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FEDERAL RESERVE BANK OF CLEVELAND

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Job Ladders and Earnings of Displaced Workers

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Workers who suffer job displacement experience surprisingly large and persistent earnings losses. This paper proposes an explanation for this robust empirical puzzle in a model of search over match-quality with a significant job ladder. In addition to capturing the depth and persistence of displaced-worker-earnings losses, the model is able to match a) separation rates by tenure; b) the empirical decomposition of earnings losses into reduced wages and employment; c) observed wage dispersion; d) the pattern of employer-to-employer transitions after layoff, and e) the degree of serial correlation in separations.

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1 Introduction

In the United States, displacements (e.g. layoffs) affect many participants of the labor market. According to the Displaced Worker Supplement of the Current Population Survey, 6.9 million workers with at least three years of tenure experienced job loss due to layoff from 2007 to 2009 (Bureau of Labor Statistics, 2010). An additional 8.5 million persons were laid-off from jobs they had held for less than three years. Davis and von Wachter (2011) (henceforth DV) find that, from 1980 to 1985, 16 percent of prime-aged males with three or more years of job tenure experienced a displacement.

In conjunction with the high incidence of displacement, there exists a long and distinguished literature documenting large and persistent earnings losses associated with displacement.[1] Despite heterogeneity in the findings, post-displacement earnings losses seem almost universal, affecting men and women, workers in all major industries, the young and the old, and workers with varying amounts of tenure. For example, DV find that at the time of displacement real earnings fall sharply, and even twenty years after displacement, annual earnings are 10-20 percent below pre-displacement earnings.

The model presented in this paper provides an explanation for the magnitude and persistence of post-displacement earnings losses. The first part of the explanation is the presence of a substantial job ladder through the presence of match-specific human capital, similar in spirit to Jovanovic (1979, 1984).[2] The job ladder captures the idea that workers suit some jobs better than other jobs, and it takes time for workers to find the jobs for which they are well suited. This concept prolongs earnings recovery after displacement as non-employed workers enter poor employment relationships and search for better matches while employed.

The second key outcome of the model is that it endogenously delivers elevated separation rates into non-employment after an initial employment-to-non-employment (E-N) transition.[3] These transitions slow down workers' climb up the job ladder because each separation event sends workers back to the first rung on the ladder. The model captures the following intuition: compared to their job prior to job loss, workers might not be as well matched in their first job coming out of non-employment. This results in tentative new employment

[1]For a rough progression of the frontier see Ruhm (1987), Topel (1990), Jacobson, LaLonde and Sullivan (1993), Stevens (1997), Couch and Placzek (2010), and Davis and von Wachter (2011).

[2]Insofar as it tests the extent to which observed wage dispersion can account for the earnings losses of displaced workers, the current paper is a quantitative investigation into many of the themes in Rogerson (2011).

[3]Although in a different framework, Menzio and Shi (2011) also have this feature implicitly when matches are experience goods. Pinheiro and Visschers (2013) have a job ladder model where the jobs at the bottom of the ladder have the highest probability of unemployment associated with them. Neither paper studies displaced worker earnings.

relationships; small downward movements in productivity (demand) can terminate these relationships. This serial correlation coincides with empirical work by Stevens (1997) who finds that multiple additional job losses are an important part of workers' post-displacement experiences. I also present evidence for this phenomenon in Section 5.2.2. This serial correlation in E-N transitions helps the model match the decomposition of lost earnings into reduced employment and lower wages.

The following analysis shows that the current model, when calibrated to match the average job ladder in the economy, goes a long way towards capturing the earnings time-path of displaced workers. As part of the calibration, the model matches average worker flows, separation rates by tenure, including employment-to-non-employment and employer-to-employer (E-E) probabilities, and wage dispersion, all of which play an important role in the success of the model. In addition to capturing these aspects of the data, the model also matches several moments of the data that it was not calibrated to target. These over-identification tests reveal that the model delivers the empirical decomposition of earnings losses into reduced wages and employment, the pattern of E-E and E-N transitions after layoff, the tenure distribution, and is broadly consistent with observed wage gains associated with E-E transitions and empirical returns to tenure.[4] What emerges is a coherent picture of displaced worker earnings dynamics that dovetails neatly into other prominent stylized facts on wages, employment, tenure and mobility patterns.

The current framework also provides a resolution to the tension described in Hornstein, Krusell and Violante (2011). These authors find that equilibrium search models, even those featuring on-the-job search, consistent with observed data on worker flows, deliver far less wage dispersion than empirically observed. The tension arises because non-employed workers are observed to accept jobs relatively quickly, which means that wage dispersion has to be small. To capture the magnitude of observed wage dispersion, the current framework requires a notion of newly hired individuals transitioning to jobs with poor quality matches.[5] This "stepping stone" nature of the first job not only induces an increased hazard of separation into non-employment, but it also grants workers access to jobs with a better match-quality component. This investment motive of initial jobs can reduce initial wages, thereby raising equilibrium wage dispersion. Furthermore, non-employed workers can be quick to accept

[4] When measuring the returns to tenure I use the approaches highlighted in Altonji and Shakotko (1987). The estimates of the empirical returns to tenure are not conclusive. Altonji and Shakotko (1987), Altonji and Williams (2005), and Altonji, Smith and Vidangos (2013) find small effects, while Topel (1991) finds large effects. When measuring the wage gains associated with E-E transitions I use the approach of Topel and Ward (1992).

[5] I provide empirical support for this structure using worker transitions in Section 5.2.2.

jobs, while the economy features substantial wage dispersion, because they do not sample the entire wage distribution.[6]

This paper is not the first to consider a model of displaced workers' earnings losses with E-E transitions. The work of DV is most closely related to the work presented here. They show that a standard Mortensen-Pissarides (MP) model, and a more sophisticated model found in Burgess and Turon (2010) (henceforth BT), cannot explain observed displaced worker earnings losses. The BT model features E-E transitions and match-specific productivities, but the model presented in this paper differs from BT in two crucial ways. First, as described in the previous paragraph and consistent with empirical observation, workers recently transitioning from non-employment to employment face higher hazard rates of separation into non-employment than workers in established employment relationships. This serial correlation causes cycles of job loss which propagate the effect of one displacement. All workers in the model of BT face the same hazard rate into non-employment. Second, the model presented here matches observed wage dispersion. This feature implies a substantial job ladder, far "longer" than the job ladder found in BT, and it takes time for workers to move from a poorly suited job to a very well suited job.

The concurrent work of Jung and Kuhn (2014) is also highly relevant. That paper and the current work share many themes, including a robust quantitative explanation for the earnings losses of displaced workers, the decomposition of lost earnings into reduced wages and employment, accurate worker mobility patterns, and realistic wage dynamics. Many of the conclusions are also similar. For example, Jung and Kuhn (2014) suggest that 85 percent of the wage losses resulting from displacement stem from losses of match-specific skills, and 15 percent due to worker-specific skills. The current paper reaches a similar conclusion by delivering the wages of displaced workers without appealing to worker-specific skills. Aside from these shared themes, the main difference between these two analyses is that Jung and Kuhn (2014) examine a richer model that incorporates life-cycle considerations, while the present model abstracts from these in the interest of parsimony. The modeling challenge of explaining the very persistent earnings losses of displaced workers in a stationary environment comes down to endogenously generating a strong internal propagation mechanism. Jung and Kuhn (2014) appeal to the worker's life-cycle in order to achieve this, and this is natural since life-cycle considerations generate non-stationarity in an individual's lifetime, while preserving stationarity in the overall economy. In the current paper, I show that even without modeling the life-cycle dimension of the worker's problem, matching separation rates by tenure and observed wage dispersion also is able to deliver the earnings trajectory of displaced workers.

[6] I thank an anonymous referee for framing the resolution in this way.

Low, Meghir and Pistaferri (2010) investigate a model that has similar features to the one described here, such as on-the-job search, match-quality and search frictions. In contrast to my paper, their emphasis is on distinguishing between employment risk and productivity risk. However, they do report the implications of their model for the cost of layoff, noting that these losses are relatively small and short-lived. This underscores the key contribution of the present paper, which is its ability to match the magnitude and persistence of displaced worker earnings losses.[7]

Pries (2004) is an early, closely related paper. His model generates serially correlated job loss by making matches experience goods. Pries shows that this recurring job loss contributes to displaced worker earnings trajectories. The current paper makes two contributions relative to the work of Pries. First, the baseline model presented here includes on-the-job search and can therefore speak to additional issues, like E-E flows after separations, and average E-E probabilities by tenure. In particular, my model suggests a reduction in E-E probabilities by tenure as high-tenured workers are more likely to be well-matched and therefore less likely to find more suitable employment opportunities, and increased E-E flows after a separation into non-employment as workers switch jobs more readily when low on the job ladder. Sections 4.3 and 5.2.2 present evidence from the Panel Study of Income Dynamics (PSID) that corroborates these implications of the model. Second, Pries reports that in the six years after displacement, lower employment accounts for about two-thirds of the decline in earnings post-displacement, with lower average wages accounting for the remaining one-third. In contrast, the data suggest that one year after displacement, reduced wages are responsible for the majority of the earnings loss, and four years after displacement reduced employment is responsible for only one-fourth of the earnings losses. In Section 5.2.1 I show that the model presented here captures this decomposition of earnings losses into reduced employment and lower wages.

Den Haan, Ramey and Watson (2000) analyze a class of models without on-the-job search and conclude that the productivity of a match must drift upwards to explain the wage and employment evidence presented by displaced workers. The authors note that due to rising within-match productivity their framework requires implausibly large productivity shocks to induce a separation. With on-the-job search, productivity within the match does not have to grow over time as wages can rise from employer-to-employer transitions. Hence, the

[7] Since the present work and Low, Meghir and Pistaferri (2010) have different emphasis, and the models differ substantially, with distinct calibration approaches, it is difficult to pinpoint why the two approaches imply different costs of displacement. One potential reason is that the current paper targets the E-N transition probabilities by tenure, whereas Low, Meghir and Pistaferri (2010) do no consider these worker mobility patterns.

model described in this paper can match the evidence on displaced workers with a reasonable productivity process.

Ljungqvist and Sargent (1998) present a model that also features earnings losses following displacement. Their framework exogenously stipulates skill accumulation on the job as well as human capital loss due to layoff. Moreover, their model features exogenous separations only and therefore cannot match the observed separation rates by tenure. My model endogenizes match-specific skill accumulation while employed, and therefore the earnings losses following displacement, and matches empirical separation rates by tenure.[8]

The framework here does not incorporate adverse selection; workers do not vary ex-ante by ability. Non-employed workers are all identical, and the following analysis ignores selection. The reason for this is twofold. First, von Wachter, Song and Manchester (2011) investigate selection extensively, controlling for observed characteristics, such as differential trends by industry and firm, unobserved characteristics, such as time-invariant worker attributes, as well as selection within and between employers. These authors conclude that the baseline approach presented in this paper provides a reasonable account of the earnings experience of displaced workers.[9] Second, this project highlights that, despite ex-ante homogeneity among workers, the losses from displacement can be large and persistent.

The rest of the paper is organized as follows. Section 2 presents the details of the model and Section 3 discusses the relevant empirical data. Section 4 discusses the calibration strategy and outcomes, and Section 5 presents the main results of the analysis, including the earnings losses of displaced workers and numerous other un-targeted moments. Section 6 presents a discussion about the inadequacy of alternative versions of the model. Section 7 summarizes and draws lessons for future research.

[8]Another potential explanation for displaced worker earnings losses is loss in occupation-specific human capital as in Kambourov and Manovskii (2009). The estimates regarding the earnings losses after displacement by occupational status are inconclusive. Stevens (1997) (Table 5, column 4) reports a complete recovery for displaced workers who did not switch occupations in the PSID. However, she also reports a complete recovery for workers who do not switch industries, and this is contradicted by administrative data used by Jacobson, LaLonde and Sullivan (1993), who report significant earnings losses for displaced workers even if these workers find jobs in their old four-digit industry.

[9]Some literature argues that non-random selection occurs prior to the mass layoff event (see, for example, Bowlus and Vilhuber, 2002, and Schwerdt, 2011). It appears that these early leavers experience earnings losses that are around 20 percent smaller than displaced individuals. This still leaves significant earnings losses many years after displacement.

2 The Model

This section presents a theoretical framework of job search and provides intuition for the model's key implications.

2.1 Model Introduction

The work on search and matching by Mortensen, Diamond and Pissarides provides the foundation for this paper. Two quantities characterize every match: the quality of the match and idiosyncratic productivity (demand). The framework incorporates endogenous privately efficient separations, which means that worker and firm act to maximize their joint value, as well as exogenous separations and on-the-job search. In this model all non-employed workers are identical and workers are endowed with linear utility (risk-neutrality).

2.2 Setup

A partial equilibrium model serves as the basis for analysis. Workers look for jobs and firms post vacancies to attract workers. Non-employed workers receive utility from leisure and encounter vacancies at an exogenous probability p_U.[10] Employed workers receive a flow payment w and produce a flow output. Employed workers participate in on-the-job search and contact vacancies at a different probability p_E.[11] All employer-employee matches are characterized by two state variables: match-quality denoted by y, and idiosyncratic productivity (demand) denoted by x. The product of x and y ($x \cdot y$) provides the flow output of the match. When a non-employed worker contacts a firm, the match draws an initial, deterministic match-quality, y_0.[12] Match-quality remains constant within a job. The notion that newly hired workers transition to jobs with low match-quality is necessary for the model to match observed wage dispersion as documented by Hornstein, Krusell and

[10]The model does not feature differing job-finding rates by duration of non-employment. Empirically, it is not obvious that the decline in job-finding rates by unemployment duration is a causal effect of duration, or an artifact of dynamic selection (see, for example, Salant, 1977). In the absence of definitive empirical evidence on this issue, it seems reasonable to look for alternative explanations for the large and persistent earnings losses faced by displaced workers. Moreover, to the extent that unemployment duration lowers job-finding rates and affects employment probabilities, this effect would be seen through reduced employment after displacement, which is relatively short-lived among displaced workers. Even if one assumed low monthly job-finding rates for the unemployed, on the order of 10 or 15 percent, this would only lower employment rates for a couple of years relative to the current framework.

[11]The differing job contact probabilities on and off the job may result from differing search technologies for the employed and non-employed. The model presented here does not formally address this difference.

[12]It is not imperative that the initial match-quality be fixed; rather, the distribution of match-quality faced by the non-employed must be to the left of the distribution of match-quality faced by the employed.

Violante (2007), a point to which I return to later. One way to motivate this low match-quliaty for workers coming out of non-employment is in the context of internal labor markets as described by Doeringer and Piore (1971), and more recently Martins, Solon and Thomas (2010). These initial jobs can be thought of as "port-of-entry" jobs; jobs into which employers are consistently observed to hire new workers.

All initial idiosyncratic productivities (demands) are fixed at a deterministic value, x_0, and then exhibit persistence within a match evolving according to $F_x(x'|x)$. Setting x to x_0 in all new matches follows Mortensen and Pissarides (1994). On-the-job search results in offers to the employed with match-quality drawn from $y \sim F_y(\tilde{y})$. This induces a job-ladder which agents climb over time. This can be interpreted as finding more suitable jobs while employed and slowly transitioning to one's "ideal" job.

The idiosyncratic component delivers endogenous flows into non-employment; when the realization of the idiosyncratic random variable is low enough, the worker and the firm decide to part ways. Involuntary endogenous separations on either side of the market do not occur in this model. The model does incorporate exogenous separations, however.

2.3 Timing of Events within a Period

Within each period, events among non-employed workers unfold according to the following timing. At the outset of a period firms post vacancies to recruit non-employed workers, and workers look for jobs. When workers contact open vacancies the worker and firm consummate the match. New matches wait until next period to produce, where δ denotes the discount factor. For established employment relationships the timing for workers and firms is as follows. First, firm and worker bargain over the wage. Second, production occurs and the firm pays the worker. Third, the exogenous separation shock occurs with probability p_s. Fourth, the idiosyncratic component, x, undergoes a shock. Finally, workers receive outside offers with probability p_E. If an employed worker receives a favorable outside offer, he moves to the poaching firm. If an employed worker receives no outside offer, the firm and the employee decide to preserve the match or separate.

2.4 Bargaining

At the beginning of each period, every worker-firm pair bargains over the wage that the firm pays the worker for production. This model features a linear surplus sharing rule, so that the worker (firm) receives a fraction, β $(1-\beta)$ of the total match surplus. If an employed worker receives a favorable outside offer, he moves to the poaching firm, and renegotiates his wage using non-employment as his outside option.[13] If an employed worker receives an outside offer that does not induce a switch, the worker cannot use that outside offer to negotiate with his current employer. Appendix A outlines a model with efficient rigid wages, similar to a framework found in MacLeod and Malcomson (1993).[14] In that model, workers can use their current offer to bargain with an outside firm, and they can use outside offers to raise their wage at the current firm. This alternative model delivers very similar results to the model that features the simple surplus sharing rule. To remain consistent with previous work, the benchmark model in this paper implements the standard surplus sharing protocol.

2.5 Intuition for the Partial Equilibrium Model

The model delivers a slow recovery in earnings post-displacement for three reasons. First, immediately post-displacement the calibrated model suggests that workers take jobs with lower match-qualities compared to their pre-displacement jobs. Second, the job ladder introduces persistence in earnings; it takes time for employed workers to find good quality matches. Third, low post-displacement match-qualities mean that newly created jobs are likely close to the job destruction threshold. This makes it more likely that these matches will be destroyed, resulting in multiple separations into non-employment. This serial non-employment dovetails with empirical work by Stevens (1997) who finds that multiple job losses explain some of the persistence of earnings losses.

2.6 Bellman Equations

This subsection deals with the formal recursive equations of the model. The value of work satisfies the following equation:

[13] Nagypal (2007) also uses this convenience in an on-the-job search model. In the setup of Postel-Vinay and Robin (2002) workers can use the surplus at their previous firm as an outside option. That setup includes no idiosyncratic productivity so that all wage changes within a firm result from outside offers. Including idiosyncratic productivity into this type of model gives the efficient rigid wage model presented in Appendix A. Also, Shimer (2006) points out that with on-the-job search the simple surplus splitting rule may not be Pareto efficient. Given that the efficient rigid wage model in Appendix A delivers qualitatively similar results, I suspect that amending this model's bargaining structure will not yield substantially different conclusions.

[14] The appendices are provided for the reader's interest and are not necessary in the published version of this paper.

$$
\begin{aligned}
W(x,y) = w + \delta(1-p_E)(1-p_s) \int & \underbrace{\max\{U, W(x',y)\}}_{\substack{\text{Match continues or}\\ \text{terminates}}} dF_x(x'|x) + \underbrace{\delta p_s U}_{\substack{\text{Exogenous}\\ \text{separation}}} \\
+ \delta p_E(1-p_s) \int\int & \underbrace{\max\{U, W(x',y), W(x_0,\tilde{y})\}}_{\substack{\text{Worker moves to non-employment,}\\ \text{stays at current firm,}\\ \text{or goes to new firm}}} dF_x(x'|x) dF_y(\tilde{y})
\end{aligned} \tag{1}
$$

The first term on the right hand side is the flow payoff from working, which is the current wage: w. The second term on the right hand side corresponds to the event of no outside job offer. Since the productivity shock arrives every period, this term captures what happens when the productivity changes. If $W(x',y) > U$ there is positive surplus, and the worker and firm bargain over the new wage. If $W(x',y) < U$ the relationship is no longer viable. The employment partnership comes to an end. The third term on the right hand side captures exogenous separation, in which case the worker flows into non-employment and receives U.

The fourth term on the right hand side corresponds to the worker contacting an outside firm. The worker leaves the current employment relationship only if the match value of the new match exceeds the value at the current firm. In this case, the worker chooses between two options: non-employment and working at the new firm. In the latter case, the worker bargains with the outside firm using non-employment as his outside option. In the event that the match value at the current firm exceeds both the value of non-employment and the match value at the outside firm, the worker remains at the current firm receiving value $W(x',y)$. If the value of non-employment exceeds the worker's value at the current firm and at the outside firm, the worker moves to non-employment receiving continuation value U.

The value of a filled job to the employer satisfies the following equation:

$$
\begin{aligned}
J(x,y) = x \cdot y - w + \delta(1-p_E)(1-p_s) \int & \underbrace{\max\{0, J(x',y)\}}_{\substack{\text{Match continues or}\\ \text{terminates}}} dF_x(x'|x) \\
+ \delta p_E(1-p_s) \int\int & \underbrace{\mathbb{I}\{J(x',y) \geq J(x_0,\tilde{y})\}}_{\substack{\text{Worker turns down}\\ \text{poaching firm}}} \underbrace{\max\{0, J(x',y)\}}_{\substack{\text{Match continues or}\\ \text{terminates}}} dF_x(x'|x) dF_y(\tilde{y})
\end{aligned} \tag{2}
$$

The first term on the right is the flow payoff from a filled job, the output $x \cdot y$, less the wage paid to the worker for production w. The second term on the right corresponds to the event of no outside job offer, and no exogenous separation shock. It is completely analogous to the value of work. The third term on the right hand side corresponds to the worker contacting an outside firm. If the worker stays at the current firm, the expression is the same as if no outside offer was made. If the worker leaves the current employment relationship, the current firm's continuation value equals zero.

The value of non-employment satisfies:

$$U = b + \delta(1-p_U)U + \delta p_U \underbrace{\max\{U, U + \beta[W(x_0,y_0) + J(x_0,y_0) - U]\}}_{\text{Match consummates or not}} \tag{3}$$

where p_U is the probability that an non-employed worker contacts a vacancy. The first term captures the flow payoff from non-employment: b. The second term corresponds to no job offer, so the worker remains non-employed. The third term corresponds to a job offer. In this case the worker chooses between working at the contacting firm and non-employment. The payoff from working at the firm is the outside option, U, plus β times the surplus.

2.7 Solving the Model

The expressions in the previous section can be summarized in one central functional equation: the surplus from a match, $S(x,y)$. Appendix B provides the details of this derivation. Here I simply present the result:

$$\begin{aligned} S(x,y) = {} & x \cdot y + \delta \underbrace{(1-p_E)}_{\substack{\text{No outside}\\ \text{offer}}} \underbrace{(1-p_s)}_{\substack{\text{No separation}\\ \text{shock}}} \int \max\{0, \underbrace{S(x',y)}_{\substack{\text{Match}\\ \text{continues}}}\} dF_x(x'|x) \\ & + \delta p_E(1-p_s) \int\int \Bigg[\underbrace{\mathbb{I}\{S(x',y) \geq S(x_0,\tilde{y})\}}_{\substack{\text{Worker turns down}\\ \text{poaching firm}}} \underbrace{\max\{0, S(x',y)\}}_{\substack{\text{Match continues or}\\ \text{terminates}}} \\ & + \underbrace{\mathbb{I}\{S(x',y) < S(x_0,\tilde{y})\}}_{\substack{\text{Worker leaves}\\ \text{current firm}}} \underbrace{\max\{0, \beta S(x_0,\tilde{y})\}}_{\substack{\text{Match at new firm}\\ \text{or non-employment}}} \Bigg] dF_x(x'|x) dF_y(\tilde{y}) \\ & - \underbrace{[b + \delta p_U \beta \max\{0, S(x_0,y_0)\}]}_{\text{Worker's outside option}} \end{aligned} \tag{4}$$

The first part of the right hand side is the flow payoff from a match, $x \cdot y$. The second piece captures the event of no outside job offer, no exogenous separation shock and the continuation surplus of the match. In this case, the match either comes to an end or the match continues with the new idiosyncratic productivity. The third piece captures the event of the worker receiving an outside offer and potentially moving to the poaching firm. When the worker moves to the poaching firm he uses non-employment as a threat point, and then the current firm has zero continuation value and the worker's continuation value is $\beta S(x_0, \tilde{y})$. The final piece is the outside option of an employed worker: he forgoes the value of non-employment, b, and the possibility of finding a new job with surplus $S(x_0, y_0)$ and receiving β of this surplus. Notice that equation (4) is a functional equation in only $S(x, y)$, and the surplus sharing rule pins down the equilibrium wage equation as a function of (x, y).[15]

3 Data

Aside from the empirical results on displaced worker earnings from Davis and von Wachter (2011), and the estimates of wage dispersion from Hornstein, Krusell and Violante (2007), the data come exclusively from the PSID family and individual-merged files. The PSID began in 1968 with an interview of approximately 5,000 families, and follows any new families formed from the original group of families. I use the 1988-1997 waves of the PSID. In the survey years prior to 1988 the PSID did not collect monthly strings on employment status at different employers so it is not possible to calculate monthly E-E probabilities for these years. To avoid the complication of biennial interviews, I only use data up to the 1997 survey. To obtain results that are comparable to alternative data sources, I restrict the sample to working-age males, aged 18 through 65. I omit the self-employed and use individual weights to account for the PSID's poverty over-sample and non-random attrition.

For the years 1988-1997, respondents were asked to report their employment status in each month of the previous calendar year, as well as monthly employment strings for up to two main employers.[16] From these monthly strings I construct transition probabilities between employment and non-employment, as well as between employers. Appendix C provides benchmark average transition probabilities that are broadly consistent with values obtained from the Survey of Income and Program Participation (SIPP) and Current Population Sruvey (CPS).[17] I use information from these flows together with the respondent's time at the present employer to calculate monthly employer tenure. Appendix C provides average employment-to-unemployment (E-U) transitions probabilities by age and tenure. These profiles line up well with identical plots from the SIPP, as in, for example, Menzio, Telyukova and Visschers (2012) (Figure 2 and Figure 9).

[15] See Appendix B for the derivations. This appendix also provides details regarding the numerical solution.

[16] To remain consistent with the model, I treat unemployment and out-of-the-labor-force as the same state when calculating layoff rates.

[17] These PSID data have also reliably been used in papers such as Low, Meghir and Pistaferri (2010).

4 Calibration

This section discusses the processes of state variables, the calibration strategy and the results of the calibration exercise for targeted moments.

4.1 Idiosyncratic Productivity (x) and Match-Quality (y)

The model period length is one month. Idiosyncratic productivity starts out at a fixed and deterministic level x_0 in all new matches, and then within the match follows a log AR(1) process:

$$\ln x' = \rho_x \ln x + \epsilon'_x \tag{5}$$

where $\epsilon'_x \sim \mathcal{N}(0, \sigma^2_{\epsilon_x})$. This process captures the intuition that productivity at the match level, or demand for the match's output, exhibits some persistence. Match-quality follows the process:

$$\ln y' = \begin{cases} \ln y_0 & \text{for jobs out of non-employment (N} \rightarrow \text{E)} \\ \ln y & \text{if no job change} \\ \epsilon'_y & \text{if changes jobs (E} \rightarrow \text{E)} \end{cases} \tag{6}$$

where $\epsilon'_y \sim \mathcal{N}(0, \sigma^2_{\epsilon_y})$. Hence, match-quality remains constant within a job, and is log-normally distributed when a worker meets a new firm. In the first job coming out of non-employment, match-quality is set to y_0.

4.2 Calibration Methodology

This section presents the key moments of the data and discusses the calibration strategy.

To accurately capture the empirical mobility patterns, I use the average E-N and E-E probabilities for different levels of tenure to discipline the model.[18] This model delivers increased hazard rates of separation into non-employment for individuals recently hired out of non-employment due to the "slippery stepping stone" nature of the first job out of non-employment. This implication follows from an interaction between the low match-quality in first jobs, along with the idiosyncratic productivity process. Without an idiosyncratic component, matches would terminate via exogenous separations only and the E-N transition would be the same for every level of tenure. With idiosyncratic variation there exists a non-trivial profile of average E-N probabilities by tenure. For a starting idiosyncratic component,

[18] I thank an anonymous referee for suggesting these as calibration targets.

x_0, and idiosyncratic volatility, σ_{ϵ_x}, the initial match-quality level, y_0, will determine the E-N probability in the month right after non-employed individuals find jobs. With a smaller y_0, there will be a larger E-N probability for recently hired individuals due to a smaller surplus in first jobs. The volatility of the idiosyncratic process, σ_{ϵ_x}, will shift this entire profile up and down as it affects the probability of separation into non-employment at all match-quality levels. The persistence of the idiosyncratic process, ρ_x, will help determine the rate at which the separation rate into non-employment, and between employers, declines with tenure. I use the separation rate of high-tenured workers to identify the exogenous separation rate p_s. Workers in sufficiently high-quality matches will be insulated from layoffs due to idiosyncratic productivity movements; however, the data call for non-trivial separation rates for these individuals. The model will deliver separation rates for very well-matched individuals via exogenous separation shocks. Hence, the average E-N tenure profile helps identify the idiosyncratic volatility, the starting match-quality, and the exogenous separation probability.

To calibrate the standard deviation of match-quality, σ_{ϵ_y}, I use the empirically observed wage dispersion, as documented by Hornstein, Krusell and Violante (2011) (henceforth HKV) and Tjaden and Wellschmied (2014). In their working paper, Hornstein, Krusell and Violante (2007) use data from the Census, Occupational Employment Survey and PSID to document mean-min wage ratios between 1.5 and 2. Tjaden and Wellschmied (2014) use data from the SIPP to document a mean-min wage ratio of 2.14.[19] HKV show that standard search models generate mean-min wage ratios much closer to one. They suggest that models with on-the-job search can attain more realistic mean-min wage ratios. I choose the standard deviation of match-quality to target a mean-min wage ratio of two, at the upper end of the HKV estimates, and below the estimate of Tjaden and Wellschmied (2014). The current model has several features that deliver this substantial wage dispersion. First, consistent with HKV, the model features on-the-job search, which helps raise the sustainable mean-min wage ratio. Second, the "stepping stone" nature of the first job grants workers access to jobs with a better match-quality component. This investment motive of initial jobs can reduce initial wages, as workers are willing to pay for this when bargaining with their employer, thereby raising equilibrium wage dispersion. Moreover, non-employed workers can be quick to accept jobs, while the economy features substantial wage dispersion, because they do not sample the entire wage distribution. Rather, all jobs coming out of non-employment have match-quality fixed at y_0. I will show that delivering substantial wage dispersion is important for

[19] Both papers report a conservative estimate of the mean-min wage by calculating the observed ratio of the mean wage to the fifth percentile of the wage distribution. I follow this approach in the simulated data.

the success of the baseline model in explaining the depth and persistence of displaced worker earnings losses. Put another way, it seems that the "bad luck" associated with losing one's job can explain much of the poor recovery in post-displacement earnings observed in the data.

The value of leisure, b, is chosen to target an average layoff rate into non-employment of 1.4 percent in the PSID data. The intuition here is straightforward: the higher the value of non-employment, the more attractive non-employment becomes and hence the higher the average layoff rate. As HKV point out, this parameter is important for the amount of wage dispersion in search models. Reducing the value of non-employment can raise the amount of wage dispersion because large non-employment-to-employment (N-E) flows may be the result of small (even negative) flow payments while out of work, not necessarily little wage dispersion.

The observed E-E transition probability is targeted using the contact rate for the employed, p_E. Raising the number of contacts employed workers have with outside firms raises the probability that workers experience E-E switches. Intuitively, this implies that E-E flows in the model are monotonically increasing in p_E. The PSID data imply that an average of 1.7 percent of employed persons change employers each month.

The contact probability for the non-employed, p_U, is determined by targeting a 17 percent monthly job-finding probability for the non-employed.[20] As in Bils, Chang and Kim (2011), the starting idiosyncratic productivity is set to the mean value of the unconditional distribution of x, denoted by $\mathbb{E}[x]$, implying no drift in the idiosyncratic component within a match. The bargaining power of the worker, β, is set to 0.5, realistic adjustments of which I have found to be immaterial. Finally, δ targets a five percent annual interest rate. I relegate the details of the calibration methodology and implementation to Appendix B.

[20] This is a convex combination of the 22 percent job-finding probability for the unemployed and the 4 percent job-finding probability for those workers that are not in the labor force (NILF), where the weights are determined by the fact that worker displacement results in unemployment three-quarters of the time, and NILF one-quarter of the time. The astute reader will notice that the non-employment state is treated asymmetrically for separation rates and job-finding rates. The job-finding rate for unemployed workers is markedly higher than for workers not participating in the labor market. Consequently, I include the NILF state in non-employment when calculating separation rates, but use the described convex combination when calculating job-finding rates.

4.3 Calibration Outcomes

The model has eight free parameters targeting 124 moments.[21] This section outlines how well the model delivers these targeted moments.

Table 1 summarizes the baseline parameters and the targeted empirical outcomes. Table 2 displays the simulated moments at the calibrated parameter values and shows that the model matches well the calibration targets. The model delivers the empirical mean-min wage ratio, as well as the average worker mobility patterns, including the average E-E, N-E and E-N flow probabilities. The model also delivers the separation probability of high-tenured workers.

Figure 1 compares the separation-tenure profile in the model and the data. It takes simulated data based on the calibration in Table 1, and plots the (smoothed) results of averaging the E-N dummies for each month of tenure. The model delivers the observed separation rates by tenure with around a four percent E-N probability for new hires, and around a 0.5 percent E-N probability for workers with five years of tenure. High-tenured workers separate from their employers due to exogenous separations, and therefore the exogenous separation probability pins down the E-N probability for these workers. The model delivers the rest of the profile via low match-qualities in initial matches and the idiosyncratic productivity component.

Similarly, the model speaks to E-E transitions by tenure. As workers make their way up the job ladder, their employment at the current job becomes more secure because they are less likely to find an even better match while searching on the job. Hence, the E-E probabilities should fall with tenure. I show the average E-E probabilities by tenure in Figure 2 in the baseline model and the PSID data. The calibrated model delivers E-E transitions by tenure that are entirely consistent with the data. For individuals with one month of tenure, E-E rates are approximately four percent, and they decline to around 0.6 percent for those with five years of tenure.

It is worth mentioning a few aspects of the calibration. The calibrated value of b in the current model turns out to be around 65 percent of the average labor productivity. This presents a reasonable estimate, compared to 40 percent of the flow wage in Shimer (2005) and 71 percent in Hall and Milgrom (2008). Previous estimates of the volatility and persistence of idiosyncratic shocks vary widely. Cooper, Haltiwanger and Willis (2005, 2007) estimate σ_{ϵ_x} from about 0.2 (in their 2007 paper) to 0.5 (in their 2005 paper). My estimate is on the

[21] The eight parameters are ρ_x, σ_{ϵ_x}, y_0, σ_{ϵ_y}, p_E, p_U, p_s, and b. The moments include the first five years of the E-N by tenure profile (60), the first five years of the E-E by tenure profile (60), the average E-E probability (1), the average layoff rate (1), the average N-E probability (1), and the mean-min wage ratio (1).

upper end of this broad range. As far as the persistence of idiosyncratic productivity shocks, the monthly estimates in Cooper, Haltiwanger and Willis (2005, 2007) are below 0.5, which is relatively low compared to estimates in, for example, Foster, Haltiwanger and Syverson (2008), which are around 0.95. My estimate is well within this range.

The amount of wage dispersion, as determined by the volatility of match-quality, is difficult to compare to DV, because they do not report the mean-min wage ratio for their calibrated BT model. A comparable statistic is the max-min wage ratio. In the calibrated model of this paper, at the average idiosyncratic productivity among employed workers, the maximum wage exceeds the minimum wage by around 400 percent, which compares to only 49 percent in the BT model presented in DV. Finally, at the solution, y_0 falls around one and a half standard deviations below the average match-quality among employed workers.

5 Results

This section presents results concerning the earnings losses of displaced workers, and compares numerous other un-targeted moments of the model to the observed data.

5.1 Earnings Losses of Displaced Workers

To compare the simulated and observed data, the simulated monthly wage information is aggregated into annual earnings data and the following equation is estimated, which is equivalent to equation (1) in DV:

$$e_{it}^y = \alpha_i^y + \sum_{k=-6}^{20} D_{it}^k \delta_k^y + u_{it}^y \tag{7}$$

where the superscript y denotes the displacement year, the outcome variable e_{it}^y is annual earnings of individual i in year t, α_i^y represents an individual fixed effect, D_{it}^k are dummy variables equal to one in the worker's kth year before or after his displacement and zero otherwise, and the error u_{it}^y represents random factors. Note that $k = 1$ denotes the displacement year and $k = 0$ denotes the final year of positive earnings from the pre-displacement employer. I omit time fixed effects because the model of this paper does not feature time variation in aggregate earnings. Exactly as in DV, I make the baseline seven and eight years before displacement. Although DV estimate this equation separately for each displacement year y, in the model presented in this paper all years are identical, so y is averaged over arbitrary years.

Sample selection follows DV exactly. I only include individuals in the treatment and control group if they have positive earnings in year y. I impose an identical tenure restriction on the sample: the worker must have positive earnings from the employer in question in $y-3$, $y-2$, and $y-1$. Furthermore, a worker "separates" from an employer in year y when he has earnings from the employer in $y-1$ but not in y and the worker experiences a separation into non-employment in year $y-1$. Conditioning on job loss is important because a worker may not have earnings from his previous employer in year y because of an E-E transition. These workers are not included in the treatment or the control groups.[22] I cannot impose the same "mass layoff" definition as DV because the model features one-worker firms.

For year y, the treatment group includes those workers displaced in year y, $y+1$ and $y+2$. Including workers from three years serves to smooth the estimated earnings effects of job displacement from year to year. The control group includes individuals with the same tenure requirement who remain with their employer in years y, $y+1$, and $y+2$. For the control group, $D_{it}^k = 0$ for all t so that the dummy variables reflect the change in earnings relative to this control group. The tenure restriction implies that around 75 percent of the displacements are due to exogenous separations and endogenous separations are responsible for the remaining displacements. Nonetheless, endogenous separations play a key role in explaining repeated transitions into non-employment after the displacement event.

Figure 3 presents a comparison between the results from the baseline model and the results from DV. The outcome is very encouraging, with the baseline model delivering an earnings trajectory that closely resembles the empirical counterpart. In terms of the present discounted value of earnings, DV find that for workers displaced in a boom, post-displacement earnings losses are worth roughly 1.7 years of pre-displacement earnings. The current model delivers over 95 percent of these losses. The search model outlined in this paper can account for much of the time-path of displaced worker earnings.

On impact the model predicts the losses in annual earnings well: around 35 percent. Additionally, the model captures the movements in earnings post-displacement very well. In the first year or two, the model overshoots slightly the earnings recovery, much like in Jung and Kuhn (2014), but subsequently provides a remarkable fit for the first 10 to 15 years. The model cannot deliver the plateauing, and even declining, earnings time-path after 10 years observed in the data. The model features ex-ante homogeneous agents and a stationary wage distribution, which together imply that eventually the earnings of displaced workers

[22] DV cannot condition on separation into non-employment because they use administrative earnings data; however they impose separation from a firm undergoing a "mass-layoff." This restriction limits the amount of quitters in the treatment group.

will recover. Nevertheless, after 20 years, the model implies earnings losses around three percent, above those found in the data, but similar to those found in the related Jung and Kuhn (2014) paper.[23]

Loss in match-quality results in the on-impact dip in earnings, as workers fall from higher rungs of the job ladder, to a low job rung in their first job out of non-employment. Earnings fall slightly in the year following displacement because workers who lose their jobs in year '0' take time to find new jobs. In addition, since $y_0 < \mathbb{E}[y|match]$, first jobs pay very little, meaning that wages in the year after displacement are particularly low.

The slow recovery in earnings represents the slow move up the job ladder for recently displaced workers, and manifests serially correlated E-N transitions, an effect I document quantitatively in Section 5.2.2. Agents experience serially correlated E-N transitions because match-quality remains low in first jobs and therefore only small movements in idiosyncratic productivity cause further separations into non-employment. The "long" ladder significantly postpones the worker's time to "ideal" job.[24,25]

The fact that the model can deliver the earnings losses of displaced workers without explicitly targeting this outcome is a remarkable accomplishment. DV show that a standard MP model, extended to incorporate on-the-job search, as in BT, delivers only about one-fourth of the earnings losses of displaced workers. Similarly, Low, Meghir and Pistaferri (2010) find that their model delivers relatively short-lived earnings losses associated with separation. The additional ingredients to the BT framework, including endogenously generated, elevated separation rates into non-employment after an initial E-N transition, and realistic wage dispersion, reconcile the current framework with the observed data. Jung and

[23]Davis and von Wachter (2011) do not present results that do not distinguish between expansions and recessions so a direct comparison to the model is not possible. In the live data, since times of expansion are much more prevalent than times of recession, most displacements occur during times of expansion. Thus, I suspect that results averaged over expansions and recessions would appear close to the "expansion" estimates.

[24]The model delivers larger earnings losses and a slower earnings recovery if one conditions on at least six years of tenure, as opposed to three years of tenure. In this regard, the model is consistent with empirical evidence. For example, Topel (1990) presents earnings losses for displaced workers by tenure from the PSID and the Displaced Worker Survey. He finds that, almost monotonically, the on-impact dip in earnings, and the long-run losses in earnings, rise with tenure. More recent evidence can be found in von Wachter, Song and Manchester (2007) where the earnings losses of displaced workers with at least six years of tenure are larger than for workers with at least three years of tenure for 20 after the displacement event.

[25]To compare to the non-mass-layoff results in the data, I estimate the same specification but allow for E-E transitions in the treatment group. The control group remains the same as in the case of displacement. The earnings losses of this treatment group are about 50 percent of the displaced group on impact, and recover after about ten years. Empirical results differ, but Jacobson, LaLonde and Sullivan (1993) find that this group experiences earnings losses that are about 45 percent of the displaced group on impact, and recover fully within three to five years following their separations. Jung and Kuhn (2014) perform a similar robustness check.

Kuhn (2014) also present a model that delivers the observed earnings trajectory of displaced workers while featuring many aspects of the observed economy, including wage dynamics and worker mobility. However, their model incorporates a life-cycle dimension to the worker's problem. The current paper shows that even without modeling the life-cycle dimension of the worker's problem, matching separation rates by tenure and observed wage dispersion delivers the earnings trajectory of displaced workers.

5.2 External Validity

Now that I have established that the calibrated model presented in this paper matches well the earnings time-path of displaced workers, this section describes the fit of the model in un-targeted dimensions, including wage related moments, decomposition of earnings losses into reduced wages and employment, and the movement of workers between employers and into non-employment following a separation. In summary, the calibrated model provides an economic environment that is broadly consistent with observed facts about wage and employment dynamics.

5.2.1 Wage Related Moments

Table 3, along with Figure 4, compare wage-related moments in the simulated data and the observed data. Despite having very few parameters, the model does a relatively good job at matching important aspects of the data.

To determine whether the calibrated job ladder in this paper resembles the average job ladder faced by workers in the economy, it is important to compare the average wage gains associated with switching employers. Topel and Ward (1992) find that the average wage gains from an E-E transition for workers aged 18 to 34 are around 10 percent. Using the PSID data, I find that around 50 percent of E-E transitions for workers older than 18 are accounted for by workers aged 18 to 34. This is also entirely consistent with estimates from Nagypal (2008). This implies that, if older workers experience average wage gains from E-E transitions of around three to four percent, as suggested by evidence in Topel and Ward (1992) and Jung and Kuhn (2014), the average wage gains from E-E transitions are around seven percent.[26] This seven percent target is also consistent with the model implications of Tjaden and Wellschmied (2014), where the average wage gains from E-E transitions are

[26]Here I use the law of total expectation: $\mathbb{E}[\Delta w|EE] = \mathbb{E}[\Delta w|EE, age \leq 34] \times \mathbb{P}[age \leq 34|EE] + \mathbb{E}[\Delta w|EE, age > 34] \times \mathbb{P}[age > 34|EE]$, where $\mathbb{E}[\Delta w|EE, age \leq 34] = 0.1$, $\mathbb{P}[age \leq 34|EE] = \mathbb{P}[age > 34|EE] = 0.5$, and $\mathbb{E}[\Delta w|EE, age > 34] = 0.03$.

reported at 7.1 percent. That model is also consistent with wage gains reported by Topel and Ward (1992) and the convex decrease of these gains over experience.[27]

When calculating the wage gains associated with an E-E transition in the simulated data, I use the method outlined in Topel and Ward (1992) and quantify the quarterly wage growth between jobs. In an independent regression, I estimate the within-job wage growth using annual changes in quarterly earnings in main jobs among job stayers, beginning with the sixth quarter on a job, exactly as in Topel and Ward (1992). Then I assess the wage gains associated with switching employers by looking at wage changes at job transitions (that result in a new job lasting more than one quarter) and subtracting off the expected wage growth on the new and old jobs. The simulated data suggest wage gains of 15 percent, within reasonable proximity of the empirical counterpart of seven percent, but substantially higher.[28] These wage gains determine how quickly agents' earnings recover after experiencing a spell of non-employment. To the extent that the calibrated model overshoots the wage gains from E-E transitions, the model will have a more difficult time delivering the persistent earnings losses of displaced workers as workers climb the wage ladder faster than in the data. Nevertheless, as I have shown in Section 5.1, the baseline model in this paper delivers the vast majority of the earnings losses associated with displacement, although it does predict a slightly faster recovery in wages in the couple of years after displacement. Lowering the wage gains from E-E transitions would probably help rectify this slight misalignment.[29]

Returns to tenure are important for judging how well the model describes the rise in earnings of workers who remain at their employer. I use two approaches proposed by Altonji and Shakotko (1987) to assess this in the model. Both approaches are relatively close to the data. In the model, a regression of log wages on a constant, time, tenure, tenure squared and an indicator for the first year on the job yields a 18 percent effect of 10 years of tenure.

[27]It is worth mentioning that this seven percent target, however, is substantially higher than the 3.3 percent average wage gains reported by Tjaden and Wellschmied (2014) among SIPP respondents aged 23 to 55. Conditional on young workers experiencing 10 percent increases in wages when switching employers, these 3.3 percent average wage gains imply that workers aged 35 to 55 experience roughly three percent reductions in wages when switching employers. At face value, this seems too low. Ultimately it is not within the scope of the current paper to reconcile the findings of Topel and Ward (1992) and Tjaden and Wellschmied (2014) as relates to wage gains from E-E transitions, and so for the purposes here I propose that the empirical target is around seven percent.

[28]The model struggles in this dimension because it has a tight relationship between the level of wage dispersion, and the wage gains from E-E transitions. One could modify the baseline model in this paper to weaken this relationship and lower the wage gains upon E-E transitions without compromising equilibrium wage dispersion by introducing, for example, reallocation shocks like in Tjaden and Wellschmied (2014).

[29]In an alternative version of model that allows the idiosyncratic component to change to something other than x_0 when switching employers, the framework can deliver the observed short-run (monthly) wage gains from E-E transitions without affecting the implications for displaced worker earnings. In this alternative framework, however, the long-run wage gains are still too high.

In the data, this reduced-form correlation between tenure and wages, is slightly higher at 26 percent. Implementing the instrumental variables approach used by Altonji and Shakotko (1987), by constructing within spell deviations, yields virtually no returns to tenure.[30] The empirical counterpart is slightly higher at 2.7 percent.[31] Hence, the model delivers returns to tenure that are slightly understated compared to the data, but broadly consistent with the facts. Since these returns to tenure capture the movement in earnings of non-separators, understating these returns makes it slightly harder for the model to generate persistent earnings losses after displacement.

The model also speaks to the decomposition of earnings losses into wages and employment. Topel (1990) uses the PSID to find that "two-thirds of the initial loss in annual earnings for the typical worker is caused by unemployment" and "virtually all of the short-run recovery of annual earnings...is due to an increase in weeks worked..." In the long run (four years after displacement), Topel (1990) finds that "three-fourths of [the post-displacement earning loss] is due to lower wages..." Bender, Schmieder and von Wachter (2009) corroborate these results with a study of German displaced workers. They also find that reduced employment explains a substantial part of the initial loss in earnings. They find that after five years reduced employment is responsible for one-third of the earnings losses, and after about 10 years the effect of displacement on employment dissipates; reduced wages are responsible for all subsequent earnings losses. One can estimate equation (7) with wages on the left hand side. Figure 4 presents the model's decomposition of earnings losses into lost wages, with the remaining losses in earnings attributable to non-employment.

The model suggests that around 70 percent of the initial loss in annual earnings is accounted for by lost employment and 30 percent by reduced wages. This resembles the data's values: 66 percent and 33 percent respectively. After the initial decline in earnings, the model correctly predicts that in the short run the earnings recovery is almost solely due to increased employment. The employment effect dissipates significantly within the first five years, and is virtually resolved within the first 10 years. Wages recover slowly. After four years earnings are around 17 percent below their expected level and wages are responsible for roughly 75 percent of this reduction. This is entirely consistent with findings in Topel (1990)

[30] I use average wages over employment spells in year t as a measure of the annual wage. I use the tenure (in years) in the eighth month of each year t as the measure of tenure. I do not include experience in the regressions because experience is meaningless in the model: agents are infinitely-lived. In theory the causal impact of tenure on earnings in the model is zero since match-quality is fixed within the job, and I set x_0 to $\mathbb{E}[x]$. Practically, the estimates are not quite zero due to the timing of tenure and average wages, something discussed in Altonji and Williams (2005).

[31] See Altonji and Shakotko (1987) Table 1, column 2 for the empirical OLS result, and Table 1, column 4 for the IV result.

and Bender, Schmieder and von Wachter (2009). Given that these employment and wage trajectories were not targeted, it is encouraging that the model's decomposition resembles the decomposition we observe in the data. This employment trajectory finds its roots in the serial correlation in E-N transitions exhibited by the model, something expanded upon in Section 5.2.2. With high persistence in layoffs, reduced employment lingers for many years. The wage pattern post-displacement recovers steadily as workers climb the job ladder.

The model also generates wage cuts upon E-E transitions due to fluctuations in the idiosyncratic component, and the possibility of taking jobs with relatively low idiosyncratic component, but high match-quality component. Due to the timing of the model, agents who face the possibility of large declines in idiosyncratic productivity within their current match, can choose to switch to an alternative employer, even if their wage is lower at the poaching firm than their current wages. More importantly, workers in matches with particularly high idiosyncratic productivity may choose to take an outside offer with significantly lower idiosyncratic productivity, but higher match-quality, thereby experiencing a short-run reduction in wage. Quantitatively, the calibrated model implies that around 26 percent of E-E transitions are associated with wage cuts. This is close to the empirical counterpart from Tjaden and Wellschmied (2014): 34 percent. Moreover, the model matches the average loss in wages upon E-E transitions, implying losses of 22 percent, whereas the relevant empirical counterpart is 20 percent. Hence, in addition to matching the average number of E-E transitions, the model also delivers realistic wage dynamics associated with job switching.

5.2.2 Non-Wage Related Moments

The model also speaks to E-E flows around the time of separation, suggesting increased E-E flows after an E-N transition as workers climb the job ladder in search for a better suited job. I use data from the PSID to verify these predictions of the model. Table 3 shows the average E-E probability after the first E-N transition from the model and the PSID. This takes the average E-E probability a year after the first E-N transition that an individual experiences.[32] In order to experience an E-E transition, a worker must be employed, so this average implicitly conditions on re-employment. The table shows that, on average, workers in the PSID exhibit elevated E-E probabilities immediately after separating into non-employment: the average E-E probability a year after an initial E-N is around three percent, compared to the average E-E probability of 1.7 percent. The model delivers this

[32]In practice, I average over months 12 to 23 after the first E-N transition to remove the effects of noise in the PSID data. I choose the twelfth month to start averaging because after one year most job losers will have found a new job. The first E-N transition is chosen to avoid double-counting future E-N transitions for individuals, but the result is robust to looking at *any* E-N transition as opposed to the first such transition.

pattern qualitatively, although overshoots the empirical target. In particular, the average E-E probability a year after an initial E-N transition is around 5.7 percent in the simulated data.

The baseline model assumes that all jobs coming out of non-employment begin with a fixed and deterministic match-quality, y_0. In addition to elevated E-E probabilities after an initial E-N transition, the hallmark implication of this assumption is that individuals who recently experience an E-N transition are subject to an increased risk of subsequent E-N transitions. Table 3 compares the level of serial correlation in E-N transitions in the model with the data. As with the E-E probability, in order to experience an E-N transition, a worker must be employed, so this average implicitly conditions on re-employment. In the data, one year after an initial E-N transition, the average E-N transition probability is around three percent. Recall that the average layoff rate is 1.4 percent, which means that the average E-N probability roughly doubles after an initial E-N event. The model delivers this sharp rise in the E-N transition following an initial separation into non-employment, although the model does overshoot this empirical regularity. The model delivers this drastic rise in the layoff rate shortly after an initial E-N transition via low initial match-qualities in first jobs and the idiosyncratic productivity component, and I use this aspect of the data as evidence for a low match-quality in first jobs out of non-employment.

Since I condition on tenure when estimating the earnings losses of displaced workers in the model, it is important that the model match the empirical distribution of tenure. In this regard the model performs well. Average tenure and the dispersion of tenure in the simulated data are consistent with their empirical counterparts. Average tenure is 96 months in the simulated data, compared to 84 months in the PSID data. Tenure dispersion, as measured by the coefficient of variation, is around 1.1 in the PSID data, whereas in the model it is around 1.3.

6 Robustness Checks

The model presented in this paper includes a variety of components. This section demonstrates the importance of each feature. Figure 5 presents the δ_k coefficients from equation (7) (normalized by pre-displacement earnings) from alternative versions of the model. The alternate models are calibrated in a comparable fashion to the baseline.[33]

[33]The MP model has three parameters: b, p_s and p_U. I calibrate p_s to match the average 1.4 percent layoff rate and p_U to target a 17 percent job-finding probability. b targets a ratio of 0.65 of b/$\mathbb{E}[xy]$, as turns out to be the case in the baseline model. The MP model with an AR(1) idiosyncratic process has six parameters: ρ_x, σ_{ϵ_x}, x_0, b, p_U and p_s (note that I have freed up x_0 here to resemble the low y_0 in the

The top-left graph presents a standard MP model, like the one in DV. In the year of displacement, earnings fall, and they recover within two years because of the high job-finding rate. Since all workers earn the same wage in this model, the mean-min wage ratio is exactly equal to one.[34]

The top-right graph takes the standard MP model and adds idiosyncratic productivity which follows an AR(1) process. To remain as close as possible to the baseline model, this simplified framework features endogenous and exogenous separations. I fix the initial x to a fixed, deterministic x_0. The model delivers slight persistence in earnings losses via a wage effect due to a low starting x_0 and persistence in the idiosyncratic component. Employment is also slightly slow to recover due to persistence in the E-N probability after the first E-N transition. More importantly, this model delivers a non-trivial E-N probabilities by tenure, but fails to deliver the earnings losses of displaced workers. This implies that merely matching the sharp decline in separation probabilities into non-employment is insufficient to deliver the observed earnings trajectory of displaced workers.

The bottom-left graph features a job ladder and exogenous separations, with no idiosyncratic productivity. This model features no serial correlation in E-N transitions because the flow hazard into non-employment is constant and exogenous. This calibration misses the data on displaced workers by predicting a quick initial recovery, and therefore a faster recovery than the baseline model. The initial recovery is too steep because this model has no serial correlation in E-N transitions. Hence, employment bounces back immediately. The remainder of the recovery is driven by workers climbing the job ladder and raising their wage. Nevertheless, this does show that a model with match-quality and the observed amount of wage dispersion goes a long way towards explaining the persistence in earnings losses of displaced workers.[35]

baseline model). I use the three idiosyncratic parameters and p_s to target the separation-tenure profile and the average E-N probabilities after the first E-N transition and use b to target the average layoff rate of 1.4 percent. p_U targets a 17 percent job-finding probability. The model with a job ladder but no idiosyncratic productivity has five parameters: σ_{ϵ_y}, b, p_s, p_U and p_E. I use p_s to target the average layoff rate of 1.4 percent. p_U targets a 17 percent job-finding probability, and p_E targets an average E-E probability of 1.7 percent. b targets a ratio of 0.65 of b/$\mathbb{E}[xy]$. σ_{ϵ_y} targets a mean-min wage ratio of 2. I normalize $y_0 = \mathbb{E}[y]$. The efficient rigid wage model is calibrated in precisely the same way as the baseline model, although I target a mean-min wage ratio of 1.5 to obtain on-impact reductions in earnings comparable to the baseline model and the data. To make the earnings profile around displacement comparable to the baseline model, I also add as a target a 35 percent reduction in earnings on impact for the intermediate models.

[34]As in the baseline model, there is a slight rise in earnings prior to displacement due to the tenure restriction.

[35]Experience with the model suggests that drawing match-quality for the non-employed from the same distribution as the employed means that the model cannot deliver sufficient wage dispersion. This is essentially the critique of HKV, and is one of the reasons that in the baseline model I fix match-quality in first jobs to y_0.

The details of an efficient wage model are discussed in Appendix A. The result of this model appears in the bottom-right graph, and matches closely the results from the baseline model. For simplicity, this paper demonstrates results using the simple surplus sharing solution.

7 Summary and Discussion

Previous literature documents large and persistent earnings losses associated with worker displacement. I propose a parsimonious search and matching model to help understand the time-path of earnings for displaced workers. Match-quality in the form of a job ladder, in conjunction with low match-quality in first jobs, helps explain post-displacement earnings losses via serially correlated layoffs and increased time to "ideal" job. With relatively few parameters, the model performs remarkably well in explaining the post-displacement recovery in earnings and the long-run earnings losses experienced by displaced workers. Importantly, the model has a stationary structure, so that the prolonged earnings losses generated are an outcome of "bad luck." In conjunction with serially correlated layoffs, the model matches observed wage dispersion. Many alternative models, including models with a job ladder, but no idiosyncratic productivity and serially correlated E-N transitions, cannot deliver the observed earnings losses of displaced workers. The model presented here also successfully matches the decomposition of earnings losses into reduced wages and employment, and is broadly consistent with observed returns to tenure and average wage gains associated with E-E transitions. The model correctly predicts increased E-E transitions after layoff as workers more readily switch jobs when low on the job ladder, while at the same time matching E-E probabilities by tenure. The outcome is an accurate portrayal of the wage and employment dynamics in the economy, worker mobility, and the earnings outcomes of displaced workers.

Furthermore, the model provides a resolution to the tension described in Hornstein, Krusell and Violante (2011). These authors find that equilibrium search models, even those featuring on-the-job search, consistent with observed data on worker flows, deliver far less wage dispersion than empirically observed. The tension arises because non-employed workers are observed to accept jobs relatively quickly, which means that wage dispersion has to be small. In the current setup, the "slippery stepping stone" nature of the first job not only induces an increased hazard of separation into non-employment, but it also grants workers access to jobs with a better match-quality component. This investment motive of initial jobs can reduce initial wages, thereby raising equilibrium wage dispersion. Furthermore, non-employed workers can be quick to accept jobs, while the economy features substantial wage dispersion, because they are constrained to start new employment relationships with a low match-quality.

When estimating the earnings losses of displaced workers within the current framework, the tenure restriction implies that most individuals in the treatment group separate from their employer via an exogenous separation. Although in any given year, endogenous separations account for most of the E-N flows, individuals with three years of tenure rarely experience endogenous separations and therefore their displacement is an exogenous event. This raises an important question for future research: are displacements exogenous? This touches upon a long-standing issue of whether separations are efficient; whether there exists a distinction between quits and layoffs.[36] Endogenizing the separation of well-matched individuals seems like a promising avenue for future research.

[36] See, for example, Hall (2005).

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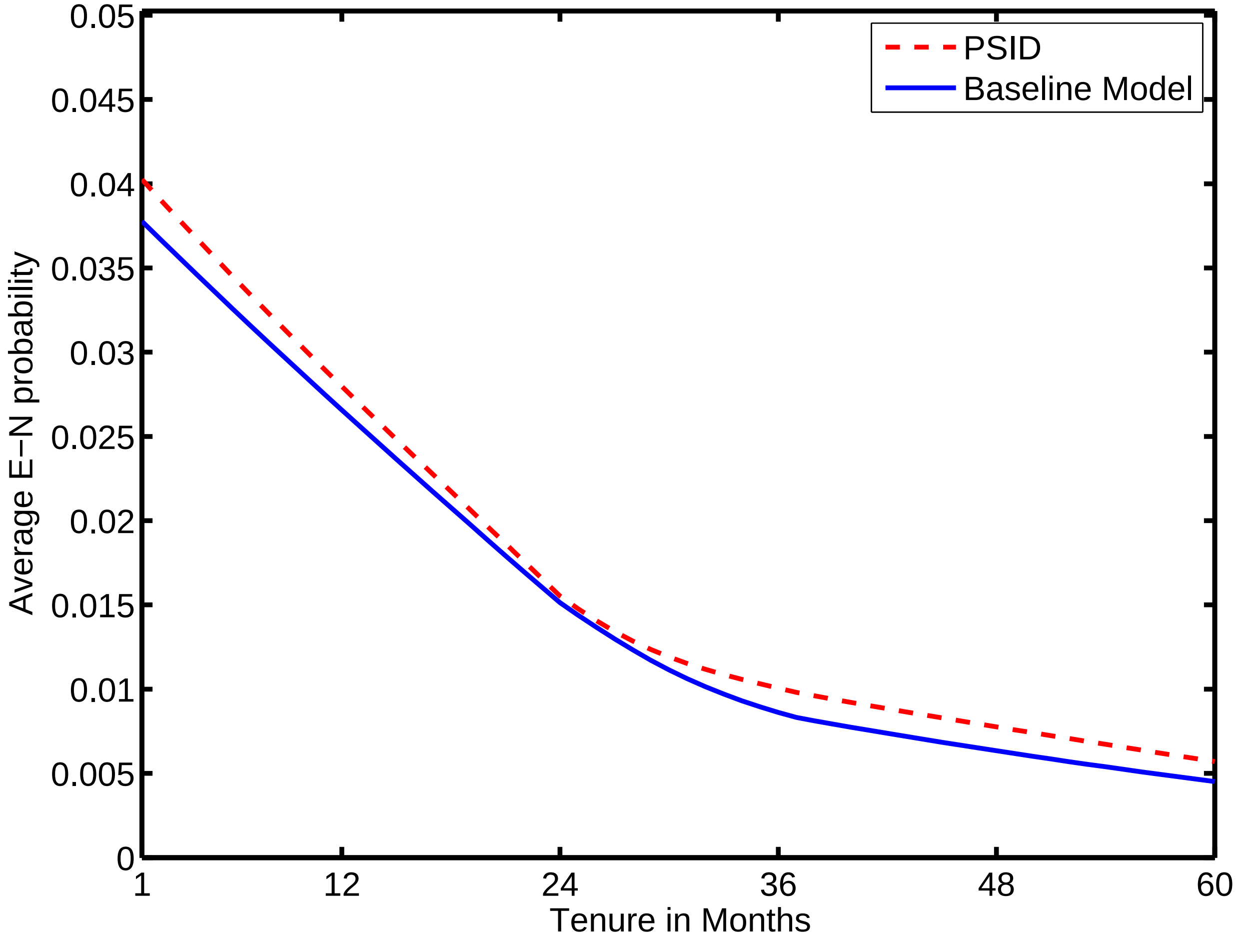

Figure 1: Average E-N Probabilities by Tenure

Note: The model delivers the observed separation rate into non-employment by tenure. This is the (smoothed) average E-N probability for each month of tenure in the simulated data and the PSID. Smoothing is performed using locally weighted (LOWESS) regressions scatter-plot smoothing.

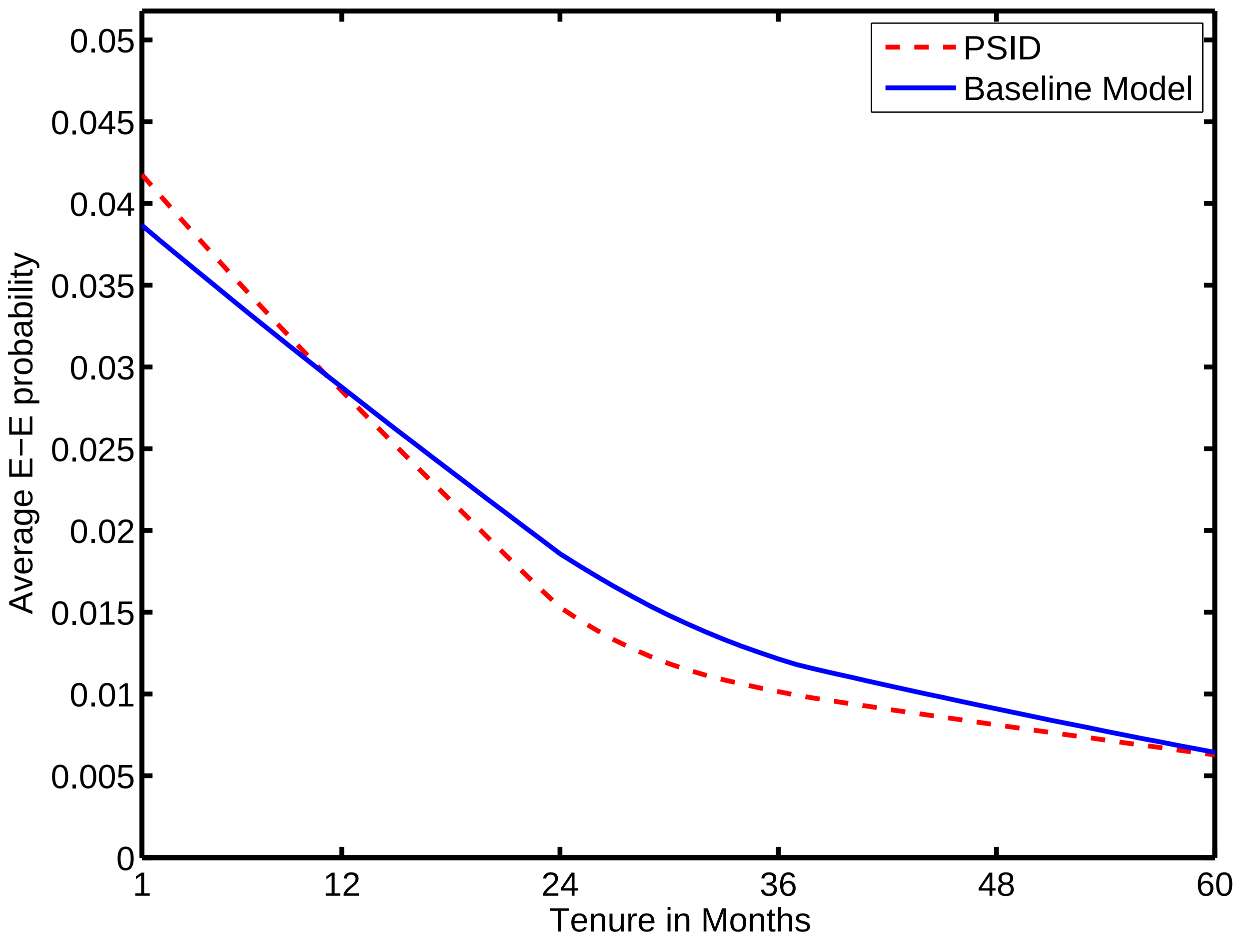

Figure 2: Average E-E Probabilities by Tenure

Note: The model delivers the observed employer-to-employer profile by tenure. This is the (smoothed) average E-E probability for each month of tenure in the simulated data and the PSID. Smoothing is performed using locally weighted (LOWESS) regressions scatter-plot smoothing.

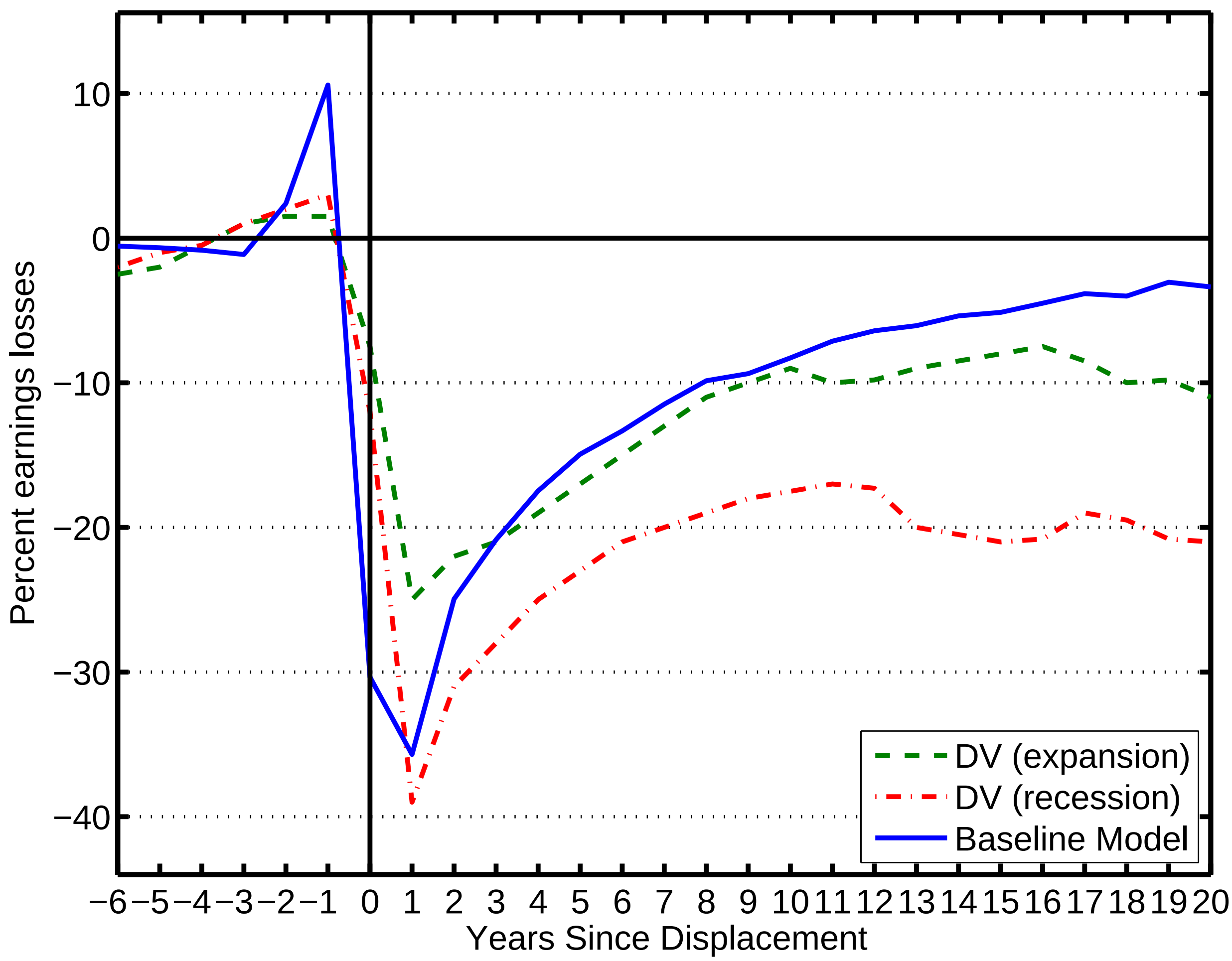

Figure 3: Annual Earnings Around Displacement

Note: On impact and for the first 10-15 years of the recovery the model provides a remarkable fit. These are the estimated coefficients δ_k from equation (7), as a fraction of average pre-displacement earnings of the treatment group in the four years prior to displacement. This figure includes the results from DV and the results from the model. The earnings losses are relative to a non-displaced control group with the same three year tenure requirement as the displaced treatment group, and the control group does not separate for two additional years after the event. For a definition of displacement and the tenure requirement see the text.

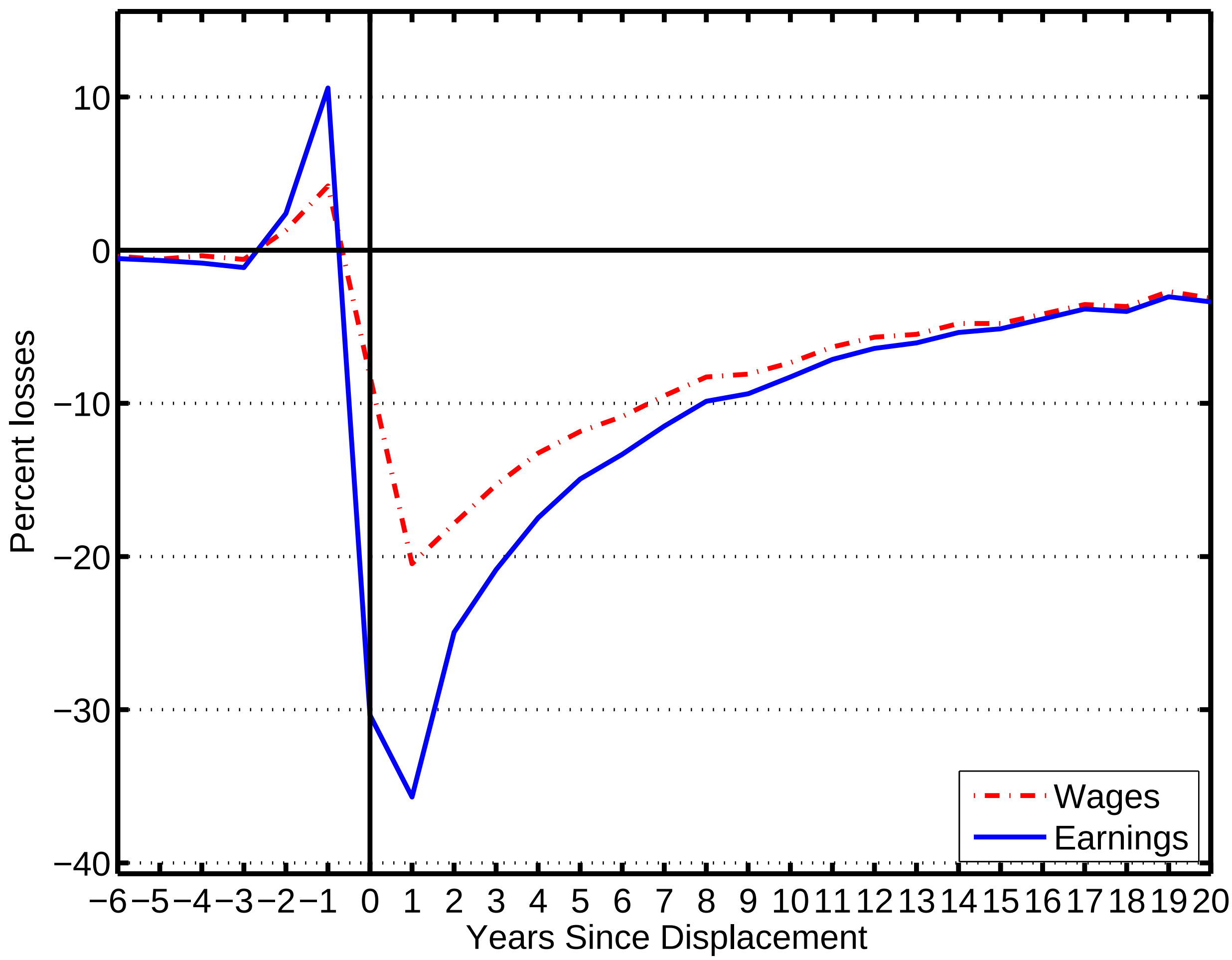

Figure 4: Decomposition: Employment and Wages

Note: The model generates the decomposition of lost earnings into reduced employment and lower wages. The earnings time-path is the same as in Figure 3. Since workers do not have a valid wage when they are non-employed, this analysis uses the average non-zero monthly wage in a year to measure the annual wage.

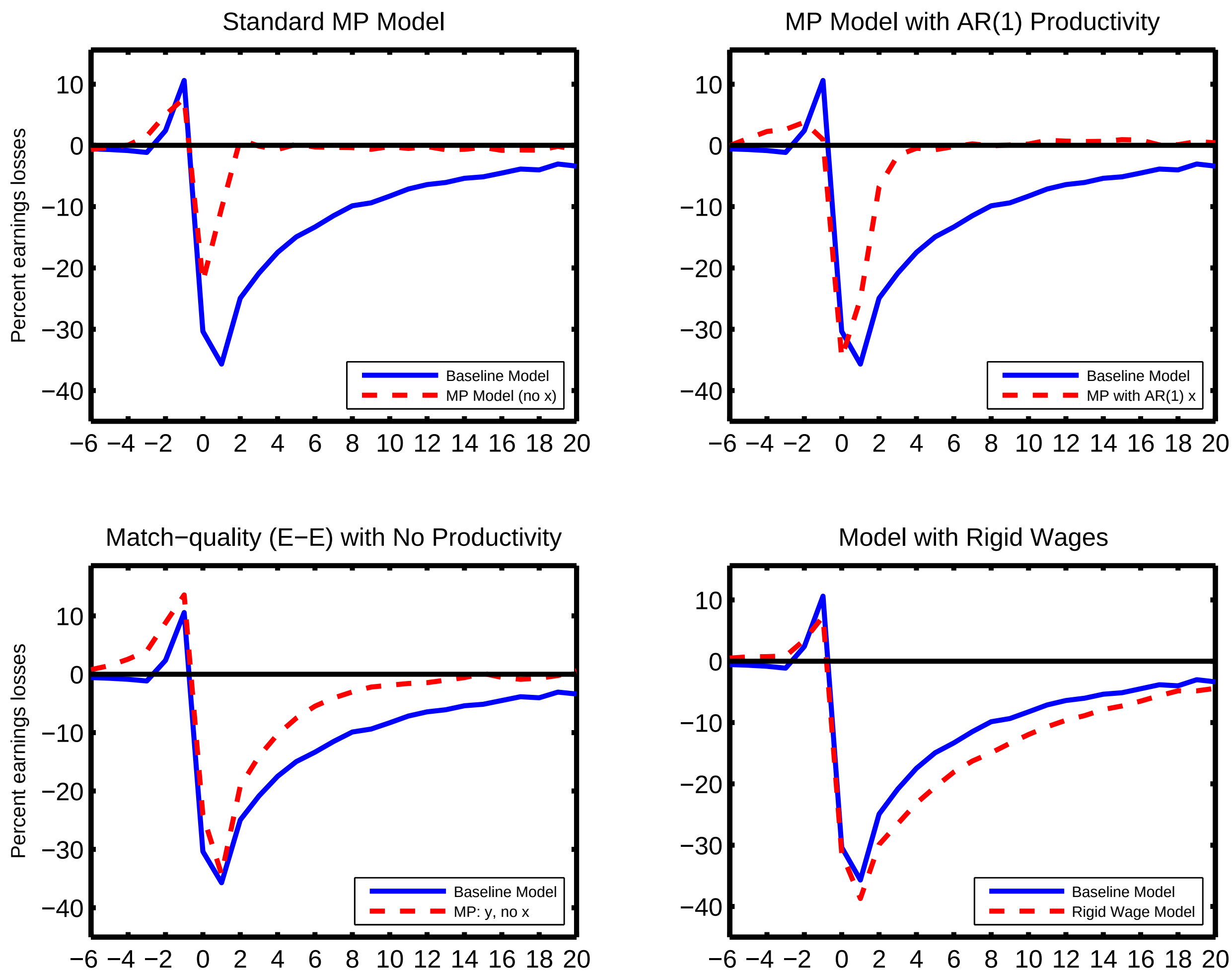

Figure 5: Annual Earnings Losses: Alternative Models

Note: Simpler versions of the baseline model without idiosyncratic productivity and match-quality cannot match the data. These are the estimated coefficients δ_k from equation (7) for alternative models. See the text for a description of each of the models and their calibrations.

Table 1: Calibrated Model Parameters

Parameter	Meaning	Calibrated Value	Main Source of Identification
ρ_x	Productivity persistence	0.80	E-N and E-E tenure profiles
σ_{ϵ_x}	Std. dev. of productivity	0.49	E-N and E-E tenure profiles
y_0	Match-quality in first jobs	$0.15 \times \max[y]$	E-N and E-E tenure profiles
σ_{ϵ_y}	Std. dev. of match-quality	0.45	Mean-min wage ratio
p_E	Contact probability (E)	0.28	E-E flow probability
p_U	Contact probability (U)	0.17	N-E flow probability
p_s	Exo separation probability	0.0049	E-N prob. for high-tenured workers
b	Value of leisure	2.45	E-N flow probability
β	Worker's bargaining power	0.5	Benchmark
δ	Discount factor	0.9959	5% annual interest rate

Note: Calibrated parameters of the model at monthly frequency. The citations and values of these empirical moments appear chiefly in Table 2, along with Figure 1 and Figure 2.

Table 2: Calibration Targets

Moments in the data	**Data**	**Model**
Mean-min wage ratio	HKV and TW: 2	2.01
E-E flow probability	Author (PSID): 1.7%	1.6%
Average N-E flow probability	Author (PSID): 17%	17%
E-N prob. for high-tenured workers	Author (PSID): 0.57%	0.45%
E-N flow probability	Author (PSID): 1.4%	1.5%

Note: The model matches the empirical targets well. The middle column of this table presents the value of the moment in the data and the citation. The column on the right presents the value of the equivalent moment in the model at the calibrated parameter values. 'E-E' stands for employer-to-employer, 'E-N' stands for employment-to-non-employment, and 'N-E' stands for non-employment-to-employment. All probabilities are at the monthly frequency. See Figure 1 and Figure 2 for the entire profiles of E-N and E-E probabilities by tenure. 'HKV' stands for Hornstein, Krusell and Violante (2007), and 'TW' stands for Tjaden and Wellschmied (2014).

Table 3: Non-Targeted Moments

Moments	**Data**	**Model**
Wage gains from E-E transition	Topel & Ward (1992): 7%	15%
Returns to 10 years tenure	AS: 26% (OLS); 2.7% (IV)	18% (OLS); -0.04% (IV)
Frac wage cuts after E-E	Tjaden & Wellschmied (2014): 34%	26%
Mean loss $\mid$ wage cut	Tjaden & Wellschmied (2014): 20%	22%
Avg. E-N prob after first E-N	Author (PSID): 2.8% (M)	5.8% (M)
Avg. E-E prob after first E-N	Author (PSID): 3.0% (M)	5.7% (M)
Average tenure	Author (PSID): 84 (M)	96 (M)
Coeff. of variation (tenure)	Author (PSID): 1.12 (M)	1.34 (M)

Note: The model performs relatively well in matching un-targeted moments. The parenthetical (M) denotes monthly frequency moments. For additional un-targeted moments, see Figure 3 and Figure 4. 'Frac wage cuts' refers to the fraction of E-E transitions that are associated with wage cuts. 'Mean loss | wage cut' is the mean wage loss in log points conditional on a wage cut upon E-E transition. For a discussion about the target for wage gains from E-E transitions, see the text. 'Avg. E-N prob after first E-N' is the average E-N probability after the first E-N transition. This is an average over months 12 to 23 after the first E-N transition to remove noise from the PSID data. 'AS' stands for Altonji and Shakotko (1987).

A Appendix: Model with Rigid Wages (For Online Publication)

This section outlines an alternative model that features efficient rigid wages, as opposed to a surplus sharing rule, as well as the ability for workers to use their current and outside offers in bargaining over their new wage with an outside or current firm, respectively. The time-path of earnings around displacement implied by this alternative model resembles the time-path of earnings in the baseline model, and so the main text develops the surplus sharing model, which is standard in the search and matching literature.

The alternative bargaining solution results in an efficient rigid wage. I follow the approach of MacLeod and Malcomson (1993), Malcomson (1999) and more recently Yamaguchi (2010). When the worker and the firm first meet, they (Nash) bargain over an employment contract given all relevant information such as idiosyncratic productivity and match-quality. Once they sign the contract, the firm pays a fixed flow wage w and the worker supplies a flow of labor services until a possible renegotiation or separation. At this point the two parties renegotiate the wage up/down if the worker/employer can credibly threaten to leave the employment relationship. The model therefore exhibits bargaining with non-employed workers, bilateral bargaining with employed workers when productivity fluctuations induce wage renegotiation, and trilateral bargaining with employed workers when workers encounter outside job offers. The solution to the trilateral bargaining problem comes from Cahuc, Postel-Vinay and Robin (2006) who show that the worker's threat point is the match value with the losing firm. The model still features privately efficient separations alongside exogenous separations.

A.1 Bellman Equations

This section details the Bellman equations characterizing the efficient rigid wage model.

A.1.1 Joint Value of a Match

Define the continuation value of employed workers and firms as $W(x, y, w)$ and $J(x, y, w)$ respectively. Let U be the continuation value of non-employed workers. Free entry into vacancies implies that the firm's value of a vacancy is zero. For notational convenience, define the joint value as the sum of the value of a match to the worker and the firm:

$$V(x, y) = W(x, y, w) + J(x, y, w)$$

Notice that w does not change the joint value of a match V; it merely determines the allocation of the joint value between worker and firm. A higher w implies that the worker receives more of the match value. The joint value function satisfies:

$$\begin{aligned} V(x,y) &= x \cdot y + \delta(1-p_s) \underbrace{(1-p_E)}_{\substack{\text{No outside}\\ \text{offer}}} \int \underbrace{\max\{U, V(x',y)\}}_{\substack{\text{Match continues or}\\ \text{terminates}}} dF_x(x'|x) + \delta p_s U \\ &+ \delta(1-p_s) \underbrace{p_E}_{\substack{\text{Outside}\\ \text{offer}}} \int\int \max\{U, \underbrace{V(x',y)}_{\substack{\text{Match}\\ \text{continues}}}, \underbrace{(1-\beta)\max\{U, V(x',y)\} + \beta V(x_0,\tilde{y})}_{\substack{\text{Worker moves to}\\ \text{poaching firm}}}\} dF_x(x'|x) dF_y(\tilde{y}) \end{aligned} \tag{8}$$

where p_E is the probability of contacting an outside firm, δ stands for the discount factor and β represents the bargaining power of the worker. The flow payoff from the match equals $x \cdot y$, the product of productivity and match-quality. Every period a shock to productivity arrives. In the event of no outside job offer (occurs with probability $1-p_E$), the employment relationship either continues with joint value $V(x',y)$, or a separation occurs. In the event of separation, the worker receives continuation value U and the firm is left with nothing (remember that the value of a vacancy is zero in equilibrium), which makes the joint continuation value U. Notice that the $V(x',y)$ term captures renegotiation: the employment relationship continues, but a new wage, w', divides the surplus differently.

When a productivity shock occurs and the worker contacts an outside firm, three things can happen. First, the outside offer could be worse than the current match, and the productivity shock makes the current match unbearable. This causes a separation, which leaves the worker with U and the firm with zero. Second, the current employment relationship continues with $V(x',y)$. This includes the case of a newly renegotiated wage at the current firm because changing the wage contract does not change the match value. Third, the outside offer induces renegotiation and the worker leaves the current firm ($V(x_0,\tilde{y})$ exceeds $V(x',y)$). The continuation value here looks like the outcome of generalized Nash bargaining with the new employer using the value of the old relationship (or non-employment, whichever is larger) as a threat point. This result comes from Appendix A of Cahuc, Postel-Vinay and Robin (2006).

A.1.2 Value of Work to the Employee

The value of work satisfies the following equation:

$$W(x,y,w) = w + \delta(1-p_s)(1-p_E)\int \underbrace{\max\{U, \min\{V(x',y), W(x',y,w)\}\}}_{\substack{\text{Match continues or terminates;}\\ \text{possible wage renegotiation}}} dF_x(x'|x) + \delta p_s U$$
$$+ \delta(1-p_s)p_E \int\int \underbrace{\mathbb{I}\{V(x_0,\tilde{y}) > V(x',y)\}}_{\text{Worker leaves current firm}} \max\{U, (1-\beta)\max\{V(x',y), U\} + \beta V(x_0,\tilde{y})\} \tag{9}$$
$$+ \underbrace{\mathbb{I}\{V(x_0,\tilde{y}) \leq V(x',y)\}}_{\text{Worker turns down outside firm}} \max\{U, \min\{V(x',y), W(x',y,w)\}, V(x_0,\tilde{y})\} dF_x(x'|x) dF_y(\tilde{y})$$

The value of work is a function of three state variables: the idiosyncratic productivity x, the match-quality y, and the previous wage w. The first term on the right hand side is the flow payoff from working, which is the current wage: w. Note that I assume a linear utility function (risk-neutrality).

The second term on the right hand side corresponds to the event of no outside job offer. Since I assume the productivity shock arrives every period, I need to consider what happens when the productivity changes. The are several possibilities. First, if $W(x',y,w) > V(x',y) \geq U$ the relationship is still viable (there is positive surplus), but the firm can credibly threaten to leave. In this case, the wage is reduced until $W(x',y,w') = V(x',y)$, i.e., $J(x',y,w') = 0$ so that the firm is indifferent between separation and continuation. Second, if $V(x',y) \geq U > W(x',y,w)$ the relationship is still viable, but the worker can credibly threaten to leave. In this case the wage rises until the worker is indifferent between non-employment and working at the current firm: $W(x',y,w') = U$. Third, if $V(x',y) < U$ the relationship is no longer viable. The employment partnership comes to an end. Finally, if anything else happens the employment relationship continues with continuation value $W(x',y,w)$.

The third term on the right hand side corresponds to the worker contacting an outside firm (and a productivity shock). The worker leaves the current employment relationship only if the match value of the new match exceeds the value at the current firm. The function $\mathbb{I}\{V(x_0,\tilde{y}) > V(x',y)\}$ captures this outcome. The timing here is important: the value from the current match and the value at the poaching firm are compared *after* the shock to current productivity (demand) arrives. In this case, the worker chooses between two options: non-employment and working at the new firm. In the latter case, the worker bargains with the outside firm after renegotiating with his current firm. The worker's continuation value is "Outside Option + β × Match Surplus". In this case the outside option is either $V(x',y)$ or U. The latter occurs when the productivity shock induces a separation. If no separation occurs, the current firm is willing to raise the wage until it is indifferent between separation and continuation, and hence the outside option for the worker is $V(x', y)$.

The function $\mathbb{I}\{V(x_0, \tilde{y}) \leq V(x', y)\}$ captures the situation where the worker does not go to the outside firm. There are several cases here. First, if $U > V(x', y)$ the relationship is no longer viable. The employment partnership comes to an end. Second, if $V(x_0, \tilde{y}) > \max\{W(x', y, w), U\}$ the worker can use the outside offer to raise the wage at the current firm. Third, if $V(x', y) \geq U > \max\{V(x_0, \tilde{y}), W(x', y, w)\}$ the current match still has positive surplus but worker can credibly threaten to leave. The wage is bid up so that worker is indifferent between staying at current firm and flowing into non-employment. Fourth, if $W(x', y, w) > V(x', y) \geq U$ then there is positive surplus but the firm can credibly threaten to leave. In this case, the wage is bid down so that the firm is indifferent between staying and going. The continuation value in this case is $V(x', y)$. If anything else happens, then the employment relationship continues with continuation value $W(x', y, w)$.

Given the previous definitions, the value of a filled job to the firm is simply:

$$J(x, y, w) = V(x, y) - W(x, y, w) \tag{10}$$

A.1.3 Value of Non-employment

The value of non-employment satisfies:

$$U = b + \delta(1 - p_U)U + \delta p_U \underbrace{\max\{U, U + \beta[V(x_0, y_0) - U]\}}_{\text{Match consummates or not}} \tag{11}$$

where p_U is the probability of making a contact with a vacancy for non-employed workers. The first term captures the flow payoff from non-employment: b. The second term corresponds to no outside job offer. In this case the worker simply remains non-employed. The third term corresponds to an outside job offer. In this case the worker chooses between working at the contacting firm and non-employment. The payoff from working at the firm is the outside option, U, plus β times the surplus, which is $[V(x_0, y_0) - U]$. Again, this is proved formally in Cahuc, Postel-Vinay and Robin (2006). In particular, this generalized Nash outcome is the result of an infinitely repeated game where worker and firm make alternating wage offers. Note that $V(x_0, y_0) - U = W(x_0, y_0, w')$, where w' is chosen so that this is true.

A.2 Solving the Model

I derive one central functional equation in the surplus from a match, $S(x, y)$. The derivation is similar to the baseline model, and I present the equation here:

$$
\begin{aligned}
S(x,y) = {} & x \cdot y + \delta(1-p_s) \underbrace{(1-p_E)}_{\substack{\text{No outside}\\ \text{offer}}} \int \max\{0, \underbrace{S(x',y)}_{\substack{\text{Match}\\ \text{continues}}} \} dF_x(x'|x) \\
& + \delta(1-p_s)p_E \int\int \max\{0, \underbrace{S(x',y)}_{\substack{\text{Match}\\ \text{continues}}}, \underbrace{\max\{0, S(x',y)\} + \beta[S(x_0,\tilde{y}) - \max\{0, S(x',y)\}]}_{\substack{\text{Worker moves to}\\ \text{poaching firm}}} \} dF_x(x'|x) dF_y(\tilde{y}) \\
& - \underbrace{[b + \delta p_U \beta \max\{0, S(x_0, y_0)\}]}_{\text{Worker's outside option}}
\end{aligned} \tag{12}
$$

The first part of the right hand side is the flow payoff from a match, $x \cdot y$. The second piece captures the event of no outside job offer and the continuation value of the match. In this case, the match either comes to an end or the match continues with the new idiosyncratic productivity (demand). The third piece captures the event of the worker receiving an outside offer and potentially moving to the poaching firm. When the worker moves to the poaching firm he uses the surplus at his previous firm (or zero if his old relationship implies negative surplus at the new idiosyncratic level) as a threat point. The final piece is the outside option of an employed worker: he forgoes the value of non-employment, b, and the possibility of finding a job at a new firm with surplus $S(x_0, y_0)$ and receiving β of this surplus. Notice that equation (12) is a functional equation in only $S(x, y)$. Value function iteration yields a close approximation to this function, denoted by $\hat{S}(x, y)$.

Calibration and identification follow the baseline model and I omit them here.

B Appendix: Surplus/Wage Equation and Numerical Details (For Online Publication)

This section details the derivation of the surplus equation and the wage equation used in the main text, as well as briefly describing the numerical approach.

B.1 The Surplus Equation

Here I outline how to solve for the surplus equation. I derive one central functional equation in the surplus from a match: $S(x, y) = W(x, y) + J(x, y) - U$. First, re-arrange equation (1) slightly to yield the equivalent expression:

$$
\begin{aligned}
W(x,y) &= w + \delta(1-p_E)(1-p_s)\int \max\{U, W(x',y)\}dF_x(x'|x) + \delta p_s U \\
&+ \delta p_E(1-p_s)\int\int \Big[\mathbb{I}\{W(x',y) \geq W(x_0,\tilde{y})\}\max\{U, W(x',y)\} \\
&+ \mathbb{I}\{W(x',y) < W(x_0,\tilde{y})\}\max\{U, W(x_0,\tilde{y})\}\Big] dF_x(x'|x)dF_y(\tilde{y})
\end{aligned}
\tag{13}
$$

Now simply combine equations (13), (2) and (3) to write:

$$
\begin{aligned}
&J(x,y) + W(x,y) - U = S(x,y) \\
&= x\cdot y - w + \delta(1-p_E)(1-p_s)\int\Big[\max\{0,(1-\beta)S(x',y)\} + \max\{0,\beta S(x',y)\}\Big]dF_x(x'|x) \\
&+ \delta(1-p_E)(1-p_s)U + \delta p_s U \\
&+ \delta p_E(1-p_s)\int\int\Big[\mathbb{I}\{S(x',y) \geq S(x_0,\tilde{y})\}\big[\max\{0,(1-\beta)S(x',y)\} + \max\{0,\beta S(x',y)\}\big] \\
&+ \mathbb{I}\{S(x',y) < S(x_0,\tilde{y})\}\max\{0,\beta S(x_0,\tilde{y})\}\Big]dF_x(x'|x)dF_y(\tilde{y}) \\
&+ \delta p_E(1-p_s)U - \delta(1-p_U)U - \delta p_U \max\{0,\beta S(x_0,y_0)\} - \delta p_U U \\
&\Rightarrow S(x,y) = x\cdot y - w + \delta(1-p_E)(1-p_s)\int \max\{0, S(x',y)\}dF_x(x'|x) \\
&+ \delta p_E(1-p_s)\int\int\Big[\mathbb{I}\{S(x',y) \geq S(x_0,\tilde{y})\}\max\{0,S(x',y)\} \\
&+ \mathbb{I}\{S(x',y) < S(x_0,\tilde{y})\}\max\{0,\beta S(x_0,\tilde{y})\}\Big]dF_x(x'|x)dF_y(\tilde{y}) \\
&- (1-\delta)U
\end{aligned}
$$

where like terms have been combined and Nash bargaining has been used to substitute $J(x,y) = (1-\beta)S(x,y)$ and $W(x,y) - U = \beta S(x,y)$. Using equation (3) to solve for $(1-\delta)U$, and plugging into this equation yields the desired result.

Value function iteration yields $\hat{S}(x,y)$. Once I have $\hat{S}(x,y)$ I also have $\hat{U}$ because U can be written as a function of $S(x,y)$. With $\hat{S}(x,y)$ and $\hat{U}$ I can simulate the economy and observe workers moving between employment and non-employment and from job to job.

B.2 The Wage Equation

Start with equation (1) and subtract and add U under the integrals to obtain:

$$\begin{aligned}W(x,y) = w &+ \delta(1-p_E)(1-p_s)\int \max\{0, W(x',y)-U\}dF_x(x'|x) \\ &+ \delta(1-p_E)(1-p_s)U \\ &+ \delta p_E(1-p_s)\int\int \max\{0, W(x',y)-U, W(x_0,\tilde{y})-U\}dF_x(x'|x)dF_y(\tilde{y}) \\ &+ \delta p_E(1-p_s)U + \delta p_s U\end{aligned}$$

Simplifying the terms with U, subtracting U from both sides and using the fact that the Nash bargain implies that $W(x,y) - U = \beta S(x,y)$ yields:

$$\begin{aligned}\beta S(x,y) = w &+ \delta(1-p_E)(1-p_s)\int \max\{0, \beta S(x',y)\}dF_x(x'|x) - (1-\delta)U \\ &+ \delta p_E(1-p_s)\int\int \max\{0, \beta S(x',y), \beta S(x_0,\tilde{y})\}dF_x(x'|x)dF_y(\tilde{y})\end{aligned}$$

$$\begin{aligned}\therefore w(x,y) = \beta S(x,y) &+ [b + \delta p_U \beta \max\{0, S(x_0,y_0)\}] \\ &- \delta(1-p_E)(1-p_s)\beta\int \max\{0, S(x',y)\}dF_x(x'|x) \\ &- \delta p_E(1-p_s)\beta\int\int \max\{0, S(x',y), S(x_0,\tilde{y})\}dF_x(x'|x)dF_y(\tilde{y})\end{aligned}$$

B.3 Numerical Details

I solve the model numerically using a contraction mapping in a discretized state space. I discretize the AR(1) process for idiosyncratic productivity (x) onto 29 grid points using the Rouwenhorst method. This method is most often attributed to Rouwenhorst (1995) and in a recent article, Galindev and Lkhagvasuren (2010) have shown that this discretization method outperforms the approaches described in Tauchen (1986) and Tauchen and Hussey (1991). In particular, for persistent AR(1) processes, as turns out to be the case here, the Tauchen (1986) method requires a large number of grid points to produce close approximations, which causes increased computational time. Galindev and Lkhagvasuren (2010) show that the Rouwenhorst method provides a close approximation "robust to the number of discrete values for a wide range of the parameter space." Finally, the match-quality process has 29 grid points and I also use the Rouwenhorst method for discretizing this state variable. I solve the value function on a grid, and in the simulation interpolate for points off the gird using linear interpolation. I do not allow state variables to take values above and below the respective minimum and maximum values on the gird, although in practice this does not affect the results because the probability of state variables falling outside the grid remains extremely small.

Given the optimal decisions of workers and firms, the model generates simulated data at a monthly frequency. In particular, I simulate 20,000 agents for 600 months (50 years). To remove the effects of initial conditions, I simulate the model for 2100 months and then discard the first 1500 months of the sample. This simulation provides a time-path of wages and annual earnings, as well as an employment history.

I calibrate the parameters of the model using simulated method of moments. The procedure minimizes the distance between the summary statistics of the simulated data and the summary statistics of real data. Specifically, if θ represents the vector of structural parameters, $\hat{g}$ represents the moments of the actual data, and $g(\theta)$ represents the moments of simulated data, then the simulated minimum distance estimator is defined as:

$$\hat{\theta} = \arg\min_{\theta} \mathcal{L}(\theta) = \arg\min_{\theta} [g(\theta) - \hat{g}]' W [g(\theta) - \hat{g}] \tag{14}$$

Here $g(\theta)$ represents a non-linear transformation of the structural parameters by the model and a transformation of the simulated data to achieve moments that match observed moments. In practice, the weighting matrix used is the diagonal of the efficient weighting matrix, which weights the moments by the inverse variance-covariance matrix. I do not use the entire efficient weighting matrix because I do not have the variability of the mean-min wage ratio estimates from HKV.

The optimization is implemented using a coarse grid search across the relevant state space to obtain areas where the loss function might be minimized. Once the initial points are evaluated, I use MATLAB's Nelder-Mead optimization routine, *fminsearchbnd*, from each candidate solution to find the minimum objective function value in that region of the state space. The global minimum is taken as the minimum of all these local minima.

C Appendix: Benchmarking the PSID Worker Flows (For Online Publication)

This section shows that the average worker flow probabilities from the PSID that are used to calibrate the model are broadly consistent with results from other data sets. Moreover, the PSID data is consistent with life-cycle separation rates, and E-U probabilities by tenure.

Table 4 lines up the PSID worker flows data with similar data from the CPS and SIPP. The PSID monthly strings are broadly consistent with other data sets. In particular, the E-E probability in the PSID is around 1.7 percent, whereas in the SIPP and CPS it ranges from 1.8 to 2.6 percent. The U-E probability in the PSID is in the middle of the estimates from the other two datasets. Finally, the layoff rate into unemployment in the PSID is consistent with the SIPP and CPS, and the layoff rate ending in non-participation is slightly lower in the PSID.

I also present E-U probabilities by tenure and age and show that they are consistent with similar analyses using the SIPP. Figure 6 shows the average separation probability into unemployment in the PSID data. The average E-U probability is around three percent for 18 year old men, 1.5 percent for 25 year old men, and then falls significantly over the life-cycle to around 0.3 percent at age 65. Figure 2 in Menzio, Telyukova and Visschers (2012) shows a very similar pattern in the SIPP.

Figure 7 presents the results of E-U probabilities for different months of tenure. At low levels of tenure the E-U probability is around two percent and falls steadily over the next five years to around 0.3 percent. Figure 9 in Menzio, Telyukova and Visschers (2012) shows an almost identical pattern in the SIPP.

Figure 2 in the main text shows the average E-E probabilities by tenure. A similar figure can be found in Menzio, Telyukova and Visschers (2012) (Figure 10). The two profiles are generally the same, showing a four percent E-E probability for workers with one month of tenure and a monotonic reduction in E-E probabilities with increased tenure. The SIPP data, however, shows slightly higher E-E probabilities for workers with more than two years of tenure, as the PSID profile continues to decline after this tenure level, whereas the SIPP profile plateaus.

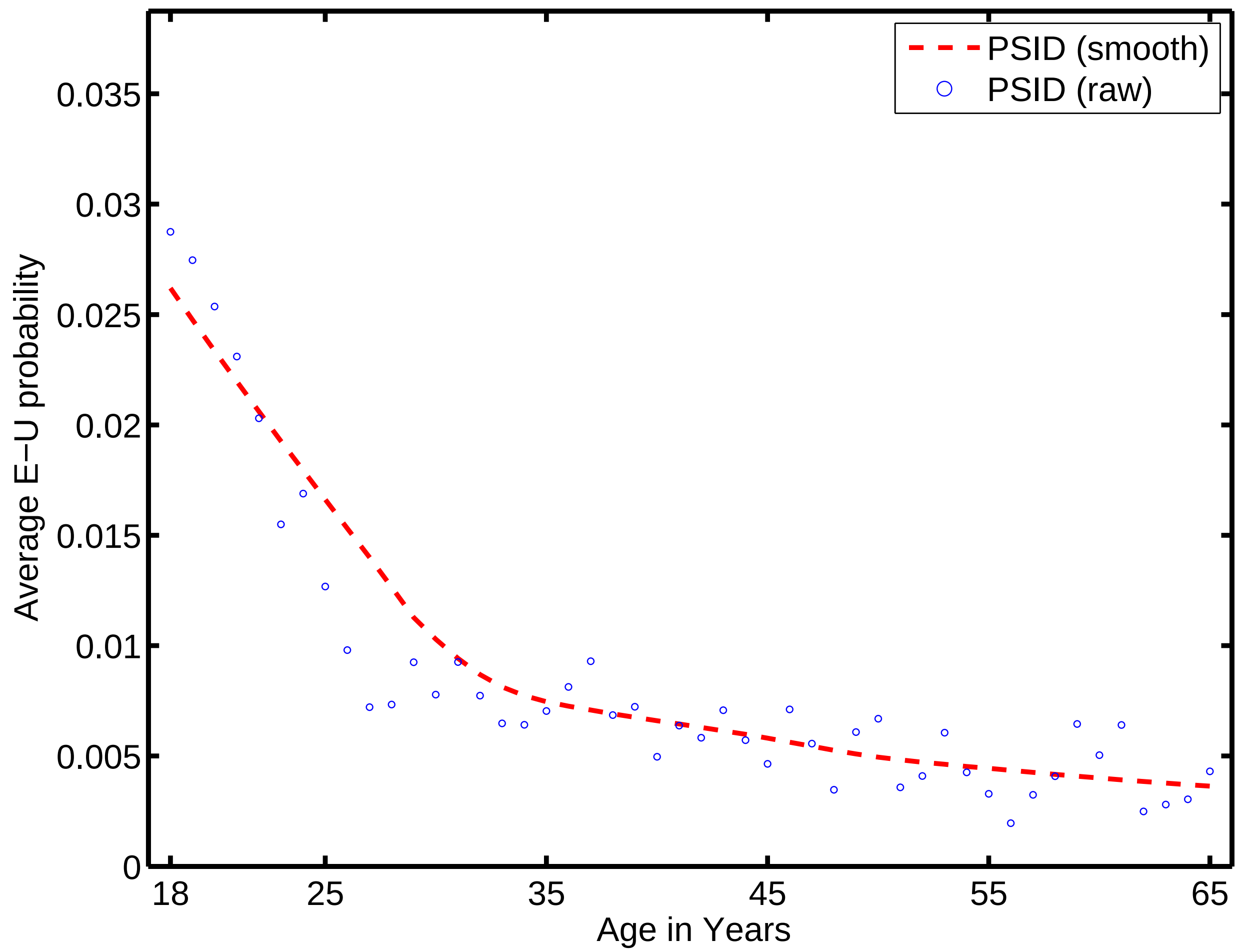

Figure 6: Average E-U Probability by Age in the PSID

Note: The empirical separation-age profile using the PSID. This includes the raw data and the (smoothed) average E-U probability at each age in the PSID. Smoothing is performed using locally weighted (LOWESS) regressions scatter-plot smoothing.

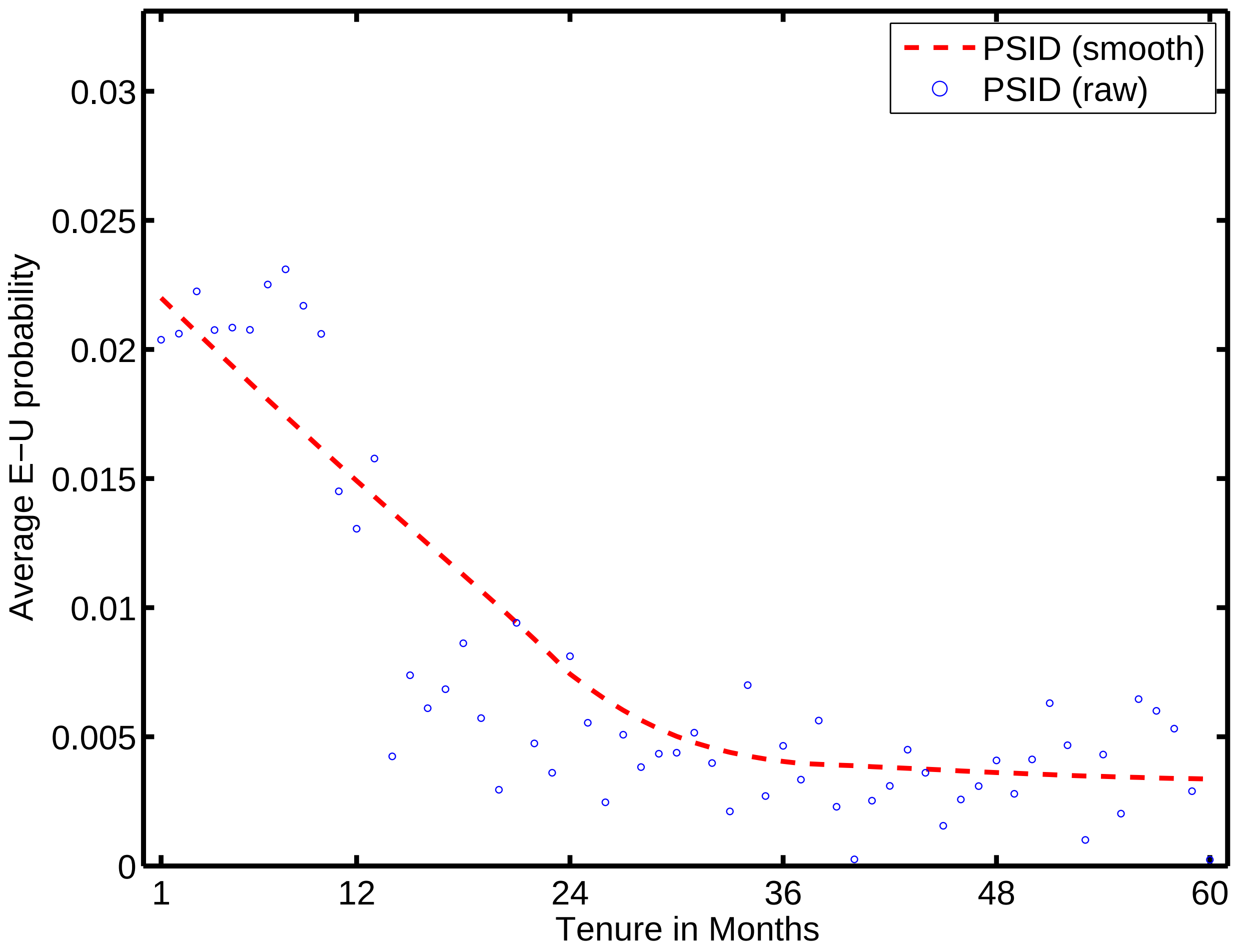

Figure 7: Average E-U Probabilities by Tenure in the PSID

Note: The empirical separation-tenure profile using the PSID. This includes the raw data and the (smoothed) average E-U probability for each month of tenure in the PSID. Smoothing is performed using locally weighted (LOWESS) regressions scatter-plot smoothing.

Table 4: Comparing Worker Flows

Flow	**PSID**	**SIPP**	**CPS**
E-U	0.8	0.5-0.9	0.9-2
E-N	0.6	1.4	1.5
U-E	22	21-25	20-30
N-E	4.3	N/A	2.5
E-E	1.7	1.8-2.2	2.5-2.6

Note: The PSID worker flows are broadly consistent with SIPP and CPS counterparts. All values are in percent. As an example, 1.7 percent for E-E means that, as a fraction of those employed in month $t-1$, 1.7 percent of individuals switched employers between months $t-1$ and t. The CPS values are taken from Nagypal (2007), Elsby, Hobijn and Sahin (2013) and Fallick and Fleischman (2004), and the SIPP values are taken from Nagypal (2007) and Menzio, Telyukova and Visschers (2012).