young and prime-age workers in the presence of these aggregate shocks. Our model delivers three insights.

First, we find that including time variation in the risk premium is essential in capturing the business cycle dynamics of the unemployment rates of young and prime-age workers, especially during deep, prolonged recessions. To illustrate this point, we compare the predictions of two models with identical ingredients; the only difference between the two models is that one includes time-varying risk premium and the other does not. We make the models comparable by calibrating them to match the average volatilities of the unemployment rates of both young and prime-age workers. Despite this, we find a large difference in the predicted path of unemployment rates for the two groups of workers over the Great Recession. In particular, our model which includes time-varying risk premium better matches the realized path of unemployment rates observed in the data.
Second, we use our model which includes time-varying risk premium to carry out a counterfactual exercise. We focus on the period in the later stages of the Great Recession when the dividend-price ratio declined sharply after a steady, rapid increase. This period coincided with the implementation of the Troubled Asset Relief Program (TARP) through which some $300 billion worth of troubled assets were purchased between November 2008 and March 2009 by the U.S. government. To the extent we believe that TARP was responsible for the decline in the market risk premium, our model predicts that youth (prime-age) unemployment would have been 2.3% (1.1%) higher by June 2009, had the dividend-price ratio not declined rapidly beginning in March 2009. While a full welfare computation would have to further take into account the potential costs of TARP, we nevertheless view our model as a useful input into any welfare assessment exercise. Our results indicate that there is substantial heterogeneity in the response of youth and prime-age unemployment rates to policy interventions such as TARP. Modeling cross-sectional heterogeneity in unemployment responses to policy innovations is important to the extent that policy-makers care differentially about the unemployment experience of young versus prime-age workers.

Our third finding is that explicitly modeling heterogeneity in job separation rates can provide a potential explanation of the simultaneous increase in average output per worker accompanied by an increase in the aggregate unemployment rate. We show that this pattern is exhibited by the four largest recessions in post-war US data. Viewed through the lens of our model, this phenomenon is the result of labor market cleansing of relatively poor matches, which improves the average output per worker of surviving matches. A prolonged period of such cleansing can overcome the exogenous drop in productivity towards the end of long recessions. In such scenarios, the average output per worker can increase even while the aggregate unemployment rate is simultaneously rising.

Since our focus in this paper was to highlight the response of unemployment rates to changes in the risk premium, we used shocks to the market price of risk as an input for our baseline model. This choice greatly simplified our analysis. One avenue of future research
would be to allow changes in output resulting from changes in workforce composition to feedback into the consumption-savings decision of investors who determine the equilibrium risk premium. This will allow us to study the asset pricing implications of business cycle variations in the demographic composition of the workforce.
References


**Table 1: Summary statistics.** The sample is quarterly and is for the period 1951Q1-2016Q4. All series are deseasonalized and HP filtered with smoothing parameter 1600 (and therefore have zero means). Unemployment rates are taken from the BLS for the age groups 20-24 (young) and 35-44 (prime-age). Labor productivity is log real output per hour, also taken from the BLS. The dividend price ratio is the ratio between quarterly dividends and the end of quarter stock price, and is computed using the value weighted aggregate market index taken from CRSP.

<table>
<thead>
<tr>
<th></th>
<th>std</th>
<th>5%</th>
<th>50%</th>
<th>95%</th>
<th>Obs</th>
</tr>
</thead>
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<tr>
<td>Unemployment rate, young</td>
<td>0.0118</td>
<td>-0.18</td>
<td>-0.001</td>
<td>0.0232</td>
<td>264</td>
</tr>
<tr>
<td>Unemployment rate, prime-age</td>
<td>0.0069</td>
<td>-0.0099</td>
<td>-0.0009</td>
<td>0.0128</td>
<td>264</td>
</tr>
<tr>
<td>Labor productivity</td>
<td>0.0104</td>
<td>-0.0204</td>
<td>-0.0002</td>
<td>0.0162</td>
<td>264</td>
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<tr>
<td>Dividend price ratio</td>
<td>0.0011</td>
<td>-0.0015</td>
<td>-0.0001</td>
<td>0.0024</td>
<td>264</td>
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**B. Correlations**

<table>
<thead>
<tr>
<th></th>
<th>Unemployment, prime-age</th>
<th>Labor productivity</th>
<th>Dividend yield</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemployment rate, young</td>
<td>0.94</td>
<td>-0.056</td>
<td>0.13</td>
</tr>
<tr>
<td>Unemployment rate, prime-age</td>
<td>-0.01</td>
<td>0.13</td>
<td></td>
</tr>
<tr>
<td>Labor productivity</td>
<td></td>
<td></td>
<td>-0.38</td>
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Table 2: Unemployment, labor productivity, and discount rates. Predictive regressions of one-quarter ahead unemployment rates. The dependent variables are: $u^Y$, which is the unemployment rate of young workers who are individuals with ages between 20-24, $u^P$, which is the unemployment rate of prime-age workers who are between 35-44 years old, and the difference in these unemployment rates. Right hand side variables are non-farm business sector real output per hour per worker ($z_t$), and the dividend price ratio ($p_t = D_t/P_t$). The data is quarterly between 1951Q1 to 2016Q4. All variables are de-seasonalized, and de-trended using an HP filter with bandwidth 1600. Standard errors are Newey-West with 4 lags. Numbers in parentheses are t-statistics.

<table>
<thead>
<tr>
<th></th>
<th>$u_{t+1}^Y$</th>
<th>$u_{t+1}^P$</th>
<th>$u_{t+1}^Y - u_{t+1}^P$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$z_t$</td>
<td>-0.29 (2.38)</td>
<td>-0.17 (1.45)</td>
<td>-0.15 (3.04)</td>
</tr>
<tr>
<td>$dp_t$</td>
<td>3.31 (3.44)</td>
<td>2.06 (2.47)</td>
<td>1.43 (3.07)</td>
</tr>
<tr>
<td>$z_t \times dp_t$</td>
<td>-216.48 (3.29)</td>
<td>-130.88 (3.25)</td>
<td>-85.6 (3.06)</td>
</tr>
<tr>
<td>$const$</td>
<td>0 (0.01)</td>
<td>0 (0.74)</td>
<td>0 (0.01)</td>
</tr>
</tbody>
</table>

| N     | 263 | 263 | 263 | 263 | 263 | 263 |
| $R^2$ | 0.063 | 0.091 | 0.182 | 0.041 | 0.086 | 0.17 |

45
**Table 3: Parameter values.** This table displays parameters for the two models. Model 1 is the baseline calibration and it features discount rate shocks. Model 2 is the risk-neutral model. Both models are calibrated at a monthly frequency.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
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<tbody>
<tr>
<td>AR(1) coefficient of labor productivity</td>
<td>$\rho_z$</td>
<td>0.900</td>
<td>0.900</td>
</tr>
<tr>
<td>Volatility of labor productivity</td>
<td>$\sigma_z$</td>
<td>0.010</td>
<td>0.010</td>
</tr>
<tr>
<td>Unconditional mean of log-discount rate process</td>
<td>log $\bar{x}$</td>
<td>-1.51</td>
<td>–</td>
</tr>
<tr>
<td>AR(1) coefficient of discount rate process</td>
<td>$\rho_x$</td>
<td>0.985</td>
<td>–</td>
</tr>
<tr>
<td>Volatility of log-discount rate process</td>
<td>$\sigma_x$</td>
<td>0.035</td>
<td>–</td>
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<tr>
<td>Risk-free rate</td>
<td>$r_f$</td>
<td>0.0017</td>
<td>0.0017</td>
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<tr>
<td>Log-productivity of $H$ type</td>
<td>$\mu(H)$</td>
<td>0.87</td>
<td>0.87</td>
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<tr>
<td>Match specific output volatility</td>
<td>$\sigma$</td>
<td>2.728</td>
<td>2.728</td>
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<tr>
<td>Worker’s bargaining power</td>
<td>$\eta$</td>
<td>0.040</td>
<td>0.040</td>
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<tr>
<td>Fixed cost of vacancy creation</td>
<td>$\kappa$</td>
<td>4.000</td>
<td>4.100</td>
</tr>
<tr>
<td>Curvature of matching function</td>
<td>$\iota$</td>
<td>3.200</td>
<td>3.200</td>
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<tr>
<td>Initial prior for match quality belief</td>
<td>$p_0$</td>
<td>0.295</td>
<td>0.295</td>
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<tr>
<td>Exogenous separation probability (%)</td>
<td>$s$</td>
<td>0.370</td>
<td>0.350</td>
</tr>
<tr>
<td>Unemployment benefit parameter</td>
<td>$b$</td>
<td>1.950</td>
<td>2.000</td>
</tr>
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</table>
Table 4: **Labor market and asset pricing moments.** Model 1 refers to the baseline calibration featuring discount rate shocks. Model 2 is the risk-neutral model. Labor market moments in the model and in the data are quarterly averages of monthly series reported by the FRED and constructed by the BLS from the Current Population Survey (CPS) between Q1 1951–Q4 2016. Market tightness is from the JOLTS series between 2001 – 2017. All variables are as deviations from an HP trend with smoothing parameter 1600.

<table>
<thead>
<tr>
<th>Moment</th>
<th>Data</th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Labor market tightness:</strong></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Mean</td>
<td>0.54</td>
<td>0.56</td>
<td>0.58</td>
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<tr>
<td>Volatility (%)</td>
<td>9.2</td>
<td>8.6</td>
<td>7.90</td>
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<td>Autocorrelation</td>
<td>0.94</td>
<td>0.81</td>
<td>0.80</td>
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<tr>
<td><strong>Aggregate unemployment:</strong></td>
<td></td>
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<td></td>
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<tr>
<td>Mean (%)</td>
<td>5.6</td>
<td>5.2</td>
<td>4.9</td>
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<tr>
<td>Volatility (%)</td>
<td>0.75</td>
<td>0.70</td>
<td>0.50</td>
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<tr>
<td>Autocorrelation</td>
<td>0.94</td>
<td>0.85</td>
<td>0.84</td>
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<tr>
<td>Correlation (unemployment, market tightness)</td>
<td>-0.89</td>
<td>-0.91</td>
<td>-0.92</td>
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<tr>
<td>Job finding rate</td>
<td>0.45</td>
<td>0.53</td>
<td>0.55</td>
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<tr>
<td>Expected tenure at entry (months)</td>
<td>52</td>
<td>54</td>
<td>57</td>
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<tr>
<td>Elasticity of wages to productivity</td>
<td>0.45</td>
<td>0.50</td>
<td>0.45</td>
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<tr>
<td>Dispersion of plant output: 90 percentile/10 percentile</td>
<td>1.92</td>
<td>2.09</td>
<td>2.07</td>
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</table>
Table 5: Unconditional moments of unemployment rates of young and prime-age workers. Model 1 refers to the baseline calibration featuring discount rate shocks. Model 2 is the risk-neutral model. Moments in the data are calculated from the unemployment rates for young (20–24 year old) and prime-age workers (35 –44 years old) constructed by the BLS from the Current Population Survey (CPS). The raw series is first de-seasonalized and then de-trended using an HP filter with bandwidth 1600. Quarterly data is computed by averaging monthly numbers. The model is simulated at monthly frequency. Moments of quarterly simulated data are computed by averaging monthly numbers.

<table>
<thead>
<tr>
<th></th>
<th>Data</th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemployment rate, young (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>9.8</td>
<td>10.5</td>
<td>10.1</td>
</tr>
<tr>
<td>Std. dev.</td>
<td>1.1</td>
<td>1.4</td>
<td>1.1</td>
</tr>
<tr>
<td>Unemployment rate, prime-age (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>4.6</td>
<td>5.3</td>
<td>4.9</td>
</tr>
<tr>
<td>Std. dev.</td>
<td>0.7</td>
<td>0.7</td>
<td>0.5</td>
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Figure 1: Unemployment rates of Young and Prime-age workers. Panel A shows the unemployment rates of young (20-24 year old) and prime-age (35-44 year old) workers. Each series is constructed by the BLS from the Current Population Survey (CPS). Panel B shows the difference in seasonally adjusted unemployment rates of young and prime-age workers. The quarterly data shown here is computed by averaging deseasonalized monthly numbers and the trend is removed using an HP filter with smoothing parameter 1600. The grey bands are NBER recessions.
Incumbent matches $\{p_{it}\}_{i \in [0,N_t]}$.

Aggregate state $\omega_t$ realized.

Hiring/firing takes place. Wages are determined.

Production $y_{it}$ takes place. Bayesian updating for $p_{i,t+1}$.

Wages $w(p_{it}, z_t, x_t)$ are paid. Consumption takes place.

Separation shocks realized.

Figure 2: Timing of events within each period. (i) At the start of the period, the economy inherits $N_t$ incumbent matches from the previous period. Matches may differ in their beliefs regarding the probability of the match being of high type. (ii) The aggregate state $\omega_t = (z_t, x_t)$ is realized. (iii) Matches are made in labor markets, hiring and firing decisions are made, and wages are determined. (iv) Production takes place and beliefs are updated. (v) Wages are paid, the government pays out unemployment benefits financed with lump sum taxation, and consumption takes place. (vi) Finally, idiosyncratic separation shocks are realized.
Figure 3: Match pool quality and hazard rates. Panel A shows the cumulative distribution function of match quality beliefs as a function of experience in the stochastic steady-state. Panel B shows the hazard rate for match termination within the next month as a function of duration of the current match in the stochastic steady state.
Figure 4: Job finding rates and separation rates. Panel A shows the job finding rates as a function of $z$ for three different levels of the market price of risk. Labor productivity ($z$), is standardized by the unconditional volatility of the AR(1) process, $\sigma_z/\sqrt{1 - \rho_z^2}$. Panel B shows the threshold at which matches separate.
Figure 5: Unemployment rate sensitivity to fundamentals. Panels A and B show the variation of unemployment rates across aggregate states for young and prime-age workers, respectively, as a function of aggregate labor productivity for three different values of risk-premia in our baseline Model 1. Panel C shows the difference in the unemployment rates of young and prime-age workers. Labor productivity ($z$), is standardized by the unconditional volatility of the AR(1) process, $\sigma_z/\sqrt{1 - \rho_z^2}$. The figure shows the unemployment rate at the start of each period, before that period’s hiring and firing decisions have been made.
Figure 6: Response of unemployment. Panels A through C respectively plot the response of youth unemployment, prime-age unemployment, and their difference corresponding to a minus two standard deviation shock in labor productivity $z$ (solid line), a two standard deviation shock in the market price of risk $x$ (dashed line), as well as a combination of labor productivity and risk-premia shocks (dash-dot line). In all cases, the economy starts off at the steady state in which both labor productivity $z$ and the market price of risk $x$ are both at their mean values.
Figure 7: Labor productivity and discount rate shocks over the Great Recession.
Panels A and B show labor productivity and the market price of risk during the Great Recession. The market price of risk is inferred from the series for the dividend-price ratio of the value weighted market index taken from CRSP by assuming that first, log changes in the dividend-price ratio are perfectly correlated with log changes in the market price of risk, and second, that the mean value of the market price of risk is 0.22. Panel C compares the corresponding model implied labor market tightness series to that of the data. The dashed, black line corresponds to our baseline model with time-varying market price of risk. The dotted red line corresponds to a risk-neutral model.
Figure 8: Realized and predicted path of unemployment rates over the Great Recession. Panel A (B) compares model implied youth (prime age worker) unemployment rates to that of the data during the Great Recession. Panel C plots the difference between young and prime age unemployment rates. The dashed, black line corresponds to our baseline model with time-varying market price of risk. The dotted red line corresponds to a risk-neutral model.
Figure 9: Predicted path of unemployment rates without decline in the risk premium post TARP. Panel A plots various scenarios for the market price of risk corresponding to the data (solid blue line) and a Great-Depression-like scenario corresponding to the absence of TARP (red dotted line). Panel B (C) compares model implied changes in the unemployment rate of young (prime-age) workers since December 2008.
Figure 10: Labor productivity and unemployment during recessions. Labor productivity is the cycle component (HP-filtered with a value of 1600) of log real output per hour for non-farm businesses and is available at a quarterly frequency. Unemployment is changes with respect to unemployment levels one month prior to the NBER starting date of the recession. The recessions shown above are the four largest in the post-war period.
Figure 11: Labor market cleansing and endogenous productivity. Panel A plots the response of endogenous labor productivity in the baseline model to a minus two standard deviation shock in labor productivity $z$ (solid line), a two standard deviation shock in the market price of risk $x$ (dashed line), as well as a combination of labor productivity and risk-premia shocks (dash-dot line). In all cases, the economy starts off at the steady state in which both labor productivity $z$ and the market price of risk $x$ are at their mean values. Panels B and C plot the difference of the conditional match quality distribution relative to the steady state distribution. In panel B, labor productivity $z$ is two unconditional standard deviations below its mean while the log market price of risk $\log x$ is drawn from its steady state distribution. For Panel C, $z$ is two unconditional standard deviations below its mean while $\log x$ is two unconditional standard deviations above its mean.
Appendix

A Validity of assuming a common job-finding rate for young and prime-age workers

Our model makes the simplifying assumption of a common job-finding rate for all workers, irrespective of experience. This assumption avoids the need to keep track of the distribution of experience of unemployed workers. In this section, we test the validity of this assumption. Figure A.1 compares the actual unemployment rate to a synthetic unemployment-rate series constructed using our approximation. Panels A and B of Figure A.1 show results for young and prime-age workers, respectively. From these plots we see that our simplifying assumption is able to capture a significant amount of the business-cycle variation in the data. This section outlines the details of the construction of this synthetic time-series. Our treatment follows the analysis of Elsby, Michaels, and Solon (2009) and Shimer (2012).

To construct the synthetic unemployment series for each group, we need to estimate the job-finding rate \( f_t \) and the job-separation rate \( s_t \). The necessary inputs for this estimation are the total number of individuals \( L_t \), the number of unemployed workers \( U_t \), and the number of workers who recently became unemployed in that month \( U_{sep}^{t} \). The Current Population Survey (CPS) reports these time-series at monthly frequency for workers in different age groups. We focus on 20 – 24 years (“young”) and 35 – 44 (“prime-age”) workers. To avoid clutter, we suppress an index labelling the group.\(^{16}\)

The change in the stock of unemployed workers \( U_t \) from the previous month is from the addition of newly unemployed workers over the month and from unemployed workers finding work and therefore leaving the unemployment pool

\[
U_{t+1} - U_t = U_{sep}^{t+1} - F_t U_t
\]

where \( U_{sep}^{t+1} \) is the number of newly unemployed workers. In the CPS survey, these are workers who report being unemployed less than 5 weeks. \( F_t \) is the monthly outflow probability from unemployment to employment. Solving (A.1) for the outflow probability

\[
F_t = 1 - \frac{U_{t+1} - U_{sep}^{t+1}}{U_t}
\]

from which the monthly job-finding hazard rate is

\[
f_t = - \log(1-F_t)
\]

We follow the procedure outlined in Shimer (2012) to estimate the job-separation rate.

\(^{16}\) A 1994 redesign of the CPS surveys resulted in an underestimate of the number of recently unemployed workers (see Polivka and Miller (1998) and Abraham and Shimer (2001) for more details). We follow Elsby, Michaels, and Solon (2009) and multiply the CPS reported number of recently unemployed workers, \( U^* \), from February 1994 and after, by the same constant 1.1549. See the discussion at the bottom of page 94 of Elsby, Michaels, and Solon (2009).
We start with the ODE
\[
\frac{dU_t}{dt} = s_t(L_t - U_t) - f_tU_t = -(s_t + f_t)(U_t - U^*_t)
\] (A.4)

where

\[
U^*_t = s_tL_t/(s_t + f_t)
\] (A.5)

is the steady-state unemployment rate\(^{17}\). Assuming that the size of the labor force \(L_t\), and the flows \(s_t\) and \(f_t\) stay constant between surveys, the solution of this ODE is

\[
U_{t+1} = U_t^* - (U_t - U_t^*)e^{-(s_t+f_t)}
\] (A.6)

We use our estimated series, \(f_t\), in (A.6) to solve for \(s_t\) each period.

Finally, using our estimate of \(s_t\), we use (A.5) to generate a synthetic unemployment series for each group. Since our model assumes the same job-finding rate for all workers, for \(f_t\), we use the job-finding rate estimated using the entire population surveyed by CPS. In other words, our measure of \(f_t\) is the average job-finding rate in the population.

Figure A.1 shows the quarterly averages of the monthly series obtained and compares each series with the realized quarterly average unemployment rate. We see that the synthetic time-series for both young and prime-age workers matches the business-cycle variation of the actual realized series.\(^{18}\) The synthetic series, however, misses the level. For instance, the average realized unemployment rate for young workers is lower than the synthetic series. This is because in the data, young workers have a higher job-finding rate than the average job-finding rate.

B Proofs

We characterize the equilibrium in a two step procedure. First, we characterize the surplus function taking market tightness as a parameter. Afterwards, we then characterize market tightness through the free entry condition for vacancy creation.

We work exclusively with the match surplus function \(S : [0, 1] \times \Omega \mapsto \mathbb{R}_+\), which is defined by

\[
S(p, \omega) = J_e(p, \omega) - J_{eu}(\omega) + F(p, \omega),
\] (A.7)

where \(\omega = (z, x)\) denotes the exogenous state, \(J_e\) is the value for an employed worker, \(J_{eu}\) is the value function for a newly unemployed worker, and \(F\) is the value of the match to the firm. It is sufficient to work with the surplus function alone as all other values of interest can be recovered from the surplus function (and equilibrium conditions).

\(^{17}\)In (A.4), following Shimer (2012), we assumed that the labor-force participation rate for each group does not vary over time.

\(^{18}\)If we regress our synthetic series on the actual series, we obtain a slope coefficient of 0.729 for young workers and 1.050 for prime-age workers.
**Match surplus.** By combining the respective definitions (9), (13), and (14) for the value functions, and the Nash bargaining condition for worker’s surplus, \( J_e(p, \omega) - J_{eu}(\omega) = \eta S(p, \omega) \), we can show that the match surplus function satisfies the following Bellman equation:

\[
S(p, \omega) = \max \left\{ 0, e^{z(\omega)} \left( pe^{\mu(H)} + (1 - p)e^{\mu(L)} \right) - b + (1 - s)E \left[ \Lambda(\omega, \omega') S(p', \omega') | p, \omega \right] \right\} .
\]  

(A.8)

Next, we simplify the above Bellman equation by noting that

\[ f(\omega)\eta S(p_0, \omega) = \frac{\eta \kappa \Theta(\omega)}{1 - \eta} \]  

(A.9)

must hold in equilibrium. To see this, observe that when the free entry condition (12) is slack, complementary slackness implies that no vacancies are posted in equilibrium so that \( f(\omega) = \Theta(\omega) = 0 \) and both the left and right hand side of (A.9) equal zero. On the other hand, when the free entry condition (12) is satisfied exactly, the Nash bargaining condition for a firm’s share of the surplus, \( F(p, \omega) = (1 - \eta)S(p, \omega) \), gives \( \kappa = g(\omega)F(p_0, \omega) = (1 - \eta)g(\omega)S(p_0, \omega) \) which immediately imply (A.9).

By substituting (A.9) into the Bellman equation (A.8), we see that the surplus function \( S(p, \omega) \) can be viewed as the fixed point of an operator, \( T \), defined as follows:

\[
T(S)(p, \omega) = \max \left\{ 0, e^{z(\omega)} \left( pe^{\mu(H)} + (1 - p)e^{\mu(L)} \right) - \tilde{b}(\omega) + (1 - s)E \left[ \Lambda(\omega, \omega') S(p', \omega') | p, \omega \right] \right\} ,
\]

(A.10)

where

\[
\tilde{b}(\omega) \equiv b + (1 - s)E \left[ \Lambda(\omega, \omega') \frac{\eta \kappa \Theta(\omega')}{1 - \eta} | \omega \right].
\]  

(A.11)

In the above expression, market tightness \( \Theta = \Theta(\omega) \) is treated as a parameter, and the matching probability \( g(\omega) = g(\Theta(\omega)) \) is computing according to its definition \( g(\Theta) = m(U, V)/V = (1 + \Theta)^{-\frac{1}{1-s}} \).

**Proposition 1.** The operator \( T \) defined in (A.10) is a contraction mapping for any given profile of match probability \( g(\omega) \) (equivalently market tightness \( \Theta(\omega) \)). Hence, the surplus function \( S(p, \omega) \) is the unique fixed point of \( T \). Furthermore, the surplus function is non-decreasing in \( p \).

**Proof.** It is easy to verify that \( T \) satisfies Blackwell’s sufficiency conditions for a contraction mapping (see Theorem 3.3 of Stokey and Lucas (1999)). This immediately implies the existence of a unique fixed point for \( T \). For the final claim, observe that \( T(S) \) is non-decreasing in \( p \) whenever \( S \) is non-decreasing in \( p \), hence the fixed point of \( T \) will also be non-decreasing in \( p \) (see Corollary 1 in Stokey and Lucas (1999)).

**Equilibrium labor market tightness.** Having already characterized the surplus function taking market tightness as given, we now characterize the equilibrium value of market
tightness. To this end, we now recast the equilibrium in a form that is more convenient for this analysis.

**Definition 1** (Equilibrium). An equilibrium consists of a pair \((g, S)\) where \(g \in [0, 1]^{\Omega}\) is a probability vector for a firm getting matched to a worker in each of the \(|\Omega|\) states, and \(S = S(p, \omega)\) is a surplus function. The pair must satisfy the following:

(i) The surplus function must satisfy the fixed point problem \(S = T_g(S)\), where \(T_g\) denotes the operator \((A.10)\) with \(g = g(\omega)\) taken as a parameter.

(ii) The matching probabilities \(g = (g(\omega))\) must satisfy the following set of complementary slackness conditions:

\[
\kappa \geq g(\omega)(1 - \eta) \int_0^1 S(p, \omega) \mathcal{P}_0(dp_0), \forall \omega \in \Omega
\]

\[
0 = (1 - g(\omega)) \left[ \kappa - g(\omega)(1 - \eta)S(p_0, \omega) \right], \forall \omega \in \Omega
\]

We could equivalently state condition (ii) as

\[
g = \Upsilon(g) \quad (A.12)
\]

where the coordinates of \(\Upsilon : [0, 1]^{\Omega} \mapsto [0, 1]^{\Omega}\) are defined as

\[
\Upsilon(g)(\omega) = \frac{\kappa}{\max \{\kappa, (1 - \eta)S(p_0, \omega; g)\}} \quad (A.13)
\]

**Proposition 2** (Existence). An equilibrium exists.

**Proof.** Observe that \(\Upsilon\) maps the unit cube \([0, 1]^{\Omega}\) into the unit cube \([0, 1]^{\Omega}\). Furthermore, the fact that \(S\) is continuous in \(g\) implies that \(\Upsilon\) is a continuous map. Brouwer’s fixed point theorem then guarantees that \(\Upsilon\) has a fixed point.

**Remark.** The above existence theorem only makes use of that fact that \(\Upsilon\) is a continuous map. While Brouwer’s fixed point theorem then guarantees that an equilibrium exists, there are no guarantees of uniqueness—all that we know from Brouwer’s fixed point theorem is that (1) there is at least one equilibrium, and (2) when multiple equilibria exist, the number of equilibria is generically odd (cases with a non-odd number of equilibria are all pathological and can only occur for, possibly, a set of parameters of zero measure).

Consider the partial ordering, \(\succeq\), on \([0, 1]^{\Omega}\) defined according to \(x = (x_1, ..., x_{|\Omega|}) \succeq y = (y_1, ..., y_{|\Omega|})\) if and only if \(x_i \geq y_i\) for all \(1, ..., |\Omega|\). That is, the partial ordering \(\succeq\) is defined coordinate-wise. We have the following:

**Proposition 3** (Least and greatest equilibrium). Under the den Haan, Ramey, and Watson (2000) parameterization for the matching function, \(m(U, V) = UV/(U^\alpha + V^\alpha)^{1/\alpha}\), the least and greatest fixed point of \(\Upsilon\), according to the partial order \(\succeq\), can be computed by iterating \(g_{n+1} = \Upsilon(g_n)\) from a starting point of \(g_0 = 0 = (0, ..., 0)\) and \(g_0 = 1 = (1, ..., 1)\), respectively.
Proof. Under the den Haan, Ramey, and Watson (2000) parameterization for the matching function, $\Theta(g)$ is a strictly decreasing function of $g$. Hence, the operator $T$ is weakly increasing in $g$. As a result, $\Upsilon$ is weakly decreasing in $g$. Since $([0, 1]^{[\Omega]}, \succeq)$ is a complete lattice, Tarski’s fixed point theorem then guarantees the existence of a least and greatest fixed point. The iterative procedure is guaranteed to locate the extremal fixed points because we initiate the algorithm from the extremal points of the unit cube and $\Upsilon$ is also a continuous operator (see for example, Echenique (2005)).

Remark (Numerical verification of uniqueness). Proposition 3 allows us to numerically verify whether or not an equilibrium is unique. More specifically, the equilibrium is unique if the least and greatest fixed points of $\Upsilon$ agree. So far, we have not noticed cases of multiple equilibria in our numerical experiments.

The separation threshold. The separation threshold is the point at which the surplus is worth zero.\(^{19}\) That is, $p(\omega)$ is the solution to the following indifference condition:\(^{20}\)

$$
\Psi(p(\omega), \omega) = 0, \quad \text{(A.14)}
$$

where

$$
\Psi(p, \omega) = e^{z(\omega)} \left[ pe^{\mu(H)} + (1 - p)e^{\mu(L)} \right] - \hat{b}(\omega) + (1 - s)E \left[ \Lambda(\omega, \omega')S(p', \omega') \right] |p, \omega]. \quad \text{(A.15)}
$$

The solution to the indifference condition (A.14) is unique because $\Psi$ is strictly increasing in $p$ (to see this, note that the surplus function is increasing in $p$ according to Proposition 1 and that the Bayesian posterior function (8) is also monotone increasing in the prior $p$).

C Numerical Implementation

We first discretize the processes for labor productivity $z$ (see equation (3)) and the market price of risk $x$ (see equation (7)) using the Rouwenhorst (1995) method. For each of the two processes, we use 25 grids points which covers $\pm 4.9$ standard deviations of the unconditional distribution. We then solve the discretized model by iterating on equations (A.10) and (A.13) using the following iterative procedure:

1. Initialize the vacancy filling probability $g(0) = g(0)(z, x)$.

2. For a given $g(n)$, solve the Bellman equation for the match surplus, $S(n) = T(n)[S(n)]$, where $T(n)$ is defined according to (A.10) with $\Theta(z, x) = g^{-1}(g(n)(z, x))$. This is done through value function iteration with stopping criteria $\|S(n) - T(n)[S(n)]\|_\infty < 10^{-10}$.

3. Given match surplus $S(n)$, compute $\hat{g}(n) = \Upsilon(S(n))$ where $\Upsilon$ is defined by (A.13).

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\(^{19}\)This is equivalent to the characterization in terms of firm value (10) because, under Nash bargaining, the firm value is proportional to the surplus: $F(p, \omega) = (1 - \eta)S(p, \omega)$.

\(^{20}\)In the event that $\Psi(p, \omega)$ lies uniformly above (below) 0, then $p(\omega) = 0$ ($p(\omega) = 1$).
4. Stop the algorithm if \( \|g(n) - \hat{g}(n)\|_\infty < 10^{-6} \). Otherwise, update \( g(n+1) = 0.98g(n) + 0.02\hat{g}(n) \) and repeat steps 2 and 3.

In the above procedure, the surplus value along the \( p \) dimension is stored over 32 evenly spaced grid points \( \{p_i\} \) between 0 and 1, and interpolation is used when computing the conditional expectation \( \mathbb{E}_{p'|p}[S(p')] \approx \mathbb{E}_{p'|p} \left[ 1 \{p_i \leq p' < p_{i+1}\} \left\{ S(p_i)\frac{p_{i+1}-p'}{p_{i+1}-p_i} + S(p_{i+1})\frac{p'-p_i}{p_{i+1}-p_i} \right\} \right] \).

Auxiliary quantities can be computed after the equilibrium is computed. In particular, we compute the separation threshold \( p \) from (A.14) using a standard root-finding scheme. In addition, we approximate the cross-sectional distribution of match quality beliefs \( \mathcal{P} \) using a histogram with 31 bins. The evolution of the approximate cross-sectional match quality distribution is then computed with the assumption that match qualities are uniformly distributed within each bin.
Figure A.1: Validity of assuming equal job-finding rates for young and prime-age workers. Panels A and B compare the realized unemployment rate for young and prime-age workers respectively, with a synthetic unemployment rate series. The latter series is computed using our model’s simplifying assumption that young and prime-age workers have the same job-finding rate. The exact procedure in which the synthetic series is constructed is outlined in Appendix A. Young workers are those between the ages of 20—24 years and prime-age workers between 35—44 years.