Triple Whammy: Low Pay, Low Security, and Increased Exposure to a Downturn

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Abstract

A triple whammy buffets low-wage workers: they earn less, they lose their jobs more often, and they are more exposed to economic downturns. I build a job search model that explains these patterns, provides a missing mechanism for differential job destruction based on the premise that firms vary in productivity, higher productivity translates into higher wages and higher profits, and firms lay off workers whose jobs stop being profitable. Using the model, I compare the labor market impact of asset transfers, unemployment benefits, and an earnings subsidy, and evaluate how precautionary savings moderate consumption losses. An earnings subsidy raises consumption and reduces poverty relative to other policies, reaching more people at a lower unemployment rate. Simulations suggest that in the absence of intervention, average consumption falls by twice as much when an unexpected shock is accompanied by the loss of savings, and the poverty rate is 33% higher.

Keywords: layoff risk; productivity; wage premium; job displacement; risk aversion; saving

1 Introduction

We know a lot about productivity, wage premiums, and job loss—in pieces. What we need is a useful way to tie these facts together. A few facts: some firms are more productive than others (Syverson, 2011). More productive firms pay higher wage premiums (Card et al., 2018), and the loss of these premiums helps explain the diminished earnings of displaced workers (Fackler et al., 2021). Jobs with higher wage firms last longer (Card et al., 2013). More productive firms are more likely to survive in general (Foster et al., 2008), and less productive firms are disproportionately likely to lay off their workers during a downturn (Haltiwanger et al., 2021). Recessions increase earnings inequality because of churning at the bottom of the distribution (Heathcote et al., 2020). I elaborate further in Section 2. Meanwhile, why does job destruction differ between high and low premium firms? What changes during a downturn? What can workers do about it? What can governments?

Before turning to these questions, I contribute two additional facts in Figures 1 and 2. Fact One: not only do higher earnings come with greater job security, but there is a clear shape to the pattern of layoff risk across the earnings distribution. Using 2019 data from the Current Population Survey (CPS), Figure 1 plots the monthly transition rate into unemployment against weekly earnings for wage and salary workers.\(^1\) Job loss is most likely for the lowest earners. Layoff risk decreases as earnings increase, levelling off around

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\(^1\)See Appendix F for data details and additional figures by subgroup to show that this pattern is not driven by composition effects.
$1000 per week, or just below median full-time earnings in the United States as of 2021.² Fact Two: the earnings-risk gradient grows steeper during a downturn.³ The chart on the left in Figure 2 depicts the monthly transition rate into unemployment against weekly earnings in the boom of 2006 against those in 2008 after the onset of the Global Financial Crisis. Layoff risk jumps by almost 50% for the lowest earners, from about 0.009 to 0.013, rises less for median earners, and is only slightly higher or unchanged for workers earning $1500 or more. The same wedge appears in a comparison of 2019 and 2020 data on the righthand side. During the Covid-19 pandemic of 2020, layoff risk rises by about 1 percentage point for the lowest earners over the previous year, by half a percentage point for median earners, and only a quarter percentage point for higher earners.

Figure 1: Monthly transition rate into unemployment by weekly earnings

Figure 2: Layoff risk and earnings before and during two recent downturns

The shape of the curve in Figure 1 is not the obvious result of any of the collected facts above, nor do we have a workable mechanism for why job destruction should differ between high and low premium workers.

³Farber (2015) observes that cyclical variation in displacement is higher for less educated workers.
firms, which we need to conduct counterfactual policy analysis. Combining elements from the literature on firm wage premiums, job search theory, and macroeconomics, I propose a model that reproduces these empirical facts. It generates differential job destruction rates through the mechanism that firms vary in total factor productivity, that higher productivity translates into higher wages and higher profits, and that firms lay off workers whose jobs stop being profitable. Specifically, I modify a dynamic job search model to allow for heterogeneous, endogenous job destruction. In the model, firms that differ in productivity and face transitory shocks choose when to lay off workers, who dislike consumption instability and can save as self-insurance in case they become unemployed. To make a model with all of these feature empirically tractable I make stronger assumptions about wage determination than is common in the search literature, with the tradeoff being that I can relax other common strong assumptions. In particular, I gain the features that firm endogenously decide when to layoff workers and workers dislike income uncertainty and can save against it.

This also lets me simulate a policy of asset transfers and evaluate the role of precautionary savings. The few related papers that consider firm heterogeneity in job destruction assume Burdett & Mortensen (1998) style equilibrium wage determination (Pinheiro & Visschers, 2015) or Cahuc et al. (2006) sequential wage bargaining (Jarosch, 2021) yet must assume that workers are risk neutral and cannot save, and that riskiness is an exogenous, innate feature of each firm, in order to obtain a solution. Beyond delivering job destruction rates that decrease in earnings, the model also contains a mechanism, described in Section 3, for simulating a downturn that causes layoff risk to increase disproportionately among lower earners. This is essential for conducting counterfactual policy analysis.

In conducting that analysis, unlike with most search models I can directly study consumption because I use the Panel Study of Income Dynamics (PSID) as a data source. The PSID is one of the only longitudinal studies to measure consumption. In tandem, I allow for savings. Savings are important to include because consumption is what determines welfare, and consumption is the joint product of income and savings. Consumption, therefore, may be even more affected by a downturn than income, especially if that downturn also reduces the value of savings. As shown in Lise (2013), desired precautionary savings increase with income, as workers at the top of the wage ladder have the most to lose from starting over in unemployment. When layoff risk is inversely related to earnings, the workers most likely to lose their jobs are the workers more likely to experience a drop in consumption in the event of job loss. Because a downturn disproportionately affects the people who are already the least well off, a government interested in poverty reduction may seek to provide consumption support. Indeed, this characterizes the U.S. government response during the Covid-19 pandemic, where unemployment benefits increased and most households received direct cash transfers in the form of tax refunds. Because I model savings, which is extremely rare in the job search literature, I am uniquely positioned to use counterfactual experiments to compare the costs, employment, and welfare effects of these programs against each other. In addition, I can quantify the role of precautionary saving in supporting consumption during a downturn. Finally, I evaluate a less considered policy approach, earnings subsidies, which have been advocated for in the past by economists (Phelps, 1997) and discussed in the literature (see Moffitt (2002) for a summary), yet are uncommon in the United States outside of the earned income tax credit. Earnings subsidies have not, to my knowledge, been examined within the context of a dynamic structural model. This is important because I find that a low-income earnings subsidy provides such strong incentives to work that the program can actually end up costing only slightly more than a pure

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4One partial exception is Winter-Ebmer (1995), who assumes that intrinsically less stable workers select into intrinsically less stable firms. I show that the pattern can be reproduced without any sorting.

5Although it is outside the scope of the current paper, lower earners may also have less access to savings and the formal banking system.
unemployment insurance scheme while subsidizing many more people at a fraction of the unemployment rate.

The remainder of the paper is structured as follows: Section 2 summarizes the multiple strands of the literature that underlie the current work. Section 3 develops a job search model that has the necessary components for addressing the policy questions of interest, discusses the assumptions made in order to do so, and shows how the results are robust to sorting on the basis of worker skill. Section 4 describes the PSID data used to estimate the model and provides details about the sample constructed. Section 5 details the strategy for estimating the model. Section 5 reviews the estimation results and evaluates how well the model fits the data. Section 6 takes the estimated parameters and conducts the counterfactual analysis of a downturn and policy experiments. Section 8 reviews the main conclusions of the paper and considers their implications. Additional details about the model, estimation procedure, and sensitivity of the results are provided in the appendices.

2 Related literature

The ideas in this paper are built on an extensive groundwork of previous economic research. In this section I do my best to characterize that diverse body of related literature and explain how those studies inform my work. Underpinning my approach is the idea that there are widespread productivity differences among firms. Evidence for such differences is summarized in Syverson (2011). Two empirical estimates are Syverson (2004), who finds that the average difference in log total factor productivity between the 90th and 10th percentile of firms in the United States is 0.651, and for Hsieh & Klenow (2009), who estimate a ratio in levels of 5 to 1 in India and China. The U.S. Census Bureau and Bureau of Labor Statistics now measure the dispersion of intra-industry productivity with the Dispersion Statistics on Productivity (DiSP) series. Their initial statistics show that an establishment at the 75th percentile of within-industry productivity is more than twice as productive as one at the 25th percentile (Cunningham et al., 2019).

Given productivity differences among firms, my model claims that those differences relate to differences in wages and in survival. The relationship between wages and productivity receives particular attention in the literature seeking to explain wage dispersion. Card et al. (2018) summarize the evidence that changes in the dispersion of productivity correlate with changes in the dispersion of wages, characterizing estimates of the wage-productivity elasticity as falling in the range 0.05-0.15 and the importance of firm wage effects as explaining about 20% of the variance of wages. Lamadon et al. (2019) find that matches differ in the rents they produce, interpreted as reflecting some sense of productivity, which workers and firms split fairly evenly. Evidence of pass-through from productivity to wages is also reviewed in Taber & Vejlin (2016). Much of this work, following the two-way fixed effects approach of Abowd et al. (1999), is concerned with controlling for positive sorting between skilled workers and productive firms. I do not model skill heterogeneity because my primary focus in on firm behavior related to job destruction; however I do show that the main implications of the model are robust to that refinement. To do so I rely on the claim in Lamadon et al. (2019) that sorting is due to production complementarities, and the finding in Card et al. (2018) that firms offer the same premiums to workers of all skill levels.

What the literature on productivity and wage dispersion leaves somewhat open is the link between productivity and job destruction. Gibbons & Katz (1991) posit that firms lay off their least productive workers first, but that is within a model of employer learning about overpaid lemons, and assumes shock-driven job loss affects all workers equally. The question is considered more thoroughly in the literature on
firm turnover and productivity dynamics. The idea is that aggregate productivity changes are driven by reallocation of production from less to more efficient firms. Individual job destruction as it relates to wages is not often considered per se; the connection I make is to infer that firm exit causes job destruction, which pairs with the productivity-wage correlation described above to yield my modeling assumption. See Foster et al. (2008) for a summary of the literature on turnover and productivity. In two examples, Griliches & Regev (1995) show that Israeli firms exhibit lower productivity in the years before they exit, and Aw et al. (2001) find that changes in average industry productivity in Taiwan result from the more productive firms within each cohort being more likely to survive. In the micro search literature, the idea that jobs with some firms are more likely to end than with others has been studied by Pinheiro & Visschers (2015) and Jarosch (2021). Both conclude that wages and job security are most likely positively correlated, yet both treat layoff risk as an innate characteristic of each firm. Bridging the gap between these lines of inquiry, what I propose is a mechanism to explain why survival rates differ across firms, relating productivity to profitability to the job destruction decision.

My model is a steady state one, though I use it to simulate the differential turnover effects of a stylized downturn. From the displaced worker literature we know that there is cyclical variation in job loss, which itself is greater for less educated workers (Farber, 2017). I interpret education in this case as a proxy for wage differences, because the gradient in Facts One and Two persists within education groups, though I also show that the model can accommodate the evidence if education indicates ability. The broader study of labor market dynamics and productivity over the business cycle typically falls under the purview of macroeconomics. Robin (2011) shows how aggregate productivity shocks can lead firms to terminate matches endogenously in a model that captures wage dynamics well but does not consider firm-level shocks and is less successful at capturing the dynamics of job destruction. In a calibrated exercise, Burgess & Turon (2010) allow for idiosyncratic and aggregate productivity shocks to better capture cyclical dynamics, with the tradeoff that the distribution of accepted wages for job-to-job movers must be the same as that for people leaving unemployment. (Haltiwanger et al., 2018) document that lower productivity firms are more likely to contract in a recession, while Baily et al. (2001) find that plant level productivity is highly procyclical. They also find that equivalent shocks have a greater magnitude effect on productivity for firms that are more likely to downsize, which supports the approach I take later in modeling a downturn. Supposing productivity and wages are linked, related evidence of this downturn effect includes the finding that wage losses of displaced workers are attributable in part to lost firm wage premiums (Fackler et al., 2021), and that recessions increase earnings inequality because of greater churning at the bottom of the distribution (Heathcote et al., 2020).

When workers are subject to the baseline and cyclical layoff risks detailed above, we might expect them to save for a rainy day. In job search models that address these risks, such as Robin (2011), Pinheiro & Visschers (2015), and Jarosch (2021) the prevailing assumption is that workers cannot save, and are in fact risk-neutral. Part of the reason is that consumption data is rarely available, even though Carroll & Samwick (1998) estimates that precautionary saving against shocks accounts for 32 to 50% of wealth. The few empirical search models that do incorporate saving make the tradeoff of taking firms and layoffs as exogenous (Rendon (2006), Lentz (2009), Lise (2013)), or are calibration exercises (Herkenhoff, 2019), and all treat workers as having identical risk preferences even though empirically these are widely dispersed (Kimball et al., 2008). Here I make a different set of assumptions to get the type of model I need to evaluate the policies of interest, incorporating heterogeneous firms, endogenous job destruction, savings, and

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6Life cycle firm productivity is outside the scope of this paper. As I assume a “firm” here is one job, to extend in that direction I might think of an establishment as a collection of such jobs, with differential destruction leading to changes in average productivity.
heterogeneous worker risk aversion.

On the policy front, there is longstanding evidence in the search literature that unemployment insurance prolongs unemployment spells (see Mortensen (1977) for an early treatment, Acemoglu & Shimer (1999) and Lentz (2009) for models of the optimal unemployment insurance level given its disincentives). Rendon (2006) analyzes a large cash transfer and finds that higher initial wealth leads to longer unemployment durations but higher accepted wages. I am not aware of any search models that incorporate a low earnings subsidy as I do, though the principle is well developed (see Moffitt (2002) for a summary). Evaluations find that the earned income tax credit in the United States has a positive effect on employment, especially for single mothers (Hotz & Scholz, 2007), as does the Working Families’ Tax Credit in the United Kingdom (Francesconi & Van der Klaauw, 2007).

While the current paper does touch on a broad range of research fields, as discussed in this section they actually share many implications in common. What I do in the next section is show how to combine all of the elements from each of these areas of the literature into a single model that is well suited to policy analysis.

3 Model

In this section, I develop a model that can reproduce the gradient of job destruction across the earnings distribution observed in the data in a way that will later allow me to analyze a downturn and the policies of interest. The central features of the model are that firms subject to transitory shocks differ in total factor productivity and that workers with different risk preferences can save to self-insure against layoff risk. After presenting the model, I discuss the underlying assumptions and how they relate to the literature and the main conclusions of the model. In particular, I show how the central implications are robust to potential sorting of high wage workers into high wage firms due to production complementarities. Finally, I demonstrate how I can use the model to simulate an aggregate downturn that is consistent with the patterns in Figure 2 and other empirical evidence about the disproportionate impact on workers at the bottom of the earnings distribution.

3.1 Notation

Firm total factor productivity is \( x \), drawn from distribution \( \Gamma(x) \). Transitory productivity shocks are denoted \( \varepsilon \), drawn from distribution \( F(\varepsilon) \) with density \( f(\varepsilon) \). Wages are functions of \( x \), \( w(x) \), as is the job termination productivity shock threshold, \( \varepsilon^*(x) \). The capital (firm) share of income is \( \alpha \), and the labor share \( 1-\alpha \). The probability of a worker staying when receiving an outside offer is \( P_s(x) \), and the complement, \( 1-P_s(x) \), is \( \bar{P}_s(x) \). The value to a firm is \( H(x,\varepsilon) \), denoted \( H_\varepsilon \). Worker value functions are \( U(a) \) when unemployed and \( V(a,x) \) when employed, where \( a \) denotes assets. The shock arrival rates are \( \lambda_0 \) for an offer when a worker is unemployed, \( \lambda_1 \) for an on-the-job offer, \( \eta \) for shocks to the firm, and \( \delta_0 \) for exogenous job termination unrelated to productivity. A worker’s coefficient of relative risk aversion is \( \gamma \) drawn from distribution \( F(\gamma) \), and the flow benefit in unemployment is \( b \). The discount factor and rate are \( \beta \) and \( \rho \), where \( \beta = \frac{1}{1+\rho} \).

3.2 Model

Suppose that a match between one worker and one firm produces output \( x \). Firms are heterogeneous in \( x \sim \Gamma(x) \), which represents total factor productivity in converting the combination of a firm and a worker
into output. The two factors split this output according to the predetermined rule\footnote{Determined by Human Resources, or the marginal products of labor and capital in a Cobb-Douglas function with $K, L = 1$.}

\[ r(x) = \alpha x \]
\[ w(x) = (1 - \alpha)x. \] (1)

I assume as in Mortensen & Pissarides (1994) that all matches are subject to persistent random shocks $\varepsilon > 0$ that will affect flow profits to the firm.\footnote{I could allow for shocks in the other direction as well without affecting the results, which I show in Appendix X.} What is new in this type of model is that I allow for a distribution of $x$. Conceptually, this $x$ lets me map firm total factor productivity to the firm wage premium found in AKM-style analysis (Abowd et al., 1999). In addition to this mapping to the firm wage premium, what a full distribution of firm productivity facilitates here is a mechanism for heterogeneity in job destruction rates.

The assumption about wage determination differs from those in Burdett-Mortensen style wage posting models, where wage setting is often the object of interest. In work in that literature that does model heterogeneous firm productivity (Bontemps et al., 2000), and especially when worker heterogeneity is incorporated as well (Bontemps et al., 1999), the solution mapping productivity to wage offers is extremely complex even though worker utility is assumed linear in wages, while on the other end they do not model job destruction, treating it as exogenous and identical for all firms. As my focus here is on job destruction, where those models make strong assumptions about the termination process in order to relax others about wage setting, I make strong assumptions about wage setting in order to more flexibly model termination so I can obtain a tractable solution amenable to policy analysis.\footnote{The assumption is not without precedent, as Flinn & Heckman (1982) assume that firms and workers split match output via a fixed contract that lasts for the duration.} I further assume that matches are fixed contracts, even if match output changes. Specifically, workers are perfectly insured against transitory productivity shocks. I assume that firms do face such shocks ($\varepsilon$), which arrive at rate $\eta$, and firms terminate a job when the present discounted expected value of continuing it becomes negative.\footnote{Here I follow Mortensen & Pissarides (1994) and appeal to free entry driving the firm’s outside option to zero, which may not be automatic under heterogeneous productivity. See Appendix A for discussion.} Hence, wages are always $(1 - \alpha)x$, whereas the firm’s flow profits are initially $\alpha x$, but following shock $\varepsilon$ become $\alpha x - \varepsilon$. A common alternative approach in the job search literature is to model wage setting through bargaining between the firm and worker with renegotiation when outside offers arrive. However, I will argue in the discussion of the model that 1) this simpler process is still fairly consistent with empirical evidence on downward wage rigidity, the prevalence of wage bargaining, and productivity shock pass-through 2) a more sophisticated wage determination process would complicate the model solution considerably yet should not materially alter the central dynamics I wish to study.

As noted, I assume that workers exhibit are risk averse, exhibiting constant relative risk aversion over consumption\footnote{This is a standard choice in the literature and is also supported empirically by Chiappori & Paiella (2011).} and differ in the degree of those preferences $\gamma \sim F(\gamma)$:

\[ u(c_t; \gamma) = \begin{cases} 
\frac{c_t^{1-\gamma}}{1-\gamma} & \gamma > 0 \\
\log(c_t) & \gamma = 1.
\end{cases} \]

The primary reason for incorporating risk aversion is that it gives workers a reason to save. Previous models that consider heterogeneous job destruction rates (Pinheiro & Visschers (2015), Jarosch (2021)) assume risk neutrality, which is mathematically convenient yet creates an odd pairing where workers pur-
portedly value income stability while having linear preferences. Allowing for saving not only lets me examine self-insurance and consumption smoothing behavior, but it also lets me look at a policy of large one-off asset transfers, which would be irrelevant if workers were risk neutral because they would consume the entire amount immediately. I model heterogeneity in these preferences for two reasons. First, it aligns the model with the data. As I show in Section 4, workers choose a wide range of savings for a given level of earnings. Different preferences over risk can help explain the conditional dispersion in assets. Second, I need it to account for how people respond differently to offers and expectations about the future. Third, it permits workers to sort into jobs based on job security. However, as I show, under the assumptions of the model no such sorting will occur.\footnote{It could, though, potentially occur in a multi-sector form of the model where the sectors differ in terms of exposure to shocks or the worker share of output.}

Assume that workers face an infinite, discrete planning horizon. In each period, they can be employed (E) earning $w$ or unemployed (U) with a flow benefit $b$. Given flow income $i_t$ and current assets $a_t$, workers choose consumption $c_t$, and, if an offer is received, whether to accept it or remain in their current state. Assume that the rate of return on assets $r$ is constant, and that workers have time discount factor $\beta$. Then workers face the budget constraint

$$c_t + a_{t+1} = i_t + (1 + r)a_t.$$  \hspace{1cm} (2)

subject to a lower bound on assets, $a = 0$, meaning that markets in this environment are incomplete, and workers cannot borrow against future income.\footnote{Several search models that allow saving also allow for borrowing (Rendon (2006), Lise (2013)), and Herkenhoff (2019) argue that credit access is important following job loss, yet Rendon (2006) concludes that borrowing constraints are tight and workers can only borrow up to 14% of the present discounted value of income, and the model in Lise (2013) implies much more borrowing than appears in the data. Sullivan (2008) shows that the least well off households do not borrow to smooth consumption in unemployment. While borrowing behavior is outside the scope of this study, if it were included it should tend to reduce precautionary saving yet increase consumption in unemployment.}

The reason workers might save at all is that there is a possibility that they will lose their jobs. This can happen for two reasons: first, there is a baseline rate of job destruction $\delta_0$ that is unrelated to firm productivity; second, the firm can be hit by a large enough negative shock that swamps the option value of keeping the job filled. To see this, let the present discounted expected value of a match for the firm be

$$\Pi_\varepsilon = \frac{1}{1 + \rho} \left( \alpha x - \varepsilon + \lambda_1 P_s(x) \Pi_\varepsilon + \eta \int_0^{\varepsilon^*(x)} \Pi_{\varepsilon'} f(\varepsilon') + (1 - \lambda_1 - \eta - \delta_0) \Pi_\varepsilon + \delta_0 0 \right)$$  \hspace{1cm} (3)

where $P_s$ is the probability that a worker stays after receiving an outside offer, the discount factor $\beta = \frac{1}{1 + \rho}$, $f(\varepsilon)$ is the density of $\varepsilon$ shocks, and $\varepsilon^*(x)$ is the threshold for a shock that is large enough for the firm to terminate the match. In a new match, $\Pi_0, \varepsilon = 0$.

This can be rewritten (see Appendix E) as

$$D \Pi_\varepsilon = \alpha x - \varepsilon + \frac{\eta}{D} \int_0^{\varepsilon^*(x)} F(\varepsilon')d\varepsilon'.$$  \hspace{1cm} (4)

where

$$D = \rho + \lambda_1 P_s(x) + \eta + \delta_0.$$  \hspace{1cm} (5)

Define $\Pi_{\varepsilon^*(x)}$ to be the value where the firm is indifferent between continuing the match or ending it.
We know $\Pi_\varepsilon^0(x) = 0$ because the firm’s outside option is zero, hence the termination threshold $\varepsilon^*(x)$ is
\[
\varepsilon^*(x) = \alpha x + \frac{\eta}{D} \int_0^{\varepsilon^*(x)} F(\varepsilon) d\varepsilon.
\] (6)

To interpret that threshold, a firm is willing to keep a match going beyond the point where the flow profit is zero because of the option value associated with drawing a less negative shock in the future. From the worker’s perspective, the probability that the firm terminates the match is
\[
\delta(x) = \delta_0 + \eta (1 - F(\varepsilon^*(x))).
\] (7)

Therefore, a worker meeting a firm with a posting initially producing $x$ receives the offer
\[
\{w(x), \delta(x)\} = \{(1 - \alpha)x, \delta_0 + \eta (1 - F(\varepsilon^*(x)))\}.
\] (8)

The value to a worker depends on her employment status:
\[
U(a) = u(c) + \beta \left( \lambda_0 \int \max \{V(a', x), U(a')\} d\Gamma(x) + (1 - \lambda_0)U(a') \right)
\] (9)
\[
V(a, x) = u(c) + \beta \left( \lambda_1 \int \max \{V(a', \tilde{x}), V(a', x)\} d\Gamma(\tilde{x}) + \delta(x)U(a') + (1 - \lambda_1 - \delta(x))V(a', x) \right)
\] (10)
where consumption is subject to the budget constraint (2) and the no borrowing constraint $a \geq 0$.

Given the assumptions of the model, wage offers are increasing in firm productivity and layoff risk is decreasing (see Appendix E). Because of this relationship, all workers desire the same types of jobs: a worker who cares more about income wants a high $x$ firm, as does one who cares more about stability. The result simplifies the probability that a worker stays after receiving an outside offer, $P_s(x)$, as values are increasing with productivity for everyone. Therefore,
\[
P_s(x) = \Gamma(x)
\]
\[
\implies \overline{P}_s(x) = 1 - \Gamma(x).
\] (11)

Furthermore, similar to the result in Pinheiro & Visschers (2015), unemployed workers do not value layoff risk when deciding whether to accept a job (see Appendix E). Observe that a worker is indifferent between two offers when the values are the same:
\[
V(a, x') = V(a, x) \implies u(c(a, w')) = u(c(a, w)) + (\delta' - \delta)(V(a, w) - U(a))
\] (12)
and the difference in risk term drops out when the current state is unemployment. Given assets and risk preferences, the reservation wage is independent of the risk offer (see Appendix E). This creates a tension regarding risk preferences, as more risk averse workers have lower reservation wages, which come with a higher probability of sending them back into unemployment.
3.3 Illustration of model dynamics

To illustrate the offer curves resulting from the model, in this section I calibrate a version of equation 6, parameterizing the firm productivity and shock distributions as described later in Section 5 and using the data from Monte Carlo simulations I use to validate the estimator in Section C.

In accordance with the motivating pattern in Figure 1, Figure 3 simulated from the model implies that the lowest paying jobs will be associated with the highest termination risk, risk will decrease as the wage increases, and ultimately it will level off as productivity outstrips even the largest possible transitory shocks. The observed monthly transition rates into unemployment for the workers simulated from the model shown in Figure 4 decrease in earnings as in the CPS data.

![Figure 3: Wage-risk offer pairs (calibrated)](image)

![Figure 4: Monthly transition rate to unemployment by income (calibrated)](image)

Given these dynamics, allowing for heterogeneity in risk preferences generates much more dispersion in savings behavior. To see this, I generate two versions of the Monte Carlo data: one with a full distribution of preferences and one where preferences are homogeneous and equal to the mean, with a coefficient of relative risk aversion of about 0.8. Table 1 show how much it matters. Although both assumptions produce similar mean levels of savings, the model with heterogeneous preferences generates substantially wider dispersion. Even with a low degree of risk aversion, the 10th percentile of savings is over $5000, vs. $100 assuming a distribution of preferences. The 90/10 ratio is 7.6 with common risk preferences compared to 702 with the same mean preference but a continuous distribution around it.
Table 1: Distributions of savings with homogeneous vs. heterogeneous risk preferences

<table>
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<th>Mean</th>
<th>Std Dev</th>
<th>10%</th>
<th>25%</th>
<th>50%</th>
<th>75%</th>
<th>90%</th>
<th>99%</th>
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<td>12484</td>
<td>24372</td>
<td>33220</td>
<td>41155</td>
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<td>39617</td>
<td>100</td>
<td>3149</td>
<td>12940</td>
<td>37774</td>
<td>70260</td>
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</tbody>
</table>

3.4 Discussion of main assumptions

In this section I discuss the main assumptions I make to construct the model. I explain what I gain from each and what evidence there is in favor or against it in the literature. While some of the assumptions are strong relative to what is typical in a structural job search model, my emphasis here is on the dynamics of job destruction and labor market policy responses to a downturn, and these assumptions let me relax other assumptions so that I can match a specific empirical pattern that those models cannot.

3.4.1 Wage determination process

I assume that the wage offered is a direct function of firm total productivity and does not result from bargaining over a surplus. Although bargaining is more standard in a search model, survey evidence reports that two-thirds of workers did not negotiate their current salary (Hall & Krueger, 2012), and empirical estimates of wage bargaining shows that it is uncommon at low and medium wage jobs (Cahuc et al. (2006), Card et al. (2016)). In this paper I am particularly interested in how lower wage workers are affected by job destruction dynamics, and these are the workers for whom there is the least evidence of bargaining. For workers who do bargain, estimated magnitudes of the bargaining are very small, with an elasticity with respect to increases in the outside option on the order of just 0.1-0.2% percent (Caldwell & Harmon (2019), Lachowska et al. (2021)).

The conclusion about the relationship between wages and layoff risk does not necessarily require as strong an assumption as exogenous wage determination. The conclusion should hold so long as 1) wage offers are increasing in match productivity, an empirical regularity reviewed in Card et al. (2018), and 2) wages do not rising significantly faster than productivity to the point where more productive firms earn lower profits. Estimates of the elasticity of wages with respect to productivity tend to be around 0.05 to 0.10 (Card et al., 2018), which is far below that threshold.

One reason I believe bargaining is not crucial here is that the Mortensen & Pissarides (1994) model with bargaining still results in firms having a productivity threshold below which they will terminate a match, and this threshold is increasing with the initial productivity of the match. That model delivers a tractable bargaining solution by assuming no on-the-job search and homogeneous, risk-neutral workers. Once workers are allowed to differ and to weigh outside offers, which are valued differently over time according to worker preferences and the current wage, the bargaining solution quickly becomes unwieldy. To flip the implications in the model and get layoff risk to increase with wages, bargaining power would need to rise so steeply with match productivity as to cause profits to decrease, which does not accord with intuition, the magnitude of the bargaining power estimates in the literature, or the empirical evidence that, if anything, the labor share of income is decreasing with firm productivity (Dorn et al., 2017). Because the bargaining approach does not deliver a fundamentally different conclusion regarding the relationship between productivity and job security, while adding firm and worker heterogeneity and on-the-job search to the model, I make the simplifying assumption that there is no bargaining. In Appendix A I show how bargaining could be incorporated in a
simplified version of the model without changing the relationship between wages and layoff risk.

### 3.4.2 No wage renegotiation

I assume that wages are fixed for the duration of a match. That is, firms have a set pay for a position and do not like to change it.\(^{14}\) This is equivalent to supposing that workers, who are risk averse, are fully insured against transitory shocks by the risk-neutral firms, after Azariadis (1975). Recent evidence that firms act as insurers comes from Guiso et al. (2005), who find that transitory shocks to firms are not generally passed through to workers; Altonji & Devereux (1999), who observe that downward wage cuts without changes in job status are rare; Haeckel et al. (2013), who show that new hires have much more flexible wages than current workers; and Barattieri et al. (2014), who conclude that workers who switch jobs have a much higher probability of changing wages than workers who continue to be employed at the same firm. Jardim et al. (2019) and Elsby & Solon (2019) argue that nominal wage cuts are more prevalent than found in studies using household survey data, finding that about 15-25% of job stayers experience nominal wage cuts in a year, but this is contradicted by Grigsby et al. (2021), who use administrative data to show that only 2.5% of job stayers experienced a wage cut between 2008-2016. Lamadon et al. (2019) show that pass-through of shocks, though low, is not zero. Kaur (2019) extends the analysis to India, finding that positive transitory shocks may increase nominal wages but negative shocks do not.\(^{15}\) Fallick et al. (2020) shows that most U.S. employers did not adjust wages during the Great Recession even though unemployment spiked.

Qualitatively, there is a long documented history that firms do not like to adjust wages downward, and the current push for wage transparency is specifically intended to prevent firms from paying different wages to similar workers. Bewley (2009) finds that employers prefer not to cut wages because they believe it will reduce worker morale and engagement with the firm’s objectives. Similarly, Campbell III & Kamlani (1997) documents resistance to wage reductions particularly because of employee morale and effort issues and the risk of losing their most productive workers. One implication of wage rigidity is that unemployed workers could underbid current employees by being willing to accept a lower wage for an equally productive match. Solow (1990) argues that the absence of underbidding could explain observed patterns in downward wage rigidity, while Fehr & Falk (1999) finds it is actually firms that refuse to accept that underbidding. The explanation offered is that since effort is often unobservable, firms prioritize fairness to maintain worker cooperation, which wage reductions put in jeopardy. This is consistent with survey results in Kaur (2019) showing workers see wage cuts as unfair, and that cuts reduce effort.

The alternative in the other direction is to allow for full pass-through of shocks as in Mortensen & Pissarides (1994). That assumption has been criticized in the macro literature for being unable to capture the volatility of unemployment fluctuations (Shimer, 2005). In what direction would renegotiation changes the results? First, in the data I would expect frequent wage adjustment within job spells. Second, in the model firms should keep jobs open for longer because they could endure larger shocks. However, as I show in Appendix A, the order ranking between firm productivity and job termination probability would be unaffected. Although a model of imperfect pass-through is the most realistic, I opt for the stronger assumption because it is simpler, because I interpret the empirical evidence to lean towards wages not adjusting frequently, and because incorporating updating would not affect the job destruction dynamics I am interested in capturing.

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\(^{14}\) An assumption more readily accepted by anyone who has had to deal with the Human Resources Department.

\(^{15}\) Inflation may allow firms to cut real wages without adjusting nominal wages. I abstract away from that here, as it affects all firms equally and is not a viable individual firm response to a transitory shock.
3.4.3 Homogeneous worker skill

I assume that workers do not have innate productivity differences. While it is not uncommon in the search literature, clearly this abstracts from reality. Here I discuss that assumption and show how skill differences could enter into the model as a production complementarity, motivated by the finding in Lamadon et al. (2019). A first reason for maintaining the assumption is comparability: the most closely related work on savings and search (Rendon (2006), Lise (2013)), and on heterogeneous job risk and search (Jarosch (2021), Pinheiro & Visschers (2015)) make the same assumption. Shutting down the dimension of innate worker skill differences allows for more direct examination of the dynamics of layoff risk itself. That being said, while the literature broadly finds that “trends in aggregate wage dispersion closely track trends in the dispersion of productivity” (Card et al., 2018), it may be because high skill workers are sorting into high productivity firms (Winter-Ebmer (1995), Abowd et al. (1999)). As discussed in Postel-Vinay & Robin (2002), reaching such a conclusion by examining worker fixed effects in labor market histories may suffer from an endogeneity problem if those prior trajectories result from search frictions and not innate skill differences. That is, workers who initially match randomly with a lower productivity firm could churn into unemployment more frequently over their careers than identical workers who initially match with a higher productivity firm.

The current paper is agnostic on the question of worker sorting because any such behavior should not affect the fundamental relationship between earnings and layoff risk. Although the equilibrium earnings distribution would differ by skill in the model, layoff risk conditional on earnings would be unaffected. To see how, suppose that skill $s$ enters into the model by multiplying firm productivity:

$$x' = sx$$  

such that total productivity is the product of the firm component and a worker component. Wage offers will reflect this total productivity:

$$w(x; s) = (1 - \alpha)x'.$$  

The firm’s threshold for terminating a match will also be a function of the combined product, but that is equivalent to the problem facing a firm in the baseline model that has productivity $x = x'/s$.

To demonstrate this result, I simulate a calibrated version of the model where half of the workers are “low skill” ($s = 1$) and half are “high skill” ($s = 1.2$). Figure 5 shows how layoff risk relates to earnings. Conditional on earnings, both skill groups experience the same risk, even though as shown in Figure 6 the high skill group has higher earnings. Across and within skill groups, workers in more productive matches will still earn more and enjoy greater job security.
Figure 5: Quarterly transitions into unemployment by earnings and skill (calibrated)

Figure 6: Distribution of earnings by skill (calibrated)

One could more directly align the model with an AKM approach by supposing that firm and worker effects enter additively, an approach which has been shown to explain a substantial amount of the residual variation in wages (Card et al., 2016). If the worker effect is \( s \), let match total factor productivity be

\[
x' = x + s
\]

with corresponding wage offer

\[
w(x; s) = (1 - \alpha)x'.
\]

As in the multiplicative case, the inverse wage-layoff risk relationship follows in the same way as in the base case. Higher worker effect workers will receive higher offers, yet layoff risk conditional on total match productivity will be unchanged. Note that this suggests a mechanism for partial worker sorting. If higher skill workers mechanically are faced with higher productivity matches, those matches will be less likely to terminate, giving the higher skill workers more time and opportunity to climb the job ladder. Sorting is only partial because labor market frictions prevent all workers from racing to the highest paying firms right away.

If instead innate worker differences affect the labor share of income, a mechanical tradeoff will arise. The workers who earn a higher fraction of the marginal product will face greater termination risk at all wage levels, as the firm will have a lower profit margin given the match productivity. Note that this implies lower wages are not a pure lose-lose for the “underpaid” workers: lower pay conditional on productivity
mechanically comes with higher job security.\footnote{While the notion that workers with greater bargaining power take on high layoff risk appears odd in the context of skill, it is more plausible for a discrete difference such as gender, where differences in bargaining power have been detected (Card et al., 2016). Exploration of differential bargaining or sector sorting is outside the scope of this paper.}

### 3.5 Incorporating a downturn

By combining search frictions and the ability to save, the model provides a novel framework for analyzing the level and distribution of consumption in an aggregate downturn and the important role of prior wealth accumulation in moderating its effects. As suggested by the trends during the Great Recession and the Covid-19 pandemic, the impact is likely unequal because layoff risk appears to increase relatively more for lower earners. In this section I demonstrate how to use the model to simulate an unexpected aggregate downturn.

To produce an aggregate downturn in the model, I suppose that there is a permanent, unexpected shock that drives down all match output by $s$.\footnote{While combinations of shifts in multiple parameters could affect layoffs, such as a change in the shock arrival rate or the variance of those shocks, this is the simplest, most direct approach that reproduces the patterns observed in the data.} Technically, this is not exactly a recession, as this is a steady state model while recessions are by nature cyclical. We can either view this type of downturn as more like the permanent local labor market shocks experienced by many U.S. commuting zones exposed to Chinese export competition in the early 2000s (Autor et al., 2016), or simply as a stylized depiction of how the labor market responds at the onset of a recession before any recovery begins.\footnote{A stylized recovery could then be simulated, if desired, by undoing the aggregate shock.} Furthermore, this stylized consideration of an aggregate downturn can capture several findings in the macroeconomic literature about productivity and cyclical labor market sorting. In particular, I will show that lower productivity firms are more likely to contract in a recession (Haltiwanger et al., 2018). The model also accommodates the evidence that wage losses of displaced workers are attributable in part to lost firm wage premiums (Fackler et al., 2021), and that recessions widen earnings inequality because of increased churning at the bottom of the distribution (Heathcote et al., 2020).

Suppose that a match previously producing $x$ now produces $\tilde{x} = x - s$. I make this additive assumption because it aligns with the finding by Baily et al. (2001) that the fall in productivity from a negative shock for firms that tend to downsize is significantly larger in magnitude than that for other firms facing the same degree shock. Because prevailing wages are rigid, what previously earned the firm a net flow profit of $\alpha x - \varepsilon$ now earns $\alpha x - s - \varepsilon$. Profit margins have narrowed, meaning a smaller transitory shock could lead to job destruction and hence layoff risk is higher. This can be seen in the new equation for the firm’s termination threshold:

$$\tilde{\varepsilon}^* = \alpha x - s + \frac{\varepsilon^*}{D} \int_0^{\varepsilon^*} F(\varepsilon) d\varepsilon \quad (17)$$

For newly formed matches, assume that offers adjust to the downturn conditions. The new distribution of wage and corresponding layoff risk offers maps from $\tilde{x}$, e.g. $w(\tilde{x}) = (1 - \alpha)(\tilde{x})$. This is an order preserving shift in the values offered to unemployed workers by these new firms. For firms in current matches at the onset of the downturn, the probability that their worker leaves for another firm has become slightly more complicated, as outside offers reflect the new distribution whereas the current offer has a higher wage and higher risk than it would if the shock were passed through to the worker. In practice, this nuance should not affect layoff risk much because it only enters into the termination threshold as a multiplier on the option...
value of continuing the match. Recalling that $D = \rho + \lambda_1 P_s(x) + \eta$, and probability is bounded between 0 and 1, the unconditional bounds on $\eta/D$ are $\left\{ \frac{\eta}{\rho + \lambda_1 + \eta}, \frac{\eta}{\rho + \eta} \right\}$. Since outside offers have in general become worse, the probability of leaving will decrease, raising the lower bound to $\frac{\eta}{\rho + \lambda_1 P_s(x) + \eta}$. In the policy section simulations, I leave the probability unchanged because accounting for this nuance would complicate the code considerably without materially affecting the results.

Having developed a model with the necessary properties to capture the mechanics of differential job destruction across the earnings distribution in this section, in the next section I turn to describing the data that will let me estimate the structural parameters of the model.

4 Data

In this section, I describe the main data source used to estimate the model and details the construction of the sample. The source is the Panel Study of Income Dynamics (PSID), which is a national longitudinal household survey based out of the University of Michigan that has been interviewing the original sample members and their descendants since 1968. Since 1999, the PSID has collected detailed information about household wealth and consumption in each biennial survey wave. Consumption data is rare, and the fact that it collects such data in conjunction with the standard variables makes the PSID one of if not the only longitudinal panels in the United States that reports earnings, employment status, savings, and consumption. Saving stocks and annual consumption are reported once per wave. Beginning with the 2003 wave, the PSID has constructed a monthly employment matrix for primary respondents covering up to four distinct jobs in each survey year. Together, these features of the data provide the necessary inputs for estimating the model developed in the paper: consumption, savings, monthly employment status, and earnings. I use the full set of survey waves containing this information, which are those from 2003 to 2019.

Starting from the full set of primary respondents in the 2003 to 2019 waves, I limit the sample to individuals ages 21-64 who report that they are either working or looking for work, removing respondents who are self-employed, retired, disabled, students, or in an institution. Second, I remove female household heads because of the PSID sampling procedure. Women can only be considered heads of household if they are unmarried. A married woman’s husband becomes the new head, leading to a selection problem. For a similar reason, I remove what are called “non-gened” males. These are men who married into a survey family as opposed to being born into one. The PSID does not follow these men if they get divorced; therefore non-gened males can only be married, creating an inverse problem to that caused by the rules for women as household heads. Finally, I trim assets, consumption, and earnings observations at the 1 and 99 percentile of the data in each wave to minimize the influence of outliers that are likely to be caused by errors in reporting or classification of responses (for instance, if in the data earnings are coded as per hour instead of per week). The resulting sample includes 4284 unique individual respondents with a total of 16505 wave-to-wave observations.

The specific measurements used as model inputs are defined as follows. Employment status is treated as binary for each month. A worker is coded as unemployed in a month if they are unemployed at any point during the month. Reported earnings for each job are converted to monthly values. To convert, I divide annual wages by 12, multiply biweekly wages by 2, multiply weekly wages by 4, multiply daily wages by 20 and multiply hourly wages by 4 times average hours worked per week. I divide annual consumption by

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19https://psidonline.isr.umich.edu/

20Wave year t-1. Monthly data for wave year t-2 is available but not in a format I can use to estimate the model without imposing extreme assumptions about earnings and job transitions. Thus, I have a monthly panel in alternating years.
12 to obtain a monthly average. Savings are defined as liquid savings that might be accessible to finance consumption in unemployment, which I calculate as the sum of cash, bonds, stocks, and IRA annuity holdings. All values are converted to 2010 dollars using the U.S. consumer price index. Table 2 displays descriptive statistics for the constructed sample.

Table 2: Descriptive statistics for PSID sample

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Median</th>
<th>Std Dev</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Waves per worker</td>
<td>3.85</td>
<td>3.00</td>
<td>2.31</td>
<td>1.00</td>
<td>8.00</td>
</tr>
<tr>
<td>Monthly Earnings</td>
<td>4591.38</td>
<td>4257.61</td>
<td>2058.26</td>
<td>1139.88</td>
<td>12747.78</td>
</tr>
<tr>
<td>Savings</td>
<td>49443.82</td>
<td>9072.38</td>
<td>129592.00</td>
<td>0.03</td>
<td>959890.30</td>
</tr>
<tr>
<td>Savings/earnings</td>
<td>11.34</td>
<td>2.23</td>
<td>33.36</td>
<td>0.00</td>
<td>825.23</td>
</tr>
<tr>
<td>Consumption</td>
<td>4022.18</td>
<td>3711.59</td>
<td>1957.26</td>
<td>604.97</td>
<td>14625.92</td>
</tr>
</tbody>
</table>

To adjust for level differences on the basis of observable heterogeneity, I follow Jarosch (2021) and Lise (2013) and residualize certain measures by projecting them onto a set of covariates, removing the predicted variation, and using the remaining variation as the sample measurement. To adjust assets for family composition and demographic background, I project the log of assets + 1 onto marital status, the number of children, race, education, and year, and then translate the distribution by adding back in the mean of log sample assets. For wages, I project onto a Mincerian specification to get residual wages, including time fixed effects because this is a steady state model. To do so, I regress log wages on age, age-squared, education, and year dummies, and restore the mean of log wages to the residual values to generate the residualized wage distribution.

Two key features of the data that the estimation will match are the transition rates into unemployment across the earnings distribution, which will be used to make inferences about layoff risk, and the ratio of savings to earning across the earnings distribution, which will be used to make inferences about risk preferences. Figure 7 shows a local polynomial plot with a 95% confidence interval of the quarterly transition rates into unemployment for the constructed sample. I present quarterly rates because the dynamic moments I match in the estimation will be from quarter to quarter. The figure demonstrates the same pattern observed in the motivating pattern in the CPS data from Figure 1, whereby layoff risk is highest for the lowest earners, slopes down up to around median earnings, and then levels off. This information will be used in the estimation to characterize the distribution and arrival rate of shocks faced by firms.
Figure 7: Quarterly transition rate to unemployment in the PSID sample

Figure 8 shows a local polynomial plot with a 95% confidence interval of the stock of savings holdings as a function of monthly earnings in the PSID sample. Mean savings rise nearly linearly with earnings at a ratio in the neighborhood of 10 to 1. This information will be used in the estimation to locate the mean of risk preferences among workers. Within each earnings band, there is a fairly wide distribution of savings to earnings ratios, depicted with kernel density plots in Figure 9. The distribution has a higher central tendency and wider dispersion in higher earnings buckets relative to lower ones. This information will be used in the estimation to characterize the variance of risk preferences among workers.

Figure 8: Savings per earnings in the PSID sample

Figure 9: Distribution of savings to earnings ratios in the PSID sample
In building the model I will allow for workers to save. Figure 10 presents descriptive evidence that savings is important in order for the model to fit the data. It plots a local polynomial regression of mean monthly consumption against monthly earnings for the PSID sample. Most workers consume less than they earn, and the consumption rate decreases with earnings. Mean consumption does exceed earnings for the very lowest earners. Borrowing, which I do not model, could be one explanation, but two others consistent with my no-borrowing assumption are that 1) the PSID consumption data is reported net of any government transfers, 2) some of these workers could be consumption smoothing by dissaving.\textsuperscript{21}

Figure 10: Consumption as a function of earnings in the PSID sample

In this section I introduced the PSID panel and the construction of the estimation sample. I presented a descriptive overview of the sample and highlighted the key elements of the data that will inform the estimation process. The next section explains the estimation approach and how each element of the data maps to the structural parameters I want to measure.

5 Estimating the model

In this section, I describe how I estimate the structural parameters of the model using the PSID data introduced in the previous section. First, I review the set of parameters and the additional parametric assumptions I impose in order to identify them empirically. Then, I discuss the set of moments I match in the simulated method of moments estimation and how they map from the data to the parameters. Finally, I discuss how restrictive the identifying assumptions I make are, and how dependent I am on those assumptions in order to estimate the model.

The full set of parameters in the model is the following:

\[
\Theta = \{\lambda_0, \lambda_1, \delta_0, \eta, \alpha, b, r, \rho, F(\gamma), \Gamma(x), F(\varepsilon)\}.
\] (18)

To recap from the model section, these are, in order, the arrival rate of job offers in unemployment and employment, the baseline exogenous job termination rate, the arrival rate of shocks to the firm, the worker share of output, the flow benefit in unemployment, the risk-free interest rate, the discount rate, the distribution of risk preferences, the distribution of firm total factor productivity, and the distribution of firm shock magnitudes.

\textsuperscript{21} A third explanation outside the scope of the model is that this is household consumption plotted against individual labor earnings. Some households may have additional sources of income.
I fit most of the parameters by the simulated method of moments, but first I calibrate a few and estimate one other in a first stage. Following standard practice in the literature, I calibrate the interest rate and discount rate: \( r = 0.00125 \) and \( \rho = 0.006 \) \((\beta = 0.996)\). I also fix the worker share of income as \( 1 - \alpha = 0.6 \), to match the aggregate labor share of income prevailing in the United States between 2002-2016 (University of Groningen and University of California, Davis, 2021).\(^{22}\) Next, extending an argument from Flinn & Heckman (1982) about identifying the reservation wage by the minimum wage in the sample, I estimate the flow value of unemployment \( b \) as minimum value of consumption in the sample: \( \hat{b} = \min_{i} \{c_i\} \).

Simulated moments (McFadden, 1989) works by calculating that set of moments using the sample data \((m_d)\), simulating the same set of moments from the economic model using a candidate set of parameters \((m_s)\), and computing the distance between the two vectors. The objective is to choose the set of parameters that minimizes this weighted distance:

\[
\hat{\Theta} = \arg\min_{\Theta} (m_d - m_s)' W (m_d - m_s)
\]

where to make the problem scale well to ease estimation I follow a typical practice of setting \(W\) as a diagonal matrix containing the inverse moment variances, which, also following convention, I obtain by bootstrapping the sample.

To fit the remaining parameters, I need to choose an appropriate set of moments \(m_d\) in the data that should uniquely or jointly map to each parameter. The full set of moments I use in estimation is listed in Table 3. For some parameters, like the job offer arrival rates, there are standard moments that many papers use. For instance, the unemployment rate, the quarterly transition rate from unemployment to employment, and the rate of wage increases target the offer arrival rates \(\lambda_0\) and \(\lambda_1\). To target the wage offer distribution, I choose several moments from the full wage distribution among employed workers and also just for wages accepted out of unemployment, specifically the mean, median, and standard deviation, as well as the ratios of the 90th to 50th and 75th to 25th percentiles of accepted wages. In many papers, given the model assumptions the distribution of wages accepted out of unemployment exactly identifies the wage offer distribution, but that is not the case here because workers all have unique reservation wages depending on their preferences and savings levels. For the wage distribution itself, I assume a flexible parametric distribution for log firm productivity \(x\), supposing it is distributed Beta\((\alpha_x, \beta_x)\). This maps to wages through \(\alpha\). I then need a way to scale it appropriately, as a beta distribution has support between 0 and 1. To do so, I follow Bontemps et al. (2000) who show that the upper and lower bounds for the support of the wage distribution, \(\underline{w}\) and \(\overline{w}\) can be estimated consistently by the sample minimum and maximum.

The two less standard types of parameters I fit here are those related to firm shocks and endogenous job destruction and the distribution of worker risk preferences, so I will discuss the choice of those moments in more detail. First, the parameters relating to layoff risk. For these I choose moments capturing a range of conditional transitions into unemployment. Recall that the overall termination rate in the model is \(\tilde{\delta}(x) = \delta_0 + \eta(1 - F(\varepsilon^*(x)))\). For the highest paying firms \(F(\varepsilon^*(x)) \to 1\), meaning moments for transitions to unemployment among high earners identify \(\delta_0\). Likewise, for the lowest paying firms \(F(\varepsilon^*(x)) \to 0\), hence I choose the transition rate into unemployment for the lowest earners to match the arrival rate of productivity shocks \(\eta\). Lastly, I make a parametric form assumption for \(F(\varepsilon)\), assuming it follows an exponential

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\(^{22}\)Recognizing that there is a strand of the literature that seeks to explain why this share appears to be falling more recently (Grossman & Oberfield, 2021).

\(^{23}\)Relying on this order statistic for identification may not be valid if the model allowed for borrowing, and the statistic itself could be sensitive to sample trimming. I check this second possibility in the sensitivity analysis.
distribution with parameter $\theta$. I target $\theta$ by the overall average transition rate into unemployment and the rates of intermediate earners across the distribution.

To find moments to match for the risk preference parameters, consider that under the buffer stock theory of precautionary saving (Carroll & Samwick, 1998), and as in Lise (2013), workers will have a target savings-to-earnings ratio given their level of earnings and the risk of unemployment. More risk averse workers will choose a higher target at all levels of income. To demonstrate, in Figure 11 I plot the density and relationship of the savings-to-income ratio for three groups of risk preferences based on a calibrated simulation of the model. The lower the level of risk aversion, the lower the desired level of savings at all wages, and the more mass there is concentrated at low levels of the savings-to-income ratio. Technically, what we observe is a mixture of such ratios over the people with each risk preference, so a parametric assumption is important to be able to recover the distribution. I assume a fairly flexible parametric form for risk preferences, supposing they follow a beta distribution $\text{Beta}(\alpha, \beta)$, and then I target those parameters with moments capturing the mean and spread of the ratio between savings and earnings for several groups across the earnings distribution.24

An alternative approach would be to make use of the stated risk preferences of some of the workers. These are available for household heads who were interviewed in the 1996 wave, and are a popular source of variation in papers that study risk preferences. However, as I show in Appendix D, these responses do not correlate with savings behavior as one would expect if they represented preferences over income risk. Therefore, I prefer to model preferences as unobserved heterogeneity.

Figure 11: Empirical identification of risk preferences

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24Since support for the beta distribution is between 0-1, I scale those values to 0-3. This is conservative given the claim in Chetty (2006) that the theoretical upper bound on the coefficient of relative risk aversion is about 2, yet restrictive given the much higher estimates of 5 or more in Kimball et al. (2008). I ultimately chose the scale I did after estimates with a much wider scale consistently supported Chetty (2006), yielding a distribution with all of the mass below 3.
Table 3: List of sample moments targeted in estimation

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<tbody>
<tr>
<td>1</td>
<td>UE %</td>
<td>Median wage</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>U-&gt;E %</td>
<td>Median wage U-&gt;E</td>
<td>90:50 quantile ratio of wage U-&gt;E</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>E-&gt;U %</td>
<td>90th quant. wage U-&gt;E</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>E-&gt;U wage quant. 1-10</td>
<td>Mean ln(savings)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>E-&gt;U wage quant. 10-25</td>
<td>Std ln(savings)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>E-&gt;U wage quant. 25-50</td>
<td>Median ln(savings)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>E-&gt;U wage quant. 50-75</td>
<td>Mean ratio assets:wage</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>E-&gt;U wage quant. 75-99</td>
<td>Std ratio assets:wage</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>Mean wage</td>
<td>Median ratio assets:wage</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>Std wage</td>
<td>Mean assets given wage quant. 10-25</td>
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<tr>
<td>11</td>
<td>Mean wage U-&gt;E</td>
<td>Mean assets b/w wage quant. 25-50</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>Std wage U-&gt;E</td>
<td>Mean assets b/w wage quant. 50-75</td>
<td></td>
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<td></td>
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</tbody>
</table>

A single iteration of the estimator consists of finding a fixed point for the value functions given the candidate parameters, simulating the worker histories, calculating the simulated moments, and evaluating the objective function. The estimation procedure involves 20,000 such iterations carried out using the controlled random search with local mutation global optimization algorithm described in Kaelo & Ali (2006) as implemented in the NLopt toolkit for Python (Johnson, 2014). I then polish the global estimates by running the NLopt implementation of a local subplex algorithm (Rowan, 1990) for 1,000 additional iterations.

While the above discussion of how the structural parameters are identified is not treated formally, I do show a form of empirical identification in Appendix C, where I generate a Monte Carlo sample of work histories from the model and then run the estimator on that data. As shown, it successfully recover the true parameters. Having established an estimation strategy and validated it against data generated by a known process in this section, in the next section I run the estimator against the PSID sample and analyze the results.

6 Estimates and model fit

In this section, I present the results from estimating the model against the PSID data. I contextualize the results given previous estimates in the literature and evaluate how well the estimates fit the data. I also present the results of a sensitivity exercise investigating how dependent the estimated values are on the choice of optimization algorithm and some of the parametric assumptions.

Table 4 displays the parameter estimates. To obtain the standard errors given in parentheses below the estimates, I took 1000 bootstrap draws and ran the estimator on each of those samples. The estimates seem reasonable given other findings in the literature. For instance, unemployed workers are estimated to have about a 19% chance of receiving an offer in a given month, and employed workers have a lower arrival rate of about 9%. The on-the-job offer arrival rate is consistent with the calibrated ranges implied for the U.S. labor market by Hornstein et al. (2011), who argue that it takes a rate between about 7-14% to reproduce the job-to-job transitions observed in the data. The arrival rate of offers in unemployment is in a range consistent with the finding in a BLS analysis of a 2018 CPS data supplement that active job seekers have on average a 26.24% chance of receiving a job offer (Dalton & Groen, 2020). This exceeds the monthly transition rate out of unemployment of 8% observed in the data because heterogeneity in worker preferences and savings implies that some offers will be rejected even though no offers will be below the minimum reservation wage. In a model with sequential bargaining, the arrival rate would exactly equal this transition rate, as every

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meeting between a firm and worker forms a match. My results imply that workers accept about one out of every three offers they receive, which rationalizes the low median earnings offer I find of about $25,000 per year relative to the prevailing median earnings level in the U.S. of $30,200 in 2012. The arrival rate estimates mean about that half of unemployed workers will take longer than three months to receive their first offer. Therefore, every time a worker loses their job, search frictions imply a substantial loss of income. This point is highlighted Burdett et al. (2020), who find that an unemployment spell in Germany costs 8–9% of expected lifetime discounted earnings. The gap between the arrival rate and the acceptance rate also has important implications for the earnings subsidy I analyze in the next section. The larger the gap, the more leverage the subsidy has to incentivize workers to accept an offer. If everyone was already accepting every offer, no amount of subsidy could increase the acceptance rate.

### Table 4: Parameter estimates

<table>
<thead>
<tr>
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<th>estimate</th>
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</thead>
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<td>(2.4260)</td>
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<tr>
<td>$\beta_x$</td>
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<td>(4.8067)</td>
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<td>(0.0426)</td>
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<td>$\alpha+\gamma$</td>
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<td>(1.0526)</td>
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<td>$\beta+\gamma$</td>
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<td>(4.8274)</td>
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<td>(3.6191)</td>
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</tr>
<tr>
<td>$\max(x)$</td>
<td>21246.3033</td>
<td>(35.8364)</td>
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</table>

*Bootstrap standard errors in parentheses.*

### Table 5: Comparison of sample and simulated moments

<table>
<thead>
<tr>
<th>Sample Moments</th>
<th>Simulated Moments</th>
</tr>
</thead>
<tbody>
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<td>4.18E-02 4.21E-01 1.42E-02 5.15E-02</td>
</tr>
<tr>
<td>M05-08</td>
<td>2.12E-02 1.03E-02 7.38E-03 5.67E-03</td>
</tr>
<tr>
<td>M09-12</td>
<td>3.36E+03 1.87E+03 2.92E+03 4.27E+03</td>
</tr>
<tr>
<td>M13-16</td>
<td>4.61E+03 2.07E+03 5.74E+03 8.68E+00</td>
</tr>
<tr>
<td>M17-20</td>
<td>2.74E+00 9.12E+00 1.14E+01 3.37E+01</td>
</tr>
<tr>
<td>M21-24</td>
<td>2.23E+00 8.05E+00 8.43E+00 9.03E+00</td>
</tr>
<tr>
<td>M25-28</td>
<td>9.47E+00 1.96E+00 2.12E+00 2.09E-02</td>
</tr>
<tr>
<td>M29-32</td>
<td>7.53E-01 2.32E+00 5.00E-01 2.51E+00</td>
</tr>
<tr>
<td>M33-34</td>
<td>1.75E-01 2.75E+00</td>
</tr>
</tbody>
</table>

Table 5 lists the sample value and the simulated value for the full set of moments. As a reminder, explanations for what each moment represents appears in Table 3. Because the emphasis of the model is on differential layoff risk and heterogeneous savings behavior, I am going to focus more on those sets of
parameters in exploring the results checking the fit of the model. The moments related to job destruction are numbers 3 to 8: overall transitions into unemployment and the transition rate for quantile subgroups across the earnings distribution. The estimator fits these fairly well, which I also show in Figure 12, which plots a local polynomial regression for the transition rate into unemployment across the earnings distribution. This pattern of decreasing transitions into unemployment in Figure 12 cannot be matched by a standard search model that has a single exogenous job termination arrival shock. Jarosch (2021) does model a negative correlation between layoff risk and earnings, but that approach would not capture the fact that the layoff rate stabilizes after a certain earnings level. Robin (2011) allows for a form of differential layoff rates for high and low earners following an aggregate shock, but cannot produce such a pattern during “normal” times. Matching this pattern is unique to my model. Furthermore, the presence of this pattern holds important policy implications which I explore in the next section, as it implies some workers with low initial earnings can be stuck in an unstable zone of continued low earnings and more frequent churning into unemployment, while those who reach a higher earnings level are better shielded from future shocks. This speaks to the “unemployment scarring” literature, which observes that the best predictor of future unemployment is past unemployment (Arulampalam et al., 2001). A model without differential job destruction could not reproduce that pattern.

Figure 12: Quarterly transition rate into unemployment - model vs. data

The fit of the model with the ratio of savings to earnings across the earnings distribution is plotted in Figure 13, with the distribution of those ratios in Figure 14. Of course in a model without savings there could be no such figure. My model produces a pattern of savings that increase with earnings in a way that does match that data. It also accords with the conclusion in Lise (2013) that desired saving increases with earnings. The evidence also supports the proposition in Carroll & Samwick (1998) that workers having a target level of savings given earnings. Moreover, I match the dispersion in those targets. Conditional on earnings, there is a range of target savings levels, which the model rationalizes as reflecting heterogeneous preferences over risk. As shown in the illustration in Figure 11, given those preferences we should expect the variance of savings to be increasing with income, which Figure 14 seems to suggest.
Figure 13: Average savings per earnings level - model vs. data

Figure 14: Savings per earnings ratios - model vs. data

Ideally, the distribution of risk preferences as I estimate it here will match other estimates from the literature. Chetty (2006) reports that the approach based on labor supply elasticities consistently finds an estimate of the mean coefficient of relative risk aversion around 1. Search model approaches that assume homogeneously risk averse workers (Lentz (2009); Rendon (2006); Lise (2013)) report results in the range of 1.2-2.2. Using bounded expected utility, Kimball et al. (2009) estimate a mean for the PSID sample of 3.8. I find a symmetrical distribution with a mean coefficient of relative risk aversion of 1.17, a median of 1.14, and a standard deviation of 0.49, which I plot in Figure 15. Inspecting the figure, it appears that if anything I slightly overestimate risk aversion because the workers simulated from the model save more on average given earnings than do the workers in the data. Thus my estimates generally match those of Chetty (2006) and are far from Kimball et al. (2009). One question to look into in the future is why these two approaches get results so far apart, and what the informational content is of the elicited risk preference survey questions in the PSID that yield such high values.
Because the model relies on several parametric assumptions and the use of order statistics, it is useful to know how sensitive the estimates are to these choices. I present the results from a series of these checks in Table 6. First, in the “direct” column I use a brute force optimization algorithm that searches the entire parameter space by dividing it into increasingly smaller hyperrectangles (Johnson, 2014). The new estimates are fairly close to the main ones, and all are within a standard deviation. Another issue to consider is whether the estimate of the flow benefit is influenced by sample trimming. One reassuring result is that my estimate of about 600 is close to the estimate obtained by Rendon (2006) of 650. To see how different estimates would influence the results, in the $b +/\sim 100$ columns I re-estimate the model by setting the flow benefit to 500 and 700. In general, the parameters related to shocks stay about the same, and the parameters related to risk preferences shift in a logical pattern. When the flow benefit is lower, the model rationalizes the same job acceptance rate and savings decisions by concluding that workers are less risk averse; when it is higher, a more risk averse distribution of preferences rationalizes the data. Third, in attempting to be flexible yet parametric, I model firm productivity and worker risk preferences as following beta distributions. For productivity this also leans on order statistics of the sample minimum and maximum earnings to obtain the scale for the draws. To avoid order statistics, the most manageable alternative to check is the lognormal distribution. In addition to being a common parametric assumption for wage offers, this fits with the finding in (Cunningham et al., 2019) of long right tails: the 99-90 firm productivity ratio is approximately equal to the 75-25 ratio. For risk preferences, Kimball et al. (2009) impose a lognormal distribution to obtain their estimates of risk tolerance. When I switch to lognormal distributions and rerun the model (column “lognormal”), I obtain very similar shock parameters. For risk preferences, this and the main specification find a mean of 1.17. Wage offers under the main specification have a mean of $2200 and a standard deviation of 708, while under the lognormal model they have a mean of $2552 and a standard deviation of 684. If anything, the more restrictive parametric assumptions fit the data slightly better based on the value of the objective function at the minimum. In contrast, reducing risk preferences to a single value for all workers results in a much poorer fit, as shown in column “1 risk”. Several additional sensitivity checks are presented in Appendix B.
In this section I combined the model with the PSID data to estimate the structural parameters governing labor market dynamics and worker behavior. I analyzed the results, checking how they fit the data, how they compared to other estimates in the literature, and how sensitive they were to some of the identifying assumptions I made. In the next section I will use these parameters to conduct a counterfactual policy analysis and to simulate the impact of an aggregate downturn.

### Table 6: Sensitivity of estimates to identifying assumptions

<table>
<thead>
<tr>
<th>parameter</th>
<th>main</th>
<th>direct</th>
<th>b-100</th>
<th>b+100</th>
<th>lognorm</th>
<th>1 risk</th>
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<td>0.086</td>
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<td>0.141</td>
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<td>0.062</td>
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<td>3.141</td>
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<td>—</td>
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<td>604.974</td>
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<td>—</td>
<td>—</td>
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<tr>
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<td>—</td>
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<td>$\gamma$</td>
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<td>—</td>
<td>0.728</td>
<td>—</td>
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<tr>
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<td>1892.882</td>
<td>2127.347</td>
<td>1335.956</td>
<td>4016.951</td>
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</table>

In this section I used the model to conduct counterfactual analysis. First, I use the parameters I estimated in the previous section to compare the cost, welfare, and labor market effect of three social insurance policies. Then I simulate a downturn as described in Section 3 and show how important saving is as a means of consumption smoothing. Finally, I combine the two analyses by studying the impact of the three social insurance policies during a downturn.

#### 7 Policy experiments and downturn simulation

In this section I use the model to conduct counterfactual analysis. First, I use the parameters I estimated in the previous section to compare the cost, welfare, and labor market effect of three social insurance policies. Then I simulate a downturn as described in Section 3 and show how important saving is as a means of consumption smoothing. Finally, I combine the two analyses by studying the impact of the three social insurance policies during a downturn.

The three policies I study are 1) unemployment insurance, 2) a one-time cash transfer, and 3) an earnings subsidy. My model is uniquely well positioned to do this because of two features: first, because it has savings I can look at a cash transfer without assuming people have to spend the entire amount immediately, and because I allow for different preferences I can allow for different degrees of responsiveness to transfer. Second is the related fact that I can actually look at consumption, which is a closer proxy for welfare than income alone. The uniqueness of the PSID data let me estimate a model with consumption in the previous section, and having consumption separate from in the model is invaluable for actually getting at welfare. This will be doubly useful later on in the analysis of the role of savings in a downturn, as shocks that affect the labor market often affect the stock of wealth as well.

Unemployment insurance is a common policy to study with a search model. Such a policy should raise consumption for those out of work and enable them to be more patient and wait for better job offers. The other side of that coin, of prominence in policy debates during the Covid-19 pandemic, is that this greater patience means that the unemployment rate will be higher than it would be otherwise, which many policymakers find an undesirable outcome. While one way to reduce unemployment in that scenario is to reduce the unemployment benefit, this may run counter to the original policy objective. The U.S. government also provided large stimulus checks to most Americans to support them during the pandemic, but outside
of Rendon (2006) I am not aware of any papers that evaluate a large payment like that in the context of a dynamic model of the labor market, and that paper only looks at an initial transfer upon first starting out in the labor market. The third alternative is an earnings subsidy that constitutes a gradual tapering off of unemployment benefits for people who accept new jobs instead of taxing benefits at 100% when someone resumes work. This type of policy is also uncommon in counterfactual analysis though it has received more attention in other strands of the literature (see Phelps (1997) for an argument in favor of wage subsidies, and Moffitt (2002) for a discussion and summary of the evidence, with a focus on the earned income tax credit in the United States).

I present the results from simulating each of the three policies in Table 7 up to two years after implementation in the steady state. The specific values I use are $1000 per month for unemployment insurance, $5000 for the cash transfer, and a taper rate of $0.75 per dollar of earnings above $1300 for the earnings subsidy. As expected, unemployment benefits raise the unemployment rate relative to the baseline. Even though it also pays the same unemployment benefit, the low-income earnings subsidy has a much smaller impact on the unemployment rate, which by the eighth quarter rises by one percentage point instead of over four, as the marginal tax rate on benefits after accepting a job is not automatically 100%. Workers can accept lower paying jobs and search on the job rather than wait in unemployment for a high offer. Consumption at the 10th quantile is 14% higher than in the baseline scenario, and the 90-10 ratio of consumption, a proxy for inequality, falls by 9%. As a rough proxy for poverty, I calculate the share of workers earning less than $2000 per month, which is between the U.S. poverty thresholds for a household with one or two children. Unemployment insurance does not affect this much. The earnings subsidy cuts it in half, from 5.9% to 2.9% after eight quarters. As for the one-time transfer, that has a short run increase in consumption and a decrease in the poverty proxy, yet little impact on unemployment and no discernible long run effect. To me this suggests that even though workers could choose to save the transfer, many of them are already at or near their target level of savings and so consume most of it quickly to regain that target. Consumption at the 10th quantile is about 6% higher in the first few quarters after the transfer, and by two years out it remains just 3% above the baseline level.

Table 7: Effect of policies to support consumption

<table>
<thead>
<tr>
<th>Outcome</th>
<th>Policy</th>
<th>Quarter</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>6</th>
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<td></td>
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<tr>
<td>10th quantile</td>
<td>Baseline</td>
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<td>2312</td>
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<td>2294</td>
<td>2274</td>
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<tr>
<td></td>
<td>UI</td>
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<td>2473</td>
<td>2445</td>
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<td></td>
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<td>2633</td>
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<td></td>
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<td></td>
<td></td>
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<tr>
<td>% under $2000</td>
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<td>0.052</td>
<td>0.053</td>
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<td>0.055</td>
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<tr>
<td></td>
<td>UI</td>
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<td>0.033</td>
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<tr>
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<td>UI</td>
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<td>0.032</td>
<td>0.034</td>
<td>0.032</td>
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</table>

Not only does the earnings subsidy affect unemployment less than pure unemployment insurance, but as shown in Table 8 the relative rise in employment is eventually enough such that after two years, total
monthly program expenditures are nearly the same even though the policy reaches twice as many workers. Initially, the subsidy costs nearly twice as much because the unemployment rate has not had the chance to rise to its new steady state level, yet by two years out the subsidy costs just 13% more, and the gap is shrinking as unemployment adjusts to the new benefit level. The transfer is the most expensive policy by far. In this case, I allocated the subsidy to every worker. It would be cheaper if I imposed an income cap, but still pricier than the other policies relative to its effect on employment.

Table 8: Policy costs ($1000) and population coverage

<table>
<thead>
<tr>
<th></th>
<th>Policy</th>
<th>Quarter</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost</td>
<td>UI</td>
<td>0</td>
<td>729</td>
<td>858</td>
<td>967</td>
<td>1038</td>
<td>1170</td>
<td>1223</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Subsidy</td>
<td>0</td>
<td>1392</td>
<td>1397</td>
<td>1392</td>
<td>1386</td>
<td>1414</td>
<td>1388</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Transfer</td>
<td>82525</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coverage</td>
<td>UI</td>
<td>0.000</td>
<td>0.044</td>
<td>0.052</td>
<td>0.059</td>
<td>0.063</td>
<td>0.071</td>
<td>0.074</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Subsidy</td>
<td>0.000</td>
<td>0.188</td>
<td>0.187</td>
<td>0.187</td>
<td>0.185</td>
<td>0.185</td>
<td>0.185</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Transfer</td>
<td>1.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Next, I repeat the exercise while simultaneously simulating a downturn. First, I discuss its anticipated impact and calibrate an appropriate magnitude. A downturn in the model reduces profit margins for prevailing jobs, which should send a greater fraction of employed workers into unemployment each period. These workers are more likely to be from lower productivity, and therefore lower wage, matches. Accordingly, the unemployment rate should rise, and there should be more frequent churning into unemployment. Since wage offers for new matches are be lower, this should lead to slower job productivity growth for the workers beginning to climb back up the ladder. Wage inequality may widen, as the initial highest earners (with the corresponding lowest risk) are most likely to keep their current jobs. Furthermore, re-employed “displaced” workers could earn lower wages even at similar looking firms than identical, consistently employed counterparts.

How does these implications align with what occurred during recent actual downturns? Examining income losses by displaced workers in the Great Recession, Lachowska et al. (2020) find that “displaced workers’ earnings losses occurred mainly because hourly wage rates dropped at the time of displacement.” When comparing them to non-displaced workers, they observe, “five years after job loss, displaced workers’ earnings were 16 log points less than those of a stably employed comparison group.” As additional evidence of the unequal impact, Figure 16 plots wage and consumption inequality over the two-year intervals available for the PSID sample. The 90-10 wage ratio increases by about 25% between 2008 and 2010, and the 90-10 consumption ratio rises about 15% over its 2006 low point. Both fall as the recovery begins yet remain above their pre-recession levels.

26 Technically, in the model this is a permanent negative shock, not a cyclical recession. I abuse the term here for illustrative purposes.
Some additional facts from the Great Recession that can help calibrate the reasonableness of the modeled downturn are that the unemployment rate approximately doubled, rising from 5% to 10% in 2008-2009, and as shown in Figure 17 mean non-housing consumption dropped by slightly over 8% for the PSID sample. As for the magnitude of the downturn, one useful metric is the “output gap”, which is the difference between actual and potential output as estimated by the Congressional Budget Office. The output gap in the United States reached 5.5% in 2009 and 10.5% in 2020.\(^{27}\) To calibrate the magnitude to the output gap observed during the Great Recession, I set \(s\) to shock every match product downwards by 500 units—an amount equivalent to about 6% of mean productivity.

For simplicity of exposition and to focus on the dynamics of a downturn, I model the downturn here as affecting the entire economy, though one could readily imagine this as the scenario affecting a specific local labor market or sector. As an example, consider the local labor market impact of the China Shock of the early 2000s. The reduced form empirical results from the China Shock literature (Autor et al., 2016) describe the local labor market impact as follows: “Adjustment in local labor markets is remarkably slow, with wages and labor-force participation rates remaining depressed and unemployment rates remaining elevated for at least a full decade after the China trade shock commences. Exposed workers experience greater job churning and reduced lifetime income.”

Figure 18 shows that the simulated downturn matches the unequal expansion in layoff risk for the lowest

\(^{27}\)https://fred.stlouisfed.org/graph/?g=Ffx7
earners as seen in the Great Recession and Covid-19 pandemic depicted in Figure 2.

Figure 18: Quarterly transition rate into unemployment before and after downturn

In the simulation, the new equilibrium distribution of earnings offers shifts downward. I compare the scenarios in Figure 19, where it is clear that workers who accept jobs during the downturn are accepting much worse offers than before. In other words, one reason workers may remain at their current job even when the layoff risk rises is that their outside option has also worsened.

Figure 19: Accepted earnings offer distribution before and after downturn

In the simulation, as in the Great Recession, the unemployment rate roughly doubles within the first two quarters and nearly triples after two years, which I show in Table 9. We can also see that my proxy for the poverty rate rises by 50% within a few quarters and doubles after two years. By then, consumption inequality has risen about 60% compared to the steady state counterfactual, and the 10th percentile of consumption is down one-third while overall mean consumption falls by 5%. Here we also see the importance of savings. In the no savings scenario, I suppose that the downturn also wipes out accumulated wealth. When that happens, mean consumption drops by about $600, or 8% more than otherwise in the downturn, and 13% relative to the normal scenario. Consumption inequality is about 4% higher. The poverty proxy rises by several percentage points, which translates to a nearly 33% higher level immediately. The unemployment rate is actually slightly lower when the downturn wipes out savings, because workers without savings have a lower reservation wage and are accepting worse offers.
Next, I implement the same three counterfactual policies starting at the onset of the simulated downturn. The results are in Table 10. Here, the relative labor market effect of the earnings subsidy is more pronounced. Under the subsidy, the unemployment rate is actually slightly lower than without any policy intervention. By contrast, with unemployment insurance alone, the gap rises over time, reaching three percentage points after a year and five points after two years. The subsidy cuts the post-transfer proxy poverty rate significantly, from 6.8% to 2.2% in the first quarter of the downturn. Consumption for the 10th quantile is 31% higher under the earnings subsidy a year into the downturn, compared to 10% under unemployment insurance. The 90-10 consumption ratio is 19% lower after a year than if there were no intervention. Meanwhile, the effect of the asset transfer is again short-lived. It props up consumption for the first quarter or two, and then the impact dissipates and the scenario begins to resemble the one with no intervention.

### Table 10: Effect of policies to support consumption in a downturn

<table>
<thead>
<tr>
<th>Outcome</th>
<th>Policy</th>
<th>Quarter</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>6</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consumption</td>
<td>Downturn</td>
<td></td>
<td>2320</td>
<td>2252</td>
<td>2155</td>
<td>2042</td>
<td>1929</td>
<td>1730</td>
<td>1624</td>
</tr>
<tr>
<td></td>
<td>Downturn transfer</td>
<td></td>
<td>3109</td>
<td>3.135</td>
<td>3.299</td>
<td>3.488</td>
<td>3.696</td>
<td>4.125</td>
<td>4.403</td>
</tr>
<tr>
<td>Consumption</td>
<td>90-10 ratio</td>
<td></td>
<td>2320</td>
<td>2252</td>
<td>2155</td>
<td>2042</td>
<td>1929</td>
<td>1730</td>
<td>1624</td>
</tr>
<tr>
<td></td>
<td>Downturn</td>
<td></td>
<td>3109</td>
<td>3.135</td>
<td>3.299</td>
<td>3.488</td>
<td>3.696</td>
<td>4.125</td>
<td>4.403</td>
</tr>
<tr>
<td></td>
<td>Downturn transfer</td>
<td></td>
<td>3109</td>
<td>3.135</td>
<td>3.299</td>
<td>3.488</td>
<td>3.696</td>
<td>4.125</td>
<td>4.403</td>
</tr>
<tr>
<td>Consumption</td>
<td>% under $2000</td>
<td></td>
<td>2320</td>
<td>2252</td>
<td>2155</td>
<td>2042</td>
<td>1929</td>
<td>1730</td>
<td>1624</td>
</tr>
<tr>
<td></td>
<td>Downturn</td>
<td></td>
<td>0.050</td>
<td>0.068</td>
<td>0.083</td>
<td>0.095</td>
<td>0.107</td>
<td>0.125</td>
<td>0.142</td>
</tr>
<tr>
<td></td>
<td>Downturn UI</td>
<td></td>
<td>0.050</td>
<td>0.051</td>
<td>0.063</td>
<td>0.075</td>
<td>0.085</td>
<td>0.103</td>
<td>0.118</td>
</tr>
<tr>
<td></td>
<td>Downturn subsidy</td>
<td></td>
<td>0.050</td>
<td>0.051</td>
<td>0.063</td>
<td>0.075</td>
<td>0.085</td>
<td>0.103</td>
<td>0.118</td>
</tr>
<tr>
<td></td>
<td>Downturn transfer</td>
<td></td>
<td>0.050</td>
<td>0.049</td>
<td>0.068</td>
<td>0.083</td>
<td>0.096</td>
<td>0.117</td>
<td>0.135</td>
</tr>
<tr>
<td>Unemployment</td>
<td>Downturn</td>
<td></td>
<td>0.036</td>
<td>0.040</td>
<td>0.055</td>
<td>0.058</td>
<td>0.062</td>
<td>0.068</td>
<td>0.070</td>
</tr>
<tr>
<td></td>
<td>Downturn UI</td>
<td></td>
<td>0.036</td>
<td>0.040</td>
<td>0.055</td>
<td>0.058</td>
<td>0.062</td>
<td>0.068</td>
<td>0.070</td>
</tr>
<tr>
<td></td>
<td>Downturn subsidy</td>
<td></td>
<td>0.036</td>
<td>0.040</td>
<td>0.055</td>
<td>0.058</td>
<td>0.062</td>
<td>0.068</td>
<td>0.070</td>
</tr>
<tr>
<td></td>
<td>Downturn transfer</td>
<td></td>
<td>0.036</td>
<td>0.040</td>
<td>0.055</td>
<td>0.058</td>
<td>0.062</td>
<td>0.068</td>
<td>0.070</td>
</tr>
</tbody>
</table>

### 8 Discussion

The combination of low wages and high layoff risk works against the upward income mobility of the job ladder. Because this dynamic intensifies in bad economic times, lower earners bear a disproportionate share of the
costs of a negative shock. The model developed here provides a foundation for the empirical patterns that firms with higher total factor productivity also pay higher wages and provide greater job security, and that lower paid workers face higher job churning.28 The gap widens during a downturn, as lower productivity firms are more likely to shed jobs. These modeling refinements can generate large drops in welfare from job loss that vary with aggregate conditions at the the time, matching the empirical evidence in Davis & Von Wachter (2011). In the other direction, if new wage offers fall in a downturn this could moderate the welfare impact. Given some degree of wage rigidity, workers hired in a bad economy are more profitable for the firm relative to those earning higher wages. When the economy recovers, the model implies that they may earn less but should experience fewer layoffs, which would be an interesting empirical implication to check given appropriate data. However, low earners generally value higher income relative to greater job security.

From a policy perspective, a central debate considers the effect of unemployment benefits on job acceptance decisions. In this specific setting where workers have no outside considerations such as workplace safety or childcare needs, benefits do decrease employment as in most standard search models, although they also increase the welfare of recipients. What I show is that reducing benefits is not the only alternative for increasing employment. Expanding benefits to include a subsidy for low earners incentivizes people to accept jobs. The result is welfare improvements comparable to those of an unemployment insurance scheme with an employment rate close to the no-intervention baseline. Furthermore, the reduction in unemployment defrays many of the additional costs generated by the subsidy.

One concern could be that an earnings subsidy crowds out private saving. Although this may occur to some extent, even risk averse low earners already choose to save relatively little. Moreover, I estimate the distribution of the coefficient of relative risk aversion to be fairly low, with a mean around 1 and range from almost 0 to about 2.5. The mean accords with models based on a Slutsky decomposition as in Chetty (2006), but as I show, allowing for dispersion is important for fitting the data. The distribution I estimate is shifted well left of what Kimball et al. (2009) impute using the set of survey questions soliciting risk preferences over income in the PSID. Given the contradiction, a natural next step is to compare the alignment between these elicted preferences and those revealed through savings behavior.

A related direction for expanding the analysis is to consider multiple sectors. One conclusion of the model is that there is no reason for workers to sort into jobs based on their risk preferences. I suppose that this holds within a sector. If the model were expanded to two sectors differing in the frequency or distribution of productivity shocks—and hence the chance of layoffs—risk preferences might prove more salient for worker labor market behavior. However, most models testing this proposition rely on survey responses such as those in the PSID, which as noted do not necessarily align with revealed preferences through savings.

Overall, I have shown that under a different set of assumptions we still obtain the result in Bonhomme & Jolivet (2009) that there is a “pervasive absence of compensating differentials” in a frictional labor market when it comes to job security. Layoff risk decreases as earnings rise. This is one sense in which inequality in total compensation exceeds inequality in income, and I suspect that there are others.

28In consequence, the widely documented health and psychological welfare costs of job loss will also fall disproportionately on the lowest earners.
References


Fallick, B. C., Lettau, M., & Wascher, W. L. (2020). Downward nominal wage rigidity in the united states during and after the great recession.


A  Relaxation of modeling assumptions

In this section, I discuss the literature regarding some of the simplifying modeling assumptions that have been made to direct focus on the layoff margin of interest and explore how relaxing those assumptions would play out in the model.
A.1 Allowing for positive shocks

In the main model, following Mortensen & Pissarides (1994) shocks to match productivity can be positive or negative conditional on the current value, yet total productivity can never exceed the initial match value. While it may be of interest to consider an environment where the shocks could also increase the match value, the assumption in the model is without loss of generality from the perspective of layoff risk.

To see why, suppose instead that $F(\varepsilon)$ has both positive and negative support. This enters into the model as a substitution of the lower bound $\varepsilon$ where in the primary model the lower bound is 0.

$$\Pi_\varepsilon = \frac{1}{1 + \rho} \left( \alpha x - \varepsilon + \lambda P_s(x) \Pi_\varepsilon + \eta \int_\varepsilon^{\varepsilon^*(x)} \Pi_{\varepsilon'} f(\varepsilon') + (1 - \lambda_1 - \eta) \Pi_\varepsilon \right) \quad (20)$$

Repeating the steps for the solution from section 3 with this new lower bound, the threshold termination shock becomes

$$\varepsilon^*(x) = \alpha x + \frac{\eta}{D} \int_0^{\varepsilon^*(x)} F(\varepsilon) d\varepsilon. \quad (21)$$

Because a firm will terminate a match only after a negative shock, there is now a subdomain of the support of $\varepsilon$ that is irrelevant to that decision, namely everything up to $F(0): \varepsilon^*(x) > 0 \forall x$. Mathematically, the termination equation can be rewritten

$$\varepsilon^*(x) = \alpha x + \frac{\eta}{D} \int_0^{\varepsilon^*(x)} F(\varepsilon) d\varepsilon + \frac{\eta}{D} F(0). \quad (22)$$

One can see immediately that the dynamics between firm productivity and layoff risk are unchanged.

A.2 Relaxing wage rigidity

The assumption that wages are constant for the duration of a match is common in basic wage posting models in the search literature (e.g. Burdett & Mortensen (1998)), and might be considered an augmented version of a partial equilibrium search model where an exogenous parametric wage offer distribution is assumed as a primitive of the model. The wage posting frame of the model here differs from models with renegotiation after outside offers arrive (Dey & Flinn (2005), Cahuc et al. (2006)), and the premise in Mortensen & Pissarides (1994) that wages are renegotiated following every transitory productivity shock. That assumption of period-by-period renegotiation has been criticized in the macro literature for being unable to capture the volatility of unemployment fluctuations (Shimer, 2005). Proposed alternatives, such as Hall (2005), address the issue by modifying the method of wage determination in the model to deliver some form of rigidity.

More broadly, there is a long documented history that firms do not like to adjust wages in the face of downturns. Azariadis (1975) sought to understand the “normal industrial practice of laying off unneeded workers and paying unchanged wages to the rest of the work force” as opposed to adjusting wages. He proposed that risk-neutral firms act not only as employers but also as insurers for risk-averse workers. More recent evidence that firms act as insurers comes from Guiso et al. (2005), who find that transitory shocks to firms are not passed through to workers. Additional empirical evidence supporting the assumption of wage rigidity includes Altonji & Devereux (1999), who observe that downward wage cuts without changes
in job status are rare; Haefke et al. (2013), who show that new hires have much more flexible wages than current workers; and Barattieri et al. (2014), who conclude that workers who switch jobs have a much higher probability of changing wages than workers who continue to be employed at the same firm. (Friedrich et al., 2019) find some pass-through of permanent firm shocks and less for transitory shocks to match productivity. Qualitatively, in a book titled Why Wages Don’t Fall During a Recession, through interviews with executives and recruiters, Bewley (2009) learns that employers prefer not to cut wages following negative demand shocks because they believe it will reduce worker morale and engagement with the firm’s objectives. Similarly, Campbell III & Kamlani (1997) survey 184 firms and document resistance to wage reductions for many reasons, particularly because of employee morale and effort and the asymmetric impact of lowering versus raising wages, replacement costs, and risk of losing their most productive workers. More recently, Jardim et al. (2019) and Elsby & Solon (2019) argue that nominal wage cuts are more prevalent than found in studies using household survey data, finding that about 15-25% of job stayers experience nominal wage cuts in a year. This is contradicted by Grigsby et al. (2021), who use administrative data to show that only 2.5% of job stayers experienced a wage cut between 2008-2016. An additional implication of the wage rigidity in the model is that unemployed workers will underbid current employees by being willing to accept a lower wage for an equally productive match. Solow (1990) believed that the absence of underbidding could explain observed patterns in downward wage rigidity, but Fehr & Falk (1999) found “massive” evidence of just such underbidding by workers in an experimental setting, yet refusal by firms to accept that underbidding. The explanation offered is that labor markets are characterized by incomplete contracts with fixed wages, and since effort is unobservable, firms prioritize fairness to maintain worker cooperation, which wage reductions put in jeopardy.

In the present paper, the objective is not to explain the phenomenon of wage rigidity, but rather to incorporate this stylized fact so as to support conducting the analysis of interest. The primary model therefore assumes that a match involves a fixed-wage contract, such that wages are not affected by shocks to the match productivity. Suppose instead that we maintained the sharing rule for the match product, yet allowed it to update fully following each $\varepsilon$ shock. This is reflected in the firm’s value function by making flow profits equal to $\alpha(x - \varepsilon)$ instead of $\alpha x - \varepsilon$

$$
\Pi_\varepsilon = \frac{1}{1 + \rho} \left( \alpha(x - \varepsilon) + \lambda_1 P_s(x) \Pi_\varepsilon + \eta \int_0^{\varepsilon^*(x)} \Pi_{\varepsilon'} f(\varepsilon') + (1 - \lambda_1 - \eta) \Pi_\varepsilon \right)
$$

(23)

In the simplest case, assume that the current draw of $\varepsilon$ does not affect the probability that a worker leaves a firm when faced with an outside offer (or affects it in a small enough way that we can assume it is constant for the sake of illustration). Then

$$
\alpha \varepsilon^*(x) = \alpha x + \eta \int_0^{\varepsilon^*(x)} F(\varepsilon)d\varepsilon
$$

$$
\implies \varepsilon^*(x) = x + \eta \int_0^{\varepsilon^*(x)} F(\varepsilon)d\varepsilon.
$$

(24)

The mapping from productivity to the maximum shock the firm is willing to absorb is a monotonic transformation from that implied by the primary model. Specifically, the firm is willing to absorb larger shocks,
yet the rank ordering of those magnitudes is still determined by $x$.

Extending this modified approach to the policy experiment of a permanent downturn where $\tilde{x} = x - s$, it matters whether we assume wages can update immediately. Here the wage rigidity assumption plays a larger role. If wages update fully, then the entire wage distribution shifts down such that current workers no longer earn rents greater than they would get by accepting identical jobs in the new labor market. Wages and layoff risk are remapped roughly to $w(\tilde{x} - \varepsilon) = w(x - s - \varepsilon)$ and $\delta(\tilde{x}) = \delta(x - s)$. Every employed worker suddenly finds themselves earning less and facing higher layoff risk with a worse outside option given the new offer distribution. Therefore, we still expect increased job churning, greater unemployment, and reduced lifetime income, yet the wedge disappears between the still employed and the newly unemployed and employed workers.

An in-between approach is to assume imperfect pass-through from shocks to wages at rate $\alpha \leq \beta \leq 1$, as in

$$
\Pi_{\varepsilon} = \frac{1}{1 + \rho} \left( \alpha x - \beta \varepsilon + \lambda_1 P_\delta(x)\Pi_{\varepsilon} + \eta \int_{0}^{\varepsilon'(x)} \Pi_{\varepsilon'} f(\varepsilon') + (1 - \lambda_1 - \eta)\Pi_{\varepsilon} \right)
$$

(25)

Holding $D$ constant, this yields termination condition

$$
\beta \varepsilon^*(x) = \alpha x + \beta \eta \frac{\varepsilon'(x)}{D} \int_{0}^{\varepsilon'(x)} F(\varepsilon) d\varepsilon
$$

(26)

$$\implies \varepsilon^*(x) = \frac{\alpha}{\beta} x + \frac{\eta}{D} \int_{0}^{\varepsilon'(x)} F(\varepsilon) d\varepsilon$$

which converges to the main case in the model or the case with full pass-through of shocks as $\beta \to 1$ or $\beta \to \alpha$. One can observe that this still has no practical impact on the baseline results of the model, while reducing but not eliminating the aforementioned wedge in the policy simulation. As a robustness check, after conducting the main policy simulation I repeat the exercise for several value of $\beta$ to demonstrate the degree to which the wage rigidity assumption influences the main conclusions of the paper.

A.3 Allowing for wage bargaining

Even if wages are negotiated, and renegotiated, the Mortensen & Pissarides (1994) model still results in firms having a productivity threshold below which they will terminate a match, and this threshold is increasing with the initial productivity of the match. That model delivers a tractable bargaining solution by assuming no on-the-job search and homogeneous, risk-neutral workers. Once workers are allowed to differ and to weigh outside offers, which are valued differently over time according to worker preferences and the current wage, the bargaining solution quickly becomes unwieldy. Furthermore, survey evidence reports that two-thirds of workers did not negotiate their current salary (Hall & Krueger, 2012), and empirical estimates of wage bargaining shows that it is uncommon at low and medium wage jobs (Cahuc et al. (2006), Card et al. (2016)), and that the magnitude of the bargaining that does take place is small, with an elasticity with respect to increases in the outside option on the order of just 0.1-0.2% percent (Caldwell & Harmon (2019), Lachowska et al. (2021)). To “flip” the implications in the model to get layoff risk to increase with wages, bargaining power would need to rise so steeply with match productivity as to cause profits to decrease, which does not accord with intuition, the magnitude of the bargaining power estimates in
the literature, or the empirical evidence that, if anything, the labor share of income is decreasing with firm productivity (Dorn et al., 2017). Because the bargaining approach does not deliver a fundamentally different conclusion regarding the relationship between productivity and job security, while adding firm and worker heterogeneity and on-the-job search to the model, I make the simplifying assumption that there is no bargaining. Compositional effects could arise if firms could bargain differently with different groups such that more risk averse workers received a lower share of the surplus, yet that assumption would entail making unrealistic or illegal assumptions like that firms perfectly observe risk preferences and asset holdings of workers, and can pay identically productive workers differently. If instead assets and risk preferences are unobserved, firms will bargain based on expectations, again treating all workers the same.

The primary model assumes a sharing rule for the match output rather than Nash Bargaining over the match surplus as is common in the literature. One reason models with Nash Bargaining are able to include it is because of the assumption that workers are risk neutral. This yields the common result that firms and workers split the match surplus. Without that assumption, the Nash Bargaining solution quickly becomes convoluted, although other solution concepts may still be viable. As a simple illustration, assume a much simplified version of the model where there is no on the job search, no saving, and all workers are homogeneously risk averse. Assume that firms and workers renegotiate wages following every shock to the match value. Denote the offer arrival rate \( \lambda \).

The value to a worker when unemployed is

\[
\rho U = u(b) + \lambda \int \max \{ V(x, 0) - U, 0 \} \, d\Gamma(x)
\]  

(27)

and when employed is

\[
(\rho + \eta)V(x, \varepsilon) = u(w(x, \varepsilon)) + \eta \int \max \{ V(x, \varepsilon), U \} \, dF(\varepsilon)
\]  

(28)

Assume as before that the firm’s outside option is 0, and the value of a filled position is

\[
(\rho + \eta)\Pi(x, \varepsilon) = x - \varepsilon - w(x, \varepsilon) + \eta \int \max \{ \Pi(x - \varepsilon), 0 \} \, dF(\varepsilon)
\]  

(29)

Denote the relative bargaining power of workers as \( \alpha \). According to the axiomatic Nash Bargaining approach, wages will be chosen to maximize the weighted joint surplus:

\[
w(x, \varepsilon) = \arg \max_w \{ [V(x, \varepsilon) - U]^{1-\alpha} \}
\]  

(30)

Dropping the parentheses, the first order condition is

\[
\frac{V'}{V - U} = -(1 - \alpha) \frac{\Pi'}{\Pi}
\]  

(31)

which, recognizing that the future terms do not depend on the current wage, can be rewritten as

\[
V - U = \alpha (u'(w)\Pi + V - U).
\]  

(32)

Unlike in the typical case, where the worker receives a constant share of the match surplus \( \Pi + V - U \), with
risk aversion the worker receives a share of the match surplus that is decreasing in the wage. Hence, while wages should be increasing in productivity $x$, the worker’s share of that product will not be rising. More productive firms should earn higher flow profits.

To see that the termination threshold is still increasing in $x$ (layoff risk is decreasing in $x$) under a bargaining assumption, consider the termination condition where $\Pi(x, \varepsilon^*(x)) = 0$:

$$
\varepsilon^*(x) = x - w(x, \varepsilon^*(x)) + \frac{\eta}{\rho + \eta} \int_0^{\varepsilon^*(x)} F(\varepsilon) d\varepsilon
$$

(33)

Simplifying notation and taking the derivative with respect to $x$, we get

$$
\varepsilon'^* = \frac{1}{1 + w' - \frac{\eta}{\rho + \eta} F(\varepsilon^*)}
$$

(34)

which is positive given that wages are increasing in firm productivity.

### A.4 Multiplicative productivity shocks

The primary models follow Mortensen & Pissarides (1994) and others by treating transitive shocks to firm productivity as additive. In theory, they could enter differently, for instance as a multiplier. This implies certain assumptions about productivity shocks, particularly that more productive firms face larger variance shocks, which seems less realistic than the additive implication that shocks are relatively more important to less productive firms. For that reason this case is left unsolved algebraically. To reiterate, the goal of the model is not to prove that a certain wage-risk relationship holds under all possible assumptions and modeling scenarios, but instead that a surprising relationship results given a few basic, reasonable assumptions.

### A.5 The firm’s outside option

In the main model I assume that there is free entry at all levels of productivity, driving the outside option to zero for all firms. Here I instead write down a firm’s value function for maintaining a vacancy and characterize the job termination threshold shock $\varepsilon^*(x)$ when the vacancy value may not be zero.

Suppose the flow cost of maintaining a vacancy is $c$. Let the value of a vacancy be $F(x)$ where

$$
F(x) = \frac{1}{1 + \rho} \left( c + \lambda_0 P_{A|x} \Pi(x, 0) + \lambda_0 (1 - P_{A|x}) \Pi(x) + (1 - \lambda_0) F(x) \right)
$$

(35)

where $P_{A|x}$ denotes the probability of a worker accepting an offer if matched with the firm. For simplicity, suppose that all jobs are above every worker’s reservation wage in expectation, such that we assume $P_{A|x} = 1$. Then

$$
(\lambda_0 + \rho) F(x) = c + \lambda_0 \Pi(x, 0).
$$

(36)

The value of a filled vacancy is

$$
D \Pi(x, \varepsilon) = \alpha x - \varepsilon + \frac{\eta}{D} \int_0^{\varepsilon^*(x)} F(\varepsilon') d\varepsilon' + \lambda_1 P_s F(x)
$$

(37)
such that at the termination threshold
\[(\rho + \eta + \delta_0)\Pi(x, \varepsilon^*) = \alpha x - \varepsilon^* + \frac{\eta}{D} \int_0^{\varepsilon^*(x)} F(\varepsilon')d\varepsilon'\] (38)

because
\[D = \rho + \lambda_1 \mathcal{F}(x) + \eta + \delta_0\] (39)

and we know from the model that at the termination threshold, \(F(x) = \Pi(x, \varepsilon^*)\).

Substituting, we get
\[\frac{\rho + \eta + \delta_0}{\lambda_0 + \rho} c + \left(\frac{\rho + \eta + \delta_0}{\lambda_0 + \rho}\right)\Pi(x, 0) = \alpha x - \varepsilon^* + \frac{\eta}{D} \int_0^{\varepsilon^*(x)} F(\varepsilon')d\varepsilon'\] (40)

or
\[\varepsilon^*(x) = \alpha x + \frac{\eta}{D} \int_0^{\varepsilon^*(x)} F(\varepsilon')d\varepsilon' - \frac{\rho + \eta + \delta_0}{\lambda_0 + \rho} (c + \lambda_0 \Pi(x, 0))\] (41)

This looks similar to the termination in the main model, which is increasing in \(x\), plus two additional terms. The vacancy cost is a negative number, meaning the costlier a vacancy, the larger a shock the firm will absorb before terminating a match. Although I have assumed that \(c\) is the same for all firms, it is easy to imagine that in a richer model, a vacancy is costlier for a more productive position, supposing the Human Resources Department spends more to find a new manager than it does for a new mail clerk. Counterbalancing this dynamic is the value of a newly filled position, which is increasing in \(x\). The higher the probability that the firm can quickly find a new worker, the more willing it is to destroy a match and try again.

B Estimation results under alternative decisions

In this appendix, I present the results from estimating the model given different sampling and estimation decisions to show how that affects the estimated structural parameters. First, Table 11 show how the estimated parameters and function value change as the number of discrete points used to approximate the distribution of risk preferences varies. The parameters are generally consistent across versions of the estimator, and the objective function is lowest at the main specification in the paper with 5 discrete points approximating the continuous distribution.
Table 11: Parameter estimates for different numbers of discrete points

<table>
<thead>
<tr>
<th>Parameter</th>
<th>3 points</th>
<th>4 points</th>
<th>5 points</th>
<th>6 points</th>
<th>7 points</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda_0$</td>
<td>0.183</td>
<td>0.204</td>
<td>0.186</td>
<td>0.290</td>
<td>0.197</td>
</tr>
<tr>
<td>$\lambda_1$</td>
<td>0.089</td>
<td>0.102</td>
<td>0.086</td>
<td>0.125</td>
<td>0.087</td>
</tr>
<tr>
<td>$\alpha_x$</td>
<td>2.461</td>
<td>2.615</td>
<td>3.283</td>
<td>1.950</td>
<td>3.494</td>
</tr>
<tr>
<td>$\beta_x$</td>
<td>7.714</td>
<td>8.532</td>
<td>9.311</td>
<td>7.361</td>
<td>9.874</td>
</tr>
<tr>
<td>$\theta_x$ (x100)</td>
<td>0.061</td>
<td>0.069</td>
<td>0.063</td>
<td>0.075</td>
<td>0.068</td>
</tr>
<tr>
<td>$\delta_0$ (x100)</td>
<td>0.153</td>
<td>0.193</td>
<td>0.164</td>
<td>0.263</td>
<td>0.246</td>
</tr>
<tr>
<td>$\eta$</td>
<td>0.040</td>
<td>0.056</td>
<td>0.051</td>
<td>0.161</td>
<td>0.046</td>
</tr>
<tr>
<td>$\alpha_\gamma$</td>
<td>2.789</td>
<td>2.927</td>
<td>3.028</td>
<td>4.770</td>
<td>4.632</td>
</tr>
<tr>
<td>$\beta_\gamma$</td>
<td>4.368</td>
<td>5.064</td>
<td>4.790</td>
<td>9.423</td>
<td>10.397</td>
</tr>
<tr>
<td>$b$</td>
<td>604.974</td>
<td>604.974</td>
<td>604.974</td>
<td>604.974</td>
<td>604.974</td>
</tr>
<tr>
<td>fval</td>
<td>1981.235</td>
<td>1944.540</td>
<td>1813.097</td>
<td>2346.095</td>
<td>2074.417</td>
</tr>
</tbody>
</table>

Although the residualized measures for assets and wages correspond more closely with the conceptual variation in the model, one might be curious to know how influential that adjustment is relative to estimation on the raw data. Table 12 contains the results from estimating the model without adjusting assets or wages for variation due to observable worker heterogeneity or time. The shock arrival rates, offer distributions, and risk preference distribution vary somewhat yet are all generally in line with those estimated for the residualized model, such that using this version would not meaningfully alter the policy implications calculated.

Table 12: Parameter estimates using nonresidualized data

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda_0$</td>
<td>0.209</td>
</tr>
<tr>
<td>$\lambda_1$</td>
<td>0.119</td>
</tr>
<tr>
<td>$\alpha_x$</td>
<td>1.687</td>
</tr>
<tr>
<td>$\beta_x$</td>
<td>8.411</td>
</tr>
<tr>
<td>$\theta_x$ (x100)</td>
<td>0.081</td>
</tr>
<tr>
<td>$\delta_0$ (x100)</td>
<td>0.228</td>
</tr>
<tr>
<td>$\eta$</td>
<td>0.104</td>
</tr>
<tr>
<td>$\alpha_\gamma$</td>
<td>4.701</td>
</tr>
<tr>
<td>$\beta_\gamma$</td>
<td>9.678</td>
</tr>
<tr>
<td>$b$</td>
<td>604.970</td>
</tr>
<tr>
<td>min($x$)</td>
<td>1899.801</td>
</tr>
<tr>
<td>max($x$)</td>
<td>21246.303</td>
</tr>
<tr>
<td>fval</td>
<td>1841.917</td>
</tr>
<tr>
<td>Calibrated</td>
<td></td>
</tr>
<tr>
<td>$\alpha$</td>
<td>0.4</td>
</tr>
<tr>
<td>$\rho$</td>
<td>0.006</td>
</tr>
<tr>
<td>$r$</td>
<td>0.00125</td>
</tr>
</tbody>
</table>

C Validation of estimator performance

To verify that the estimator is coded correctly and can recover the structural parameters of the model, I generated a sample of 20,000 labor market histories governed by a calibrated set of parameters and then ran the estimator on that sample. The main specification of the model allows for heterogeneity in risk preferences governed by a distribution known up to the parameter values. Table 13 shows that the procedure of sorting initial asset values and assigned risk preferences draws allow the estimator to recover the true structural parameters of the model. For example, the true mean coefficient of relative risk aversion is 0.86 and the estimated mean is 0.91, and the 0-1 normalized mean of the beta distribution for productivity offers is
estimated at 0.222 with a standard deviation of 0.132 compared to true values of 0.200 and 0.137.

Table 13: Validation of estimator against known parameters - heterogeneous workers

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Set Value</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \lambda_0 )</td>
<td>0.25</td>
<td>0.210</td>
</tr>
<tr>
<td>( \lambda_1 )</td>
<td>0.15</td>
<td>0.172</td>
</tr>
<tr>
<td>( \alpha )</td>
<td>1.50</td>
<td>1.988</td>
</tr>
<tr>
<td>( \beta )</td>
<td>6.00</td>
<td>6.962</td>
</tr>
<tr>
<td>( \theta_c \times 100 )</td>
<td>0.05</td>
<td>0.050</td>
</tr>
<tr>
<td>( \delta_0 \times 100 )</td>
<td>0.25</td>
<td>0.210</td>
</tr>
<tr>
<td>( \eta )</td>
<td>0.03</td>
<td>0.036</td>
</tr>
<tr>
<td>( \mu_{\gamma} )</td>
<td>2.00</td>
<td>1.997</td>
</tr>
<tr>
<td>( \sigma_{\gamma} )</td>
<td>5.00</td>
<td>4.587</td>
</tr>
<tr>
<td>( b )</td>
<td>300.00</td>
<td>300.000</td>
</tr>
<tr>
<td>( \min(x) )</td>
<td>1400.00</td>
<td>1410.014</td>
</tr>
<tr>
<td>( \max(x) )</td>
<td>22000.00</td>
<td>17070.048</td>
</tr>
<tr>
<td>( fval )</td>
<td>1006.50</td>
<td>139.873</td>
</tr>
</tbody>
</table>

Calibrated

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha )</td>
<td>0.4</td>
</tr>
<tr>
<td>( \rho )</td>
<td>0.006</td>
</tr>
<tr>
<td>( r )</td>
<td>0.00125</td>
</tr>
</tbody>
</table>

D Hypothetical risk gambles in the PSID

One empirical approach to estimating risk preferences is to elicit responses to survey questions regarding hypothetical gambles over income. For the PSID, this was done in the 1996 wave, where employed respondents were asked if they would be willing to trade a guaranteed job for life for one that could either double their income or reduce it by X%. Respondents are classified into one of six groups depending on where they drew the line. Expected utility theory provides an upper and lower bound for the preferences that are consistent with the income gamble that each participant accepts. Kimball et al. (2009) have impute estimates of risk tolerance preference parameters for each group, accounting for measurement error in responses, with the imputed coefficient of relative risk aversion ranging from 1.4 to 6.7. They fit a lognormal distribution to the data and calculate a mean of 3.8 with the vast majority of workers having a coefficient above 2.2. In my model, risk preferences this steep would imply that many workers want to many multiples of annual income in precautionary savings. Table 14 reports the full distribution of risk groups and the corresponding Kimball et al. (2009) imputed coefficients of relative risk aversion in the 1996 wave of the PSID.

Table 14: The Distribution of Risk Aversion in the PSID (Kimball et al., 2009)

<table>
<thead>
<tr>
<th>Group</th>
<th>( \gamma )</th>
<th>N</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>6.7</td>
<td>1,230</td>
<td>30.15</td>
</tr>
<tr>
<td>2</td>
<td>4.2</td>
<td>728</td>
<td>17.85</td>
</tr>
<tr>
<td>3</td>
<td>3.5</td>
<td>629</td>
<td>15.42</td>
</tr>
<tr>
<td>4</td>
<td>2.8</td>
<td>620</td>
<td>15.20</td>
</tr>
<tr>
<td>5</td>
<td>2.2</td>
<td>582</td>
<td>14.27</td>
</tr>
<tr>
<td>6</td>
<td>1.4</td>
<td>290</td>
<td>7.11</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>4,079</td>
<td>100.00</td>
</tr>
</tbody>
</table>

While it is nonetheless tempting to leverage these stated preferences in some way to identify risk aversion,
I choose not to because they do not appear to predict savings behavior. I demonstrate this in Figures 20 and 21, which use the 2003 wave as it is the closest sample year to when preferences were elicited in 1996. Figure 20 plots local polynomial regressions of savings relative to earnings separately for the most risk averse and least risk averse PSID respondents based on the hypothetical gamble questions. There is no discernible difference in their savings behavior. The same puzzle appears in Figure 21, where I plot the density of savings to earnings ratios for the purportedly most and least risk averse groups. Once again, the two groups exhibit remarkably similar behavior. Because of this lack of expected differences in behavior, I avoid using these hypothetical gambles to identify the model here, leaving further exploration of the empirical content of the risk preference survey questions to future work.

Figure 20: Savings per earnings by risk preference level (PSID)

![Figure 20: Savings per earnings by risk preference level (PSID)](image)

Figure 21: Savings-income ratios by risk preference level (PSID)

![Figure 21: Savings-income ratios by risk preference level (PSID)](image)

E Value function details

E.1 Value function for the firm

Recall that the present discounted expected value of a match for the firm be

$$\Pi_\epsilon = \frac{1}{1 + \rho} \left( \alpha x - \epsilon + \lambda_1 P_s(x) \Pi_\epsilon + \eta \int_0^{\epsilon^*(x)} \Pi_{\epsilon'} f(\epsilon') + (1 - \lambda_1 - \eta - \delta_0) \Pi_\epsilon + \delta_0 \right)$$

\[(42)\]
where $P_s$ is the probability that a worker stays after receiving an outside offer, the discount factor $\beta = \frac{1}{1 + \rho}$, $f(\varepsilon)$ is the density of $\varepsilon$ shocks, and $\varepsilon^*(x)$ is the threshold for a shock that is large enough for the firm to terminate the match. In a new match, $\Pi_0', \varepsilon = 0$.

Rewriting and collecting terms,

$$
(\rho + \lambda_1 P_s(x) + \eta + \delta_0) \Pi_{\varepsilon} = \alpha x - \varepsilon + \eta \int_0^{\varepsilon^*(x)} \Pi_{\varepsilon'} f(\varepsilon') \, d\varepsilon' \tag{43}
$$

Integrating by parts on the righthand side, the value can be rewritten as

$$
(\rho + \lambda_1 P_s(x) + \eta + \delta_0) \Pi_{\varepsilon} = \alpha x - \varepsilon - \eta \int_0^{\varepsilon^*(x)} \Pi_{\varepsilon'} F(\varepsilon') d\varepsilon' \tag{44}
$$

Further, we can see from equation 43 that

$$
\Pi_{\varepsilon'} = \frac{-1}{\rho + \lambda_1 P_s(x) + \eta + \delta_0} \tag{45}
$$

For ease of notation, define that denominator term as

$$
D = \rho + \lambda_1 P_s(x) + \eta + \delta_0. \tag{46}
$$

Then, substituting back in to equation 44,

$$
D \Pi_{\varepsilon} = \alpha x - \varepsilon + \frac{\eta}{D} \int_0^{\varepsilon^*(x)} F(\varepsilon') d\varepsilon'. \tag{47}
$$

E.2 Layoff risk is decreasing in firm productivity

This can be seen by taking the derivative of the termination condition with respect to $x$:

$$
\varepsilon''(x) = \alpha + \frac{\eta}{D} \left( \varepsilon''(x) F(\varepsilon^*(x)) \right) + \frac{\eta}{D^2} D'(x) \left( \int_0^{\varepsilon^*(x)} F(\varepsilon') d\varepsilon' \right)
$$

$$
\left( 1 - \frac{\eta}{D} F(\varepsilon^*(x)) \right) \varepsilon''(x) = \alpha - \frac{\eta}{D^2} \left( -\lambda_1 P_s'(x) \right) \int_0^{\varepsilon^*(x)} F(\varepsilon') d\varepsilon
$$

$$
\left( 1 - \frac{\eta}{D} F(\varepsilon^*(x)) \right) \varepsilon''(x) = \alpha - \frac{\eta}{D^2} \left( -\lambda_1 P_s'(x) \right) (\varepsilon^*(x) - \alpha x) \frac{D}{\eta}
$$

$$
\varepsilon''(x) = \frac{\alpha + \lambda_1 P_s'(x) (\varepsilon^*(x) - \alpha x) / D}{1 - \frac{\eta}{D} F(\varepsilon^*(x))}
$$

The numerator is positive so long as $P_s'$ is not “very negative,” which is to say we assume any marginal increase in layoff risk as productivity rises is not drastic relative to the utility gain from the marginal increase in wage. This must always be true if we assume that in equilibrium a more productive firm offers no worse value for the most risk averse worker than does a less productive firm, because then $P_s'(x) \geq 0$. Since
E.3 Worker indifference condition and risk

Unemployed workers do not value layoff risk when deciding whether to accept a job. To see this, substitute for the discount factor $\beta$ with the discount rate $\rho$ as in the firm section, where $\beta = \frac{1}{1+r}$. We can rewrite the value functions

$$\rho U(a) = u(c) + U(a') - U(a) + \lambda_0 \int \max \{V(a', x) - U(a'), 0\} d\Gamma(x)$$

$$\rho V(a, x) = u(c) + V(a', x) - V(a, x) + \lambda_1 \int \max \{V(a', x') - V(a', x), 0\} + \delta (U(a') - V(a', x))$$

A worker is indifferent between accepting or rejecting a job offer when $V(a, x') = V(a, x)$. Plugging into the value function for employment at that indifference point yields the condition

$$u(c(a, w')) + \delta' (U(a) - V(a, x)) = u(c(a, w)) + \delta (U(a) - V(a, x))$$

$$\implies u(c(a, a')) = u(c(a, w)) + (\delta' - \delta)(V(a, w) - U(a))$$

The indifference condition for an unemployed worker with a certain level of savings is $U(a) = V(a, x)$. Given assets and risk aversion, the reservation wage and risk, $r(w, \delta; a, \gamma)$, can be characterized by considering the special indifference case where the value of employment equals the value of unemployment. Making this substitution into the value functions yields

$$u(c(a, b)) + \lambda_0 \int \max \{V(a', x) - U(a'), 0\} d\Gamma(x) = u(c(a, r)) + \lambda_1 \int \max \{V(a', x) - U(a'), 0\} d\Gamma(x)$$

$$\implies u(c(a, r)) = u(c(a, b)) + (\lambda_0 - \lambda_1) \int \max \{V(a', x) - U(a'), 0\} d\Gamma(x)$$

The righthand side does not depend on the reservation risk level. Suppose there were two reservation pairs $(r_1, \delta_1)$ and $(r_2, \delta_2)$ where $r_1 \neq r_2$. The only way to equate $u(c(a, r_1))$ and $u(c(a, r_2))$ is if $a_1' \neq a_2'$, which is a contradiction given the indifference condition assumes equal assets. Given assets and risk preferences, the reservation wage is independent of the risk offer. This creates a tension regarding risk preferences, as more risk averse workers have lower reservation wages, which come with a higher probability of sending them back into unemployment.

F CPS details and subgroup analysis

This appendix describes the construction of the CPS sample used for the motivating figures in section 1 and presents additional figures for various demographic subgroups and reported reasons for jobs ending to demonstrate that the central pattern is robust to these refinements.

F.1 Sample construction

The data includes every month in 2006, 2008, 2019, and 2020, downloaded from the IPUMS CPS service Flood et al. (2018) and makes use of their constructed user id to track respondents from month to month. The sample is restricted to labor force participants ages 18 to 69 who are not self-employed. Employment
status is measured each month of the respondent’s participation cycle, and earnings for each respondent are drawn from the most recent month when they reported earnings. All figures are weighted to using the final person-level weights.

F.2 Subgroup analysis

One possible explanation for this pattern is composition: lower earners could be different from higher earners in a way that is systematically related to their likelihood of becoming unemployed (Winter-Ebmer, 1995). On the basis of observable heterogeneity, this does not appear to be the case. As shown in Figure 22, there are no clear differences comparing high school or college educated workers, men and women, black and white workers, workers over and under 40, nor within a specific industry or occupational group; the broad pattern in Figure 1 persists. To reiterate the earlier point, the claim is not that there is no sorting in the labor market; it is that in aggregate as well as conditional on any sorting factors, layoff risk still decreases as earnings rise.

Figure 22: Monthly transitions into unemployment by earnings for various subgroups

A second question involves the distinction between quits and layoffs. It may be that lower earners are more likely to quit voluntarily. Here the charts display all transitions into unemployment because stated reasons for leaving a job may not necessarily reflect the true cause. For instance, a worker may “quit” in anticipation of being laid off. Nonetheless, to show that quit behavior is not driving the observed trend, in Figure 23 I plot separately the transition rate into unemployment across the earnings distribution for people who specifically state that they were laid off versus those who specifically state that they quit their job. Stated quits into unemployment are rare in the CPS data, and the pattern of a hazard declining in earnings is clear when solely examining stated layoffs.
Figure 23: Monthly transition rate into unemployment by weekly earnings - quits vs. layoffs