

Displaced Worker Earnings: New Theory and Observation

by

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To my family

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CHAPTER I

Introduction

This dissertation comes at a time of difficult economic recovery for the United States. The unemployment rate hovers just below eight percent, partially the result of an incredible amount of involuntary job loss during the Great Recession. These recent job losers face a bleak economic outlook including long periods of suppressed earnings and numerous future job losses. This dissertation invokes novel theory and empirical analysis to help understand the experience of displaced workers, and to derive the implications of these experiences for the aggregate labor market.

Chapter II of this dissertation shows that sheer misfortune can account for the entirety of earnings losses experienced by displaced workers. Since workers can look for jobs while employed, they move up the rungs of a job ladder. Identical unemployed workers start in employment relationships that are, on average, less profitable than their jobs prior to separation. Since it takes time for newly hired workers to move up the job ladder, this induces a slow recovery in earnings after displacement.

This model matches well the earnings recovery of displaced workers observed in the data, which in large part is attributable to the model's ability to match observed wage dispersion. As a result of serial correlation in displacements, this framework also delivers the empirical decomposition of earnings losses into lower wages and lower employment. This framework is consistent with aggregate worker flows and

empirical establishment-level fluctuations in total factor productivity.

Chapter III investigates the implications of job displacement for the aggregate labor market over the business cycle. The framework features a burst of layoffs at the onset of a recession, consistent with the data. Since poor quality employment relationships are destroyed at the beginning of a recession, the average match-quality rises initially (cleansing effect). Due to fewer posted vacancies and lower job-finding rates, the average match-quality begins to fall (sully effect).

In a simpler version of the baseline model that features no on-the-job search, I demonstrate a trade-off between matching observed wage dispersion, with a large variance of idiosyncratic shocks, and matching the observed volatility of unemployment, which requires small fluctuations in idiosyncratic productivity. The model presented in Chapter II alleviates these trade-offs by allowing match-quality to be relatively low in new hires. This allows for a large mass of jobs to exist near the destruction threshold. With the baseline calibration, which matches observed wage dispersion, the model delivers significant amplification of aggregate productivity shocks due to the important job destruction margin. The model also delivers substantial propagation of aggregate productivity shocks due to the slow movement of workers up the job ladder. Increases to the separation probability confirm some of these findings.

Chapter IV uses data from the Panel Study of Income Dynamics to investigate two popular empirical specifications used in the displacement literature, and to present the earnings recovery post-displacement for different sub-groups of individuals. The chapter outlines the two approaches used and describes the difference between them. In particular, the specification that uses the never displaced as a control group implies much larger earnings losses than a specification that uses those not displaced in a given year as the control group. The analysis shows that the earnings losses seem to be universal, affecting workers in low-paid and high-paid industries and in a variety of occupations, the young and the old, and workers with varying amounts of education.

It also shows that a period of unemployment is equally detrimental to a worker's lifetime earnings as a displacement event. These facts lend credence to matching the average earnings losses using a model with ex-ante homogeneous workers, where the reason for job separation is unspecified. Finally, this chapter presents new evidence on earnings losses by worker characteristics, including heterogeneity by pre-displacement wealth.

CHAPTER II

Job Ladders and Earnings of Displaced Workers

2.1 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 displaced from jobs they had held for less than three years. Davis and von Wachter (2011) (henceforth DV) find that 16 percent of prime-aged males with three or more years of job tenure experienced a job displacement event from 1980 to 1985.

In conjunction with the high incidence of displacement, there now exists a long and distinguished literature documenting large and persistent earnings losses associated with displacement. 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. As an example, DV find that at the time of displacement real earnings fall sharply, and even twenty years after the time of displacement annual earnings are 10-20 percent below pre-displacement earnings.

The model presented in this chapter 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. 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. Together with poor quality matches among first jobs, the job ladder prolongs earnings recovery after displacement as unemployed workers enter poor employment relationships and search for better matches while employed.

The model also endogenously generates serially correlated displacements, which slow down workers' climb up the job ladder because each displacement event sends workers back to the first rung on the ladder. The model captures the following intuition: compared to their job prior to displacement, workers might not be as well matched in their first job coming out of unemployment. This poor fit results in tentative new employment relationships and 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 a workers' post-displacement experience. In the years following an initial displacement, she finds that serially correlated displacements explain much of the persistence and magnitude in lowered earnings. The serial correlation also helps the model match the decomposition of lost earnings into reduced employment and lower wages.

Aside from matching the observed earnings time-path and serially correlated displacements, the model also matches several other moments of the data. The calibrated job ladder delivers realistic wage dispersion as documented by Hornstein et al. (2011), and this goes a long way towards explaining the success of the proposed framework. Since all agents in the model are ex-ante homogeneous and the model is stationary, misfortune or "bad luck" can account for all the earnings losses associated with displacement. The model also matches the empirical decomposition of earnings losses

into reduced wages and employment, empirical establishment-level fluctuations in total factor productivity, as well as the pattern of employment-to-employment transitions after displacement.

The literature has rarely applied search models to the experience of displaced workers. The work of DV comes closest to the work presented here. They show that a standard Mortensen-Pissarides (MP) model, and a slightly more sophisticated model found in Burgess and Turon (2010) (henceforth BT), cannot explain the extent of losses observed in the data. The model presented in this chapter differs from BT in two crucial ways. First, as described in the previous paragraph and consistent with empirical observation, workers recently transitioning from unemployment to employment face higher hazard rates of separation into unemployment than workers in established employment relationships. This serial correlation causes cycles of job loss and can raise the costs of one displacement. All workers in the model of BT face the same hazard rate into unemployment. Second, the model presented here delivers realistic wage dispersion as documented by Hornstein et al. (2011). This realistic wage dispersion 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.

Pries (2004) stands as another closely related paper. However that analysis provides only a qualitative discussion about displaced worker earnings, whereas this chapter presents a quantitative exercise that matches well the empirical results on displaced worker earnings and provides calibrated values for parameters of interest. Furthermore, my story hinges on a job ladder and on-the-job search, both of which Pries (2004) omits. Hence, the baseline model presented here can speak to issues, like employment-to-employment (E-E) flows before and after separations, and the extent to which job switches account for the recovery in earnings post displacement, which Pries’ model cannot address. In particular, my model suggests increased E-E flows

after displacement as workers climb the job ladder in search for a better suited job. Section 2.5 presents evidence from the Panel Study of Income Dynamics (PSID) that corroborates this implication of the model.

Den Haan et al. (2000b) investigate a class of models without on-the-job search and conclude that the productivity of a match must drift upwards in order to explain the wage and employment evidence presented by displaced workers. Due to rising within-match productivity their framework requires implausibly large productivity shocks to induce a displacement. With on-the-job search, productivity within the match does not have to grow over time as wages can rise from E-E transitions. Hence, the model described in this chapter can match the evidence on displaced workers with a reasonable productivity process. Exogenous separations also mitigate the need for implausibly large productivity shocks. Low et al. (2010) present a similar model to the one described here, with on-the-job search, match-quality and search frictions. Their model predicts a relatively quick recovery of earnings in the year following a layoff. For the reasons discussed in the previous paragraph, the model presented here delivers greater persistence in earnings losses.

The framework presented here does not incorporate adverse selection; workers do not vary ex-ante by ability. Unemployed workers are all identical. The reason for this is twofold. First, von Wachter et al. (2011) take up the issue of selection extensively, controlling for observed and unobserved characteristics, sorting, as well as negative selection on level and trend differences. These authors conclude that, although the estimated losses vary depending on the exact specification, the baseline approach presented in this chapter provides a reasonable account of the earnings experience of displaced workers. Second, one of the purposes of this project is to highlight that, despite ex-ante homogeneity among workers, the losses from displacement can be large and persistent. This means that misfortune or “bad luck” can account for all the earnings losses associated with displacement.

Given the difficulty of finding a search model that delivers the observed earnings time-path of displaced workers, the following analysis constructs a model and chooses parameters to fit this prominent empirical fact. The ability of the model to match the persistent earnings losses of displaced workers is an achievement in and of itself. Many comparable models cannot deliver this persistence. Nevertheless, in addition to successfully capturing this dimension of the data, the model also matches several moments of the data that it was not calibrated to match. These include the decomposition of earnings losses into reduced wages and employment, empirical establishment-level fluctuations in total factor productivity, as well as observed wage dispersion and the volatility of earnings within matches. The framework also delivers the pattern of E-E transitions after displacement and the observed serial correlation in displacements.

The rest of the chapter is organized as follows. The intuition for the framework, the calibration of the model, and the main results of the analysis regarding the earnings of displaced workers and serial correlation in displacement appear in Sections 2.2, 2.3, and 2.4 respectively. Section 2.5 discusses the implications of this calibrated model for a range of un-targeted outcomes. Section 2.6 presents a discussion about the inadequacy of alternative versions of the model. Section 2.7 summarizes and draws lessons for future research.

2.2 The Model

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

2.2.1 Model Introduction

The work on search and matching by Mortensen, Diamond and Pissarides provides the foundation for this chapter. 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. In this model all unemployed workers are identical and workers are endowed with linear utility (risk-neutrality).

2.2.2 Setup

A partial equilibrium model serves as the basis for analysis. Workers look for jobs and firms post vacancies to attract workers. Unemployed workers receive utility from leisure and encounter vacancies at an exogenous probability p_U . 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 .¹ All employer-employee matches are characterized by two state variables: match-quality denoted by y , and an idiosyncratic component denoted by x that can be interpreted as either productivity or demand. The product of x and y ($x \cdot y$) provides the flow output of the match. When an unemployed worker contacts a firm, the match draws an initial, non-stochastic, match-quality equal to a fixed and deterministic y_0 . Match-quality remains constant within a job. Setting match-quality to y_0 in all new matches implies that there exists a set of entry-level positions that all workers start in. This coincides with what Doeringer and Piore (1971), and more recently Martins et al. (2010), call “port-of-entry” jobs; jobs into which employers are consistently observed to hire new workers. On a more technical note, with variation in initial y , unemployed individuals reject offers and thus the job finding rate is not equal to the unemployment-to-employment (U-E) rate. The data do not help us distinguish unemployed individuals who have rejected low offers and those who have not received any offers. In the model

¹The differing job contact probabilities on and off the job may result from differing levels of search intensity exhibited by the employed and the unemployed. The model presented here abstracts from the reason behind this difference.

all unemployment is frictional.

All initial idiosyncratic productivities (demands) are fixed at a deterministic value, x_0 , and then exhibit persistence within a match and evolve according to $F_x(x'|x)$. Setting x to x_0 in all new matches follows Mortensen and Pissarides (1994). In this model the match-quality, y provides a mean productivity level within a match and x provides some variance around this mean productivity. Over time on-the-job search results in offers to the employed with probability p_E and match-quality drawn from $y \sim F_y(\tilde{y})$. This induces a job-ladder that agents climb over time. This can be interpreted as finding more suitable jobs within the same firm (promotions) or simply learning specific skills and moving onto jobs that are better suited for the worker. In this sense, y captures the acquisition of firm specific human capital. Resetting y to y_0 in all new matches from unemployment captures the idea that workers lose all firm-specific human capital during unemployment.

The idiosyncratic component delivers endogenous flows into unemployment; when the realization of the idiosyncratic random variable is low enough, the worker and the firm decide to part ways. The worker prefers to flow into unemployment and search for a new vacancy, and the firm prefers to let the worker go and find a new worker from the pool of searchers. Involuntary endogenous separations on either side of the market do not occur in this model. Whenever there exists positive surplus in a match, the worker and firm can negotiate a wage both parties find agreeable. The model does incorporate exogenous separations, however.

2.2.3 Timing of Events within a Period

Within each period, events among unemployed workers unfold according to the following timing. At the outset of a period firms post vacancies to recruit unemployed 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.

2.2.4 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 standard linear surplus sharing rule, so that the worker receives a fraction, β , of the total surplus and the firm receives the rest of the total match surplus. If an employed worker receives a favorable outside offer, he moves to the poaching firm, and the wage is renegotiated. In this case, the worker uses unemployment as his outside option, not the match value at the previous employer.² 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. Section 2.8 outlines a model with efficient rigid wages, similar to a framework found in MacLeod and Malcomson (1993). 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. In order to remain

²Nagypal (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 Section 2.8. 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 Section 2.8 delivers qualitatively similar results, I suspect that amending this model's bargaining structure will not yield substantially different conclusions.

consistent with previous work, the benchmark model in this chapter implements the standard surplus sharing protocol used in the literature.

2.2.5 Intuition for the Partial Equilibrium Model

Before discussing the formal model equations, this section provides a simple description of the model dynamics and gives the reader intuition for the main results. 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 and the average match-quality among employed workers. Second, in conjunction with a low match-quality among first jobs, 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 displacements and serial unemployment. This serial unemployment effect dovetails with empirical work by Stevens (1997) who finds that multiple job losses explain some of the persistence of earnings losses.

2.2.6 Bellman Equations

This subsection deals with the formal recursive equations of the model.

2.2.6.1 Value of Work to the Employee

The value of work satisfies the following equation:

$$\begin{aligned}
W(x, y) = & w + \delta(1 - p_E)(1 - p_s) \int \underbrace{\max\{U, W(x', y)\}}_{\text{Match continues or terminates}} dF_x(x'|x) + \underbrace{\delta p_s U}_{\text{Exogenous separation}} \\
& + \delta p_E(1 - p_s) \int \int \underbrace{\max\{U, W(x', y), W(x_0, \tilde{y})\}}_{\substack{\text{Worker moves to unemployment,} \\ \text{stays at current firm,} \\ \text{or goes to new firm}}} dF_x(x'|x) dF_y(\tilde{y})
\end{aligned} \tag{2.1}$$

The value of work is a function of two state variables: the idiosyncratic productivity x and the match-quality y . 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 $W(x', y) > U$ the relationship is still viable (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 unemployment and receives U .

The fourth 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 value from the current match and the value at the poaching firm are compared *after* the shock to current productivity (demand). In this case, the worker chooses between two options: unemployment and working at the new firm. In the latter case, the worker bargains with the outside firm using unemployment as his outside option. In the event that the match value at the current firm exceeds both the value of unemployment and the match value at the outside firm, the worker remains at the current firm receiving value $W(x', y)$. If the value of unemployment exceeds the worker's value at the current firm and at the outside firm, the worker moves to

unemployment receiving continuation value U .

2.2.6.2 Value of Filled Job to the Employer

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

$$\begin{aligned}
J(x, y) = & x \cdot y - w + \delta(1 - p_E)(1 - p_s) \int \underbrace{\max\{0, J(x', y)\}}_{\text{Match continues or terminates}} dF_x(x'|x) \\
& + \delta p_E(1 - p_s) \int \int \underbrace{\mathbb{I}\{J(x', y) \geq J(x_0, \tilde{y})\}}_{\text{Worker turns down poaching firm}} \underbrace{\max\{0, J(x', y)\}}_{\text{Match continues or terminates}} dF_x(x'|x) dF_y(\tilde{y})
\end{aligned} \tag{2.2}$$

The first term on the right-hand side 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-hand side corresponds to the event of no outside job offer, no exogenous separation shock, and a productivity 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 (and a productivity shock). 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.

2.2.6.3 Value of Unemployment

The value of unemployment satisfies:

$$U = b + \delta(1 - p_U)U + \delta p_U \underbrace{\max\{U, U + \beta[W(x_0, y_0) + J(x_0, y_0) - U]\}}_{\text{Match consummates or not}} \tag{2.3}$$

where p_U is the probability of making a contact with a vacancy for unemployed workers. The first term captures the flow payoff from unemployment: b . The second

term corresponds to no job offer, so the worker remains unemployed. The third term corresponds to a job offer. In this case the worker chooses between working at the contacting firm and unemployment. The payoff from working at the firm is the outside option, U , plus β times the surplus.

2.2.7 Solving the Model

The expressions in the previous sections can be summarized in one central functional equation: the surplus from a match, $S(x, y)$. Section 2.9 provides the details of this derivation. Here I simply present the result:

$$\begin{aligned}
S(x, y) = & x \cdot y + \underbrace{\delta(1 - p_E)}_{\text{No outside offer}} \underbrace{(1 - p_s)}_{\text{No separation shock}} \int \underbrace{\max\{0, S(x', y)\}}_{\text{Match continues}} dF_x(x'|x) \\
& + \delta p_E (1 - p_s) \int \int \left[\underbrace{\mathbb{I}\{S(x', y) \geq S(x_0, \tilde{y})\}}_{\text{Worker turns down poaching firm}} \underbrace{\max\{0, S(x', y)\}}_{\text{Match continues or terminates}} \right. \\
& + \left. \underbrace{\mathbb{I}\{S(x', y) < S(x_0, \tilde{y})\}}_{\text{Worker leaves current firm}} \underbrace{\max\{0, \beta S(x_0, \tilde{y})\}}_{\text{Match at new firm or unemployment}} \right] dF_x(x'|x) dF_y(\tilde{y}) \\
& - \underbrace{[b + \delta p_U \beta \max\{0, S(x_0, y_0)\}]}_{\text{Worker's outside option}}
\end{aligned} \tag{2.4}$$

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 (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 unemployment 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 unemployment, 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 (2.4) is a functional equation in only $S(x, y)$. Value function iteration yields a close approximation to this function, denoted by $\hat{S}(x, y)$. Assuming a surplus sharing rule for the wage pins down the equilibrium wage equation as a function of (x, y) . The derivation of the surplus and wage equations appear in Section 2.9. That section also provides details regarding the numerical solution.

2.3 Calibration Strategy

This section highlights the major processes of the model's state variables and discusses calibration.

2.3.1 Processes for 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 matches, and then within the match follows a log AR(1) process:

$$\ln x' = \rho_x \ln x + \epsilon'_x \quad (2.5)$$

where $\epsilon'_x \sim \mathcal{N}(0, \sigma_{\epsilon_x}^2)$. 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 following distribution:

$$\ln y' = \begin{cases} \ln y_0 & \text{for jobs out of unemployment (U} \rightarrow \text{E)} \\ \ln y & \text{if no job change} \\ \epsilon'_y & \text{if changes jobs (E} \rightarrow \text{E)} \end{cases}$$

where $\epsilon'_y \sim \mathcal{N}(0, \sigma_{\epsilon_y}^2)$. In other words, 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 unemployment, match-quality is set to y_0 .

2.3.2 Calibration Methodology

Given the optimal decisions of workers and firms, the model generates simulated data at a monthly frequency. In particular, I simulate 6,000 agents for 480 months (40 years). To remove the effects of initial conditions, I simulate the model for 1280 months and then discard the first 800 months of the sample. This simulation provides a time-path of wages and annual earnings, as well as an employment history. I compare the earnings of displaced workers in the model-generated data with the earnings of displaced workers observed in real data.

I calibrate the parameters of the model using simulated method of moments. Certain key moments summarize the simulated data; among others, these moments include gross flows between employment and unemployment and the time-path of earnings for displaced workers. The calibration 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:³

$$\hat{\theta} = \arg \min_{\theta} \mathcal{L}(\theta) = \arg \min_{\theta} [g(\theta) - \hat{g}]' W [g(\theta) - \hat{g}] \quad (2.6)$$

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. Some of the targeted moments are parameters of an auxiliary

³The weighting matrix, W , is chosen so as to target percent deviations; namely the weight equals $\frac{1}{\hat{g}_i^2}$ for moment i .

model, such as coefficients from an estimated equation using the observed data. In this sense, the approach here implements a technique called indirect inference.

The optimization is implemented using MATLAB, a commonly used software package among practitioners, and KNITRO, a state-of-the-art solver, respected in the optimization community (see, for example, Byrd et al., 1999). Numerical derivatives are used throughout the implementation, as well as KNITRO’s multi-start feature (with 500 starting values) which helps avoid local minima.

2.3.3 Calibration

This section presents the key moments of the data and discusses the calibration strategy. When discussing the identification strategy I describe how changes in parameters affect moments of the simulated data. Due to the high non-linearity of the model, no single moment pins down identification of a parameter. Nevertheless elucidating the identification of key components of the model is a worthwhile exercise. Table 2.1 summarizes the baseline parameters and the moments targeted in the observed data. Table 2.2 displays the simulated moments at the calibrated parameter values and shows that the model matches well the calibration targets.

The x process represents movements in idiosyncratic productivity and affects the level and persistence of displacements. The variance of ϵ_x is set to match the displacement probability observed in the data in the year following the first displacement. If x displays no variation ($\sigma_{\epsilon_x} = 0$), then the model features exogenous separations only and there is no serial correlation in displacements, which means that the probability of displacement in the year following displacement is the same as in all other years. As the variance of ϵ_x rises the probability of separation conditional on any match-quality level rises. In particular, with initial match-quality coming out of unemployment fixed to some y_0 , the separation rate is likely to be higher in the year following displacement when σ_{ϵ_x} is higher.

Conditional on targeting the displacement probability in the year following the first displacement, ρ_x targets the persistence in this displacement probability. Fixing match-quality at some y_0 along with time-varying idiosyncratic productivity, delivers some serial correlation in displacements as individuals low on the job ladder experience a higher probability of separation than those further up the job ladder. Conditional on a relatively high x_0 , higher ρ_x will serve to mitigate serially correlated displacements as individuals experience high idiosyncratic productivity for longer. In the calibrated version of the model, x_0 is relatively high so that productivity within the match trends down over time.⁴

PSID data provide a way to measure serial correlation in displacements. The PSID began in 1968 with an interview of 5,000 families, and follows any new families formed from the original group of families. I follow Polsky (1999) closely with my empirical approach to calculating job switches. Anticipating the E-E transition analysis later in this chapter, I use the 1976-1997 waves of the PSID study. I drop the years prior to 1975 because the job history data for these years are poor (Brown and Light, 1992), and I omit the years following 1997 because of the biennial surveys. I include an individual in the sample if they appeared as a household head for three consecutive years from their first year as household head in the survey. In the data, job displacements are determined from a question that asks respondents with low levels of current job tenure “What happened to that employer (job)?” (the individual’s previous job). The two categories of responses used to identify displacements are “plant closed/employer moved” and “laid off/fired.” Using this data, in the year following their first displacement, workers’ probability of experiencing another displacement increases by around 25 percentage points. The effect of the first displacement displays serial correlation with a 0.63 annual persistence parameter.

The starting idiosyncratic productivity for unemployed individuals, x_0 , is targeted

⁴This is consistent with Mortensen and Pissarides (1994) and Hall (1999).

to generate the employment-to-unemployment (E-U) transition probability found in the United States gross flows data. As x_0 rises, unemployment becomes more appealing because the first job coming out of unemployment has higher productivity. This induces a larger fraction of the employed to flow into unemployment every period. Elsby et al. (2010) find the monthly layoff inflow rate is around 1.5 percent (table 9 in their paper). Since most displacements represent no fault termination or layoff from employment, using the layoff inflow rate is an appropriate target.

The standard deviation of match-quality is difficult to quantify in the data. The model provides a convenient way of calibrating this parameter: the on-impact dip in earnings resulting from displacement. Increasing the dispersion in y implies that agents on average move further up the job ladder, and have more earnings to lose, when they experience a displacement. This increases the on-impact dip in earnings resulting from displacements. As an alternative, in a very similar model to the one presented here, Low et al. (2010) estimate the standard deviation of match-quality at 0.22.

As mentioned in the introduction, I target the time-path of displaced worker earnings in this analysis.⁵ This shows that there exists a model and a set of parameter values that delivers something close to the observed earnings experience of displaced workers. Given the recent article by DV, which highlights the inability of standard search models to capture this fact, this model's ability to match this moment is an accomplishment in and of itself. Section 2.5 provides further implications of this calibrated model for a range of un-targeted outcomes, including wage dispersion, and a decomposition of earnings losses into reductions in employment and lost wages.

⁵In practice I target four points of this time-path: the initial point (six years before displacement), the point in the year just before displacement, the trough, and the point 20 years after displacement. The difference between the point in the year just before displacement and the initial point is referred to as the 'pre-displacement rise in earnings' in Table 2.2. The difference between the trough of this time-path and the point 20 years after displacement is referred to as the 'recovery of displacement earnings' in Table 2.2. Since there are eight calibrated parameters (y_0 is a normalization and β is fixed arbitrarily) and 10 moments, the model is over-identified.

The observed E-E transition rate is targeted using 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 . Fallick and Fleischman (2004) use data from the basic monthly Current Population Survey (CPS) from January 1994 to December 2003. They find that an average of 2.6 percent of employed persons change employers each month.

The contact probability for the unemployed, p_U , is determined by targeting the aggregate job-finding probability. Increasing the job-contact rate means that unemployed workers experience more frequent contacts and since workers accept all first offers in this model, the unemployment-to-employment probability rises. Following Shimer (2005) this analysis targets a monthly job-finding rate of 45 percent.

The exogenous separation rate (p_s) targets a slight increase in earnings for high-tenured workers prior to displacement, as in DV. With only exogenous separations ($p_s = 0.015$) in the model there would be no movement in average earnings prior to displacement. Alternatively, if all the displacements in the model were endogenous ($p_s = 0$) then earnings tend to vary more prior to displacement.

The value of leisure, b , is chosen to target the value found in Hall and Milgrom (2008): 0.71 of average productivity of labor (APL). Since the emphasis of this work is not on the cyclical behavior of unemployment and vacancies over the business cycle, the calibration of this parameter is less crucial. The value found in Hall and Milgrom (2008) serves as a benchmark.⁶

The starting match-quality is normalized to the expected value of the stochastic process for y , which is close to one. At the solution, this means that y_0 falls at around half of the average match-quality among employed workers, which is around two standard deviations below the mean. The bargaining power of the worker, β , is

⁶Table 2.2 shows that the model cannot quite hit the Hall and Milgrom (2008) target.

set to 0.5, realistic adjustments of which I have found to be immaterial. Finally, δ targets a five percent annual interest rate.

2.4 Results

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:

$$e_{it}^y = \alpha^y + \sum_{k=-6}^{20} D_{it}^k \delta_k^y + u_{it}^y \quad (2.7)$$

where the superscript y denotes the displacement year, the outcome variable e_{it}^y is annual earnings of individual i in year t , α^y represents a constant, D_{it}^k are dummy variables equal to one in the worker's k th 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. The model of this chapter does not feature individual or time variation that needs to be controlled by using individual or time fixed effects. DV estimate this distributed lag model separately for each displacement year y . In the model presented in this chapter all years are identical, so y is fixed at an arbitrary year.

As in DV, the sample is restricted to individuals with at least three years of tenure at the time of displacement. In particular, the worker must have positive earnings from the employer in question in $y - 3$, $y - 2$, and $y - 1$. This could mean as little as 14 months of tenure at the time of displacement. 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, in the simulated data, the worker experiences a separation into unemployment 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. This resembles the treatment group used by DV as they omit so-called non-mass-layoff separators from the control group. 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 do not experience a displacement in year 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 most individuals in the treatment group separate from their employer via an exogenous separation. Nonetheless, endogenous separations play a key role in explaining serial correlation in displacements.

Figure 2.1 presents a comparison between the results from the baseline model and the results from DV. The results are very encouraging, with the baseline model delivering an earnings trajectory that closely resembles the empirical counterpart. The search model outlined in this chapter can account for the time-path of displaced worker earnings.

On impact the model predicts the losses in annual earnings well: around 30 percent. Additionally, the model captures the movements in earnings post-displacement very well. For the first 10-15 years of the recovery the model provides a remarkable fit. The model cannot deliver the plateauing, and even declining, earnings time-path after 15 years observed in the data. The framework features ex-ante homogeneous agents and a steady state wage distribution, which imply that eventually the earnings of displaced workers will recover. Nevertheless, after 20 years the model implies

earnings losses similar to those found in the data.⁷

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 unemployment. Earnings fall slightly in the year following displacement because some workers lose their jobs late in the ‘0’ year and so have a substantial amount of earnings in the year of job loss. Since it takes unemployed workers time to find jobs, and $y_0 < \mathbb{E}[y|match]$ so that first jobs pay very little, in the year immediately following job loss workers may actually experience a small dip in earnings. This additional loss in earnings is also attributable to using observations from years y , $y + 1$ and $y + 2$, which serves to smooth out the effects of displacement. In addition to these timing issues, the high serial correlation in displacements implies that in the year following the investigated displacement, the worker may experience subsequent displacements that reduce his annual earnings even further.

The slow recovery in earnings represents the slow move up the job ladder for recently displaced workers, which in turn manifests serially correlated displacements. Agents experience serially correlated displacements because match-quality remains low in first jobs and therefore only small movements in idiosyncratic productivity cause further displacements.

Figure 2.2 compares the percentage-point change in the displacement probability (from the average displacement probability) for the model and the PSID after the first displacement.⁸ The line implied by the model incorporates the PSID survey algorithm. In other words, I look at individuals every 12 months and, if their tenure

⁷The time-path of earnings from the simulated data is not smooth due to the limited number of agents. Adding more agents to the simulation would smooth out this time-series. Also, 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. 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.

⁸The figures only document probabilities up to 10 years following displacement due to small sample sizes beyond this horizon in the PSID.

is less than 12 months, and their most recent job ended in an unemployment spell, I classify them as displaced. I divide the number of displacements every year by the number of employed individuals last year to obtain the model implied displacement probability.

The model endogenously generates serial correlation in displacements that quantitatively matches the evidence from the PSID. The parameters σ_{ϵ_x} and ρ_x are chosen to match the initial spike in displacement probability (around 25 percentage points above the average displacement probability) and the persistence of this process respectively. The model delivers the initial spike in displacement probability, and delivers slightly more persistence in displacements than we observe in the data, with the first displacement effect not quite subsiding after 10 years.

2.5 External Validity

Now that I have established that the calibrated model presented in this chapter reproduces 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, flow probabilities, and movements in total factor productivity (TFP).

2.5.1 Wage Related Moments

The model generates other interesting moments that can help to assess the validity of the theory described in this chapter. Table 2.3 compares some wage-related moments in the simulated data and the observed data. As an example, the simulated data imply a standard deviation of annual quarterly earnings changes within matches of 16 percent. Topel and Ward (1992) use Longitudinal Employee-Employer

Data data to estimate the same moment for young workers aged 18 to 34.⁹ They obtain a value of 19 percent, which signals relatively large movements in earnings within matches, and the model is able to match these fluctuations. The idiosyncratic productivity process is largely responsible for these large fluctuations of wages within matches (high σ_{ϵ_x}).¹⁰

Another important non-targeted moment is the mean-min wage ratio, which captures the amount of equilibrium wage dispersion. In recent important work, Hornstein et al. (2011) show that standard MP models cannot reproduce observed wage dispersion. In their working paper, they use data from the Census, Occupational Employment Survey and PSID to document mean-min wage ratios between 1.5 and 2. They document that standard search models generate mean-min wage ratios much closer to one. They suggest that models with on-the-job search can attain mean-min wage ratios that are more consistent with observed data. The baseline model implies a mean-min wage ratio of 1.9, which lies in the range of estimated values. This is quite an achievement and goes a long way towards explaining why the model presented in this chapter can account for all the earnings losses associated with displacement. It seems that generating realistic wage dispersion can help explain the persistence of earnings losses experienced by displaced workers. Put another way, it seems that the “bad luck” associated with losing one’s job can explain the entirety of the poor recovery in post-displacement earnings observed in the data. In their paper, DV 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 chapter, the maximum wage exceeds the minimum wage by around 400%, which compares to only 49% in the Burgess-Turon model presented in DV. These observations suggest that

⁹Since the model is an infinite horizon model, young workers are the more relevant empirical counterpart.

¹⁰The model undershoots the quarterly wage growth from E-E transitions. The idiosyncratic process is difficult to identify. In calibrations with similar objective function values the model can undershoot the standard deviation of annual quarterly earnings changes within matches and obtain the quarterly wage growth from E-E transitions.

the model features a significant job ladder that matches empirical facts well.

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 between the first and second year of postdisplacement experience.” In the long-run, Topel (1990) finds that “three-fourths of [the post-displacement earning loss] is due to lower wages...” Bender et al. (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 about 10 years the effect of displacement on employment dissipates, and reduced wages are responsible for all subsequent earnings losses. One can estimate equation (2.7), with three left-hand-side variables: earnings, wages and employment. Figure 2.3 presents the model’s decomposition of earnings losses into lost wages and unemployment.

The model suggests that around 80 percent of the initial loss in annual earnings is accounted for by lost employment and 20 percent by reduced wages. This resembles the data’s values: 66 percent and 33 percent respectively. As in the data, the model predicts that in the short run the earnings recovery is almost solely due to increased employment. Consistent with the empirical work, in the long run the model predicts that around three quarters of earnings losses are due to lower wages and around one quarter due to reduced employment. Given that this break down was not targeted, it is remarkable that the model’s decomposition resembles the decomposition we observe in the data. This result finds its roots in the serial correlation in displacements exhibited by the model. With high persistence in displacements, reduced employment lingers for many years.

2.5.2 Non-Wage Related Moments

The calibrated model also speaks to non-wage related moments. As an example, Foster et al. (2008) use the Census of Manufacturers to estimate the annual persistence in establishment-level productivity to be 0.75 to 0.8. They estimate the following regression with TFP on the left hand side instead of $x \cdot y$, and I estimate the same equation via OLS using the simulated data:¹¹

$$x_{t+1} \cdot y_{t+1} = \beta_0 + \beta_1 x_t \cdot y_t + \xi_{t+1} \quad (2.8)$$

where $x \cdot y$ represents TFP in the baseline model. In this calibrated version of the model, $\hat{\beta}_1$ turns out to be around around 0.65, very close to the range of values found by Foster et al. (2008), 0.75 to 0.8. This is largely due to the fixed match-quality on the job as well as the persistence of the calibrated idiosyncratic productivity process.

Foster et al. (2008) also estimate the standard deviation for plant level productivity (in logs) to be between 0.21 and 0.26 (table 1 of their paper), which implies that plant-level productivities fall within 50 percent of the average plant productivity. Again, the model does a nice job of capturing this aspect of the data with an estimated standard deviation of plant level productivity at 0.29, a little higher than in the data.¹²

The model also speaks to E-E flows around the time of displacement, suggesting increased E-E flows after displacement 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. If the individual is employed at time period t and employed at time period $t + 1$ and the tenure in the current employer is less than or equal to 12 months, and the person reports no spell of unemployment last year, a job switch is assumed to have occurred at time $t + 1$.¹³ Even though the model makes no distinction between promotions and

¹¹The results are virtually identical if the regression is specified in logs.

¹²The model takes a very micro view of the firm treating each worker as a plant.

¹³Tenure information is notoriously noisy in the PSID. I use the approach of Altonji and Shakotko (1987) to clean the tenure variable.

E-E switches, promotions are not included as a form of job switching in the empirical approach because the model was calibrated to target the average E-E rate, which does not include promotions at the same employer. To obtain a probability, I divide the number of job switches by the number of individuals employed in the previous year.

Figure 2.4 shows that, on average, workers in the PSID exhibit elevated E-E rates for around 10 years after their first displacement. In the same figure I plot the percentage-point change in the E-E probability (from the average E-E probability) for the simulated data. In the simulated data I implement the PSID survey algorithm. In other words, I look at individuals every 12 months, and note their employment status. If the individuals are employed this year, employed last year, have tenure less than 12 months and experience no unemployment in the last 12 months, they are marked as E-E switchers. I divide the number of E-E switches by the number of employed individuals in the previous year to obtain a number that is comparable to the PSID calculation. Although the magnitude is slightly higher, the model does match the qualitative shape of the E-E probability after the first displacement, remaining elevated for 10 years after the first displacement. This calibrated model faces a tension between a low y_0 that helps match the dip in earnings in the year of displacement, and a higher y_0 that would reduce the number of E-E switches among the recently employed.

2.6 Robustness Checks

The model presented in this chapter includes a variety of components. This section demonstrates the importance of each feature. The model presented here has both idiosyncratic productivity and match-quality. Dropping these elements prevents the model from explaining the data. Figure 2.5 presents the δ_k coefficients from equation (2.7) (normalized by pre-displacement earnings) from alternative versions of the model

in separate graphs, together with the baseline model. The alternate models are calibrated in a comparable fashion to the baseline.¹⁴

The top-left graph presents a standard Mortensen-Pissarides style model, like the one in DV. The coefficients before displacement are zero because the model features exogenous separations so prior to displacement all workers have the same earnings. In the year of displacement, earnings fall, and they quickly 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.

The top-right graph takes the standard MP model and adds idiosyncratic productivity that 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 . This model features no job ladder and exhibits quick earnings recovery post-displacement despite the presence of idiosyncratic productivity. This is because in the calibration $p_s \approx 0.015$ and so the model behaves like the standard MP model, with a mean-min wage ratio slightly larger than one.

The bottom-left graph features a job ladder and exogenous separations, with no idiosyncratic productivity. This model features no serial correlation in displacements because the flow hazard into unemployment is constant and exogenous. This calibration misses the data on displaced workers and predicts a full recovery after about 15 years. This model features increasing earnings prior to displacement as workers climb up the ladder and experience exogenous separations. Nevertheless, this does show that a model with match-quality goes a long way towards explaining the persistence in earnings losses of displaced workers. The mean-min wage ratio for this model is around 1.2. Adding persistent idiosyncratic productivity obtains the ‘Baseline Model’

¹⁴Details of calibration for each model are available upon request. Aside from the basic MP model, all calibrations target the earnings time-path around displacement. All calibrations target the U-E, E-U and (where applicable) E-E rates, and $0.71 \times \text{APL}$ for the value of leisure.

line in the bottom-right graph, which features all the quantitative characteristics of the data. The line implied by the baseline model captures the empirical work well and supports the choice of model; other simpler models of a similar flavor simply cannot explain all the data. As mentioned before, this model delivers realistic wage dispersion with a mean-min wage ratio equal to 1.9. This underscores the importance of replicating the observed level of wage dispersion when matching the earnings losses of displaced workers in the context of stationary search models with ex-ante homogeneous workers.

The details of an efficient wage model are discussed in Section 2.8. The result of this model appears in the bottom-right graph, and matches closely the results from the baseline model. For simplicity, this chapter demonstrates results using the simple surplus sharing solution.

2.7 Summary and Discussion

Previous literature documents large and persistent earnings losses associated with worker displacement. I propose a rich search and matching model to help understand the time-path of earnings for displaced workers. Persistence in idiosyncratic productivity (demand) helps explain the movement in earnings prior to separation. 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 displacements and increased time to “ideal” job. 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 displacements, matching the observed wage dispersion seems like an important element of any search model targeting displaced worker earnings losses. Many alternative models, including the basic MP model and even

models with a job ladder, but no idiosyncratic productivity and serially correlated displacements, cannot deliver the observed earnings losses of displaced workers. The model presented here also speaks to additional un-targeted moments. It successfully matches the decomposition of earnings losses into reduced wages and employment, as well as fluctuations in TFP and earnings within matches. The model correctly predicts increased E-E transitions after displacement as workers more readily switch jobs when low on the job ladder.

As mentioned briefly in Section 2.4, the targeted moments imply that most individuals in the treatment group separate from their employer via an exogenous separation. This is a result of the tenure restriction. Although in any given year, endogenous separations account for most of the E-U flows, individuals with three years of tenure do not experience endogenous separations and therefore displacement is an event exogenous to the model outlined here. This raises an important question for future research to address: are displacements in fact exogenous? This topic touches upon a long-standing issue of whether separations are efficient; whether there exists a distinction between quits and layoffs.¹⁵ Endogenizing the separation of well-matched individuals seems like a promising avenue for future research. In particular, an inability to borrow in tight credit markets may serve to explain why firms do not hold onto highly productive workers when experiencing reduced demand for their product. This approach could provide a reason for inefficient separations and could help us better understand the experience of displaced workers.

¹⁵See, for example, Hall (2005).

2.8 Appendix A: Model with Rigid Wages

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 skills 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 unemployed 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 et al. (2006) who show that the worker's threat point is the match value with the losing firm. The model still features privately efficient separations.

2.8.1 Intuition

Before I discuss the formal model equations, I want to provide a simple description of the model dynamics and give the reader intuition for the mechanics of the model. The model delivers two features: a fall in earnings prior to displacement (when not

relative to a control group) and a slow recovery in earnings post-displacement. Persistence in the idiosyncratic process implies that the average displaced worker in the model experiences a reduction in earnings prior to separation. This follows because conditional on being displaced, the match is more likely to have experienced a negative shock in the period prior to displacement and so the idiosyncratic component will be closer to the firing threshold than in previous periods. 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 and the average match-quality among employed workers. Second, in conjunction with a low match quality among first jobs, the job ladder effect 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 displacements and serial unemployment. This serial unemployment effect dovetails with work by Stevens (1997) who finds that multiple job losses are an important explanation for the persistence of earnings losses.

2.8.1.1 Wage Dynamics Prior to Displacement

Figure 2.6 displays the model intuition graphically. At time $t = -7$ we encounter an established employment relationship with some (x, y) and $x < x_0$. At time $t = -6$, x goes up. This causes the reservation wage of the current firm to move up and the reservation wage of the worker to move down slightly. The firm is willing to pay more because the output of the match has increased. The worker is willing to receive less because the chance of a separation relates inversely to x .¹⁶ Nonetheless, the

¹⁶The worker's reservation wage is defined as $W(x, y, w_R) = U$. Since W turns out to be increasing in w and x , an increase in x causes a reduction in w_R . Analogously, the firm's reservation wage is defined as $J(x, y, w_R^f) = 0$. Since J turns out to be decreasing in w and increasing in x , an increase in x causes an increase in w_R^f .

actual wage does not change because neither party can credibly threaten to leave the employment relationship and thus the current wage contract persists. At time $t = -5$ the worker receives an outside offer, and his reservation wage rises. There exists no mutually agreeable wage at the current firm so the worker leaves the current firm. At the new firm the match-quality is higher (y_1), the idiosyncratic productivity starts out at x_0 . Based on the new x and y , as well as the worker's previous employment relationship, a generalized Nash bargain results in a new wage. At time $t = -4$ the worker receives another outside offer. His reservation wage does not exceed the reservation wage of the firm, so the current firm keeps the worker. However, the wage at the current employment relationship is bid up because the worker can credibly threaten to leave to the poaching firm. At the new contracted wage, the worker is indifferent between staying at the current firm and leaving to the poaching firm.

At time $t = -3$, x moves up, but causes no change in the wage, as during $t = -6$. At time $t = -2$ the idiosyncratic component moves down, causing a downward movement in the reservation wage of the firm. Since there is still positive surplus from the employment relationship the wage is renegotiated downwards so that the firm is indifferent between keeping the worker and letting him go. At time $t = -1$ the idiosyncratic component falls again, and the wage is renegotiated further downwards. At time $t = 0$ the idiosyncratic component falls below $x^*(y_1)$ the cutoff associated with match-quality y_1 .¹⁷ There exists no wage above the reservation wage of the worker and below the reservation wage of the firm. The match dissolves and the worker becomes unemployed. Notice that prior to displacement, the model will, on average, predict a fall in x , and since earnings are a positive function of this component, earnings will tend to fall before displacement. This is without comparing to a control group and without conditioning on three years of tenure. The graphical pictures do not suffice to provide intuition for this more complicated case.

¹⁷Formally, $x^*(y)$ satisfies $S(x^*(y), y) = 0$ for any y .

I relate these movements in x to demand for the match's output. When demand for the match's output wanes sufficiently, the firm can credibly threaten to lay the worker off because the firm's share of the surplus becomes less than the value of posting a new vacancy. Since the worker still prefers to remain in the match, wage renegotiation results in a lower wage. As the demand for the match's output continues to fall, the bargained wage continues to fall. Sufficiently large downward movements in demand exhaust the match surplus and the employment relationship terminates. Intuitively, this suggests that as demand for the match's output falls, the firm pulls back on wages, resulting in worker earnings losses prior to displacement. As demand continues to fall, eventually the employment relationship terminates.

2.8.1.2 Wage Dynamics Post-Displacement

Figure 2.7 presents the model intuition post-displacement with a focus on serial unemployment. After a couple of periods the worker finds a new job with idiosyncratic component x_0 . By assumption this job will have a lower match-quality (y_0) than the average job that the worker climbed to before separation (y_1). Since surplus is a positive function of x and y , and y is lower, x must be higher to maintain positive surplus. This is why $x^*(y_0) > x^*(y_1)$. Since the post-displacement x is closer to the threshold, the idiosyncratic component is more likely to go under the cutoff again. In other words, the worker is likely to experience multiple spells of unemployment. This is consistent with work by Stevens (1997). In this particular figure, at time $t = 3$, the match experiences a downward movement in x that results in a subsequent separation. Serial unemployment partially explains the slow recovery of earnings after displacement. Moreover, even if the worker does not get displaced subsequently, it takes time for the worker to climb the job ladder again, and this induces persistence in earnings losses.

2.8.2 Bellman Equations

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

2.8.2.1 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 unemployed 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:

$$\begin{aligned}
V(x, y) = & x \cdot y + \delta(1 - p_s) \underbrace{(1 - p_E)}_{\text{No outside offer}} \int \underbrace{\max\{U, V(x', y)\}}_{\text{Match continues or terminates}} dF_x(x'|x) + \delta p_s U \\
& + \delta(1 - p_s) \underbrace{p_E}_{\text{Outside offer}} \int \int \underbrace{\max\{U, V(x', y)\}}_{\text{Match continues}} , \underbrace{(1 - \beta) \max\{U, V(x', y)\} + \beta V(x_0, \tilde{y})}_{\text{Worker moves to poaching firm}} dF_x(x'|x) dF_y(\tilde{y})
\end{aligned} \tag{2.9}$$

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 that 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 unemployment, whichever is larger) as a threat point. This result comes from Appendix A of Cahuc et al. (2006).

2.8.2.2 Value of Work to the Employee

The value of work satisfies the following equation:

$$\begin{aligned}
W(x, y, w) = & w + \delta(1 - p_s)(1 - p_E) \int \underbrace{\max\{U, \min\{V(x', y), W(x', y, w)\}\}}_{\substack{\text{Match continues or terminates;} \\ \text{possible wage renegotiation}}} dF_x(x'|x) + \delta p_s U \\
& + \delta(1 - p_s)p_E \int \int \underbrace{\mathbb{I}\{V(x_0, \tilde{y}) > V(x', y)\}}_{\substack{\text{Worker leaves current firm}}} \max\{U, (1 - \beta) \max\{V(x', y), U\} + \beta V(x_0, \tilde{y})\} \\
& + \underbrace{\mathbb{I}\{V(x_0, \tilde{y}) \leq V(x', y)\}}_{\substack{\text{Worker turns down outside firm}}} \max\{U, \min\{V(x', y), W(x', y, w)\}, V(x_0, \tilde{y})\} dF_x(x'|x) dF_y(\tilde{y})
\end{aligned} \tag{2.10}$$

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. There 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 unemployment 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: unemployment 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 + $\beta \times$ 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 unemployment. 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:

$$J(x, y, w) = V(x, y) - W(x, y, w) \quad (2.11)$$

2.8.2.3 Value of Unemployment

The value of unemployment satisfies:

$$U = b + \delta(1 - p_U)U + \delta p_U \underbrace{\max\{U, U + \beta[V(x_0, y_0) - U]\}}_{\text{Match consummates or not}} \quad (2.12)$$

where p is the probability of making a contact with a vacancy for unemployed workers. The first term captures the flow payoff from unemployment: b . The second term corresponds to no outside job offer. In this case the worker simply remains unemployed. The third term corresponds to an outside job offer. In this case the worker chooses between working at the contacting firm and unemployment. 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 et al. (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.

2.8.3 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:

$$\begin{aligned}
S(x, y) = & x \cdot y + \delta(1 - p_s) \underbrace{(1 - p_E)}_{\text{No outside offer}} \int \underbrace{\max\{0, S(x', y)\}}_{\text{Match continues}} dF_x(x'|x) \\
& + \delta(1 - p_s)p_E \int \int \underbrace{\max\{0, S(x', y)\}}_{\text{Match continues}}, \underbrace{\max\{0, S(x', y)\} + \beta[S(x_0, \tilde{y}) - \max\{0, S(x', y)\}]}_{\text{Worker moves to poaching firm}} dF_x(x'|x) dF_y(\tilde{y}) \\
& - \underbrace{[b + \delta p_U \beta \max\{0, S(x_0, y_0)\}]}_{\text{Worker's outside option}}
\end{aligned} \tag{2.13}$$

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 unemployment, 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 (2.13) 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.

2.9 Appendix B: Surplus/Wage Equation and Numerical Details

2.9.1 The Surplus Equation

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.

2.9.1 The Surplus Equation

Here I outline how to solve for the 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 (2.1) slightly to yield the equivalent expression:

$$\begin{aligned}
W(x, y) = & w + \delta(1 - p_E)(1 - p_s) \int \max\{U, W(x', y)\} dF_x(x'|x) + \delta p_s U \\
& + \delta p_E(1 - p_s) \int \int \left[\mathbb{I}\{W(x', y) \geq W(x_0, \tilde{y})\} \max\{U, W(x', y)\} \right. \\
& \left. + \mathbb{I}\{W(x', y) < W(x_0, \tilde{y})\} \max\{U, W(x_0, \tilde{y})\} \right] dF_x(x'|x) dF_y(\tilde{y})
\end{aligned} \tag{2.14}$$

Now simply combine equations (2.14), (2.2) and (2.3) to write:

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

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 (2.3) 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 unemployment and from job to job.

2.9.2 The Wage Equation

Start with equation (2.1) 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:

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

2.9.3 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 49 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 49 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 grid using linear interpolation. I do not allow state variables to take values above and below the respective minimum and maximum values on the grid, although in practice this does not affect the results because the probability of state variables falling outside the grid remains extremely small.

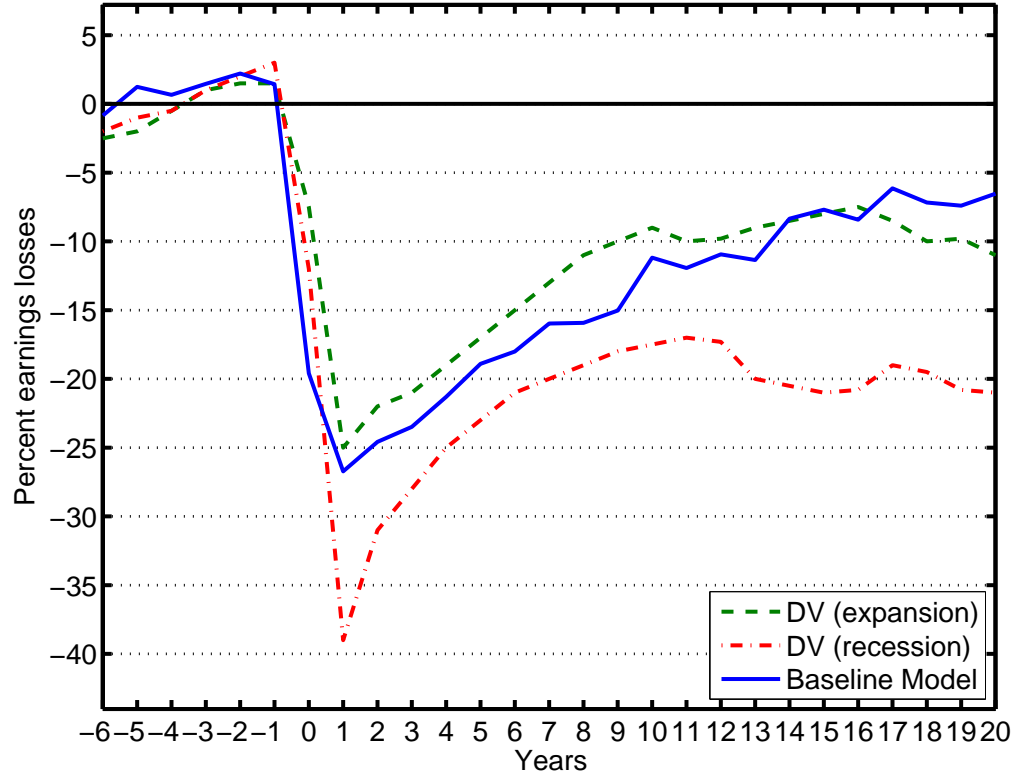


Figure 2.1: Annual Earnings Losses: Model vs. Data

Note: The estimated coefficients δ_k from equation (2.7). 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. Earnings losses are plotted as a fraction of average pre-displacement earnings of the treatment group in the four years prior to displacement. For a definition of displacement and the tenure requirement see the text.

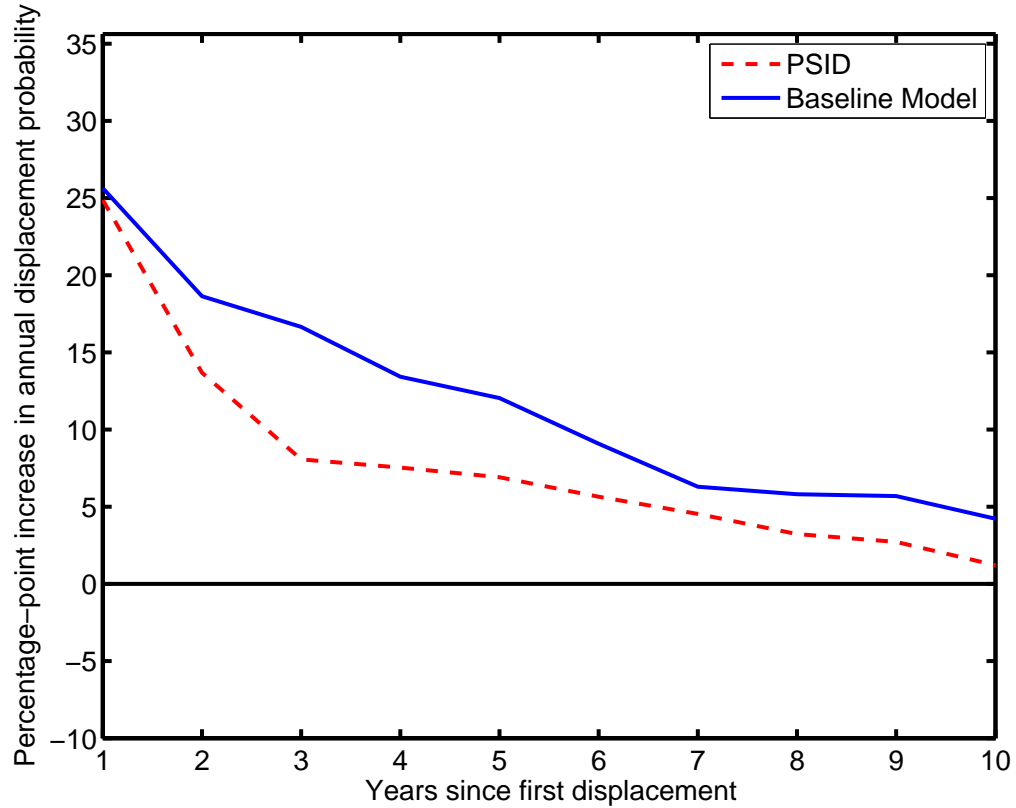


Figure 2.2: Level Increase in Annual Displacement Probability over Average Displacement Probability: Model vs. PSID

Note: For PSID, by year since first displacement, take the number of individuals reporting a displacement and divide by the number of employed individuals in the previous year. Perform precisely the same calculation with the simulated data. This includes replicating the PSID survey and classifying someone as displaced if they have less than one year of tenure at the time of the interview, and their *most recent* job ended in a displacement. In the first year after displacement there are around 850 displacements in the PSID. This number falls to around 100 after 10 years. The average displacement probability during this period in the PSID is around nine percent, which is significantly higher than results from Davis and von Wachter (2011) (around 3.5 percent annual displacement probability). This is not surprising. Davis and von Wachter (2011) focus on male employees 50 years or younger with at least three years of prior job tenure. My analysis makes no such restrictions. The implied annual layoff probability using the monthly probability of 1.5 percent is around 16 percent. This is more in line with the number from the PSID, but the annual PSID survey misses short spells of employment between surveys and makes recall bias more pronounced, which are likely to bias the displacement probability downwards.

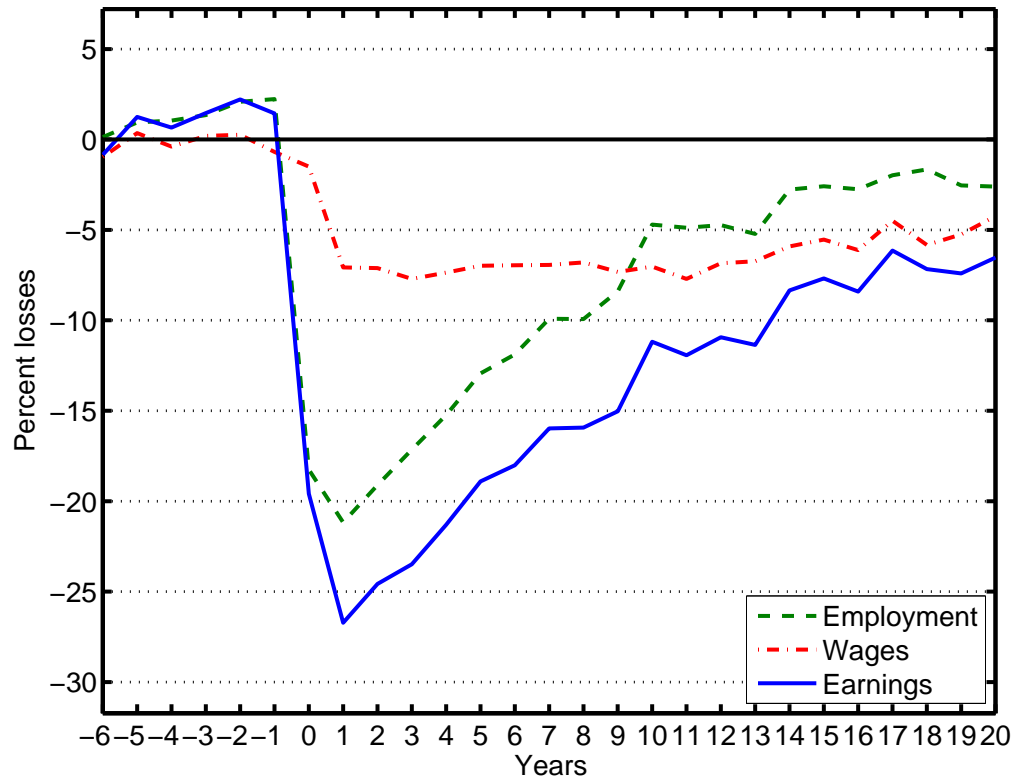


Figure 2.3: Decomposition: Employment and Wages

Note: The earnings time-path is the same as in Figure 2.1. Since workers do not have a valid wage when they are unemployed, this analysis uses the average non-zero monthly wage in a year to measure the annual wage. The average annual probability of employment is used to measure annual employment.

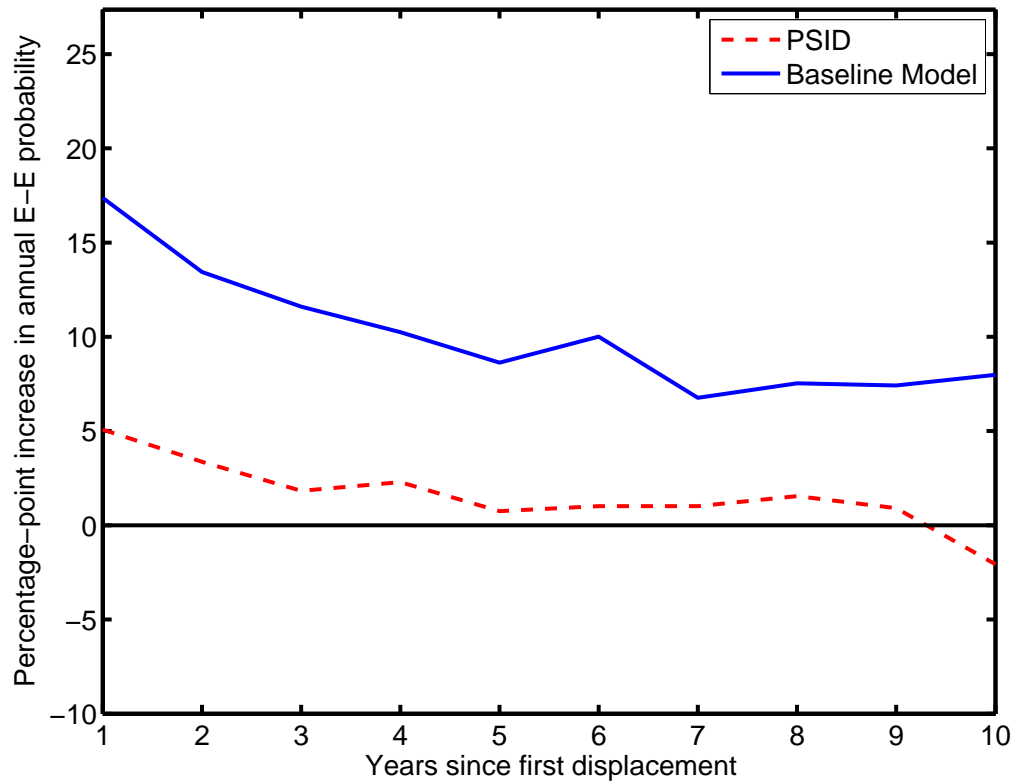


Figure 2.4: Level Increase in Annual E-E Probability over Average E-E Probability: Model vs. PSID

Note: This is relative to the first displacement. The annual E-E probability is calculated as the number of individuals who are employed this year, employed last year, report tenure of less than one year, and report no time unemployed, divided by the number of employed individuals in the previous year. The average E-E probability is simply the average of the E-E probabilities over all the sample years. In the first year after displacement there are around 350 E-E transitions in the PSID. This number falls to around 70 after 10 years. The average E-E probability during this period in the PSID is around eight percent, which is significantly lower than results from Fallick and Fleischman (2004) (around 27 percent annual E-E probability). The annual PSID survey misses short spells of employment between surveys and makes recall bias more pronounced.

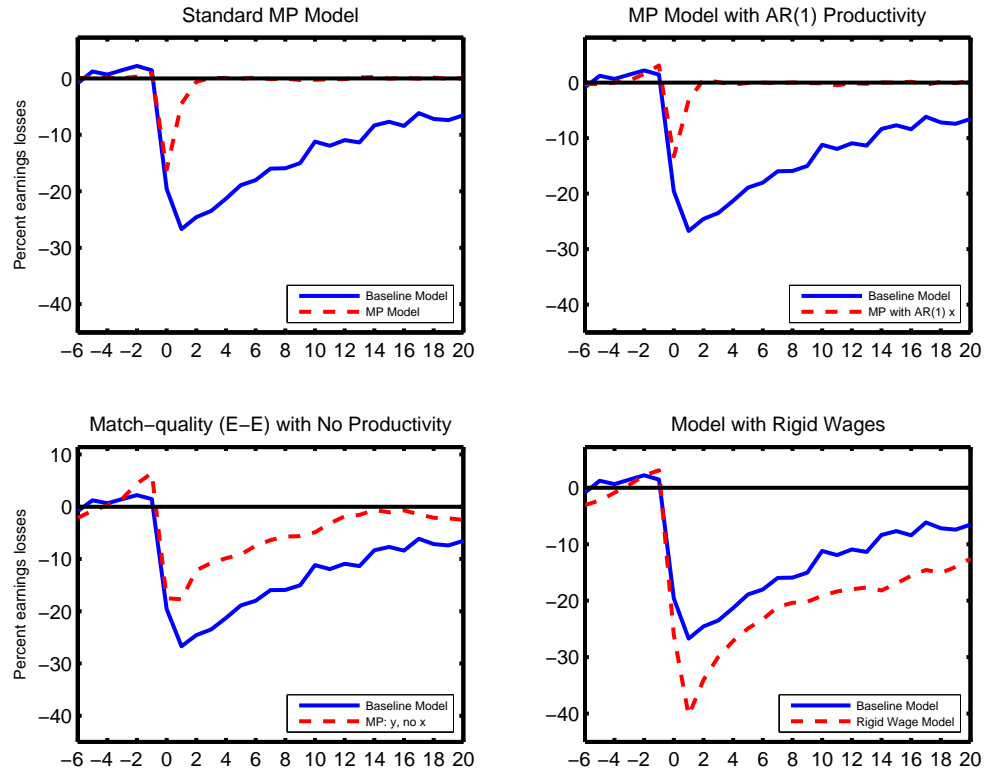


Figure 2.5: Annual Earnings Losses: Alternative Models

Note: The estimated coefficients δ_k from equation (2.7) for alternative models. See the text for a description of each of the models.

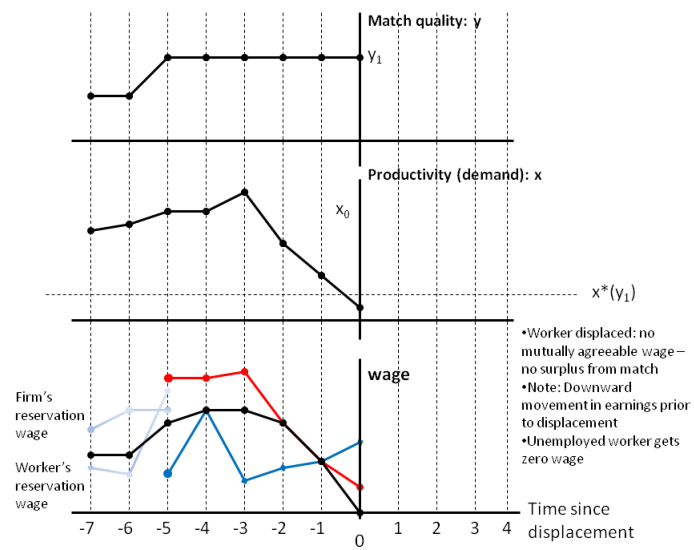


Figure 2.6: Model Intuition: Pre-Displacement

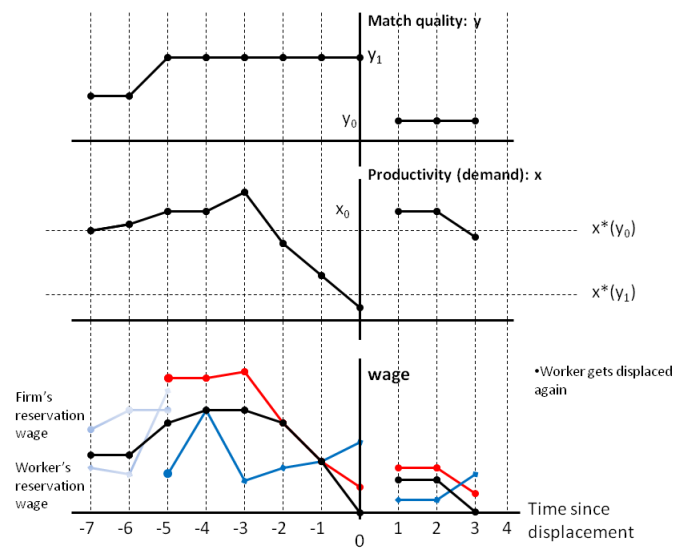


Figure 2.7: Model Intuition: Post-Displacement

Table 2.1: Calibrated Model Parameters

Parameter (θ)	Meaning	Calibrated Value ($\hat{\theta}$)	Main Source of Identification
ρ_x	Productivity persistence	0.43	Persistence of displacements
σ_{ϵ_x}	Std. dev. of productivity	0.24	Post-disp. increase in disp. prob.
σ_{ϵ_y}	Std. dev. of match-quality	0.23	On-impact dip of annual earnings
p_E	Contact probability (E)	0.26	E-E flow probability
p_U	Contact probability (U)	0.45	U-E flow probability
b	Value of leisure	1.19	Hall and Milgrom (2008)
x_0	Starting productivity	$0.58 \times \max[x]$	E-U flow probability
p_s	Exo separation probability	0.0014	Pre-displacement earnings
y_0	Match-quality in first jobs	$\mathbb{E}[y] \approx 1$	Normalization

Note: Calibrated parameters of the model at monthly frequency. ‘Reason’ refers to empirical estimates found in the literature. The citations and values of these empirical moments appear chiefly in Table 2.2. ‘APL’ stands for Average Productivity of Labor.

Table 2.2: Calibration Targets

Moments in the data	Data (\hat{g})	Model ($g(\hat{\theta})$)
Persistence of displacement probability	Author: 0.63 (A)	0.80 (A)
Initial spike in displacement probability	Author: 25pp	26pp
Recovery of displacement earnings	Davis and von Wachter (2011): ~20%	21%
On-impact dip of annual earnings	Davis and von Wachter (2011): ~30%	27%
Employer-to-employer flows	Fallick and Fleischman (2004): 0.026	0.023
Job-finding rate	Shimer (2005): 0.45	0.45
Value of leisure	Hall and Milgrom (2008): $0.71 \times APL$	$0.62 \times APL$
Employment-to-unemployment flows	Elsby et al. (2010): 0.015	0.015
Pre-displacement rise in earnings	Davis and von Wachter (2011): ~3%	2%

Note: The middle column 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. The parenthetical (A) denotes annual frequency moments. ‘APL’ stands for Average Productivity of Labor. ‘pp’ stands for percentage points.

Table 2.3: Non-Targeted Moments

Moments	Data	Model
Mean-min wage ratio	Hornstein, Krusell and Violante (2011): 1.5-2	1.9
Std. dev. of quarterly earnings within matches	Topel and Ward (1992): 19%	16%
Persistence of plant productivity	Foster, Haltiwanger and Syverson (2008): 0.75-0.8 (A)	0.65 (A)
Std. dev. of plant productivity (logs)	Foster, Haltiwanger and Syverson (2008): 0.21-0.26 (A)	0.29 (A)

Note: The parenthetical (A) denotes annual frequency moments.

CHAPTER III

Aggregate Labor Market Fluctuations

3.1 Introduction

The partial equilibrium model described in the previous chapter features persistent earnings losses of displaced workers. In this chapter, I use the the model to assess the implications of the experience of displaced workers for the cyclical dynamics of job flows. Previous literature assesses how the basic search and matching model accounts for the observed movements in unemployment and vacancies over the business cycle. The literature starts with Mortensen and Pissarides (1994) and has developed significantly over the last few years.¹ Previous models have addressed two distinct dimensions of the data: amplification and, to a lesser extent, propagation.

With regard to amplification, authors note that data based on the United States show large movements of the aggregate job-finding rate, as well as the vacancy posting and unemployment rate, in response to aggregate labor productivity shocks. Leaving aside the calibration of Hagedorn and Manovskii (2008), the basic search and matching model fails in this dimension. If one feeds in realistic aggregate labor productivity shocks into a basic Mortensen-Pissarides (MP) model, the fluctuations in the vacancy and unemployment rates are an order of magnitude smaller than what one observes

¹For a rough progression of research see Merz (1995), Andolfatto (1996), den Haan et al. (2000a) and Shimer (2005).

in the data.

As far as propagation is concerned, authors including Fujita and Ramey (2007) note that the movement of vacancies and the unemployment rate do not occur contemporaneously with productivity movements. In particular, the responses of vacancies and unemployment peak around 12 and 15 months respectively following a productivity shock. Again, the basic MP model fails in this dimension: the movement of vacancies occurs simultaneously with productivity, and, due to a high observed job finding rate, unemployment responds quickly. In the standard model, unemployment exhibits a lag of only six months.

In light of this previous literature, the natural question is whether the model outlined in the previous chapter has anything to add on this topic. One result from Chapter II is that the model provides a novel way to calibrate the match-quality distribution, using the earnings time-path of displaced workers. Intuitively, this distribution exhibits slow-moving behavior following a negative aggregate productivity shock as low quality matches are destroyed, and it takes workers time to find new jobs and slowly climb up the job ladder. One might believe that given the match-quality persistence exhibited by the partial equilibrium model, the model may deliver propagation of productivity shocks at the aggregate level. Furthermore, since it takes time for agents to transit out of low match-qualities, and agents coming out of unemployment begin at the bottom of the job ladder, this leaves many jobs susceptible to destruction during a downturn.

In this chapter, I take this possibility seriously. Thus far the model of Chapter II has featured exogenous job finding rates, and it is in this sense that that model is a partial equilibrium one. The firm's decision regarding vacancy posting, and the determination of aggregate meeting rates do not appear anywhere in the analysis. In order to study the effect of labor productivity fluctuations on the volatility of the job-finding rate, vacancies and unemployment this chapter endogenizes the contact rates

found in the model of Chapter II, and introduces aggregate productivity movements. This involves introducing an aggregate matching function and the optimal vacancy-posting decision of the firm, which in turn depends on the steady state distribution of idiosyncratic productivity (demand) and match-quality among employed workers.

The general equilibrium model is subject to an aggregate productivity shock and the endogenous response of the economy is depicted. It turns out that, in response to an aggregate productivity shock, the implications of the match-quality distribution are somewhat encouraging. The model of Chapter II delivers significant propagation of aggregate productivity shocks. Unemployment takes around 15 quarters to adjust to a permanent reduction in aggregate productivity. Vacancies, and therefore the job-finding rate, take even longer to adjust to an aggregate shock. Average match-quality initially exhibits a cleansing effect, as low quality matches are destroyed at the beginning of the downturn, and then a sullyng effect as job-finding probabilities are permanently lower. The amplification of the model is harder to assess, but using results from persistent shocks as a lower bound, the model seems to deliver sufficient amplification. The model delivers the procyclicality of the job-finding rate for both the unemployed and the employed, as well as the countercyclicality of the employment to unemployment transition rate in the United States.

These results point to a possible resolution of a tension in the search and matching literature. On the one hand, as discussed earlier, matching the wage dispersion discussed in Hornstein et al. (2011) seems important for matching the persistence of displaced worker earnings losses. In fact, this chapter continues this theme, and shows that realistic wage dispersion seems like a necessary, but not sufficient, condition for matching the earnings losses of displaced workers. On the other hand, in a recent paper, Bils et al. (2011) point out that the baseline MP model faces a trade-off between matching observed dispersion in wage growth across workers and realistic cyclical fluctuations in unemployment. In particular, with large wage dis-

persion, which requires large dispersion in match-quality, few individuals are at the destruction threshold. In the context of Bils et al. (2011), this means that an aggregate productivity shock affects few relationships and therefore engenders only small movements in unemployment and vacancies. This suggests that mere churn at the bottom of the productivity distribution is insufficient to explain the dynamics of labor market aggregates. Moreover large match-quality dispersion implies large surplus in employment relationships and small movements in accounting profits in response to aggregate productivity shocks.² The model in this dissertation helps resolve some of these tensions by introducing both match-quality and idiosyncratic productivity. Low quality matches among new hires, along with a reasonable productivity process, allow the model to simultaneously deliver the wage dispersion required to match the persistence in earnings losses associated with displacement and realistic fluctuations in unemployment in response to aggregate shocks. Moreover, fixing the initial match-quality allows the framework to deliver observed wage dispersion without requiring an implausibly small value of leisure.

The model is also subject to exogenous separation shocks, which have been used in the past in order to assess search and matching models. This type of shock has more bite because all agents are exposed to exogenous separations whereas the aggregate productivity shock only affects those individuals at the reservation threshold. A shock to exogenous separations demonstrates that the model can deliver even more propagation. On impact vacancies fall as an increased separation probability lowers the value of a filled job. As new unemployed workers find jobs they lower the average match-quality as these workers start towards the bottom of the job ladder. The average E-E probability rises as new unemployed workers find jobs at low-quality matches and move quickly up the job ladder. This increased chance of poaching an employed

²Hagedorn and Manovskii (2008) show that reducing the surplus from employment relationships can significantly increase the volatility of unemployment and vacancies in the baseline MP model. Conversely, with large accounting profits, the baseline model fails to amplify aggregate productivity shocks.

worker raises the payoff from meeting an employed worker, which encourages firms to post more vacancies. Since the average match-quality is a slow moving object, governed by endogenous worker flows, this process takes a significant amount of time.

The rest of this chapter is organized as follows. Section 3.2 presents the tension between matching wage dispersion and cyclical volatility in a simpler version of the model presented in Chapter II, a model very similar to that found in Bils et al. (2011). This simpler model is calibrated in two different ways: the “benchmark” calibration which delivers observed wage dispersion, and the “high-elasticity” calibration which delivers significant cyclical volatility. In this section I lean heavily on results and calibrations from Hornstein et al. (2011) and Bils et al. (2011), particularly with an eye towards the earnings losses of displaced workers. Section 3.3 extends the model presented in Chapter II (hereafter referred to as the full model) to a general equilibrium framework. Section 3.4 presents steady-state features of this model, and Section 3.5 presents transition dynamics of key endogenous variables in response to an aggregate productivity shock. Section 3.6 presents impulse response functions for a separation shock. Section 3.7 summarizes.

3.2 Simple Model

To gain intuition for the aggregate dynamics of the model presented in Chapter II, this section presents a simpler version of that model (henceforth referred to as the simple model). The framework still incorporates search and matching, and is in large part the same as the model in Chapter II, aside from three exceptions. First, the model presented here features no match quality, denoted by y in the previous chapter. The output of every match is a linear function of the idiosyncratic productivity, denoted by x , and distributed according to $F(x'|x)$. Second, the model presented here features no E-E transitions. Hence, this model features no job ladder. Third,

the model here features no exogenous separations. All separations are endogenous.³ There are substantive differences between this model and the full model. First, firms do not contact employed workers in the simple model. Since the evolution of productivity and match-quality among employed workers is slow, this can lead to additional propagation in the full model. Second, the addition of a second state variable in the full model allows the economy to lose many productive matches in a downturn, while still allowing new matches to survive. In the simple model, one cannot shed relationships at the starting productivity level because then no new employment relationships would form. I discuss these additions, and their important implications, when I elucidate the aggregate implications of the full model.

The number of new meetings between the unemployed and vacancies is determined by an aggregate matching function:

$$m(v, u) = m_0 u^{1-\alpha} v^\alpha$$

where v is the number of vacancies and u is the number of unemployed workers. The aggregate meeting rate is:

$$f(\theta) = \frac{m(v, u)}{u} = m(v/u, 1) = m(\theta, 1)$$

and the vacancy filling rate is:

$$q(\theta) = \frac{m(v, u)}{v} = m(1, u/v) = m(1, 1/\theta)$$

This model can be characterized by a series of Bellman equations. The value of

³In other words this is a simplification of the full model with $y_0 = 1$, $\sigma_{\epsilon_y} = 0$, $p_E = 0$ and $s = 0$. Perceptive readers will note that this is the standard Mortensen and Pissarides (1994) model where shocks to productivity arrive every period and the idiosyncratic productivity process is persistent, as opposed to memoryless.

work to the employee, $W(x)$, satisfies:

$$W(x) = w + \delta \int \max\{U, W(x')\} dF_x(x'|x) \quad (3.1)$$

The intuition here is straightforward. The flow payoff to maintaining a job equals the wage, w . In the future, shocks to idiosyncratic productivity arrive according to distribution $F(x'|x)$ and, depending on the the level of this future shock, the worker decides whether to remain at the current firm, or flow into unemployment and look for an alternative match.

The value of unemployment satisfies:

$$U = b + \delta(1 - f(\theta))U + \delta f(\theta)W(x_0) \quad (3.2)$$

The unemployed receive flow payoff b . They either receive an offer and take it or remain unemployed. Notice that all jobs start at the same level of idiosyncratic productivity, x_0 , which is set to the mean value of the unconditional distribution, denoted by \bar{x} . The calibration presented later guarantees that $W(x_0) > U$, so that the worker prefers employment to unemployment at the starting productivity level.

The value of a filled job to the firm, $J(x)$, satisfies:

$$J(x) = z + x - w + \delta \int \max\{0, J(x')\} dF_x(x'|x) \quad (3.3)$$

where z denotes aggregate productivity. The payoff to the firm includes the output, $z + x$, less the wage paid to the worker, w . In the next period, depending on the level of the idiosyncratic shock, the firm decides to continue with the match or to let the worker go and open a vacancy. In equilibrium vacancies are assumed to have value zero, which is guaranteed by a free-entry condition into vacancy posting.

Notice that I choose an additive output form between aggregate and idiosyncratic

productivity to avoid any ambiguity about whether increased aggregate productivity lowers the reservation threshold of idiosyncratic productivity. With additive output, x_R is unambiguously decreasing in z . With multiplicative output, x_R could increase with increased z . As a matter of fact, in their baseline calibration, Mortensen and Pissarides (1994) have x_R increasing with z , and they elucidate some of the conditions for this result.

These value functions can be summarized by one equation, the surplus from a match:

$$\begin{aligned} S(x) &= W(x) - U + J(x) \\ &= z + x + \delta \int \max\{0, S(x')\} dF_x(x'|x) - [b + \delta f(\theta)\beta S(x_0)] \end{aligned} \tag{3.4}$$

which is the flow payoff from the match and the continuation value of the match, less the worker's outside option that includes a flow payoff from unemployment and the chance of finding a new job with idiosyncratic productivity at x_0 .

Proposition III.1. *The surplus equation, $S(x)$, is increasing in x .*

With the monotonicity of $S(\cdot)$ established, define the reservation cutoff as the level of productivity that makes worker and firm indifferent between maintaining the current match and terminating the current employment relationship:

$$S(x_R) = 0 \tag{3.5}$$

In order to determine the number of vacancies in equilibrium, we need the value of posting a vacancy:

$$V^s = -c + \delta q(\theta)(1 - \beta)S(x_0) \tag{3.6}$$

where c is the flow cost of maintaining a vacancy, $q(\theta)$ is the job-filling probability

and s denotes the simple model. Notice that this pins down θ uniquely:

$$\theta = \left(\frac{\delta m_0 (1 - \beta) S(x_0)}{c} \right)^{\frac{1}{1-\alpha}} \quad (3.7)$$

Wage bargaining follows the standard Nash bargaining protocol so that:

$$w = \arg \max_w [W(x) - U]^{\frac{1}{2}} [J(x) - V]^{\frac{1}{2}}$$

This implies that worker and the firm split surplus evenly.

3.2.1 Calibration of Simple Model

Given the optimal decisions of workers and firms, the model generates simulated data at a monthly frequency. In particular, I simulate 6,000 agents for 480 months (40 years). To remove the effects of initial conditions, I simulate the model for 980 months and then discard the first 500 months of the sample. This simulation provides a time-path of wages and annual earnings, as well as an employment history.

This section outlines two alternative calibration methods. One includes a standard calibration that implies little aggregate volatility but matches wage dispersion. The second calibration, dubbed the “high-elasticity” calibration, delivers more cyclicalities in vacancies and unemployment at the cost of matching the observed mean-min wage ratio.

Although the first calibration delivers a large mean-min wage ratio, neither calibration manages to hit the earnings losses of displaced workers. This highlights that the ability of the model of Chapter II to hit the time-path of displaced worker earnings is an achievement in and of itself. Furthermore, this analysis shows that simply delivering a large mean-min wage ratio is not enough to deliver the earnings experience of displaced workers. A job ladder and on-the-job search are crucial ingredients to the success of the model in Chapter II.

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

$$\ln x' = \rho_x \ln x + \epsilon'_x \quad (3.8)$$

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

3.2.1.1 The Benchmark Calibration

This calibration follows Hornstein et al. (2011) and Bils et al. (2011) very closely. Table 3.1 shows the baseline parameter values for the two calibrations. I take the annualized interest rate to be five percent. The key targeted outcomes are the average rates of unemployment and separations. Following Bils et al. (2011) I target an average unemployment rate of six percent, and a monthly separation of two percent that is consistent with work using the Survey of Income and Program Participation. The two percent separation rate and the six percent unemployment rate pin down the steady-state monthly job-finding rate at 31 percent.

The vacancy posting cost c is chosen to normalize the steady-state vacancy-unemployment ratio (θ) to one. The matching technology is Cobb-Douglas; $m(v, u) = 0.31v^\alpha u^{1-\alpha}$, which hits the steady-state finding rate. The matching power parameter α is set to 0.5. In the benchmark calibration I fix the persistence of idiosyncratic productivity at 0.97, the value in Bils et al. (2011), to match highly persistent individual wage earnings. I choose the standard deviation of idiosyncratic productivity to match an observed mean-min wage ratio of 1.75, as documented by Hornstein et al. (2011). I choose the value of leisure, b , to match the two percent separation probability.⁴

⁴An alternative calibration involves fixing the value of leisure at 0.4, the value found in Shimer (2005) and choosing σ_{ϵ_x} to match the two percent separation probability. This calibration falls far short of the observed mean-min wage ratio, but conveys the same message: the standard search

Notice that in order to match the duration of unemployment and the mean-min wage ratio, the model requires a negative value of leisure. Hornstein et al. (2011) point out the same phenomenon. Their main message is that the wage dispersion delivered by search models is constrained by preference parameters and the observed size of the transition rates of workers. The intuition is that if we observe very large U-E rates this must mean that the wage offer distribution is not very dispersed, otherwise workers would be willing to wait longer for a potentially better offer. With the particular set up outlined here, the U-E probability is calibrated to 31 percent and the E-U probability at two percent. In order to simultaneously target a large mean-min wage ratio (1.75) and the large U-E flows, the model requires the value of leisure to be almost twice the (negative) average wage among the employed. This low value of leisure insures that, despite the large wage dispersion, the model can match the observed U-E probability. As Hornstein et al. (2011) point out, this means that, if the average wage is \$2000 per month, and b is equal to (negative) the average wage, in order to avoid unemployment a worker is willing to work for free for one month, pay \$2000, and at the end of the month look for a job with starting productivity x_0 . This seems economically unpalatable.

3.2.1.2 The High-Elasticity Calibration

To portray the tension in this basic model, I also consider a calibration of the model that delivers a significant elasticity of unemployment and vacancies with respect to the aggregate productivity shock. In particular, I target the empirical response of unemployment in response to a reduction in aggregate productivity. An empirical comparison to a permanent reduction in aggregate productivity is difficult to find, but Fujita and Ramey (2007) present an empirical estimate of the response of un-

model faces a trade-off between matching the observed cross-sectional wage distribution, which seems necessary for matching the earnings losses of displaced workers, and matching the cyclical volatility of unemployment.

employment to a persistent reduction in aggregate productivity.⁵ They find that the maximum response of unemployment is around 6.5 percent after five quarters. This means that if unemployment was at five percent, and aggregate productivity fell by 10 percent, then unemployment would rise to just above eight percent. Since the persistent shock response is a lower bound for the permanent shock response, I target an eight percent increase in unemployment after five quarters.

To achieve this amplification I use two parameters: b and σ_{ϵ_x} , keeping all other parameters at the benchmark values. Notice that increasing either parameter increases the average unemployment rate because higher b makes unemployment more attractive, and higher σ_{ϵ_x} makes matches more susceptible to endogenous destruction. However, the effect of increasing these parameters on the cyclicalities of unemployment moves in opposite directions. Increasing b tends to reduce the surplus from employment which raises the cyclicalities of unemployment with respect to aggregate productivity shocks. Increasing σ_{ϵ_x} makes the idiosyncratic productivity distribution more spread out. Over time workers sort into matches with significant match surplus, which makes separations less sensitive to cyclical fluctuations in productivity.

Because the level of unemployment is increasing in both b and σ_{ϵ_x} , but its cyclicalities depends inversely on σ_{ϵ_x} and positively on b , I can maintain a steady-state unemployment rate of six percent and increase the cyclicalities of unemployment by raising b and lowering σ_{ϵ_x} . I find that a combination of $b = 0.77$ and $\sigma_{\epsilon_x} = 0.05$ yields a six percent unemployment rate and the appropriate deviation from steady-state unemployment in response to a productivity shock.

⁵Section 3.8.2 replicates the findings of Fujita and Ramey (2007) by analyzing the response of unemployment and vacancies in the standard MP model. The standard model fails to amplify and propagate aggregate productivity shocks.

3.2.2 Steady State of Simple Model

This section outlines some steady-state features of the two calibrations of the simple model. The focus of the analysis is on the ability of the two calibrations to match observed cross sectional wage facts and the earnings losses of displaced workers. The distribution of idiosyncratic productivity is largely responsible for the model's earnings implications, and this distribution is described in detail.

Table 3.2 presents some steady-state moments of the simulated data, and Figure 3.1 presents the earnings losses of displaced workers in these two models, along with the empirical losses from Davis and von Wachter (2011). For the figure, I impose the same restrictions as in Chapter II.

Both calibrations can match the targeted moments exactly, hitting the unemployment rate, the separation rate and the job finding rate. Reflecting the small shocks to idiosyncratic productivity, the high-elasticity calibration exhibits very little cross-sectional variation in wages, at only 7.5 percent. This is unreasonably small. As an empirical reference, Topel and Ward (1992) report that the standard deviation of wage growth within matches is around 19 percent. As another testament to the small productivity shocks, the earnings losses of displaced workers are very small. Figure 3.1 shows that in the high-elasticity calibration earnings recover six years after displacement. Moreover, the on-impact dip in earnings is very small: only around 15 percent, whereas in the data this figure is between 25 and 40 percent.

The benchmark calibration delivers significantly more wage dispersion, obtaining an observed mean-min wage ratio of 1.75, and around 36 percent cross-sectional variation in wages. The standard deviation of wage growth within matches is around 33 percent, which exceeds 19 percent value in Topel and Ward (1992). Figure 3.1 plots the earnings losses of displaced workers associated with this calibration. The on-impact dip in earnings over-shoots the observed losses, however the recovery in earnings is far too quick. With this calibration, earnings, relative to a control group,

recover within eight years. The earnings losses are remarkably symmetric around the year of displacement.⁶

Figure 3.1 also reinforces that matching the earnings losses of displaced workers presented in Chapter II is a modeling success because many similar models simply cannot deliver this prominent empirical fact. Even models that display a realistic amount of wage dispersion, like the benchmark calibration presented here, cannot match the trajectory of earnings around the time of displacement. It seems as though wage dispersion is important for capturing the on-impact dip in earnings, but insufficient to deliver the slow recovery in earnings post displacement. All the ingredients of the model presented in Chapter II, including on-the-job search and match-quality are important ingredients for matching displaced worker earnings.⁷

One key to understanding wage dispersion in both of these calibrations, and for understanding the aggregate implications for job destruction, is the underlying steady-state distribution of idiosyncratic productivity. The numerical approach for obtaining this steady-state distribution is detailed in Section 3.8.3.1. Figure 3.2 presents these steady-state distributions above each economy’s reservation productivity x_R .⁸ Each distribution peaks at the starting idiosyncratic productivity x_0 , as there exists a mass of unemployed workers entering employment at this productivity level.

This figure highlights that the high-elasticity calibration features a very tight distribution of idiosyncratic productivity near the threshold productivity. This narrow distribution helps this calibration to match the cyclical volatility of unemployment because small movements in aggregate productivity terminate many employment relationships. This resulting increased volatility comes at the cost of missing the disper-

⁶The pre-displacement dip in earnings occurs because of endogenous separations and persistence in the idiosyncratic productivity process. Conditional on displacement in year y , agents’ earnings are falling in the years before y as idiosyncratic productivity begins to fall. In contrast, based on no separation in year y , the average idiosyncratic productivity of the control group begins to rise before year y .

⁷Note that the model presented here does feature some serial correlation in displacements because the starting idiosyncratic productivity is below the average x among the employed.

⁸This is similar to Figure 5 in *Bils et al. (2011)*.

sion of wages and the dispersion of wage growth within matches, as described earlier in this section. The benchmark calibration features a much more disperse idiosyncratic productivity distribution, which means that this economy features realistic wage and wage growth dispersion. However, this calibration exhibits very small fluctuations in unemployment and vacancies because downward aggregate productivity movements affect few matches. The figure shows that near the reservation threshold for the benchmark calibration, there exists a small mass of matches.

In addition to the job destruction margin, the job creation margin plays an important role in aggregate dynamics. As noted before, the value of leisure is very small in the benchmark calibration. This allows the model to simultaneously hit the job finding rate, and the large wage-dispersion observed in the data. A small value of leisure implies that the surplus from employment relationships is very large. Hagedorn and Manovskii (2008) show that the volatility of labor market tightness is very closely related to the value of leisure and the size of accounting profits. This calibration features large accounting profits which means that the vacancy posting incentives in this economy will largely be muted. Conversely, in the high-elasticity calibration the value of leisure is high, making the accounting profits from an employment relationships very small. This raises the cyclicalities of profits and hence raises the cyclicalities of vacancy posting. The job creation margin also features prominently in the aggregate fluctuations, which I point out in the next section.

3.2.3 Aggregate Fluctuations in Simple Model

This section presents the responses of the two calibrated economies to a permanent reduction in aggregate productivity. The algorithm for computing the perfect foresight transition is outlined in Section 3.8.3.3. The procedure follows Auerbach and Kotlikoff (1987) and Acemoglu and Hawkins (2010) quite closely and involves guessing both the time to full adjustment and the trajectory of labor market tight-

ness, solving for surplus equations via backward induction, and solving forwards for the evolution of unemployment, labor market tightness and the distribution of idiosyncratic productivity.⁹ The aggregate shock involves a one-time, unanticipated, permanent reduction in aggregate productivity.¹⁰ Once the initial shock arrives, the entire future path of z is revealed to the agents of the economy.

Figure 3.3 portrays the results for the benchmark calibration in response to this aggregate productivity reduction.¹¹ As a reference, I also depict the estimated responses of unemployment and vacancies from Fujita and Ramey (2007), keeping in mind that these are responses to a persistent shock rather than a permanent shock. The economy delivers little amplification of the aggregate productivity shock. The response in vacancies is about an order of magnitude lower than in the observed data, and exhibits none of the propagation seen in the data. Unemployment rises, but significantly less than in the observed data.

On impact, the inflow rate into unemployment jumps up as low productivity matches are destroyed due to the reduction in aggregate productivity. This destruction of low productivity matches causes the average idiosyncratic productivity in the economy to rise. Vacancies fall only slightly on impact. This is due to the low value of leisure, which implies large surplus from employment relationships so that the incentives to post vacancies do not change much in response to aggregate productivity fluctuations. The model displays a sharp rise in E-U separation in the wake of a recession that then subsides and falls to the new steady state.

⁹Computing the response of the economy to a stochastic aggregate productivity shock would be much more involved, including an application of Krusell and Smith (1998). The procedure presented here satisfactorily presents the mechanics and results of the model. I suspect that amending the nature of the shock would not alter the implications.

¹⁰Since aggregate productivity is not modeled as a stochastic process, this shock is a zero probability event.

¹¹In practice, the size of the shock is 1.2 times the standard deviation of idiosyncratic productivity in steady-state for the benchmark economy, and 1.5 times the standard deviation of idiosyncratic productivity in steady-state for the high-elasticity economy. This is so that the number of nodes switching from positive to negative surplus are the same in the two simulations. The responses here are normalized by the size of the shock so that they represent responses to a one percent reduction in aggregate productivity as a fraction of the average x in the initial steady state.

Figure 3.4 displays the aggregate fluctuations of the high-elasticity calibration. This model features the targeted amplification in unemployment, around eight percent five quarters after the shock. The model delivers the same amount of propagation in unemployment as the standard MP model: unemployment takes around two quarters to converge to the new steady-state value. Vacancies move more than in the benchmark economy, but exhibit no propagation. The larger change in vacancies is due to smaller accounting profits in employment relationships as a result of a higher value of leisure. This is analogous to the results in Hagedorn and Manovskii (2008), although the value of leisure in the high-elasticity calibration is quite far from average labor productivity and hence this economy displays less amplitude than the data. Although the inflow rate and the average idiosyncratic productivity look qualitatively the same as in the benchmark calibration, the quantitative response is much larger. Inflows respond around five times more than in the benchmark calibration. The average idiosyncratic productivity rises more than in the benchmark economy. This larger inflow at the onset of the recession follows from the tight distribution of idiosyncratic productivity near the reservation threshold. With a reduction in aggregate productivity, many employment relationships are destroyed and the unemployment rate jumps significantly. The unemployment rate also rises due to a lower job-finding rate due to fewer posted vacancies.

3.3 Closing the Full Model

For a description of the full model and the baseline calibration I refer the reader to Chapter II of this dissertation. This section outlines how to couch the full model of the previous chapter in a general equilibrium framework, including an aggregate matching function and optimal vacancy posting by firms. Suppose that two matching functions determine the number of contacts that occur between unemployed and

employed workers and firms in the economy every period.¹² Let v denote the number of vacancies in the economy. As with the simple model, I assume Cobb-Douglas matching functions so that the number of contacts equals:

$$m_i(s, v) = m_0^i v^\alpha s^{1-\alpha}, i \in \{U, E\}$$

where s denotes the measure of searchers and m_0^i is the matching efficiency. In the full model both unemployed and employed agents search and therefore $s = 1$ and the matching function satisfies:¹³

$$m_i(1, v) = m_0^i v^\alpha, i \in \{U, E\}$$

The aggregate meeting rate is:

$$f_i(v) = \frac{m_i(1, v)}{1} = m_i(1, v) = m_0^i v^\alpha, i \in \{U, E\}$$

and the vacancy filling rate is:

$$q_i(v) = \frac{m_i(1, v)}{v} = \frac{f_i(v)}{v} = m_0^i v^{\alpha-1}, i \in \{U, E\}$$

With this addition to the model, I can determine the contact rates given the number of vacancies in the economy.

I still need to determine how many vacancies firms open in equilibrium. To determine the equilibrium vacancy rate I introduce the vacancy creation condition. This condition represents the costs and benefits from opening a vacancy for an individual firm, and can be written as:

¹²As mentioned before, this is a reduced form way of incorporating search intensity into the model. It is necessary that the contact rates for the unemployed and the employed differ because $p_U \neq p_E$.

¹³See Moretensen and Nagypal (2005) for a similar set up. I use $\alpha = 0.524$ in this part of the dissertation, which is taken from Moretensen and Nagypal (2005) and captures the elasticity of the job-finding rate with respect to vacancies.

$$V = -c + \delta q_U(v)u \max\{0, J(x_0, y_0)\} + \delta q_E(v)(1-u) \times \\ \int \int \int \int \mathbb{I}\{S(x_0, \tilde{y}) > S(x', y)\} \max\{0, J(x_0, \tilde{y})\} dF_x(x'|x) dF_y(\tilde{y}) \tilde{\pi}(x, y) dx dy$$

where c is the flow cost of maintaining a vacancy and u is the unemployment rate. $\tilde{\pi}(x, y)$ is the distribution of (x, y) among employed workers, a complicated equilibrium object.¹⁴ I assume that in equilibrium $V = 0$ due to free entry into vacancies. This equation involves $J(\cdot, \cdot)$. It can be rewritten as a function of only the surplus from a match with the identity $S = J + W - U$ and the fact that Nash bargaining implies that $J(x, y) = (1 - \beta)S(x, y)$. This implies that the vacancy creation condition is:

$$V = -c + \delta q_U(v)u \max\{0, (1 - \beta)S(x_0, y_0)\} + \delta q_E(v)(1-u) \times \\ \int \int \int \int \mathbb{I}\{S(x_0, \tilde{y}) > S(x', y)\} \max\{0, (1 - \beta)S(x_0, \tilde{y})\} dF_x(x'|x) dF_y(\tilde{y}) d\tilde{\Pi}(x, y) \\ = -c + \delta m_0^U v^{\alpha-1} u \mathbb{E}_u + \delta m_0^E v^{\alpha-1} (1-u) \mathbb{E}_e \quad (3.9)$$

where $\tilde{\Pi}(x, y)$ is the cumulative density function associated with (x, y) among employed workers (conditional on employment). Notice that when we set $V = 0$, this equation implies that the flow cost of opening a vacancy must equal the expected benefit from maintaining that open vacancy. The benefit from posting a vacancy has two parts: the payoff from meeting an unemployed worker, \mathbb{E}_u , and the payoff from meeting an employed worker, \mathbb{E}_e . The payoff to meeting an unemployed worker is simply the portion of surplus that the firm receives at combination (x_0, y_0) . The

¹⁴This is in fact the distribution of (x, y) conditional on employment so that it sums to one. When finding this distribution I iterate on the unconditional distribution, $\pi(x, y)$ so that $\sum_{x,y} \pi(x, y) + u = 1$. The two functions are related by the simple equation: $\frac{\pi(x,y)}{1-u} = \tilde{\pi}(x, y)$.

payoff from meeting an employed worker depends on whether the poaching firm successfully attracts the worker and the poaching firm's payoff from this new employment relationship. If we know the expected benefit from posting a vacancy, this equation pins down the equilibrium vacancy rate. Notice that now the expected payoff from meeting an employed worker enters the optimal decision of the firm. This presents an important deviation from the simple model presented earlier and the standard MP model that both feature no on-the-job search. In this context, searching while employed has consequences for aggregate dynamics.

3.4 Steady State of Full Model

Many of the steady-state features of the full model have been presented in Chapter II. We know that this model performs well at matching displaced worker earnings, wage dispersion and the standard deviation of wage growth within matches. However, the full model manages to avoid some of the symptoms of the benchmark economy presented earlier. This is not obvious since the full model is a generalization of the simple model with additional dispersion in match-quality. The addition of match-quality, however, helps the full model alleviate some of the tensions described above. The algorithm for solving for the steady-state distribution in the full model is presented in Section 3.8.4.1.

For illustration, define $x_{max[y|S<0]}^R$ and $y_{avg[x]}^R$ as:

$$S(x_{max[y|S<0]}^R, max[y|S < 0]) = 0 \text{ and } S(avg[x], y_{avg[x]}^R) = 0 \quad (3.10)$$

That is, $x_{max[y|S<0]}^R$ is the reservation productivity level when match-quality is at the highest match-quality that accepts an endogenous separation, and $y_{avg[x]}^R$ is the reservation match-quality when x is at its average value in equilibrium.¹⁵

¹⁵There exist some match-qualities for which separation occurs only via exogenous separation, i.e. for all productivity values on the grid at these match-qualities, surplus is positive.

Figure 3.5 shows the steady-state distributions of x and y in the full model with the baseline calibration presented in Chapter II. The line labeled ' $\pi(x|max[y|S < 0])$ ' shows the distribution of idiosyncratic productivity above the reservation productivity $x_{max[y|S < 0]}^R$, holding match-quality at $max[y|S < 0]$. This shows that idiosyncratic productivity is spread out and implies that relatively few matches exist near the destruction threshold. This is analogous to the benchmark calibration of the simple model. The spike in the figure occurs at $x = x_0$, and shows that the starting productivity lies at the top of the distribution.¹⁶ The line labeled ' $\pi(y|avg[x])$ ' in the figure shows the distribution of match-quality above the reservation productivity $y_{avg[x]}^R$, holding productivity at $avg[x]$. This paints a different picture from the conditional distribution of x . In particular, there now exists a spike at the bottom of the distribution at $y = y_0$. This makes clear that y_0 is quite low in the distribution of y . It also shows that there exist a large fraction of employment relationships near the destruction threshold. Small movements in aggregate productivity will erase a large fraction of employment relationships that have the starting match-quality. This will have a large impact on the E-U probability in transition and therefore the unemployment rate. In this sense the full model can alleviate some of the tensions of the simple model. Introducing a second state variable that is particularly low among new matches means that many employment relationships are susceptible to destruction with a reduction in aggregate productivity. At the same time, new matches are still viable.

3.5 Aggregate Fluctuations in Full Model

This section presents the business cycle movements of the baseline model. The algorithm for computing the perfect foresight transition is outlined in Section 3.8.4.3,

¹⁶This stems from the properties of the model. Since $y_0 \ll \mathbb{E}[y|match]$, it is necessary for $x_0 \gg \mathbb{E}[x|match]$ to induce vacancy posting.

and is similar to the technique used for the simple economy.

Figure 3.6 depicts the outcomes of key aggregate variables in response to a permanent, unexpected, one percent reduction in aggregate productivity.¹⁷ The model displays a sharp rise in E-U separation in the wake of a recession that then falls slightly and continues to rise thereafter to its new steady state value. The rise in inflows results from a discrete mass of jobs becoming unprofitable and being destroyed immediately. The new steady state of the E-U probability is above the original steady state due to a lower aggregate productivity, which means more jobs are fragile. The response of the inflow rate is very large, reflecting that many employment relationships are near the destruction threshold due to the low match-quality of new hires. There is a slight cleansing effect as low-quality matches are destroyed. Due to lower aggregate productivity, firms post fewer vacancies which results in lower job-finding rates. This causes average match-quality to fall as agents make their way up the job ladder at a reduced rate. This is the central point of a related paper, Barlevy (2002).

The economy delivers a large response in unemployment rate due to the large rise in the inflow rate. The rise in unemployment, and the large expected payoff from meeting an unemployed worker, dampen the negative effect of lower productivity on vacancies. The economy also delivers significant propagation of shocks, with the majority of unemployment adjustment occurring within the first 15 quarters. After 60 quarters, vacancies are still not at their new steady state.¹⁸ This is due to the slow moving nature of the distribution of idiosyncratic productivity and match-quality among the employed.

¹⁷The shock is actually a reduction in aggregate productivity by half the standard deviation of $x \cdot y$ in the initial steady state (a 15 percent reduction in productivity as a fraction of the average $x \cdot y$ in the initial steady state). The responses are normalized by the size of the shock to represent the response to a one percent decrease in aggregate productivity as a fraction of average $x \cdot y$ in the initial steady state. Since the model is non-linear, this normalization may not be appropriate.

¹⁸Notice that although the expected payoff from meeting an employed worker falls and then rises, vacancies do not exhibit the same feature. This is because unemployment is rising as well, and since the expected payoff from meeting an unemployed worker exceeds the expected payoff from meeting an employed worker, vacancies actually rise after their initial reduction.

These impulse responses show that the baseline economy behaves remarkably like the actual economy. In the wake of recession there is a spike in the layoff rate, while the job-finding rate for the employed and the unemployed falls, just as observed in empirical worker flows in the United States data (see, for example, Elsby et al., 2009). The model delivers significant propagation of aggregate shocks.

3.6 Separation Shocks

Up to now the analysis has focused on the response of the economy to an aggregate productivity shock. Some authors, for example Shimer (2005), also look at the shocks to the exogenous separation rate. This section studies the effect of such a shock in the present context. This type of shock is interesting because a change in the exogenous separation rate will affect individuals with all (x, y) combinations whereas, with the productivity shock, only individuals near the destruction threshold experience separation. I could not perform this shock with the simple model because that model features endogenous separations only.

This section assumes that the exogenous separation probability rises unexpectedly.¹⁹ Figure 3.7 depicts the response of key aggregate variables in response to this separation rate shock. Notice that the model delivers significant propagation in vacancies due to the slow moving distribution of (x, y) . On impact, the inflow rate jumps due to the increased exogenous separation rate. Vacancies fall on impact as increased separation lowers the value of a filled job. As new unemployed workers find jobs they lower the average match-quality as these workers start towards the bottom of the job ladder. Match-quality in the new steady-state is lower due to the increased risk of separation, which knocks individuals off the ladder more often. After a slight initial reduction, due to the large fall in vacancies and therefore the job contact rate

¹⁹In the simulation I double the exogenous separation probability and then normalize the impulse responses appropriately.

among the employed, the average E-E probability rises as new unemployed workers find jobs at low-quality matches and move quickly up the job ladder.²⁰ This increased chance of poaching an employed worker raises the payoff from meeting an employed worker, which encourages firms to post more vacancies. Increased unemployment also encourages vacancy posting as the expected payoff from meeting an unemployed worker exceeds the expected payoff from meeting an employed worker. Vacancies and unemployment move very slowly, analogously to the aggregate productivity shock, although unemployment displays more propagation with the separation shock.

The amplification of the shock is a little harder to assess, but the unemployment rate rises by around 0.2 percent on impact. In the Great Recession, for example, layoffs rose by around 50 percent, which is 50 times the shock presented here, and the unemployment rate went up by around 100 percent. Under linearity, this would imply that the model, in response to a separation shock, does not feature sufficient amplification of separation shocks.

3.7 Summary and Discussion

This chapter investigates the aggregate labor market fluctuations associated with the model presented in Chapter II of this dissertation. Closing the model involves introducing aggregate matching functions for the unemployed and the employed, and introducing the optimal vacancy creation condition for the firm. A simpler version of the full model, with no match-quality, no E-E transitions and no exogenous separations, faces a tension between matching the observed mean-min wage ratio and the earnings of displaced workers, and matching the amplification of aggregate productivity shocks. With idiosyncratic shocks that deliver the correct mean-min wage ratio there exist very few matches at the destruction threshold which implies that aggregate productivity shocks have very little bite. In addition to little job destruction,

²⁰This is at odds with an empirically pro-cyclical E-E probability.

this calibration of the model implies large accounting profits which means that few jobs are destroyed in response to lower aggregate productivity.

This tension is mitigated in the full model. This is not obvious since the full model resembles the simple model, but features additional volatility due to variation in match-quality. Since variation in idiosyncratic productivity was the reason for a lack of amplification of aggregate productivity shocks in the simple model, it may seem that adding additional volatility via match-quality would exacerbate the amplification problem in the full model. Despite this additional volatility, the full model delivers significant unemployment amplification because new matches begin with low match-quality which implies that there exist many relationships at the reservation frontier. Relationships with this starting match-quality can be destroyed in the full model because relationships are characterized by two state variables: idiosyncratic productivity and match-quality. In the simple model eliminating employment relationships with the starting productivity was not a possibility because then no new matches would form. In the full model aggregate productivity shocks have large effects on unemployment, and responses that are qualitatively consistent with the observed facts. In the wake of recession there is a spike in the layoff rate, and the job-finding rate for the employed and the unemployed falls. An aggregate separation shock engenders far more propagation as it affects the entire distribution, not just those at the job destruction threshold.

The model is able to hit the wage dispersion documented by Hornstein et al. (2011) without resorting to a very low value of leisure because the initial match-quality does not vary. In this version of the model the initial match-quality is fixed at y_0 . This implies that there exists a large mass of jobs at the destruction frontier that results in large movements in unemployment in response to aggregate productivity shocks. The initial match-quality does not need to be fixed for this effect, but the amplification properties do require that unemployed workers draw match-quality from

a distribution that has higher mass at low-quality matches than the distribution faced by employed workers.

3.8 Appendix

3.8.1 Proofs

Proposition III.1. *The surplus equation, $S(x)$, is increasing in x .*

Proof. From Nash bargaining, $S(x) = \frac{J(x)}{1-\beta}$. Hence, showing that $J(x)$ is increasing in x will suffice to establish that $S(x)$ is increasing in x . Unfortunately, $J(x)$ depends on w which itself is a function of x . Hence, I will first derive a closed form solution for w .

Multiply equation (3.1) by $(1 - \beta)$ and equation (3.3) by β . Subtract the first equation from the second to get

$$\begin{aligned} \beta J(x) - (1 - \beta)W(x) &= \beta z + \beta x - \beta w + \beta \delta \int \max\{0, J(x')\} dF_x(x'|x) \\ &\quad - (1 - \beta)w - (1 - \beta)\delta \int \max\{U, W(x')\} dF_x(x'|x) \\ \Rightarrow \beta J(x) - (1 - \beta)W(x) &= \beta z + \beta x - \beta w + \beta \delta \int \max\{0, J(x')\} dF_x(x'|x) \\ &\quad - (1 - \beta)w - (1 - \beta)\delta \int \max\{0, W(x') - U\} dF_x(x'|x) - (1 - \beta)\delta U \end{aligned}$$

Since $(1 - \beta)(W(x) - U) = \beta J(x)$, $(W(x) - U)$ and $J(x)$ always have the same sign.

This implies that

$$\begin{aligned} \beta J(x) - (1 - \beta)W(x) &= \beta z + \beta x - w \\ &\quad + \delta \int \max\{0, \beta J(x') - (1 - \beta)(W(x') - U)\} dF_x(x'|x) - (1 - \beta)\delta U \end{aligned}$$

and the term under the integral is zero. Also, from Nash bargaining $\beta J(x) - (1 - \beta)W(x) = -(1 - \beta)U$:

$$-(1 - \beta)U = \beta z + \beta x - w - (1 - \beta)\delta U$$

which implies that

$$w = \beta(z + x) + (1 - \beta)(1 - \delta)U$$

Equation (3.2) implies that

$$(1 - \delta)U = b + \delta f(\theta)(W(x_0) - U) \quad (3.11)$$

and $W(x_0) - U = \frac{\beta}{1-\beta}J(x_0) = \frac{\beta}{1-\beta}\frac{c}{\delta q(\theta)}$ where the last equality follows from equation (3.6) and $V^s = 0$. Plugging this into equation (3.11) yields

$$(1 - \delta)U = b + f(\theta)\frac{\beta}{1 - \beta}\frac{c}{q(\theta)}$$

which in turn implies that

$$w = (1 - \beta)b + \beta(z + x + c\theta)$$

since $\frac{f(\theta)}{q(\theta)} = \theta$. This is the standard wage equation from a simple MP model.

With the wage equation in hand, the value of a filled job to the firm becomes

$$J(x) = (1 - \beta)(z + x - b) - \beta c\theta + \delta \int \max\{0, J(x')\}dF_x(x'|x)$$

Define T as the operator mapping bounded functions into bounded functions:
 $T : \mathcal{F} \rightarrow \mathcal{F}$. In particular, let T satisfy:

$$(Tf)(x) = (1 - \beta)(z + x - b) - \beta c\theta + \delta \int \max\{0, f(x')\}dF_x(x'|x)$$

I will show that T is a contraction mapping, and then show that it maps weakly increasing functions into weakly increasing functions. This will suffice to show that $J(x)$, the unique fixed point of T , is weakly increasing in x .

To show that T is a contraction mapping, I confirm that Blackwell's sufficient conditions for a contraction hold here. To verify discounting, note that:

$$[T(f + a)](x) = (Tf)(x) + a\delta(1 - f(\theta)\beta) \leq (Tf)(x) + \Delta a$$

where $\Delta < 1$. To verify monotonicity, suppose that $f(x) \geq g(x) \forall x$. Then note that:

$$\begin{aligned} [T(f)](x) - [T(g)](x) &= \delta \int \max\{0, f(x')\} dF_x(x'|x) - \delta \int \max\{0, g(x')\} dF_x(x'|x) \\ &= \delta \int [\max\{0, f(x')\} - \max\{0, g(x')\}] dF_x(x'|x) \geq 0 \end{aligned}$$

It follows from the Contraction Mapping Theorem that T has a unique fixed point.

Now, suppose that $f(\cdot)$ is weakly increasing, so that whenever $x_1 \geq x_2$ this implies that $f(x_1) \geq f(x_2)$. Then:

$$\begin{aligned} [T(f)](x_1) - [T(f)](x_2) &= (1 - \beta)(x_1 - x_2) \\ &+ \delta \left[\int \max\{0, f(x')\} dF_x(x'|x_1) - \int \max\{0, f(x')\} dF_x(x'|x_2) \right] \end{aligned}$$

The first term on the right hand side is weakly positive. The second term is weakly positive if a higher x today implies a higher expectation of $\max\{0, f(x')\}$. Since $\max\{0, f(x')\}$ is assumed weakly increasing, a sufficient condition for this term to be weakly positive is that $F_x(x'|x_1)$ first order stochastically dominates $F_x(x'|x_2)$. In other words, $F_x(x'|x_1) \leq F_x(x'|x_2)$ for all x' if $x_1 \geq x_2$. I assume a log AR(1) process for x , which implies that $F_x(x'|x_1) \leq F_x(x'|x_2)$ for all x' if $x_1 \geq x_2$. This ensures that $\int \max\{0, f(x')\} dF_x(x'|x_1) - \int \max\{0, f(x')\} dF_x(x'|x_2) \geq 0$, which means that T maps weakly increasing functions into weakly increasing functions. Hence, $J(x)$, the unique fixed point of T , is weakly increasing in x , which implies that $S(x)$ is weakly increasing in x .

□

3.8.2 Fujita and Ramey (2007) Replication

The basic MP model is yet a simpler version of the presented simple model. In particular $x_0 = 1$ and $\rho_x = \sigma_{\epsilon_x} = 0$. Calibrating the model according to Fujita and Ramey (2007), with $b = 0.9$ and $p_s = 0.039$ along with $p_U = 0.45$ and $\alpha = 0.5$ and normalizing labor market tightness in steady state to one half, yields the desired results.

This simple model yields a closed form solution for the surplus equation. To solve for the transition I take the same approach as with the more general models, by guessing the time-path of θ , solving the surplus equations in each period by backward induction and then obtaining the unemployment rate for each period by forward iterating. If the resulting unemployment rate sequence and the guessed θ result in the value of a vacancy equaling zero in every period I stop. If this is not the case, I update the guess for θ and repeat.

Figure 3.8 presents the results of this transition for a one-time, unexpected reduction in aggregate productivity by 0.0078 ($\rho_z = 0.975$). The results match Fujita and Ramey (2007) exactly (they perform a positive shock to aggregate productivity) and ensure that the algorithm I use is appropriate.

3.8.3 Numerical Solution to Simple Model

This appendix details how to solve for the steady state and transitions of the simple model.

3.8.3.1 Steady-State Algorithm: Simple Model

The approach here is the same as used for the full model, however it is easier in application due to the reduced state space, and no on-the-job search. One difference is that I choose the value of posting a vacancy c to normalize labor market tightness (as opposed to vacancies) to one. The algorithm for finding the original steady state

is as follows:

1. Pick the efficiencies of matching, m_0 to target contact probability $f(\theta)$ that ensures the correct U-E probability,²¹ i.e. $m_0 = \frac{f_T}{\theta_{SS}^\alpha} = \frac{f_T}{1} = f_T$.
2. Solve the match surplus using equation (3.4). Be sure to use the targeted contact probability p_T .
3. Use iteration on the flows into and out of each grid point x and unemployment to pin down the steady state distribution of x among employed workers $\hat{\pi}(x)$, and the steady state unemployment rate \hat{u} . See Section 3.8.3.2 for details.
4. Notice that by choosing m_0 to target a contact rate, and normalizing θ_{SS} to one, the vacancy creation condition implies that the vacancy posting cost satisfies:²²

$$c = \delta m_0 (1 - \beta) S(x_0) \tag{3.12}$$

Notice that the calibration is performed using simulated data and interpolation, so that any value of the state variable is admissible. This is because calibration on a grid results in discontinuous jumps in the simulated moments with continuous movements in the model's parameters. However, the steady state distribution of x is computed on a fixed grid with no interpolation, via flows into and out of these grid points. It is re-assuring that when simulation does occur on a fixed grid, all the moments are identical to the flows approach, which is simulation-free. Moreover, if one increases the number of grid points with the flows approach one asymptotes to the moments of

²¹In practice, this means targeting a job finding rate of $f(\theta) = 0.31$, as presented in Table 3.1.

²²Usually, researchers in this literature normalize labor market tightness to 0.72 so that c/q equals 14 percent of quarterly worker compensation, which is in accordance with the results of Silva and Toledo (2007), who use Saratoga Institute's (2004) estimate of the labor costs of posting vacancies. In this work the θ normalization is simply rigged up so that c/q turns out to be 14 percent of quarterly worker compensation. In the present setup I could normalize θ_{SS} so that c/q was also 14 percent of quarterly worker compensation.

the simulated data with interpolation. With the number of grid points used the two approaches render very similar steady-state features.

With the original steady state in hand I proceed to solve the the economy with aggregate productivity $z = z_2$. The complexity of the algorithm increases because m_0 is no longer a free parameter; its calibrated value cannot change from steady state to steady state. The algorithm for finding this new steady state is as follows:

1. Guess a steady state vacancy rate $\theta_{SS_2}^0$. This implies a new job contact rate $f(\theta_{SS_2}^0) = m_0(\theta_{SS_2}^0)^\alpha$.
2. Solve the match surplus bellman equation using equations (3.4). Use the new contact probability.
3. Use iteration on the flows into and out of each grid point (x, y) and unemployment to pin down the steady state distribution of (x, y) among employed workers $\hat{\pi}(x, y)$, and the steady state unemployment rate \hat{u} . See Section 3.8.3.2 for details.
4. Using equation (3.7) to back out the implied equilibrium labor market tightness $\hat{\theta}$. If $\hat{\theta}$ and $\theta_{SS_2}^0$ are close then stop. Otherwise, go back to step (1) with a new guess for the equilibrium labor market tightness:

$$\theta_{SS_2}^0 = \zeta_\theta \hat{\theta} + (1 - \zeta_\theta) \theta_{SS_2}^0$$

ζ_θ is chosen small enough so that the procedure converges.

This routine guarantees convergence because the resulting labor market tightness ($\hat{\theta}$) is monotonically decreasing in the initial guess ($\theta_{SS_2}^0$). Intuitively, as $\theta_{SS_2}^0$ rises the job filling rate ($q(\theta_{SS_2}^0)$) falls. This means that expected hiring costs ($\frac{c}{q(\theta_{SS_2}^0)}$) increase and thus too few workers are in fact hired and too few vacancies are posted as compared to the equilibrium vacancy rate.

3.8.3.2 Flows: Simple Model

Before I proceed to outlining the algorithm used for computing transitions I want to describe the set of flow balance equations used to solve for steady state $\hat{\pi}(x)$ and \hat{u} in the preceding section. The outflows from the unemployment pool include:

- Unemployed agents who find new jobs:

$$uf$$

The inflows into the unemployment pool include:

- Endogenous separations:²³

$$\sum_x \pi(x) \mathbb{I}\{S(x') \leq 0\} dF_x(x'|x)$$

The outflows from a particular (x) grid point of the distribution $\pi(x)$ include:

- Those that have their idiosyncratic component change to $x' \neq x$ (including unemployment):

$$\pi(x)(1 - \mathbb{P}[x' = x|x])$$

The inflows into a particular (x) grid point of the distribution $\pi(x)$ include:

- Inflow from all other cells by a change in x ; ensuring that current (x) -cell has positive surplus:

$$\sum_{x_i \neq x} \mathbb{I}\{S(x) > 0\} \pi(x_i) \mathbb{P}_x[x' = x|x_i]$$

²³Since $\pi(x)$ is the unconditional (not conditional on employment) probability of being at x , this quantity does not need to be multiplied by $(1 - u)$. Also, all these flows are performed on a fixed grid of x and y . The summations represent discretized integration.

As one special case, the inflow from unemployment, into cell (x_0) :

$$uf$$

Iterating on these flows yields the steady state distribution $\hat{\pi}(x)$ and \hat{u} for corresponding value function $\hat{S}(x)$.

3.8.3.3 Transition Algorithm: Simple Model

See the description of the transition solution for the full model as described in Section 3.8.4.3. The approach here is identical except that I iterate on θ_t here as opposed to v_t , and θ_t must satisfy equation (3.6) as opposed to equation (3.9), for all t . The approach here is simpler because the steady-state distribution depends only on one state variable and there are no E-E transitions.

3.8.4 Numerical Solution to Full Model

This appendix details how to solve for the steady state and transitions for the full model.

3.8.4.1 Steady-State Algorithm: Full Model

In order to solve the steady state I begin the economy with aggregate productivity $z = z_1$.²⁴ Furthermore, as in any standard Mortensen-Pissarides-style model, c can be chosen to normalize steady state v . I choose c so that the vacancy rate is normalized to one (1) in the steady state. The algorithm for finding the original steady state is as follows:

1. Pick the efficiencies of matching, m_0^U and m_0^E to target contact probabilities p_T^U and p_T^E that ensure the correct U-E and E-E transition probabilities respec-

²⁴In practice, $z_1 = 0$.

tively,²⁵ i.e. $m_0^i = \frac{f_T^i}{v_{SS}^\alpha} = \frac{f_T^i}{1} = f_T^i$, $i \in \{U, E\}$.

2. Solve the match surplus using equation (2.4). Be sure to use the targeted contact probability p_T^i .
3. Use iteration on the flows into and out of each grid point (x, y) and unemployment to pin down the steady state distribution of (x, y) among employed workers $\hat{\pi}(x, y)$, and the steady state unemployment rate \hat{u} . See 3.8.4.2 for details.
4. Notice that by choosing m_0^i to target a contact rate, and normalizing v_{SS} to one, the vacancy creation condition implies that the vacancy posting cost satisfies:

$$c = \delta p_T^U u \mathbb{E}_u + p_T^E (1 - u) \mathbb{E}_e \quad (3.13)$$

Use $\hat{\pi}(x, y)$ and \hat{u} to obtain the right hand side.

As with the simple model the calibration is performed using interpolation while the steady state distributions of x and y are computed on a fixed grid with no interpolation. The two approaches give very similar results for simulated data moments.

With the original steady state in hand I proceed to solve the the economy with aggregate productivity $z = z_2$. The complexity of the algorithm increases because m_0^i are no longer free parameters; their calibrated values cannot change from steady state to steady state. The algorithm for finding this new steady state is as follows:

1. Guess a steady state vacancy rate $v_{SS_2}^0$. This implies new job contact rates $f_i(v_{SS_2}^0) = m_0^i (v_{SS_2}^0)^\alpha$.
2. Solve the match surplus bellman equation using equations (2.4). Use the new contact probabilities.

²⁵In practice, this means targeting contact probabilities of around $p_T^U = 0.45$ and $p_T^E = 0.26$, as presented in Table 2.1.

3. Use iteration on the flows into and out of each grid point (x, y) and unemployment to pin down the steady state distribution of (x, y) among employed workers $\hat{\pi}(x, y)$, and the steady state unemployment rate \hat{u} . See Section 3.8.4.2 for details.
4. Using the vacancy creation condition (equation 3.9), $\hat{\pi}(x, y)$ and \hat{u} back out the implied equilibrium vacancy rate \hat{v} (can be solved for in closed form). If \hat{v} and $v_{SS_2}^0$ are close then stop. Otherwise, go back to step (1) with a new guess for the equilibrium vacancy rate:

$$v_{SS_2}^0 = \zeta_v \hat{v} + (1 - \zeta_v) v_{SS_2}^0$$

ζ_v is chosen small enough so that the procedure converges.

This routine guarantees convergence because the resulting vacancy rate (\hat{v}) is monotonically decreasing in the initial guess ($v_{SS_2}^0$). Intuitively, as $v_{SS_2}^0$ rises the job filling rate ($q(v_{SS_2}^0)$) falls. This means that expected hiring costs ($\frac{c}{q(v_{SS_2}^0)}$) increase and thus too few workers are in fact hired and too few vacancies are posted as compared to the equilibrium vacancy rate.

3.8.4.2 Flows: Full Model

Before I proceed to outlining the algorithm used for computing transitions I want to describe the set of flow balance equations used to solve for steady state $\hat{\pi}(x, y)$ and \hat{u} in the preceding section. The outflows from the unemployment pool include:

- Unemployed agents who find new jobs:

$$up_U$$

The inflows into the unemployment pool include:

- Exogenous separations for all the employed:

$$(1 - u)p_s$$

- Endogenous separations for those with no outside offer:

$$(1 - p_E)(1 - p_s) \sum_x \sum_y \pi(x, y) \mathbb{I}\{S(x', y) \leq 0\} dF_x(x'|x)$$

- Endogenous separations for those with an outside offer, but neither the value of the outside offer or the current offer exceeds unemployment:

$$p_E(1 - p_s) \sum_x \sum_y \pi(x, y) \mathbb{I}\{\max\{S(x_0, \tilde{y}), S(x', y)\} \leq 0\} dF_x(x'|x) dF_y(\tilde{y})$$

The outflows from a particular (x, y) grid point of the distribution $\pi(x, y)$ include:

- Those that receive no outside offer, and have their idiosyncratic component change to $x' \neq x$ (including unemployment):

$$(1 - p_E)(1 - p_s) \pi(x, y) (1 - \mathbb{P}[x' \neq x|x])$$

- Those that receive an outside offer and leave the current firm (including to unemployment):

$$p_E(1 - p_s) \sum_x \sum_y \pi(x, y) \mathbb{I}\{S(x_0, \tilde{y}) > S(x', y)\} dF_x(x'|x) dF_y(\tilde{y})$$

- Those that receive outside offer and either stay at the current firm with a new

x or move to unemployment:

$$p_E(1 - p_s) \sum_x \sum_y \pi(x, y) \mathbb{I}\{S(x', y) > S(x_0, \tilde{y}) \& x' \neq x\} dF_x(x'|x) dF_y(\tilde{y})$$

- Exogenous separations:

$$\pi(x, y) p_s$$

The inflows into a particular (x, y) grid point of the distribution $\pi(x, y)$ include:

- Inflow from all other cells by a change in x , with no outside offer; ensuring that current (x, y) -cell has positive surplus:

$$(1 - p_E)(1 - p_s) \sum_{x_i \neq x} \mathbb{I}\{S(x, y) > 0\} \pi(x_i, y) \mathbb{P}_x[x' = x | x_i]$$

- Inflow from all other cells by a change in x , with an outside offer that is rejected; ensuring that current (x, y) -cell has positive surplus:

$$p_E(1 - p_s) \sum_{x_i \neq x} \sum_{\tilde{y}} \mathbb{I}\{S(x, y) > 0\} \pi(x_i, y) \mathbb{I}\{\max\{0, S(x_0, \tilde{y})\} \leq S(x, y)\} \mathbb{P}_x[x' = x | x_i]$$

As one special case, the inflow from job changers, i.e. those that get good outside offers (y_i) and switch to current cell. This only happens for idiosyncratic productivity $x = x_0$:

$$p_E(1 - p_s) \sum_{x_i} \sum_y \mathbb{I}\{S(x_0, y_i) > 0\} \pi(x_i, y) \times \\ \mathbb{I}\{S(x_0, y_i) \geq S(x, y) \& (x \neq x_0 | y_i \neq y)\} \mathbb{P}_x[x' = x | x_i] \mathbb{P}_y[\tilde{y} = y_i | y]$$

As another special case, the inflow from unemployment, into cell (x_0, y_0) :

$$up_U$$

Iterating on these flows yields the steady state distribution $\hat{\pi}(x, y)$ and \hat{u} for corresponding value function $\hat{S}(x, y)$.

3.8.4.3 Transition Algorithm: Full Model

I compute a perfect foresight solution that follows Auerbach and Kotlikoff (1987), and much more recently Acemoglu and Hawkins (2010). The idea is to solve for a time-path of vacancy rates on the transition path that is consistent with optimal firm and worker choices, and perfect foresight about the evolution of (x, y) among employed workers. The algorithm looks as follows:

1. Guess when the transition will finish. Call this time period T and impose that from time T onwards the economy remains in the steady state corresponding to z_2 .
2. Guess a sequence of vacancy rates $\{v_t\}_{t=1}^{T-1}$.
3. Solve recursively for the functions $\{S(\cdot, \cdot, t)\}_{t=1}^{T-1}$ by iterating backwards in time.²⁶
4. Simulate forward the evolution of $\{\Pi(\cdot, \cdot, t)\}_{t=1}^T$ and the unemployment rate $\{u_t\}_{t=1}^{T-1}$ using the guessed time-path for $\{v_t\}$ and the flow equations presented in 3.8.4.2.²⁷
5. Using the time-path of $\Pi(\cdot, \cdot, t)$, u_t and v_t , obtain an updated time-path for the

²⁶Recall that from the steady state solution for z_2 I have $\{S(\cdot, \cdot, T)\}$ which is the steady state value function associated with z_2 . In the Bellman equation for $\{S(\cdot, \cdot, t)\}$ use $p_U(v_t)$ and $p_E(v_t)$.

²⁷Again, note that from the steady solution for p_1 I have $\Pi(x, y, 0)$ and u_0 , which is where I start the economy in this simulation. Note that the timing here implies that $\Pi(x, y, t)$ is the distribution of (x, y) among employed workers at the *beginning* of period t . To obtain $\Pi(\cdot, \cdot, T)$ I use the value functions from the steady state associated with z_2 .

vacancy rates $(\{\hat{v}_t\}_{t=1}^{T-1})$ from the vacancy creation condition for every period $(t \in 1, 2, \dots, T-1)$:²⁸

$$V_t = -c + \delta q_U(\hat{v}_t)u_t \max\{0, (1-\beta)S(x_0, y_0, t+1)\} + \delta q_E(\hat{v}_t)(1-u_t) \times \\ \int \int \int \int \mathbb{I}\{S(x_0, \tilde{y}, t+1) > S(x', y, t+1)\} \max\{0, (1-\beta)S(x_0, \tilde{y}, t+1)\} \times \\ dF_x(x'|x) dF_y(\tilde{y}) d\tilde{\Pi}(x, y, t)$$

where $V_t = 0$ for all t due to free entry into vacancies. If the implied time-path is sufficiently close to the guess, stop. If not, update the guess by selecting new guesses:

$$v_t = \zeta_v \hat{v}_t + (1 - \zeta_v)v_t$$

where ζ_v is chosen small enough to guarantee convergence.

6. Verify that the implied distribution of (x, y) among employed workers, $\Pi(x, y, T)$ is sufficiently close to the steady-state distribution Π_{SS_2} . If not, choose a larger T and repeat the whole algorithm.

Notice that I do not need to resort to an algorithm like that presented in Krusell and Smith (1998) because vacancies have to satisfy only one equation. I do not need agents to forecast today's vacancy rate, have them act optimally according to this forecasted value and then check whether these actions imply the forecasted vacancy rate. The vacancy rate from the fixed point iteration scheme outlined above is consistent with the vacancy equation for each time period and microeconomic behavior is consistent with this vacancy rate.²⁹

²⁸Contacts and match consummation happen before layoffs which occur at the end of the period. Hence, when considering posting a vacancy, firms take into account the contemporaneous unemployment rate and distribution of (x, y) among employed workers. The realization of the aggregate shock occurs after wage bargaining and production but before employer-employee contacts occur. Finally, I use $t+1$ value functions in the continuation values because production in consummated matches occurs at the beginning of the following period.

²⁹In large firm models, for example, each firm needs to forecast today's labor market tightness, act in accordance with this labor market tightness, and then the resulting labor market tightness needs

to be consistent with the forecasted value. This complication arises with heterogeneous decision makers. One aggregate labor market tightness can come from many distributions of employment across firms.

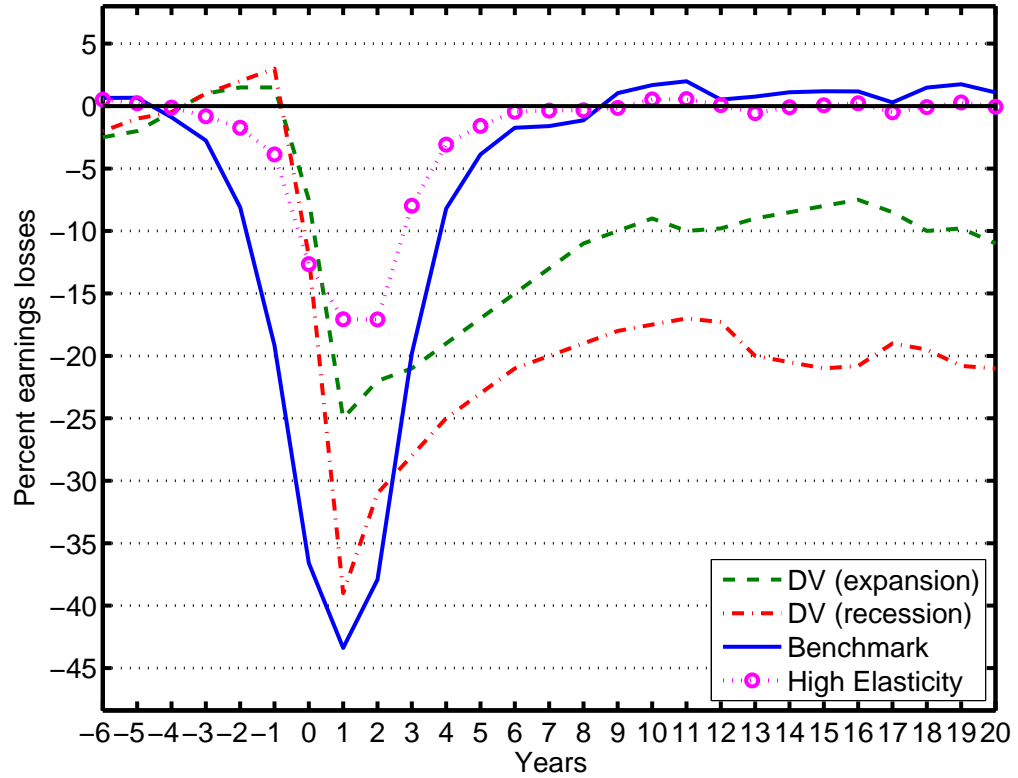


Figure 3.1: Annual Earnings Losses: Simple Model vs. Data

Note: For simplicity this is the average difference between the annual earnings of a treated individual and the average earnings of individuals in the control group. The earnings losses are relative to a non-displaced control group with the same three year tenure requirement as the displaced treatment group. Earnings losses are plotted as a fraction of average pre-displacement earnings of the treatment group in the four years prior to displacement. For a definition of displacement and the tenure requirement see the text (Chapter II).

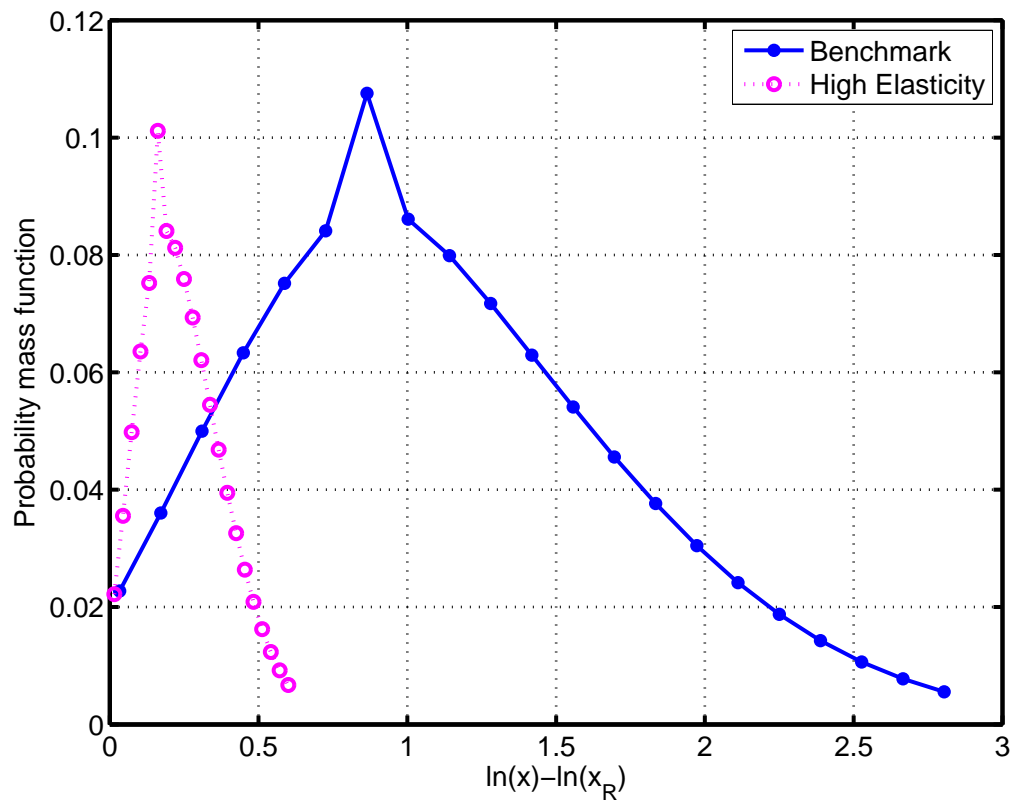


Figure 3.2: Distribution of Idiosyncratic Productivity: Simple Model

Note: Distribution of x in the simple model for the benchmark and high-elasticity calibrations.

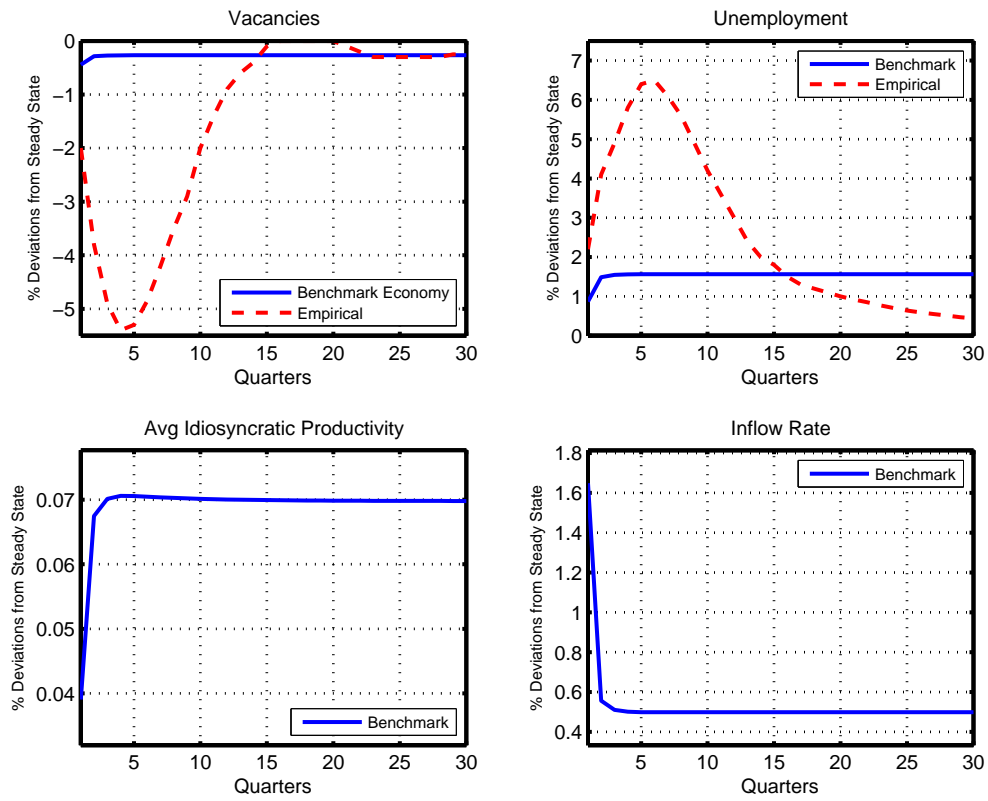


Figure 3.3: (Normalized) Impulse Response to a 1% Permanent, Unexpected Decrease in Aggregate Productivity: Simple Model (Benchmark Calibration)

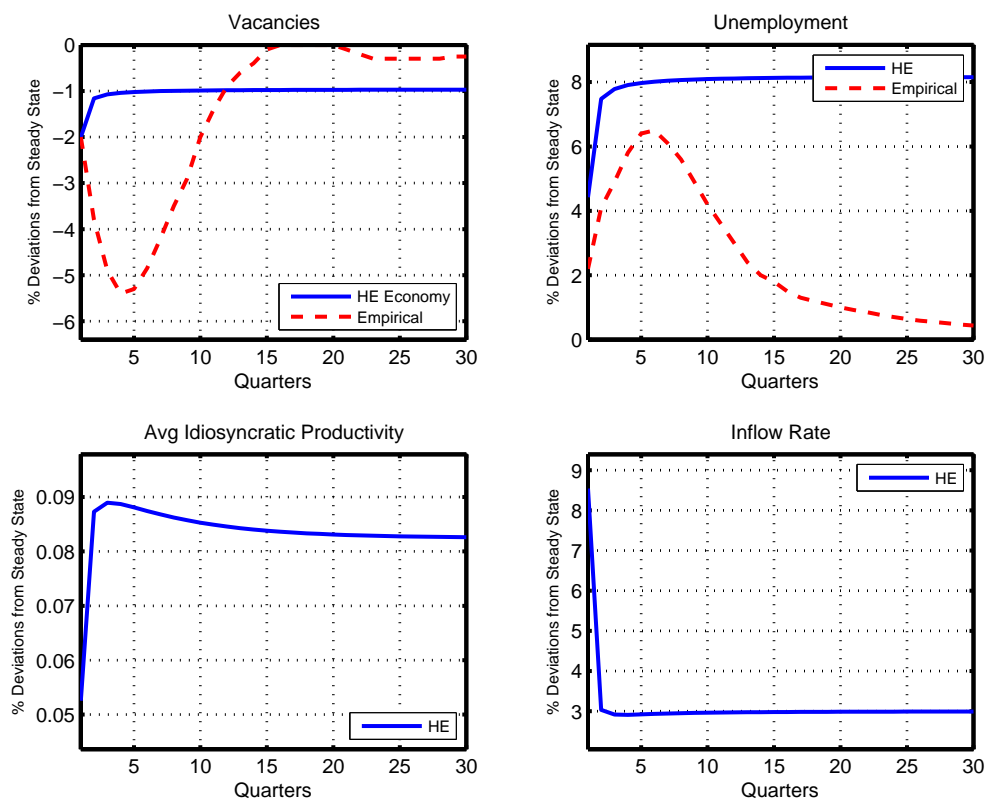


Figure 3.4: (Normalized) Impulse Response to a 1% Permanent, Unexpected Decrease in Aggregate Productivity: Simple Model (High-Elasticity Calibration)

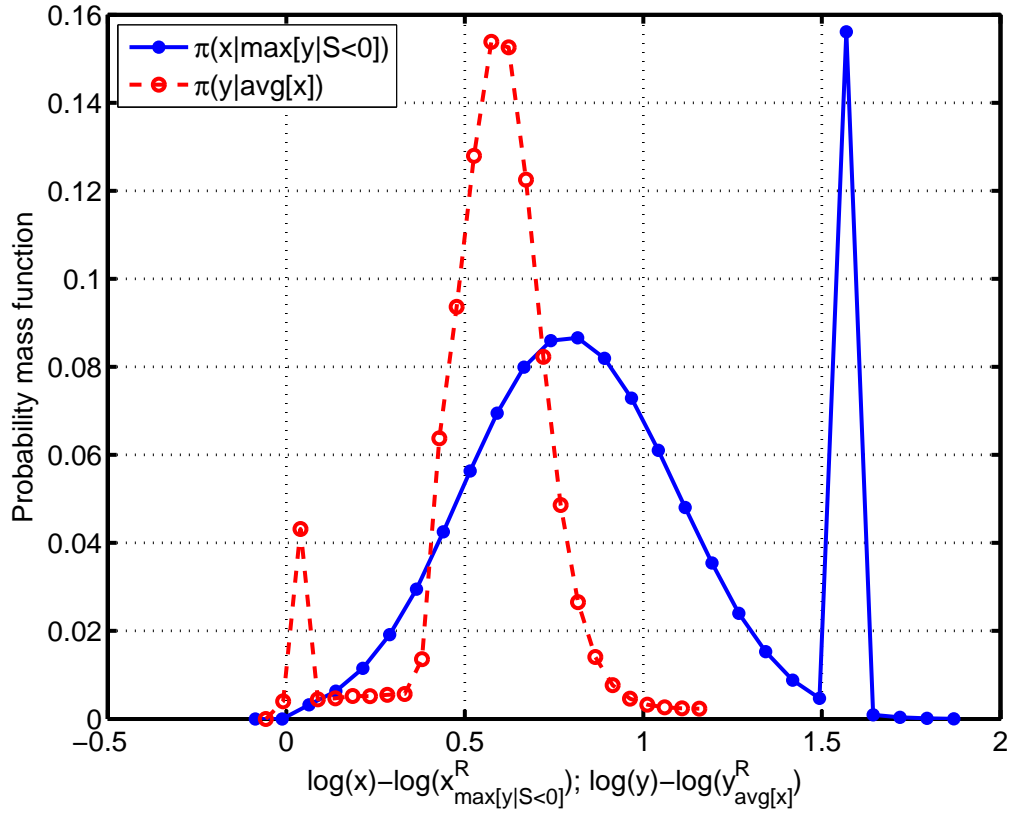


Figure 3.5: Distribution of x and y : Full Model

Note: Distribution of x , holding y at $y^R_{\text{avg}[x]}$, and y , holding x at $x^R_{\max[y|S<0]}$ in the full model with baseline calibration. For a definition of $x^R_{\max[y|S<0]}$ and $y^R_{\text{avg}[x]}$ see equation (3.10) in the text. Since these are conditional probabilities, they sum to one.

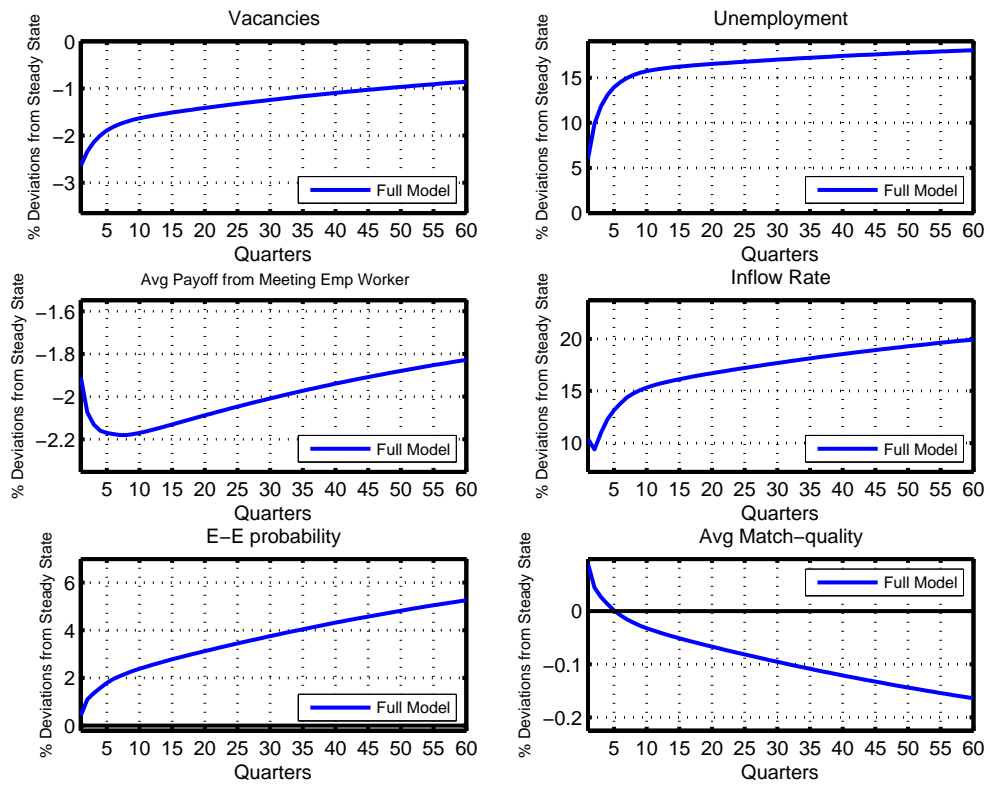


Figure 3.6: (Normalized) Impulse Response to a 1% Permanent, Unexpected Decrease in Aggregate Productivity: Full Model

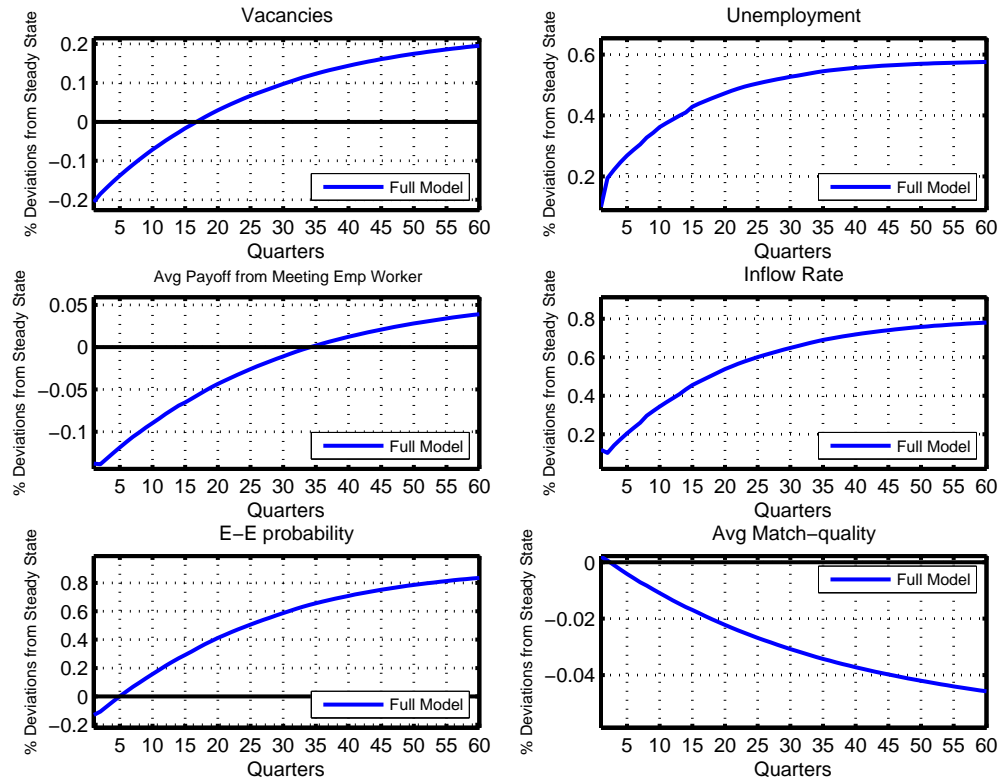


Figure 3.7: (Normalized) Impulse Response to 1% Permanent, Unexpected Increase in Exogenous Separation Probability: Full Model

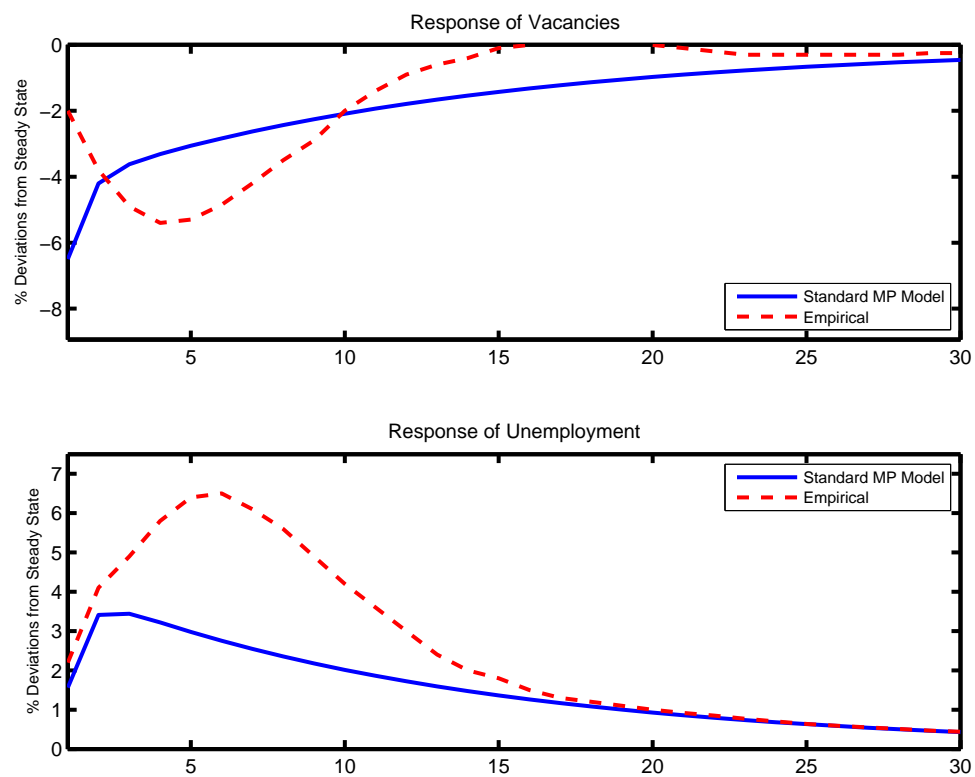


Figure 3.8: Impulse Response to 0.78% Persistent ($\rho_z = 0.975$), Unexpected Decrease in Aggregate Productivity: Basic MP Model

Table 3.1: Parameter Values for Simple Model

Parameter	Meaning	Benchmark	High Elasticity
ρ_x	Productivity persistence	0.97	same
σ_{ϵ_x}	Std. dev. of innovation to $\ln x$	0.237	0.05
r	Real interest rate (A)	0.05	same
$f(\theta)$	Job finding probability	0.31	same
b	Value of leisure	-1.44	0.77
α	Matching technology $m(v, u) = 0.31v^\alpha u^{1-\alpha}$	0.5	same
c	Vacancy posting cost	3.35	0.31
θ	Steady-state v/u ratio (normalized)	1	same

Note: The parenthetical (A) refers to annual estimates.

Table 3.2: Steady-State Features of Simple Model

Statistic	Benchmark	High Elasticity
Unemployment prob	0.06	same
Separation prob	0.02	same
Job finding prob	0.31	same
Standard deviation of $\ln w$	0.36	0.075
Mean-min wage ratio	1.75	1.13

Note: See Table 3.1 for parameter values for the two calibrations.

CHAPTER IV

Re-assessing the Earnings Experience of Displaced Workers

4.1 Introduction

Formal empirical studies of displaced workers started at least 30 years ago and have developed significantly since then. The most recent studies implement sophisticated empirical techniques using administrative data.¹ Most studies find that the earnings and wage losses of displaced workers are large and extremely persistent, remaining even 20 years after the displacement event. This chapter studies two predominant empirical specifications used in the displacement literature and compares the estimates of the earnings losses of displaced workers. The work focuses on the control group used in these approaches. The analysis also includes a robustness check of the most recent empirical specification, and assesses the earnings losses of displaced workers by individual characteristics.

Studies such as Stevens (1997) and Jacobson et al. (1993) focus on the effects of displacement using a control group of workers who are *never displaced*. For example, Jacobson et al. (1993) use Pennsylvanian administrative data from 1974 to 1986. They impose a restriction of six years of tenure at the beginning of 1980 for their

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

treatment and control groups, and further impose that their control group experience no displacements in years 1981-1985. The treatment group consists of workers displaced in the years 1981-1985. In other words, the control group is comprised of those who do not experience an employer separation throughout the observed time periods. Using data from the Panel Study of Income Dynamics (PSID), Stevens (1997) follows a very similar approach. This analysis also uses the never displaced as a control group, and focuses on the wage experience of displaced workers around their first and last displacements.

The main point of this chapter is that the choice of control group significantly colors the interpretation of the estimated coefficients. In particular, using the never-displaced as a control group yields larger estimated earnings losses for displaced workers compared to an alternative control group that includes individuals not displaced this year, but potentially experiencing displacement in other years. Although the annual displacement probability is not large in any given year, the cumulative probability of experiencing a displacement is quite large. In a recent paper studying displaced workers, Davis and von Wachter (2011) report that the annual displacement probability is around 3.5 percent for prime-aged males with three or more years of job tenure. Between 1980 and 1985, around 16 percent of these males experienced a job displacement event. Hence, workers who never experience displacement are a non-random group of individuals. In particular, they tend to have higher average annual earnings, and therefore the estimated earnings losses for displaced workers will tend to be larger with this control group.

Since the average worker experiences displacements during his lifetime it might be natural to include individuals who may experience displacement at some point in their work history in the control group. Most recently, Davis and von Wachter (2011), based on work by von Wachter et al. (2007), have used this approach, which gives a different picture of the earnings losses of displaced workers. In essence, the treatment group is

made up of those individuals who experience displacement in a particular year, and the control group is composed of those who do not experience a displacement in a particular year, but could experience displacement before or after the particular year. This control group is more representative of the average worker's experience: they could avoid displacement this year, but could experience it in the future. Using Social Security records, the authors find results similar to previous estimates of displaced worker earnings losses. In this chapter I use this more recent specification, and the previous empirical approach of Stevens (1997), to estimate the earnings losses of displaced workers using PSID data. I also present heterogeneity in the recovery of earnings for different types of workers, shedding light on the possible reasons for the persistence of earnings losses. Using the PSID, the approach of Davis and von Wachter (2011) yields very similar results to the estimates using administrative data. The approach of Stevens (1997) implies much larger earnings losses, as anticipated.

The rest of the chapter is organized as follows. Section 4.2 outlines the data used in this analysis and presents some summary statistics. Section 4.3 outlines the two empirical approaches used in previous literature. Section 4.4 presents baseline results for the two specifications, as well as results without any time trends and a decomposition of the lost earnings into reduced hours and lower wages. Section 4.5 presents results by varying worker characteristics such as age, education, pre-displacement wealth and time spent unemployed. Section 4.6 concludes.

4.2 Data

This chapter examines the heterogeneity in earnings recoveries of displaced workers using the PSID. The analysis uses an unbalanced panel version of PSID waves 1968-2009, using both the nationally representative sample and the poverty oversample.²

²Both samples are used to increase sample size and individual weights are used to maintain national representativeness and to deal with non-random attrition. The baseline results are very similar with unweighted observations using only the nationally representative sample. Note that

The sample consists of household heads who, from their first observation as household heads, have at least three consecutive observations. The final sample includes 15,817 household heads with an average of 16 years on each household head, yielding 250,611 observations.

Job displacements are determined from a question that asks respondents with low levels of current job tenure “What happened to that employer (job)?” (the individual’s previous job). The two categories of responses used to identify displacements are “plant closed/employer moved” and “laid off/fired.” Although fired workers are generally not considered to be displaced, Boisjoly et al. (1994) report that only 16 percent of the PSID workers in the laid off/fired category reported being fired. Therefore, the bias from including these fired workers is likely minimal because they constitute a small fraction of this category. I include these observations as displacements because the publically available data make no distinction, and being fired is also a shock to earnings, so it is not clear that these individuals should be excluded. In the final sample, there are 12,474 displacements with 6,140 first displacements.

As is well documented by previous authors, the year of displacement is measured with error in the PSID. The respondent’s answers about earnings and employment refer to the previous calendar year. For the first sixteen waves of the PSID, the survey asks what happened to the last job for those reporting a job tenure of less than one year. Subsequent surveys ask what happened to the previous job if the current job started since January 1 of the previous calendar year. Due to the timing of the interviews, job displacements may have occurred either during the previous calendar year or during the first few months of the current calendar year. For this study, a recorded displacement is assumed to have occurred during the survey year.

generally those that leave the PSID sample tend to be selected negatively. This would make the post-displacement earnings estimates presented here biased towards zero. The analysis excludes the Latino and immigrant supplement samples. Household head earnings data are available, using supplement files, for all years except 2005. Household head labor hours are available with supplemental files for all years except 2001, 2003, 2005, 2007 and 2009.

Finally, as is common with displaced worker studies using the PSID, household heads who report a displacement in the 1968 wave are excluded from the analysis because this displacement may have occurred any time in the 10 years prior to the survey.

Summary statistics for never-displaced household heads and displaced household heads are presented in Table 4.1. Consistent with previous literature, displaced individuals tend to be younger than the never displaced at the time of the shock. Displaced workers are slightly less educated than the never displaced, although this difference is not significant.³ In addition, displaced workers are more likely to originate from the manufacturing sector and blue collar jobs.⁴ Finally, 62 percent of household heads report never being displaced and 38 percent report at least one displacement during their observations.

4.3 Empirical Methodology

There are two main specifications that authors have used to assess the earnings losses of displaced workers. The first specification focuses on the *first* displacement and, with some slight variations, takes the following form:

$$e_{it} = \alpha_i + \gamma_t + \lambda_i t + X_{it}\beta + \sum_{k=-m_l}^{m_u^+} D_{it}^k \delta_k + \epsilon_{it} \quad (4.1)$$

where e_{it} are the annual earnings of household head i at time t , α_i and γ_t represent individual and time fixed effects respectively, λ_i allow for individual linear time trends, and D_{it}^k equal one if individual i was displaced for the first time k periods ago at time t . X_{it} includes time varying worker characteristics. The analysis treats those m_l periods

³For education I implement the cleaning method of Stephens (2001). Although years of education may change during the sample, I force it to be constant. To determine the years of education, I take the most recent, non-missing observation from the family file. If years of education are still missing I take the most recent, non-missing years of education from the individual file.

⁴White collar jobs include professional and technical workers, managers and administrators, sales workers and clerical workers. Blue collar jobs include craftsmen, operatives, transport equipment operatives and laborers.

before their first displacement as part of the control group, and those m_u or more years after their first displacement are captured in the last dummy variable. Here the ‘+’ denotes that those m_u periods or more after displacement are pooled to estimate the coefficient on the last dummy. Note that the control group for this regression are those workers that never experience displacement because these workers have $D_{it}^k = 0 \forall k$, as well as individuals who are more than m_l periods before their first displacement. This control group serves as an extreme benchmark because the never displaced are a select group of individuals. This specification forces the displacement dummy coefficients to take on the same value for all displaced cohorts. This specification finds its roots in Jacobson et al. (1993) and has been used for decades in studies such as Stevens (1997) and Couch and Placzek (2010). From now on I refer to this specification as the ‘Stevens’ specification.⁵

Sometimes this equation is specified with log earnings on the left hand side which delivers percent changes in earnings. This approach excludes all observations with zero annual earnings. These observations constitute a significant portion of the observations. Sometimes the level losses estimated using equation (4.1) are reported as a fraction of the treatment group’s average pre-displacement earnings.⁶ I include observations with zero earnings in my analysis and report losses as a fraction of average earnings prior to initial displacement.

An alternative specification alters the control group for every displaced cohort, by calendar year. In order to remain consistent with a recent study by Davis and von Wachter (2011) I follow their approach. In particular, for every displacement year y

⁵I choose to refer to it as the ‘Stevens’ specification rather than referencing Jacobson et al. (1993) because Stevens (1997) applied this specification in a way that is most comparable to the work presented here.

⁶Since this chapter is in some sense an update of Stevens (1997), I present a comparison to the results of Stevens in Section 4.7.

one can estimate the following equation:

$$e_{it}^y = \alpha_i^y + \gamma_t^y + \bar{e}_i^y \lambda_t^y + X_{it}^y \beta^y + \sum_{k=-m_l}^{m_u^+} D_{it,y}^k \delta_k^y + \epsilon_{it}^y \quad (4.2)$$

All the notation is the same as before, and \bar{e}_i^y represents the average earnings of individual i using the years $y - 5$ to $y - 1$. In year y the treatment group are those displaced in year y . The control group can be those individuals that are not displaced in year y . Alternatively, they could be individuals who do not separate from their employer in year y .⁷ Importantly, now the control group are individuals who are not separated from their employer this year, but could have been displaced in previous years or could be displaced in future years.⁸ This control group captures the average worker's experience, because individuals that are not displaced this year face the risk of displacement in the future, and faced it in the past. For the control group one sets $D_{it,y}^k = 0 \forall k$ so that the δ_k^y coefficients capture the earnings deviations from this control group, and the control group identifies the year fixed effects. One omits a time-relative-to-displacement-year dummies so that it is zero by construction. This approach yields a set of δ_k^y coefficients for every year y . One way to present these coefficients is to average them and obtain a mean treatment effect across the years. Notice that this approach allows the displacement dummy coefficients to vary with each displacement cohort. As with the first specification, these losses are often expressed as a fraction of the treatment group's average pre-displacement annual earnings. This specification appears in Davis and von Wachter (2011) and I refer to it as the Davis-von Wachter specification from now on.

⁷To raise sample sizes I take those displaced in year y , $y + 1$ and $y + 2$ as the relevant treatment group, and those who do not separate from their employer in years y , $y + 1$ and $y + 2$ as the relevant control group. This follows Davis and von Wachter (2011).

⁸Since the control group do not separate from their position in y , $y + 1$ and $y + 2$ they are restricted to employment for a couple of years after time y .

4.4 Baseline Results

This section presents earnings estimates for the two main specifications, as well as a robustness check that does not include individual specific time trends. The earnings losses are decomposed into reduced employment and lower wages.

4.4.1 Earnings

The two approaches outlined in the previous section yield potentially different results. Using the PSID I estimate both equations and present the results in Figure 4.1. The results here are the δ_k coefficients from equation (4.1) divided by the average earnings of the treatment group over the four years prior to displacement, and an average of the δ_k^y coefficients from equation (4.2) divided by the pre-displacement average earnings of the treatment group. For the latter, I estimate the equation for years 1972 through 1997.⁹

The two control groups paint a very different picture of the earnings consequences for displaced workers. First, the pre-displacement dip is a little different, with the never-displaced specification suggesting smaller downward movements prior to displacement. This follows from the fact that the never-displaced specification refers to the first displacement, so agents do not experience substantial reductions in earnings prior to this job loss. In the Davis-von Wachter specification earnings tend to fall prior to displacement as agents may experience more turbulent earnings experiences prior to the shock because this is not necessarily their first displacement. Furthermore, the Stevens specification controls for individual linear time trends to account for unobserved characteristics that could lower rates of earnings growth. The Davis-von Wachter approach controls for this with a more flexible specification by allowing the

⁹I set m_u^+ to 11+. Furthermore, all regressions include a quartic in worker age. I do not restrict the tenure or age of the treatment and control groups. This is partly due to sample size issues and partly due to the fact that since the PSID offers the reason for the separation of a respondent we do not need tenure as in much of the displacement literature using mass layoffs.

year effects to vary proportionally to the worker's pre-displacement average earnings. These trends could pick up the effects of displacement and I return to this point in Section 4.4.2.

On impact the Stevens and Davis-von Wachter approaches yield comparable estimates of earnings losses: around 30 percent. This suggests that the choice of empirical model is inconsequential for the on-impact affect of displacement on earnings. The recovery, however, is quite different for the two specifications. The Davis-von Wachter approach suggests a 10 percent earnings recovery in the 10 years following displacement, whereas the Stevens specification suggests that earnings, after only a slight initial recovery, continue to fall and are even lower 10 years after the first displacement. The choice of control group markedly alters the results and the interpretation of these results.

4.4.2 Excluding Individual Specific Time Trends

The Stevens approach outlined thus far includes individual linear time trends and the Davis-von Wachter approach allows a worker's pre-displacement earnings to interact with the aggregate time trends in affecting earnings growth. It is not clear that these are the right approaches. In particular, individual time trends could pick up some of the effects of displacement if displacement truly has a permanent effect on earnings. Hence, the two approaches are likely to understate the earnings losses associated with displacement because part of the displacement effect will be picked up by the individual time trend. In both specifications, including individual fixed effects suggests that time-invariant worker attributes that affect earnings do not pose a problem. Different trends in counterfactual earnings for the control group and the displaced workers based on unobservables may introduce a bias, which the specification in this section ignores.

In order to avoid attributing the effect of displacement on earnings to a time trend,

I also estimate the following equation:

$$e_{it}^y = \alpha_i^y + \gamma_t^y + X_{it}^y \beta^y + \sum_{k=-m_l}^{m_u^+} D_{it,y}^k \delta_k^y + \epsilon_{it}^y \quad (4.3)$$

which is the Davis-von Wachter approach with no individual time trends.¹⁰

Figure 4.2 presents the results of the Davis-von Wachter specification in the previous section, as well as results for the specification in equation (4.3), and, as a reference, the original empirical results from Davis and von Wachter (2011), using Social Security administrative data. First, notice that the Davis-von Wachter specification, with data from the PSID, gives results that are very similar to the results using Social Security administrative data. On impact both approaches imply earnings losses of around 30 percent. The recovery in earnings is very similar over the next 10 years, with annual earnings rising by around 15 percent. The two data sets provide different ideas of pre-displacement earnings losses, with the PSID sample suggesting much larger losses in years prior to displacement.

Figure 4.2 also highlights that omitting individual specific trends in the specification can significantly affect the estimated earnings losses of displaced workers. Without time trends, earnings losses on impact are about 15 percent larger, which increases the present value of earnings losses dramatically in comparison to the Davis-von Wachter specification with individual time trends.¹¹ Therefore, as expected, the interaction between pre-displacement earnings and the aggregate time trend serves to soak up some of the displacement effect. On the other hand, without controlling for individual time trends, unobservable characteristics affecting earnings growth for

¹⁰Including individual linear time trends, as in the Stevens specification, would be misleading in the Davis-von Wachter approach. Variation in earnings prior to year m_l before displacement would identify the individual linear time trend. Since individuals can experience displacement in these periods this would serve to bias the estimate of the trends downwards which would suggest a quicker post-displacement earnings recovery. Empirical analysis confirms this suspicion.

¹¹Davis and von Wachter (2011), and a closely related paper von Wachter et al. (2007), do not present results without individual time trends, so it is difficult to compare the results using PSID data with the results using administrative data.

the displaced, relative to the control group, bias the estimated earnings losses. In order to remain comparable to previous literature, I present earnings losses using the Davis-von Wachter specification with individual time trends.

4.4.3 Decomposition into Wages and Hours

In order to assess fully the implications of displacement on workers, it is important to decompose the earnings losses into lower wages and reduced hours worked. To measure hours worked I use individual responses to the labor hours worked question in the PSID, and to measure wages I use labor earnings divided by labor hours (hourly earnings).

Figure 4.3 presents the earnings, wages and hours time-profiles around a displacement, using the specification in equation (4.2) and dividing by pre-displacement averages. This plot tells a consistent story with Figure 4.1.¹² The reduction in earnings prior to displacement in the Davis-von Wachter approach comes largely due to the reduction in hours, which fall by around 15 percent. Wages hold somewhat steady prior to separation and fall by around 5 percent. On impact the reduction in hours is responsible for around two-thirds of the reduction in earnings, with the remainder explained by a reduction in wages. In the short-run, earnings recover largely due to a rise in hours worked, with the wage remaining at on-impact levels. Both the on-impact reduction and quick recovery in hours worked are consistent with previous studies, such as Topel (1990). Within five years, hours have returned to their pre-displacement levels, and the long run losses are driven by reduced wages.

¹²The percent losses in wages and hours do not sum perfectly to the percent losses in earnings because hours are not available in even years after 1997 so these observations are not included in the hours and hourly earnings regressions. Moreover, for the wage regression I trim wage below one dollar an hour and above \$100 dollars an hour.

4.5 Losses by Worker Characteristics

In this section I report different earnings recoveries by worker characteristics. The main point of this section is to show that, although the incidence of displacement varies substantially across groups, the effects of displacement conditional on incidence affects all workers, including the young and the old, workers with different levels of education, workers from various industries and occupations, and the poor and the rich. Given the previous analysis, I use the Davis-von Wachter approach with individual specific time trends from here on out. I estimate equation (4.3) but for different sub-populations.¹³ With regard to the model presented in Chapter II, the universality of displaced worker earnings losses is somewhat important because the model features ex-ante homogeneous workers. This means that the model predicts that all sub-populations of workers will lose identical amounts, on average, from displacement. This section shows that all workers face significant and persistent earnings losses after displacement. At the same time, the magnitude of these losses varies by sub-groups.

4.5.1 Age

Figure 4.4 presents results by the worker's age at the time of displacement.¹⁴ Workers of all ages face significant costs of displacements in the short and medium run. The earnings of the oldest workers (51-60 year olds) fall by more than 40 percent on impact. Other workers lose around 30 percent on impact. In the long run all workers experience similar earnings losses which means that older workers, on average, experience a faster recovery. These results are consistent with Davis and von Wachter (2011) in that they find that older workers lose more on impact but experience a faster recovery in earnings than younger workers.

¹³This is in contrast to adding interaction terms for each sub-population. The specification I run is more general because it allows all the parameters of the empirical model to differ by sub-population, which avoids attributing earnings losses due to differential time trends to displacement.

¹⁴For these regressions I use an individual's observations only if in that year the worker is at most 65 years old.

These separate regressions by age are a decomposition of the average effect in Figure 4.1 where each age group's outcome is weighted by the probability of that group conditional on displacement. Table 4.2 provides an idea of the differential incidence of displacement as well as the overall probability of a group appearing in the sample. The PSID has slightly more younger workers than older workers, and among displaced workers the young are over-represented. This is consistent with Table 4.1 in that the average age of the displaced is far smaller than the average age of the never displaced.

4.5.2 Education

Figure 4.5 shows the results by education group. These findings are somewhat consistent with other studies, like Stevens (1997). Individuals with varying education levels tend to have the same rate of recovery in earnings after displacement. However, the on-impact effect is non monotonic in education. Those with more education tend to lose less on impact. This relationship breaks down with the most educated, who tend to lose more than those with some college and about the same as those with a high school degree. Those with less than a high school education experience a 40 percent reduction in earnings in the year of displacement. They experience roughly a 15 percent recovery in earnings over the next 10 years. Those with some college experience only a 20 percent reduction in earnings at the time of displacement and recover almost fully after 10 years. One plausible interpretation for these results is that workers without a high school degree, compared to higher skilled workers, might be less flexible and possess less general human capital, making their earnings losses more severe. The non-monotonicity in earnings losses could be explained by those with some college having less access to high paying jobs to begin with, compared to those with a completed college degree. This would mean that those with some college might have less to lose than those with a completed college degree. Table 4.2 shows

that education does not really shelter individuals from displacement. Those with a bachelor degree or more are slightly under-represented in the group of displaced workers.

4.5.3 Routine vs. Non-Routine Jobs

Figure 4.6 shows the results by pre-displacement occupation. I take an individual's occupation two years prior to displacement as their pre-displacement occupation. I run the Davis-von Wachter specification for each occupation separately. I group the two-digit occupations available in the PSID into three categories: non-routine cognitive, non-routine manual and routine jobs.¹⁵ There exists a literature documenting the disappearance of wages from the middle of the wage distribution, largely characterized by routine jobs, and a rise in high paying non-routine jobs and lower paying non-routine manual jobs.¹⁶ The hypothesis is that since these well paying routine jobs are disappearing workers displaced from these occupations might suffer larger losses, because they are less likely to secure an equally paying job post-displacement. Figure 4.6 does not bear this out. Individuals losing jobs in routine occupations, in percent terms, lose about the same as the other occupations and their recovery looks very similar to the other occupations.

4.5.4 Low Wage and High Wage Industries

Figure 4.7 shows the results by pre-displacement industry. I group the industries into relatively low paying industries and relatively high paying industries, as discussed by Krueger and Summers (1988).¹⁷ Often economists argue that there are some rents

¹⁵Non-routine cognitive occupations include professional, technical, management, business and financial occupations. Routine jobs include clerical, administrative support, sales workers, craftsmen, foremen, operatives, installation, maintenance and repair occupations, production and transportation occupations and laborers. Non-routine manual jobs include service workers. These labels are based on Acemoglu and Autor (2011).

¹⁶See, for example, Goos and Manning (2007) and Autor et al. (2008).

¹⁷I place mining, construction, manufacturing and transportation, communications and other public utilities, along with finance, insurance and real estate (FIRE) in the high wage industries,

in high paying industries that are unexplained by union status, compensating wage differentials, or general skills. One might think that losing these types of jobs via a displacement might be much more detrimental to a worker's earnings than losing a low paying job. There exists some evidence for this, although both groups of workers suffer significantly following a displacement. Workers losing jobs in high paying industries suffer a 30 percent reduction in earnings on impact, while workers losing jobs in low paying industries suffer a 20 percent reduction in earnings on impact. The earnings recovery for these individuals looks very similar, although individuals from high wage industries do experience larger long run losses than displaced individuals originating from low wage industries (20 percent vs. 10 percent). The large and persistent losses across these two groups of workers suggests that rents are not solely responsible for the large earnings losses of displaced workers. Table 4.2 shows that many workers are in high-paying industries, although displaced workers are equally represented by workers from low wage and high wage industries.

4.5.5 Wealth

Theoretically it is not clear who should lose more, those with large wealth or those with little wealth. On the one hand, those with little wealth might be more liquidity constrained, and their marginal value of consumption tends to be higher, which would suggest a quicker recovery simply because of need. On the other hand, those with little wealth might not have the resources to pursue new opportunities, because they cannot, for example, move to a more prosperous geographic region. The PSID issued wealth supplements every five years from 1984 to 1999, and every other year thereafter till 2007. This supplemental wealth data are very thorough measuring assets such as net value of business assets, checking and savings accounts, value of

and wholesale and retail trade, business and repair services, and personal services in the low paying industries. According to this categorization the average (across all observations) hourly earnings in the high wage industries is around \$23 per hour and the average in the low wage industries is around \$18 per hour.

shares of stock and the value of all debts.

I estimate equation (4.2) where the groups are poor and wealthy workers at the time of displacement, deflating wealth to 2007 dollars. Measured wealth tends to be very noisy. As an example the average within standard deviation of wealth is around \$140,000. To ameliorate this issue, I use the average wealth of an individual over all wealth observation instead of the actual wealth in a given year. In order to estimate the Davis-von Wachter regression for all years, as before, I apply the average wealth of an individual to all their observations and use this in the baseline specification. This approach ignores the fact that displaced workers may draw down their wealth and hence be poorer on average. Poor workers are those below the 25th percentile in the wealth distribution in year y and the wealthy are those above the 75th percentile in the wealth distribution.¹⁸

Figure 4.8 presents the losses by wealth in the year of displacement, where the losses are divided by the appropriate group's pre-displacement earnings. The results suggest that, in the short run, poorer workers suffer considerably greater earnings losses than richer workers. On impact, the poor suffer a 45 percent reduction in earnings whereas the rich see a 30 percent reduction. A brief glance at the hours worked of these two categories suggests that this is the culprit, while wages move almost identically for the rich and the poor. This implies that poorer workers find it more difficult to find work and pre-displacement work hours. This effect persists for around 10 years following displacement.

Table 4.2 highlights that conditional on displacement the poor are over-represented. It turns out that three out of four displaced workers are poor workers. Hence, not only do poor workers suffer greater earnings reductions from displacement, they are far more likely to experience displacement.

¹⁸This finding is robust to other choices of the poor/wealthy cutoffs, such as 20/80 and 15/85. As an example, the 25th percentile in the 1984 wealth distribution was about \$4000 and the 75th percentile in the 1984 wealth distribution was about \$130,000 (2007 dollars).

4.5.6 Length of Unemployment Spell

Another interesting dimension of the effect of displacement on worker's earnings is through reduced human capital. Authors in the past have speculated that increased time out of work can extend the losses of a workers' human capital and adversely affect their earnings. Respondents in the PSID are asked how many weeks they spent unemployed or on temporary layoff in the previous year (or since January 1 of the previous year). Figure 4.9 presents results for the earnings of displaced workers by the time spent unemployed from specification (4.2). On impact, those that spend more time unemployed obviously have larger dip in earnings because they are out of work for longer. This difference in earnings persists, even 10 years after displacement. This suggests that the loss of human capital while unemployed, if it exists, does have long run consequences for displaced workers.

4.5.7 Displacement vs. Unemployment Spell

Finally, the model in Chapter II makes no substantive distinction between a displacement, a layoff or a generic period of unemployment. An unemployment spell in the model, no matter how short or for what reason, causes the worker to start at the bottom of the job ladder. Figure 4.10 presents results for those that experience displacement along with those that experience at least three months of unemployment.¹⁹ The results suggest that the difference between a displacement and a period of unemployment is very minimal, with both events resulting in similar on-impact effects and similar recovery trajectories. On impact those with at least three months of unemployment suffer slightly more than the average displaced workers, but conditioning on at least three months of unemployment for the displaced workers suggests a very similar earnings profile, as depicted in Figure 4.9. This similarity between the

¹⁹I choose at least three months of unemployment to avoid those on temporary lay off, which rarely exceeds three months.

two events bodes well for the theoretical framework developed in Chapter II of this dissertation.

4.5.8 Occupation/Industry Stayers and Switchers

Figure 4.11 shows the results by a worker's switching status by occupation and industry (at the one digit level). Here I take a slightly different approach and estimate the following equation:²⁰

$$e_{it}^y = \alpha_i^y + \gamma_t^y + \bar{e}_i^y \lambda_t^y + \sum_{k=-m_l}^{m_u^+} D_{it,y}^k \delta_k^y + \sum_{k=-m_l}^{m_u^+} D_{it,y}^k D_i^G \varphi_k^y + \epsilon_{it}^y \quad (4.4)$$

where everything is as before except now I also interact the displacement dummies with particular groups (G). For example, I might be interested in the differential effect on earnings of being displaced and switching industries. In this case I would set $D_i^G = 1$ for all workers who switched industries, and $D_i^G = 0$ for those who did not switch industries.²¹ The effect on earnings for displaced industry switchers is $\delta_k^y + \varphi_k^y$ and the effect on earnings for those displaced, but staying in their pre-displacement industry, is simply δ_k^y .²²

Figure 4.11 shows that those that switch industries suffer larger losses than those that remain within their pre-displacement industry. Switching occupations seems to have little impact on the earnings trajectory for displaced workers. These results are more in line with work that highlights industry-specific human capital rather than

²⁰The approach allows for the sub-population to be all workers, as opposed to all stayers or all switchers, which ignores the fact that other parameters of the model, such as aggregate trends, may differ by these two sub-populations.

²¹As before, the pre-displacement industry is taken from two years before the displacement shock. The post-displacement industry is taken five years after year y , except in years when this does not exist because of the biennial nature of the PSID after 1997. Then I take the industry six years after year y . For example, in survey year 1995, the industry five years after displacement does not exist because survey year 2000 does not exist. Therefore I take the industry from the survey in 2001.

²²Note that the group dummies are based on pre-displacement characteristics and remain fixed over time. Hence, they are absorbed by the individual fixed effects.

occupation-specific human capital.²³

4.6 Summary

This chapter implements two popular empirical specifications in the displaced worker literature. The original specification, used in the seminal paper Jacobson et al. (1993), uses the *never displaced* as a control group. In a more recent implementation, those that are not displaced in a particular year, but could be displaced in past and future years, serve as the control group. This chapter shows that the two specifications give very different notions of the recovery of displaced worker earnings. Since the never displaced have higher earnings, on average, the original specification implies larger earnings losses than the more recent specification. Furthermore, not controlling for individual time trends in the recent specification increases the long run earnings losses associated with displacement. This suggests that individual linear time trends soak up some of the earnings effect of displacement.

Aside from this methodological contribution, this chapter also presents results for earnings trajectories by worker characteristics. Some results are simple affirmations of previous work. For example, there tends to be a hump-shaped response of earnings losses by worker education. Those with some college tend to lose less than those who have completed a college degree. These in turn tend to lose less than those without a high school degree. Another result supports previous findings that older workers tend to lose more earnings in the year of the displacement, but experience a faster earnings recovery than younger workers.

Some results are novel. For example, I document that those losing jobs characterized by routine tasks and non-routine (cognitive or manual) tasks suffer very similar earnings losses. This presents cursory evidence that the hollowing out of the wage distribution, which includes mostly routine jobs, is not responsible for the large earn-

²³See, for example, Neal (1995) and Kambourov and Manovskii (2009).

ings losses of displaced workers. The results also suggest that whether workers start out in high paying industries or low paying industries, their earnings losses are large and persistent. This means that rents in high-paying industries cannot explain the earnings losses of displaced workers. Finally, to my knowledge, this study presents the first results for displaced worker earnings losses by wealth. Poor workers tend to lose more than rich workers, at least in the short run, and the poor are dis-proportionally affected by displacements. The larger earnings losses for the poor seem to be a result of poorer workers failing to find sufficient work, leaving them under-employed. The recovery in hourly earnings for the rich and the poor looks very similar.

4.7 Appendix: Stevens (1997) Replication

Here I restrict the sample to the sample used by Stevens (1997); that is I use a balanced sample of household heads from 1968 to 1988. As in Stevens (1997) I also impose that an individual have at least one positive earnings observation. These restrictions leave 1,609 individuals, which is very close to 1,606 in the original study. 550 individuals experience at least one displacement and the sample is largely male (80 percent). This is slightly different from Stevens' sample which is 84 percent male and has 441 people experiencing at least one displacement. Table 4.3 reports the number of displacement and first displacements for my sample and Stevens' sample. The numbers are similar, although there are apparent discrepancies. For example, in 1985 I find around 61 individuals displaced, where Stevens only finds 39 displaced. I tend to code more displacement than Stevens. Stevens (1997) attempts to control for the same displacement being reported more than once. I attempt to do the same, but if that was the only issue, first displacements should be identical. Although the numbers are very close in these two columns, my replication continues to find more first displacements than Stevens. I have not found a way to reconcile these two sets of results.

I estimate the same specification as Stevens and report the results in Figure 4.12. The top plot shows the results of my replication alongside the original results for the specification without individual linear time trends and the bottom plot includes individual linear time trends. I only report the results for annual earnings after the first displacement, although the results for the hourly wage and the last displacement are quite similar. The figure shows that the replication is very good. The specification with individual linear time trends shows an on-impact dip of around 27 percent versus 31 percent in the original study. After 10 years, the replication shows earnings losses of around seven percent versus nine percent in Stevens (1997). This confirms that the analysis is consistent with previous work and grants credibility to the rest of the

work presented in this chapter.

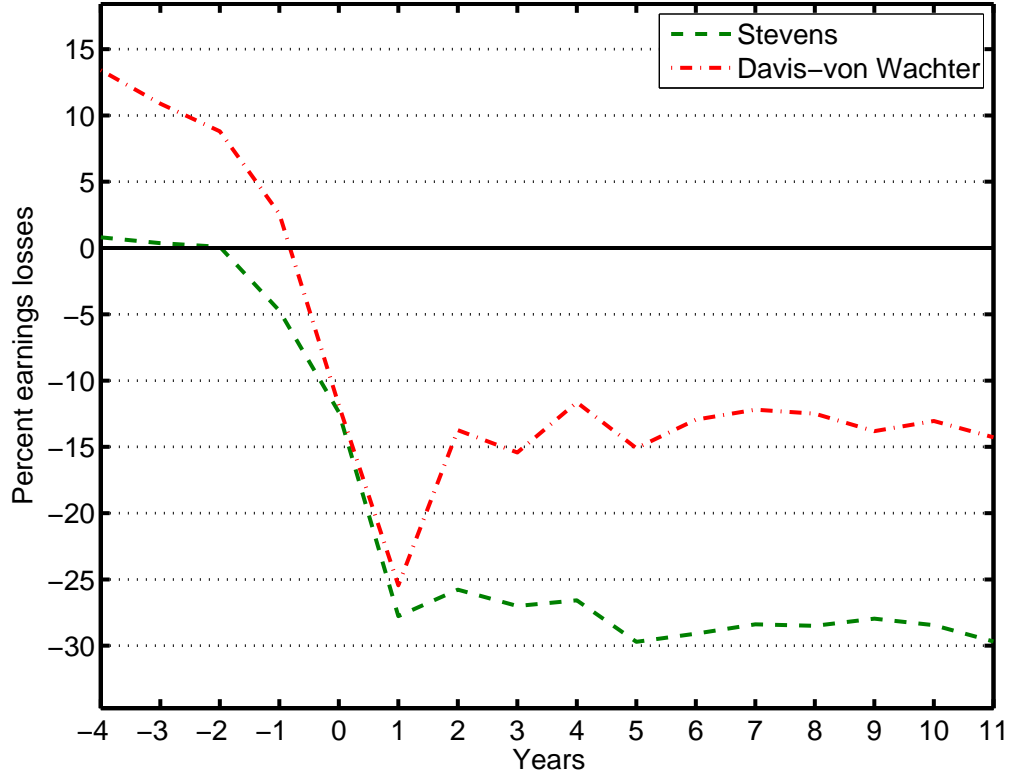


Figure 4.1: Effect of Displacement on Head's Income: Stevens versus Davis-von Wachter specifications using PSID data

Note: Both equations include dummies four years before the displacement shock and 11+ years after the displacement shock. In the annual regressions I include individuals displaced in years y , $y + 1$ and $y + 2$ to increase sample size. These regressions are estimated for 1972 through to 1997. The control group for these annual regressions are those not experiencing separation from their employer (at current job for more than 12 months). The results are similar for a control group of non-displaced workers. I plot the average of the δ_k^y coefficients. The analysis applies individual weights from the PSID, but the results are very similar with unweighted observations using only the Survey Research Center (SRC) sample. In contrast to Davis and von Wachter (2011), I do not impose age, tenure and positive earnings requirements. This is due to sample size limitations in the PSID and the unreliability of tenure information in the PSID.

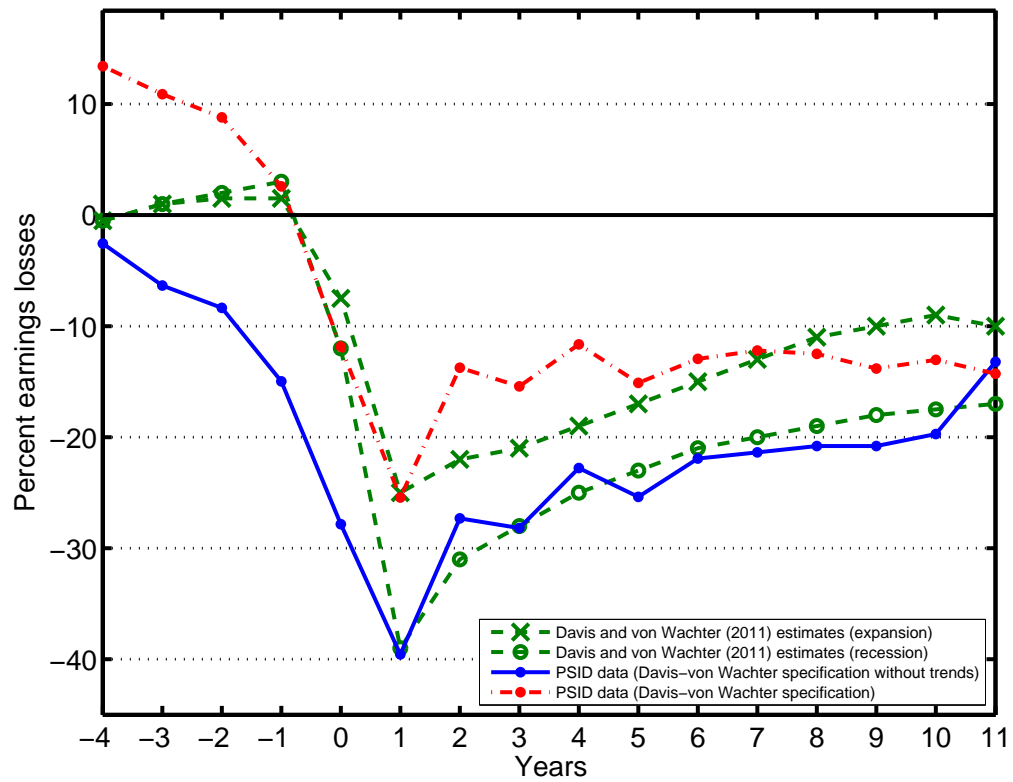


Figure 4.2: Income Around Displacement: Individual Specific Time Trends

Note: Shows the empirical results from Davis and von Wachter (2011) and the baseline results from this chapter. The solid line does not include any individual time trends.

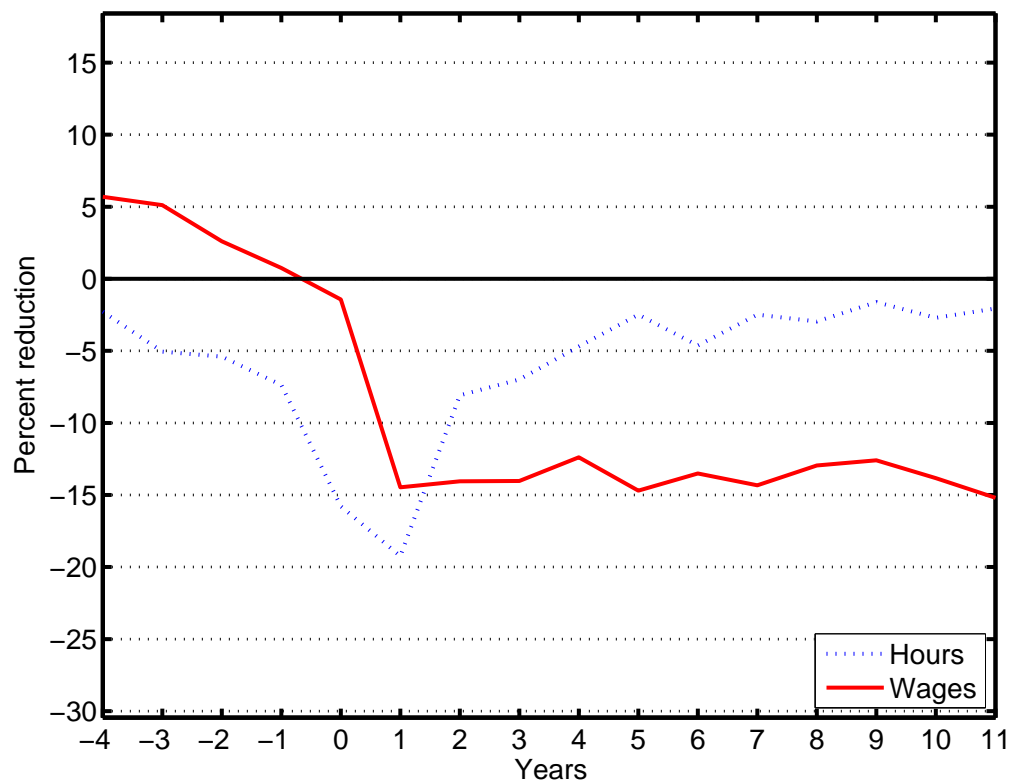


Figure 4.3: Effect of Displacement on Head's Hours and Wages

Note: See Figure 4.1 note. The estimates for wages and hours do not include observations for even years after 1997 because these do not exist in the data. To remove outliers, the wage regression does not include observations that have wages below one dollar an hour and above \$100 an hour. This removes estimates below the first percentile and above the 99 percentile in terms of annual hourly earnings.

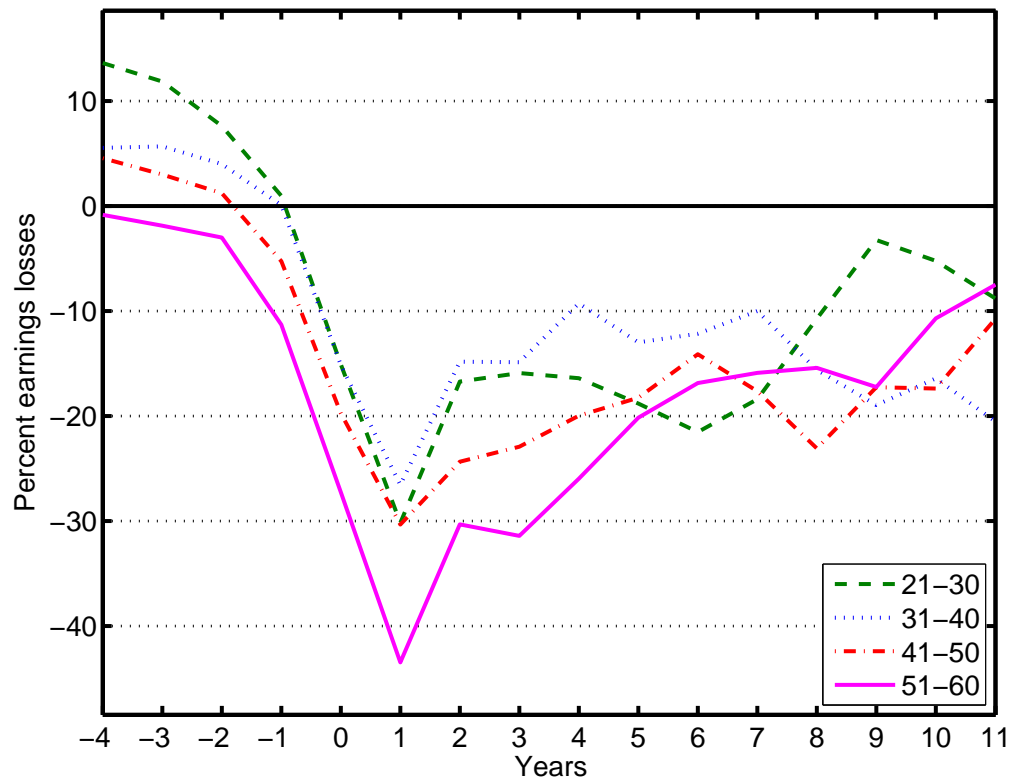


Figure 4.4: Effect of Displacement by Age

Note: This analysis uses the age at the time of displacement. Also, these results include observations only if in that year the individual is at most 65 years old.

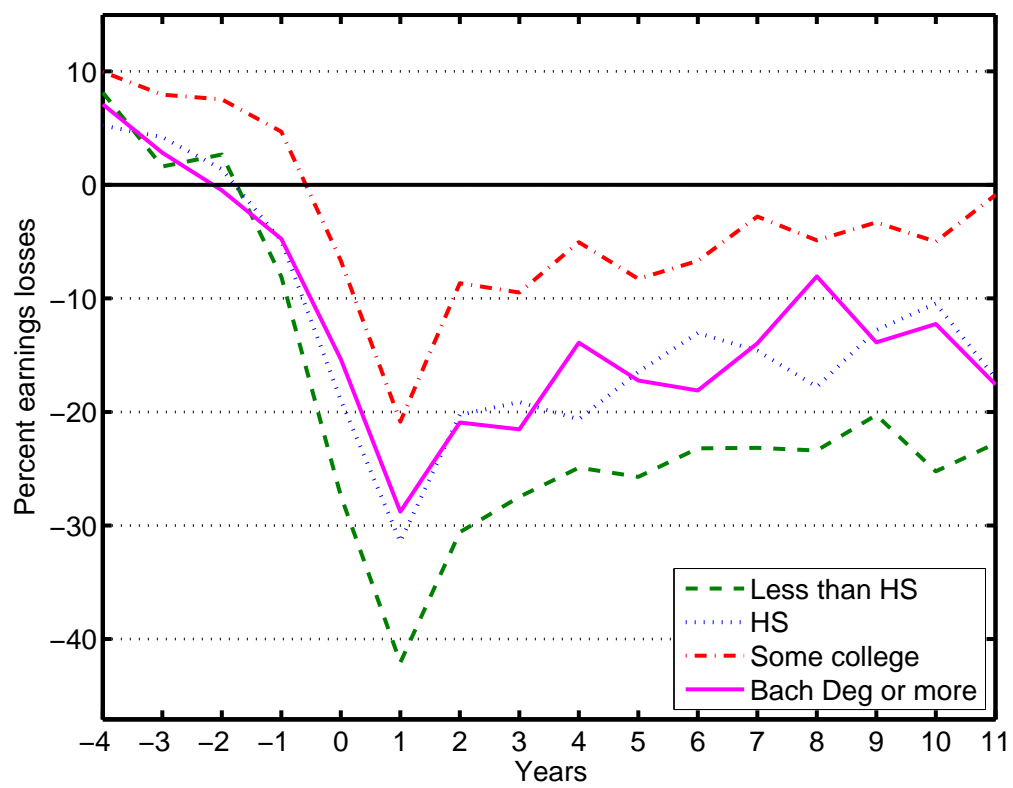


Figure 4.5: Effect of Displacement by Education Level

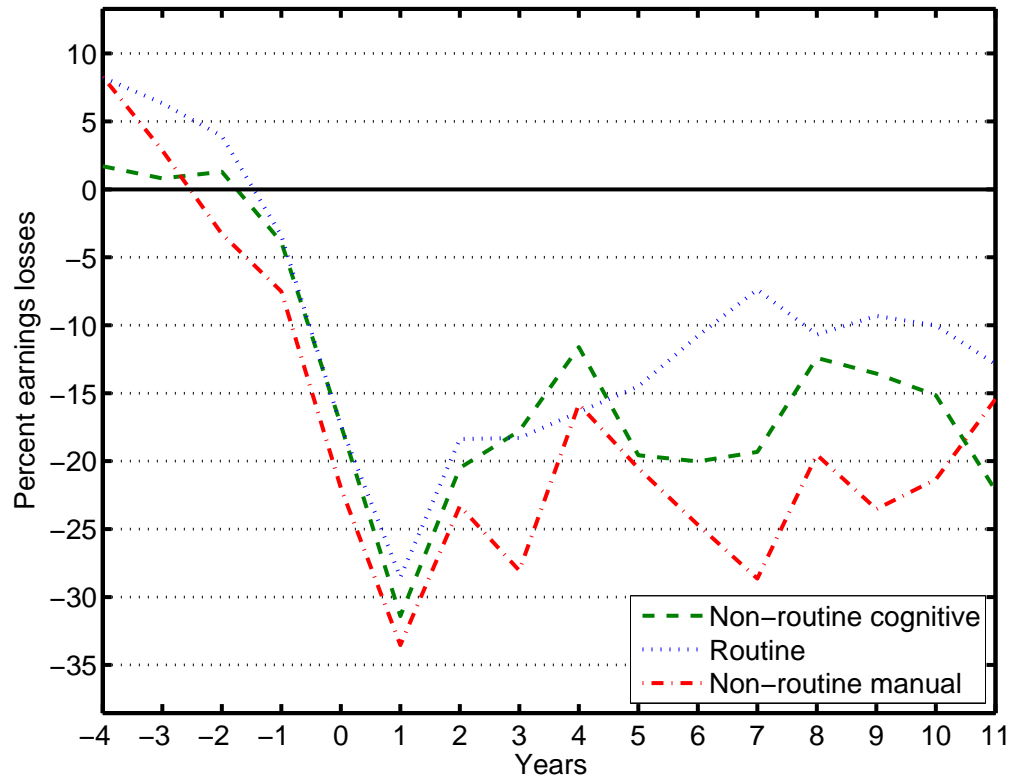


Figure 4.6: Effect of Displacement by Occupations

Note: Individuals grouped by their occupation two years prior to the displacement shock. Non-routine cognitive occupations include professional, technical, management, business and financial occupations. Routine jobs include clerical, administrative support, sales workers, craftsmen, foremen, operatives, installation, maintenance and repair occupations, production and transportation occupations and laborers. Non-routine manual jobs include service workers.

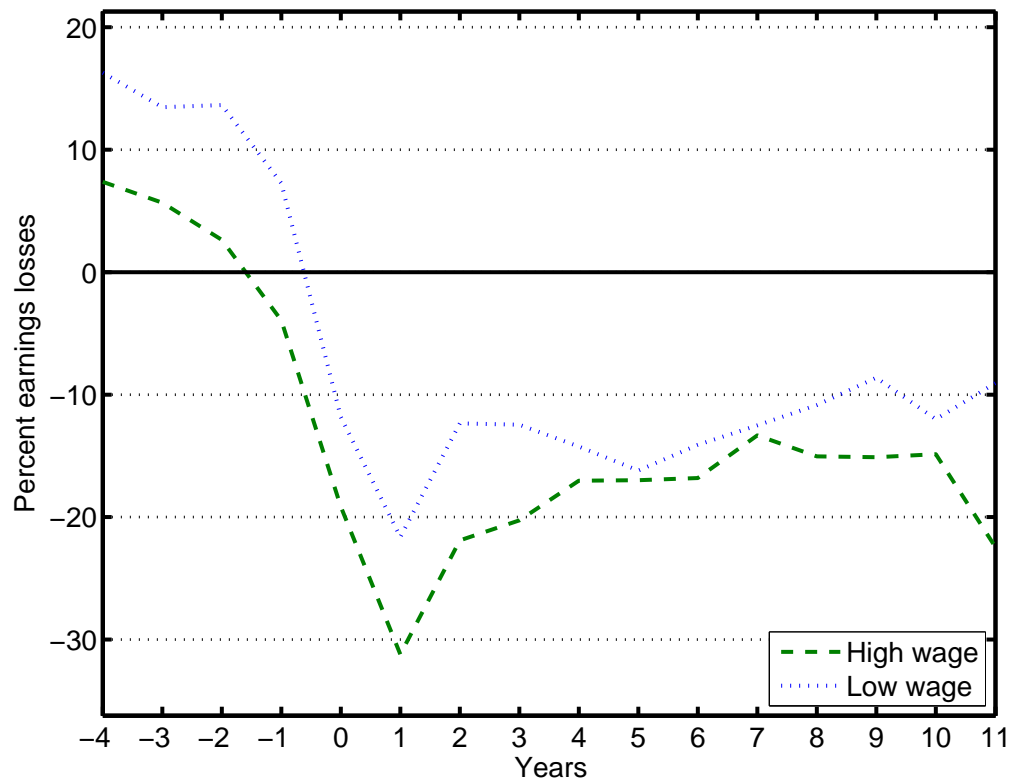


Figure 4.7: Effect of Displacement by Industries

Note: Individuals grouped by their industry two years prior to the displacement shock. I place mining, construction, manufacturing and transportation, communications and other public utilities, along with FIRE in the high wage industries, and wholesale and retail trade, business and repair services, and personal services in the low paying industries.

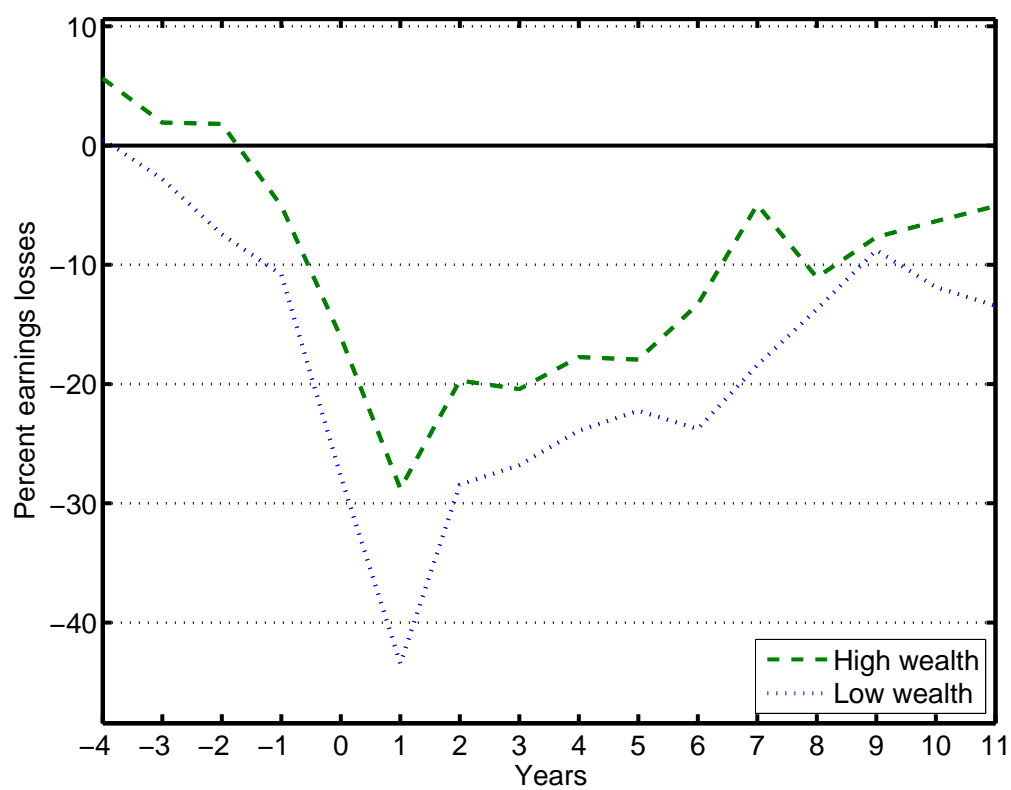


Figure 4.8: Effect of Displacement by Wealth

Note: In order to to estimate the DV regression for all years, as before, I apply the average wealth of an individual to all their observations and use this in the baseline specification. Poor workers are those below the 25th percentile in the wealth distribution in year y and the wealthy are those above the 75th percentile in the wealth distribution.

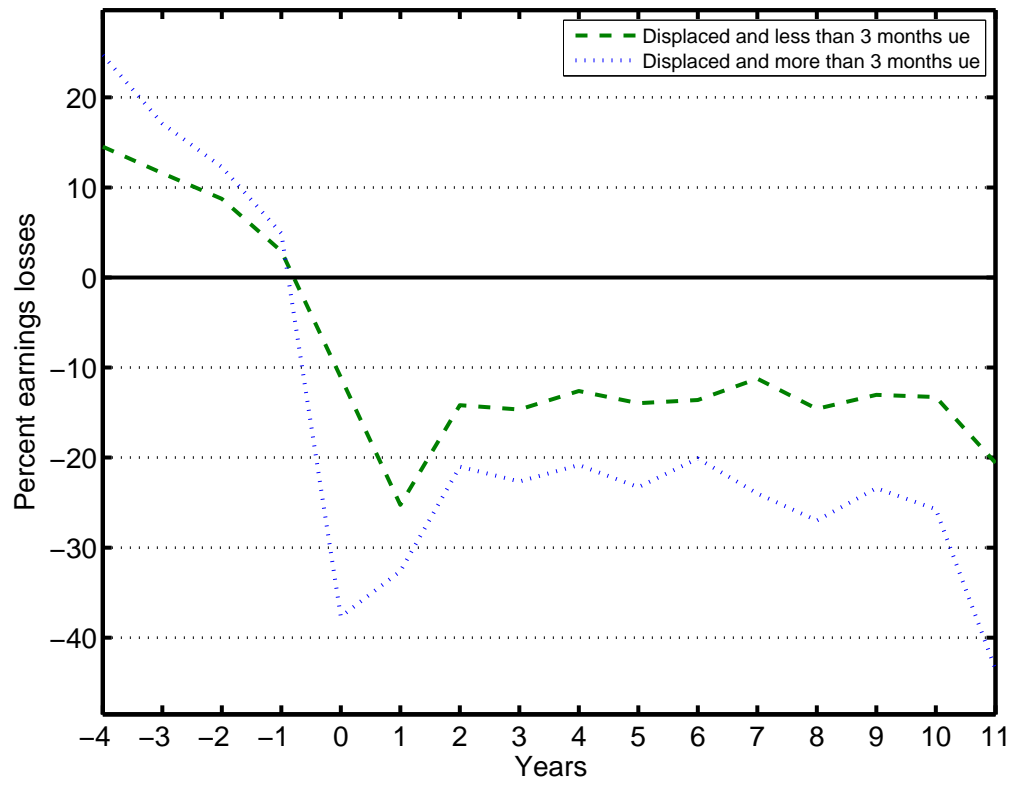


Figure 4.9: Losses by Time Spent Unemployed

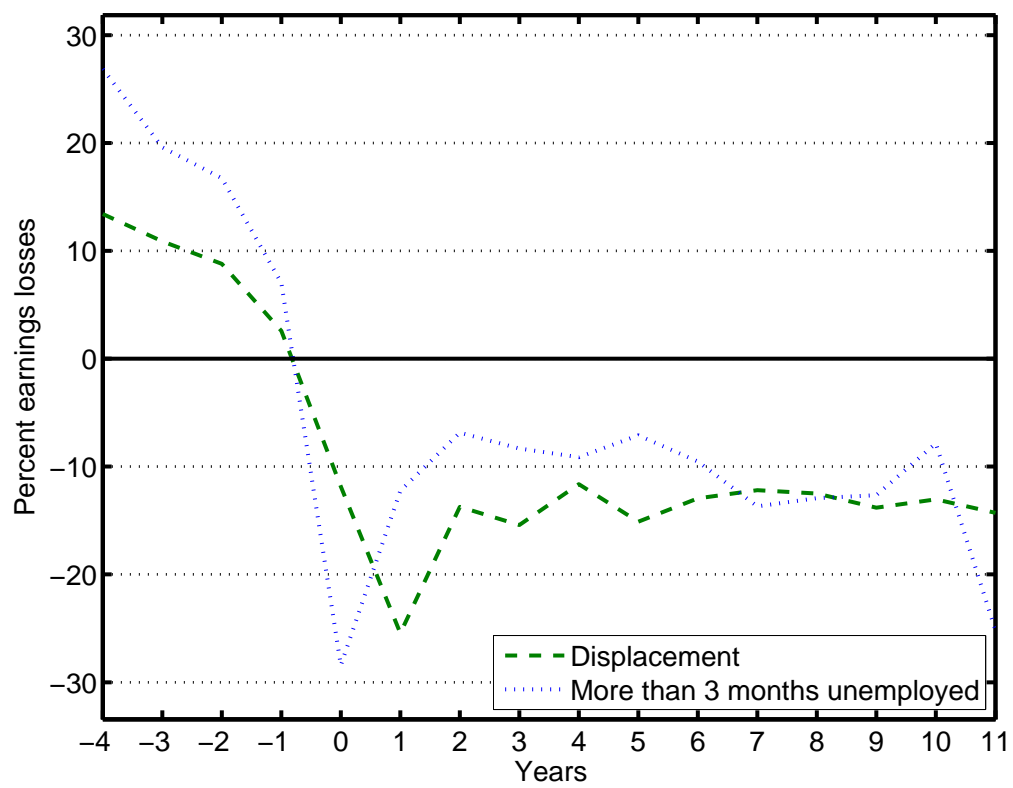


Figure 4.10: Displacement vs. Unemployment

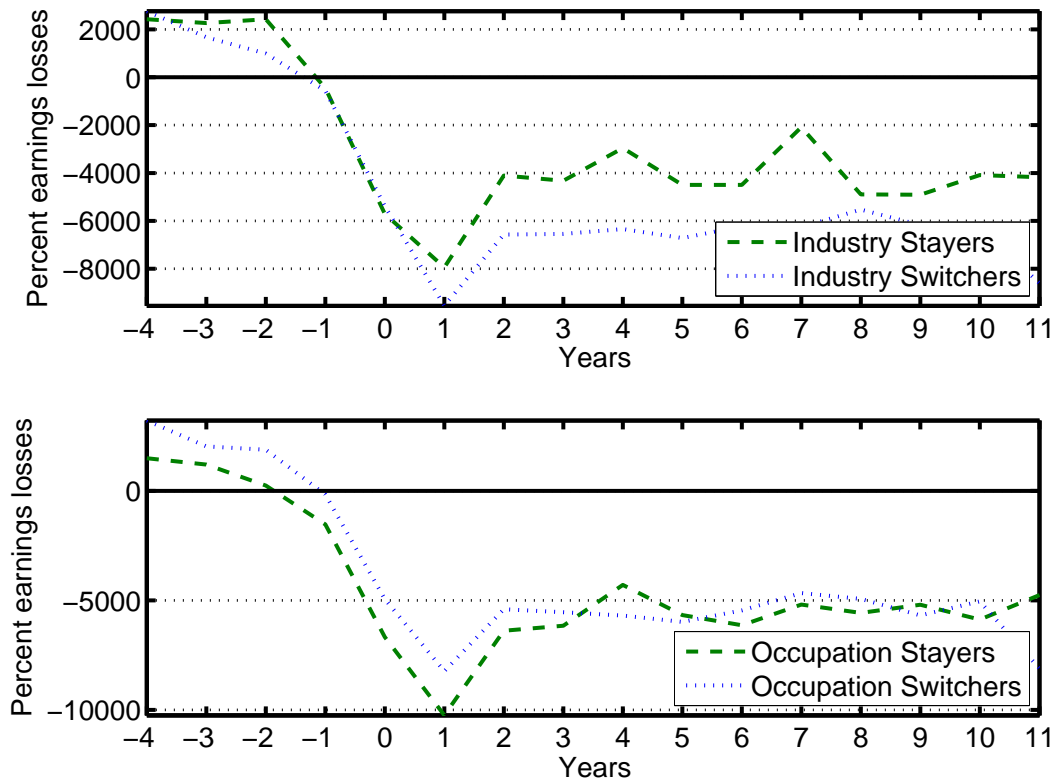


Figure 4.11: Effect of Displacement by Industry and Occupation Stayers/Switchers

Note: Individuals are categorized as switchers and stayers according to their 1-digit industry and occupation codes. The pre-displacement occupation/industry is taken from two years before the displacement shock. The post-displacement occupation/industry is taken five years after year y , except in years when this does not exist because of the biennial nature of the PSID after 1997. Then I take the industry six years after year y . For example, in survey year 1995, the industry five years after displacement does not exist because survey year 2000 does not exist. Therefore I take the industry from the survey in 2001.

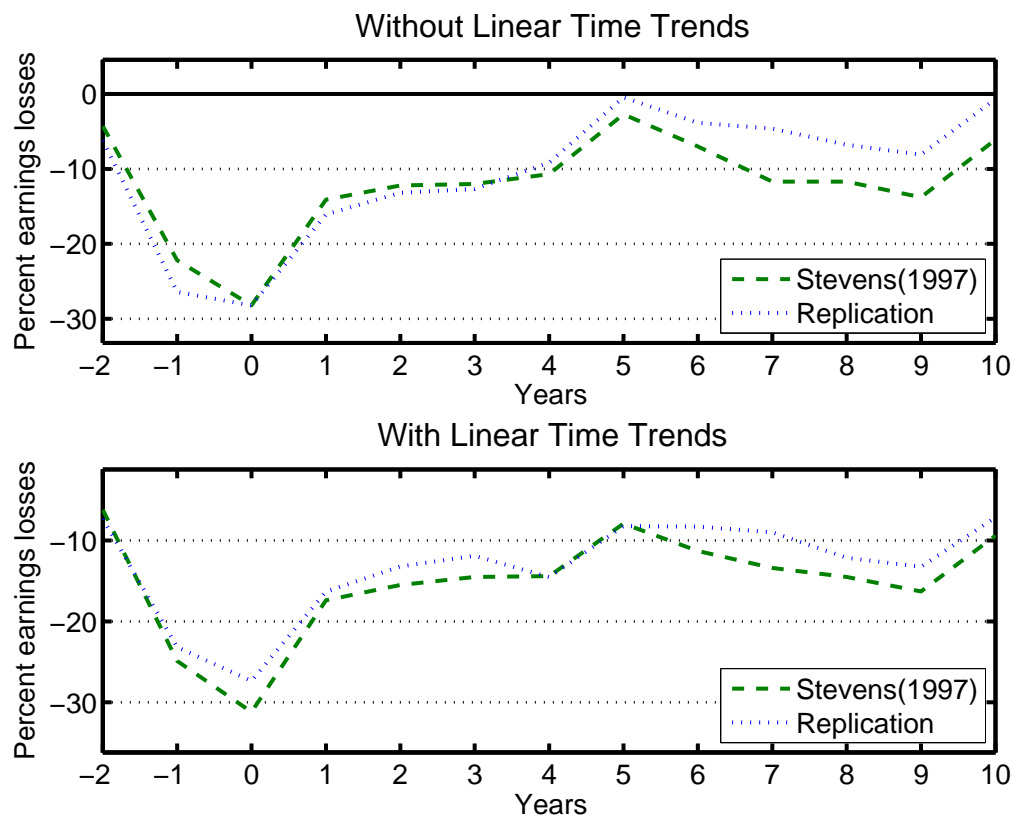


Figure 4.12: Stevens (1997) and Replication Results

Table 4.1: Summary Statistics

	Never Displaced	First Displacement	Any Displacement
Head's age	47.3	32.9	34.5
Head's education	12.2	12.1	12.0
Head's annual earnings (\$)	35288	32403	29188
Head's hourly earnings (\$)	23.2	17.7	16.7
Head's occupation			
Percentage white collar	49.2	37.0	31.3
Percentage blue collar	35.0	47.9	52.6
Head's industry			
Percentage manufacturing	19.9	26.8	26.4
Fraction of household heads	61.2	38.8	38.8

Note: Unweighted tabulations using unbalanced data from the 1968-2009 PSID surveys. Dollar figures are in 2007 dollars using the CPI-U-X1. Averages for the never displaced individuals are calculated using every observation for these individuals. Averages for displaced individuals are calculated using the observation from the year of the shock. Pre-displacement industry, occupation, wages and earnings are taken from two years prior to the shock. The analysis uses the retrospective occupation and industry where available (1968-1980) and the original industry and occupation codes elsewhere (1981-2009). Education is top coded at 16 years and is forced to be constant for every individual.

Table 4.2: Differential Incidence of Displacement

	Prob[category]	Prob[category disp]
Age		
21-30	0.24	0.53
31-40	0.24	0.25
41-50	0.19	0.14
51-60	0.13	0.07
Education		
Less than HS	0.29	0.30
HS	0.32	0.35
Some college	0.19	0.21
Bach deg or more	0.20	0.14
Occupation		
Non-routine cog	0.18	0.13
Routine	0.69	0.75
Non-routine man	0.12	0.12
Industry		
High Wage	0.61	0.65
Low Wage	0.28	0.35
Wealth		
High Wealth	0.25	0.25
Low Wealth	0.25	0.75

Note: Unweighted tabulations using unbalanced data from the 1968-2009 PSID surveys. Dollar figures are in 2007 dollars using the CPI-U-X1. The probability of being in a given category is obtained by using all non-missing observations. This does not have to sum to one because the categories are not necessarily all-inclusive. The displacement refers to the first displacement although the results are similar if the event is any displacement. Pre-displacement industry and occupation are taken from two years prior to the shock. High wealth individuals are above the 75th percentile in the wealth distribution and low wealth individuals are below the 25th percentile in the wealth distribution. This uses the mean wealth applied to all years as described in the text.

Table 4.3: Number of Displacements by Year: Stevens (1997) Replication

Year	First Displacements		Displacements	
	Stevens	Me	Stevens	Me
1969	44	42	44	42
1970	43	48	40	41
1971	58	62	48	49
1972	53	68	35	36
1973	37	46	27	32
1974	37	40	25	25
1975	54	63	36	40
1976	41	66	24	35
1977	43	65	18	23
1978	34	53	16	22
1979	25	32	11	15
1980	35	44	14	18
1981	41	59	23	30
1982	42	60	21	27
1983	41	64	21	30
1984	31	60	13	19
1985	39	61	14	20
1986	36	55	11	14

Note: Replication of the number of displacements by year from the PSID for a balanced panel from 1969 to 1986.

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