

# Three Essays on the US Labor Market: Macroeconomic Trends and Cycles

by

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to my family

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## CHAPTER I

### Introduction

At the time of writing, the labor market in the United States remains mired in a post-recession slump from the Great Recession which ended in 2009. This dissertation contributes to our understanding of the determinants of both long-term trends in unemployment as well as its prolonged response to recessions. The first two chapters study frictions that affect the labor market's adjustment to aggregate shocks. The first is the tax system instituted to fund unemployment insurance benefits. The second friction is the costs associated with adjustment of firm's productive capacity that, through the complementarity between capital and labor, produce sluggish adjustment of the labor market. The third chapter looks at long-term labor market performance by examining the underlying causes behind the rise in low-skilled nonemployment since the 1970's.

Chapter 1 studies the implications of the tax system used to finance unemployment insurance (UI), known as "experience rating." Experience-rated taxes impose higher payroll tax rates on firms that have laid off more workers in the past. Experience rating acts a layoff cost to the firm which reduces the incentive for a firm to shed workers. On the other hand, a layoff cost causes firms to reduce hiring given the prospect of having to pay the cost in the future.

The layoff cost model is confirmed in empirical analysis of confidential firm-level job flows data from the Quarterly Census of Employment and Wages, exploiting state and industry variation in experience rating. States and industries which face more steeply-sloped tax schedules have lower rates of both hiring and firing, as the layoff cost model would predict. A dynamic stochastic general equilibrium model of unemployment with realistic UI financing is then developed to conduct policy

experiments on the tax schedule.

The model predicts quantitatively consistent effects of increases in experience rating as in the data. Further, tax experiments which raise the slope of the tax schedule can both reduce unemployment and raise revenues, offering a potential policy prescription for current UI trust fund shortfalls. The implications of experience rating on the business cycle are then discussed. Higher experience rating is shown to reduce the amplitude of recessions, with firms more reluctant to lay off workers after a shock. The length of recessions is prolonged since firms face sustained higher tax rates when experience rating is more severe.

The second chapter continues the investigation of the effects of adjustment costs on the aggregate labor market. In particular, what role does costly capital adjustment play in the dynamics of the aggregate labor market? If firms intend to hire workers, they must have the capacity to employ them. If adjusting the productive capacity of a firm is costly and time-consuming, it will delay adjustment in the labor market.

Time series analysis of US macroeconomic data shows that labor market tightness—the number of vacancies per unemployed worker—responds sluggishly, peaking four quarters after an aggregate productivity shock. In the canonical model without capital frictions, labor market tightness peaks instantaneously. With reasonably calibrated capital adjustment costs—either to changing the level of capital or level of investment—the model can match the empirical stylized facts of sluggish adjustment. Labor market tightness in the capital adjustment model responds with a four quarter lag. Thus, capital frictions are shown to be crucial in understanding the prolonged response of labor markets during recessions.

Chapter 3, co-authored with Michael W.L. Elsby and Matthew D. Shapiro, focuses on the secular increase in low-skilled, male joblessness over the past thirty years. Motivated by the decline in labor market attachment, the chapter focus on incentives to supply labor over the course of a working life. A family labor supply model is developed to understand the incentives for increased nonemployment. The model yields a simple prediction: as the “replacement rate” of family income in nonemployment increases, the optimal labor supplied by the husband will decrease.

The virtue of this simple theoretical prediction is it is possible to estimate the empirical analogue of the replacement rate from Panel Study of Income Dynamics (PSID) data. The replacement rate is identified off of the the average decline in family income associated with male nonemployment. Detailed income data from the PSID uncovers that families buffer income loss from male nonemployment through significant government transfers as well as spousal income.

A simple explanation for the substantial secular rise in male joblessness would be that replacement rates have risen, causing individuals increasingly to choose not to work. In direct contrast, estimated family income replacement rates have, if anything, fallen over the past thirty years. Thus, viewed through the lens of a standard labor supply model, an important puzzle emerges: simple economic theory suggests that a key determinant of long-run employment rates is the replacement rate of family income. In contrast, the data do not support a strong relationship between the two.

## CHAPTER II

# Unemployment Insurance Experience Rating and Labor Market Dynamics

*“I might consider adding a new salesperson because my company appears to be getting busier. But if in two months I realize that business is not in fact coming back as quickly as I had thought, and I need to lay off this person, I will likely end up paying out \$5,000, \$10,000, or even \$20,000 in unemployment taxes for the person I hired and then laid off...the disincentives far outweigh the incentives.”*

—Jay Goltz, NY Times “You’re the Boss”.

### 2.1 Introduction

The United States is the only OECD country to finance unemployment insurance (UI) through a tax system which penalizes layoffs. The original intent of this institution, known as “experience rating,” was to apportion the costs of UI to the highest turnover firms and thereby stabilize employment.<sup>1</sup>

Experience rating can stabilize employment through a layoff cost. The layoff cost is levied when a firm lays off a worker and is assessed a higher tax rate in the future. The cost of layoffs, therefore,

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<sup>1</sup>The origin of the idea for experience rating is attributed to John R. Commons who helped draft the 1932 Wisconsin bill that introduced “merit-rating.”

reduces the incentive for a firm to shed workers. On the other hand, an increased firing burden causes firms to reduce hiring given the prospect of having to lay off workers in the future. In this chapter, I study experience rating both theoretically and empirically, analyzing its effects on the dynamics of the labor market.

Due to the sharp increase in unemployment during the Great Recession, state UI trust funds are deeply in debt. Between 2007 and 2011, state trust fund reserves fell by \$62 billion; as of 2011, states owe \$40 billion in loans to the federal government.<sup>2</sup> State governments are therefore grappling with new UI financing policies to cover these trust funds and ensure solvency into the future. I use a general equilibrium model of experience-rated taxes to study the labor market effects of tax changes that are similar to those currently under consideration.

This chapter is the first to empirically quantify the relationship between job flows and UI financing. Macroeconomists have long recognized that job flows are large compared to net employment growth. In fact, declining rates of job destruction can account for a substantial fraction of decreasing unemployment between the 1980's and the mid-2000's.<sup>3</sup> This chapter sheds light on the types of labor market policies that drive gross job flows and the policy changes that might affect employment volatility. This chapter also advances the literature on the effect of microeconomic employment adjustment costs on hiring and firing.<sup>4</sup> This chapter studies a quantifiable adjustment cost and provides novel evidence on its effect on job flows using firm-level data.

After reviewing the relevant features of UI experience rating, I present a dynamic labor demand problem for a firm facing increasing payroll taxes as a function of its endogenously-determined, individual layoff history. One important contribution of this chapter is that I model realistic UI tax schedules. In practice, states set minimum and maximum tax rates and therefore not all firms face increasing tax rates from a layoff. This induces economically important non-linearities in firm labor demand depending on its past layoff history.

Much of the previous literature has instead modeled experience rating as an exogenous linear

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<sup>2</sup>See Vroman (2011) for a summary of UI finances since the Great Recession.

<sup>3</sup>See Davis et al. (2010).

<sup>4</sup>A comprehensive literature review is beyond the scope of this chapter. See, for example, Hamermesh and Pfann (1996a).

layoff cost, for instance in Anderson and Meyer (1993). Consistent with the linear layoff cost model, I show that experience rating induces a “band of inaction” in which the firm does not hire or fire over a range of labor productivity. In contrast to the linear layoff cost model, experience rating imposes a cost that is a function of the stock rather than the flow of layoffs. I show that this implies a band of inaction that is a function of each firm’s entire history of layoffs. Hence, I find that firm heterogeneity in layoff experience is crucial to understanding the general equilibrium effects of experience rating.

The model predicts how experience rating affects job flows. The higher is the fraction of benefits paid back in higher taxes, the lower are the rates of both job creation and job destruction. Having established that experience rating reduces both job creation and job destruction in a dynamic model of firm labor demand, I test this prediction empirically. I collect a dataset of UI tax schedules and financing rules across states between 2001 and 2010. With these data, I calculate the “marginal tax cost” of experience rating following, for example, Topel (1983) and Card and Levine (1994). The marginal tax cost gives the fraction of benefits charged to a firm that are paid back in future higher taxes. I combine these data with confidential firm-level data on gross job flows from the Quarterly Census of Employment and Wages (QCEW). The results show that increasing experience rating by 5% would reduce job destruction by about 2% and job creation by 1.5%.

In the next section, I embed the firm’s dynamic problem in a search model of unemployment to study the effect of experience rating on the aggregate labor market. While previous work such as l’Haridon and Malherbet (2009) and Albertini (2011) has examined experience rating in a search model, the model presented is the first to study UI taxes that are endogenously-determined in a heterogeneous agent, dynamic stochastic general equilibrium (DSGE) framework. I build on the model developed by Elsby and Michaels (2011) who introduce firm heterogeneity with endogenous job destruction and aggregate uncertainty in a search and matching model of unemployment. I use the idiosyncratic layoff histories across firms to match the empirical cross-sectional distribution of firms across UI tax rates.

I then present results from tax experiments in the long run and the short run. Because I capture



more realistic features of UI tax schedules as well as heterogeneity across firms in UI tax rates, I can analyze the effect of a rich set of tax experiments which previous models could not consider. First, I study various changes to the tax schedule that all imply an equal increase in experience rating but have different effects on the labor market. All experiments that raise experience rating reduce job creation and destruction. A 5% increase in experience rating reduces job flows between 1.1% and 1.9%. These results are quantitatively consistent with the empirical estimates, which imply a drop between 1% and 2% in job flows. The unemployment rate across tax experiments is reduced by .1 to .3 percentage points (a drop of 1.8% to 4.5%). The differential effects on unemployment depend on whether the tax burden and firm profits increase or decrease.

Finally, I solve the model with aggregate uncertainty using the approximate equilibrium method of Krusell and Smith (1998). Model impulse responses from an aggregate shock show that experience rating reduces the amplitude of the labor market response to aggregate productivity shocks. For instance, a 10% difference in experience rating reduces the unemployment rate impulse response by .045 percentage points, amounting to a 6.8% smaller labor market slump. I also find that experience rating introduces strong non-linearities and asymmetries in the business cycle response to aggregate shocks. Unemployment rises more than proportionately with the aggregate shock due to the incidence of higher UI tax rates. There is also a slower recovery of unemployment as the larger stock of accumulated layoffs leads to persistently higher tax rates.

The plan of the chapter is as follows. Section 2.2 reviews important institutional details of UI financing. Section 2.3 develops a theoretical prediction for job flows and Section 2.4 estimates this relationship empirically. Section 2.5 presents a DSGE model of the labor market with realistic UI financing and Section 2.6 conducts policy experiments. Section 2.7 discusses some related literature and Section 2.8 concludes.

## **2.2 Experience Rating of Unemployment Insurance Taxes**

Before reviewing the related literature, it is necessary to understand the basic structure of UI finance. The United States finances its unemployment insurance system through a payroll tax that

increases with a firm's past layoffs. In 1938, Wisconsin introduced the first experience rating system in which each firm was independently assessed a tax rate to cover benefits drawn by its laid off workers. By 1948, all states had adopted some system of experience rating for UI financing.

Each firm pays a payroll tax on its current wage bill. For each employee, the firm pays a tax on a capped base of salary, determined by each state. In 2010, this taxable base varied from \$7,000 to \$36,800. Federal law mandates that employers with at least three years of experience with layoffs must be experience-rated but allows states to charge new employers a reduced rate not less than 1%.<sup>5</sup>

The system of experience rating, however, is imperfect since tax rates are capped at statutory minimum and maximum levels. Firms with no layoff risk are mandated to contribute to the pool of funds whereas firms with the highest layoff risk pay a lower rate than they would under a perfectly rated system. Across all states in 2010, the minimum rate varied from 0% to 2.2% and the maximum rate was no lower than 5.4% and reached 13.6%.<sup>6</sup> Thus, the finance system induces a cross-subsidy from low to high layoff firms and industries.

States generally use one of two types of experience rating. In 2010, 17 states used a "benefit ratio" method and 33 states used the "reserve ratio."<sup>7</sup> Figures 2.1 and 2.2 show examples of typical tax schedules for a reserve ratio and a benefit ratio state. In Nevada, the minimum rate charged is .25% up to a maximum rate of 5.4% with the tax rate increasing in the firm's experience factor (on the x-axis), determined by its reserve ratio. In Alabama, firms with the lowest benefit ratio (on the x-axis) are charged the minimum rate of .74% while the highest benefit ratio firms are charged the maximum rate of 7.14%.

In the benefit ratio system, each employer pays a payroll tax based on the ratio of benefits drawn by that firm's layoffs to the size of its covered payroll over a three to five year window. The tax rate takes on a minimum value for firms with low benefit ratios and a maximum value for firms with

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<sup>5</sup>In practice, most states offer a "standard" flat rate to new employers between 1% and 6.2% for one to three years before implementing experience rating. The reduced rates in some states led to a practice known as SUTA dumping by which firms would change account numbers before eligibility for the higher experience-rated rate. Legislation in 2004 attempted to curb this practice.

<sup>6</sup>The minimum value of the maximum tax rate is set by a federal tax credit of 5.4% in 2010.

<sup>7</sup>Michigan and Pennsylvania use a combination but predominantly use the benefit ratio. Oklahoma and Delaware use a benefit wage ratio system. These four states are therefore excluded from the empirical analysis.

high ratios. In a reserve ratio system, states maintain an account for each firm that is debited due to benefits associated with its layoffs and is credited with tax payments. The net reserve as a ratio of the firm's payroll over a three to five year period determines the payroll tax rate, again between some minimum and maximum rates. Therefore, an additional layoff reduces the firm's reserve ratio and increases the tax rate assuming it is not at the minimum or maximum rate.

Given the complexity of UI taxes, many previous studies, such as Topel (1983), calculated the "marginal tax cost" to quantify the degree of experience rating. The marginal tax cost is defined as the present discounted value of benefits paid back in future taxes by a firm. Consider a firm on the sloped portion of the tax schedule. If that firm lays off an additional worker, he draws benefits that are charged to the firm, causing the tax rate to rise according to the given tax schedule. The marginal tax cost determines the fraction of those additional benefits the firm pays back in taxes. Further details of the specific financing systems and marginal tax cost formulas are given in Section 2.4.

### 2.3 A Theoretical Prediction for Job Flows

In this section, I establish a theoretical prediction for the effect of experience rating on job creation and job destruction to be tested empirically. I present a stripped down version of the full model presented later in order to characterize qualitatively the effect of experience rating on labor demand and job flows.

A firm maintains a stock of workers,  $n_{-1}$ , and a stock of layoffs,  $\ell_{-1}$ . Of the laid off, a fraction  $\delta$  are no longer counted on the firm's books for taxation purposes. This occurs if the laid off find other jobs or there is a statutory time limit for benefit liability. The firm observes idiosyncratic productivity  $x$  and decides to hire or fire. If it fires, it sends those workers into the pool,  $\ell$ . Firms take the wage,  $w$ , as given and pay all workers the same rate.<sup>8</sup> Note that I have assumed that firms cannot recall workers from their stock of layoffs. Section 2.9.2 relaxes this assumption and shows that allowing the firm to rehire from its stock of layoffs is similar to reducing the marginal cost per

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<sup>8</sup>In the model developed in Section 2.5, I endogenize the wage.

layoff. The stock of layoffs evolves according to the following equation of motion

$$\ell = (1 - \delta)\ell_{-1} + \mathbb{1}^{-}\Delta n,$$

where  $\mathbb{1}^{-}\Delta n$  is the number of layoffs if the firm is firing ( $\mathbb{1}$  is used throughout as the indicator function). Tax rates are set as follows. The firm pays a payroll tax on its current employment,  $n$ , where the tax *rate*  $\tau(\ell)$  is

$$\tau(\ell) = \begin{cases} \underline{\tau} & \text{if } \ell < \underline{\ell} \\ \tau_c \cdot \ell & \text{if } \ell \in [\underline{\ell}, \bar{\ell}] \\ \bar{\tau} & \text{if } \ell > \bar{\ell}. \end{cases}$$

Figure 2.3 graphs the tax schedule as a function of layoffs. The tax schedule the firm faces thus matches the salient features of realistic state UI schedules: the tax rate is linearly increasing between a statutory minimum and maximum rate.

The firm's labor demand problem is to choose  $n$  to maximize profits as given by the following dynamic programming problem, subject to the equation of motion for  $\ell$ :

$$\Pi(n_{-1}, \ell_{-1}, x) = \max_n \left\{ xF(n) - wn - \tau(\ell)wn + \beta \int \Pi(n, \ell, x') dG(x'|x) \right\} \quad (2.1)$$

### 2.3.1 Firm policy functions

I first describe the qualitative nature of the firm's labor demand functions. Suppose  $\ell$  is low enough such that the firm is on the flat portion of the tax schedule at the minimum rate. It could lay off workers and end up at the maximum rate (eqn. 2.2), the sloped portion (2.3), or remain at the minimum rate (2.4). Alternatively, it could hire and remain on the flat portion (2.5). The first

order conditions for those possibilities are as follows

$$xF'(n) - w - w\bar{\tau} + \beta \frac{\partial}{\partial n} \int \Pi(n, \ell > \bar{\ell}, x') dG = 0 \quad (2.2)$$

$$xF'(n) - w - w\tau(\ell) + \beta \frac{\partial}{\partial n} \int \Pi(n, \ell \in [\underline{\ell}, \bar{\ell}], x') dG = wn\tau'(\ell) \quad (2.3)$$

$$xF'(n) - w - w\underline{\tau} + \beta \frac{\partial}{\partial n} \int \Pi(n, \ell < \underline{\ell}, x') dG = 0 \quad (2.4)$$

$$xF'(n) - w - w\underline{\tau} + \beta \frac{\partial}{\partial n} \int \Pi(n, \ell_{-1}(1 - \delta) < \underline{\ell}, x') dG = 0. \quad (2.5)$$

The first three terms of equation (2.2)-(2.5) are simply the marginal product of labor minus the after-tax wage. The following term is the discounted future marginal value of labor which depends on the choice of  $n$  and  $\ell$  and the expectation over future productivity. The term on the right hand side of (2.3) represents the layoff cost imposed by experience rating on the sloped portion of the tax schedule. Before examining that more closely, I turn to equations (2.4) and (2.5).

It is important to note that the flow costs in the first order conditions in equations (2.4) and (2.5) are identical. They differ only because the continuation value depends on the future stock of layoffs. The stock of layoffs is higher if the firm lays off a worker rather than hiring a worker (or remains at  $n_{-1}$ ). Since higher layoffs lead to weakly higher payroll taxes, the forward value is weakly declining in the stock of layoffs (for a given  $n$  and  $x$ ). Therefore, even away from the sloped portion of the schedule, the firm's decision is affected by the potential of increasing taxes. This highlights the importance of modeling experience-rated taxes in which the tax rate depends on the history of each firm's layoff decisions, in contrast to the previous literature which has generally modeled experience rating as a linear layoff cost.

Examining equation (2.3) further highlights the importance of realistically modeling experience rating. Recall that this is the first order condition for a firm that begins the period at the minimum rate (i.e.,  $\ell_{-1} < \underline{\ell}$ ) but lays off enough workers so that its choice of  $\ell$  is on the sloped portion. Again, the first three terms on the left hand side are the marginal product of labor minus the after-tax wage. Here, the after-tax wage is increasing in the marginal layoff. On the right hand side, the layoff cost is represented by  $wn\tau'(\ell)$ , which is the additional payroll tax paid on the *entire* wage

bill. Therefore, the layoff cost under experience rating is importantly *not only* on the flow of layoffs but rather a higher tax paid on *all* inframarginal workers, with the rate based on the entire stock of layoffs.

In contrast to this model, suppose instead the firm had to pay a constant linear cost of  $\tau_f > 0$  for each worker it laid off. In that case the first order condition for the firm, irrespective of its previous layoffs would be

$$xF'(n) - w + \beta \frac{\partial}{\partial n} \int \Pi(n, x') dG = -\tau_f. \quad (2.6)$$

This is the standard linear adjustment cost model. In this case, the policy function would exhibit a band of inaction at  $n_{-1}$  since the first layoff is always costly. In this simpler model, however, the firm's labor demand decision is not affected by its previous history of layoffs. The firm also does not take into account the higher tax rate it must pay on its *entire* current stock of employed workers.

Turning to the policy functions in this model, it is useful to break the firm's decision into three cases (see Figure 2.3): Case 1 is for firms that begin the period at the minimum tax rate; Case 2 is when the firm begins on the sloped portion and Case 3 is when the firm is at the maximum tax rate. The policy function for Case 1 is depicted in Figure 2.4, with the log of employment on the y-axis and the log of productivity on the x-axis.<sup>9</sup> The horizontal line gives the firm's stock of employment at the beginning of the period ( $\ln(n_{-1})$ ). Because the firm is on the flat portion of the schedule, the firm locally hires and fires costlessly; the policy function is, therefore, linear through  $\ln(n_{-1})$ .<sup>10</sup>

The firm's marginal lay off is costless at  $\ln(n_{-1})$ . For a low enough  $\ln(x)$ , however, the firm must decide between shedding workers and incurring a tax increase or maintaining a higher workforce than otherwise would be optimal. For a range of  $\ln(x)$ , the profit maximizing choice is to halt layoffs to avoid the adjustment cost. Because the firm defers layoffs for a slightly lower productivity, the policy function is flat for a range of  $x$  draws as shown in the flat "band of inaction" on the labor demand schedule in Figure 2.4. At a certain point, the draw of  $x$  is low enough so that a lower employment level generates higher profits despite the higher tax rate. When an additional layoff

<sup>9</sup>I choose the log of the firm's states since, in the frictionless model, the labor demand schedule is linear in the logs.

<sup>10</sup>With the addition of search costs, the firm would also have a band of inaction at  $n_{-1}$ .

does warrant the adjustment cost, the firm chooses a tax rate on the sloped portion of tax schedule. Since the first layoff generates a discontinuous cost due to the higher tax rate on current payroll, the firm sheds a fraction of its employment. This is evident in the steep negative slope of the policy function at that point.

The bottom panel of this figure plots the associated tax rate that the firm optimally chooses. As described above, the firm chooses to remain at the minimum rate until a bad enough shock induces a bout of layoffs. In that case, the tax rate (at just below  $\ln(x) = 0$ ) jumps up on to the sloped portion. As the firm lays off more workers, the tax rate continues to rise.

Figure 2.5 shows the policy function for Case 2 in which the firm begins the period on the sloped portion of the schedule. In Case 2, since the firm is on the sloped portion, the band of inaction rests at  $\ln(n_{-1})$  as the marginal layoff is costly. As  $\ell_{-1}$  increases, the policy function shifts to the right since the firm pays a higher tax rate per employee and thus holds a lower stock of employment for a given  $\ln(x)$ . The dashed, blue line depicts a policy function for a firm that starts with a relatively higher stock of layoffs. For a low enough shock (around  $-1$ ), this firm sheds enough workers to reach the maximum tax rate. The dashed, blue line shifts down as the firm reaches the maximum tax rate. Finally, the demand schedule in Case 3 (not shown) would mimic the frictionless demand schedule since the cost of an additional layoff is zero. The schedule would then be linear in the log of employment. Due to the positive payroll tax, however, the level of employment is lower than it would be without the tax.

### 2.3.2 Job Flows and Experience Rating

What does the model predict for job flows? For firms that face the upward sloping tax schedule, the marginal layoff is costly so firms defer layoffs and maintain a higher than optimal workforce. The firm would prefer to decrease its stock of employment due to lower productivity per worker, but for each layoff it pays a higher tax rate on its entire remaining workforce. As is also true in standard layoff cost model, the firing cost also acts as a hiring cost. For any worker that is hired today, the firm will pay a layoff cost for that worker with a positive probability. Millard and Mortensen (1996) show

that in a standard Mortensen-Pissarides model, linear layoff costs unambiguously reduce both job creation and job destruction. This section shows that in a model where layoff costs are determined by the entire stock of layoffs and the costs is paid on each inframarginal worker, the same is true.

I use the model of the previous section to preview the prediction for job flows by varying the degree of experience rating. Starting from the calibrated parameters of the full model of Section 2.5 but abstracting from search costs ( $c = 0$ ), I vary the degree of experience rating and measure job flows.<sup>11</sup> In practice, I do this by varying the upper threshold of the tax schedule to increase or decrease its slope. As fully described later, I calculate a marginal tax cost for this model in a similar fashion as the empirical literature—the present discounted value of benefits paid back in future taxes.<sup>12</sup>

Job flows are calculated from simulated data as they are in the empirical analysis following Davis and Haltiwanger (1992). They define job creation (destruction) as the gross increase (decrease) in employment at expanding (contracting) firms. The job creation (destruction) rate is gross job creation (destruction) divided by the average of the current and previous employment over all firms. Formally, let  $N_t$  be employment at time  $t$  and  $X_t = .5\sum(N_t + N_{t-1})$  be the average of employment in time  $t$  and  $t - 1$ . Then the rates of job creation and job destruction are given by

$$JC = \frac{\sum_{\Delta n > 0} \Delta N_t}{X_t}, JD = \frac{\sum_{\Delta n < 0} |\Delta N_t|}{X_t}. \quad (2.7)$$

Job reallocation, a measure of the total amount of job flows in the labor market, is given by  $JR = JC + JD$ . Net employment growth is  $Net = JC - JD$ . Recall that in any steady state without trend growth,  $\Delta N \equiv 0$  implies  $JC \equiv JD$ . Therefore, the sign of the change of  $JR$  with respect to a change in the marginal tax cost gives the sign of the change in both  $JC$  and  $JD$ .

Figure 2.6 shows the simulated job flows plotted for a range of marginal tax costs between 15% and 78%. Job reallocation falls monotonically with marginal tax cost, going from over 16% with a marginal tax cost of 15% to under 6% with a MTC of 78%. As shown below, the slope of this line

<sup>11</sup>The previous section assumed fixed wages for ease of exposition. In this simulation, I assume the bargained wage as derived in Section 2.5.2. The results of the simulation are robust to the wage assumption.

<sup>12</sup>The equation giving the model's marginal tax cost is described fully below in Section 2.5.5.



implies a 23% decrease in job flows if states implemented 100% experience rating from a mean of 54%. Do firms behave as the model predicts in practice? To answer this question, I now turn to an empirical evaluation of experience rating and job flows.

## 2.4 Empirical Evaluation of Experience Rating

In this section, I exploit state and industry variation in experience rating to evaluate its effect on the US job flows. Unfortunately, firm-level data on UI tax contributions are not available across states and industries. While these data would be preferable, I study differences in jobs flows across detailed industries that face varying UI tax schedules at the state level. I first compile a dataset of state UI tax provisions from the Department of Labor. For each state and year, I collect data on the minimum rate, maximum rate, and the slope of the tax schedule.<sup>13</sup> I combine these tax schedules with firm-level data from the Quarterly Census of Employment and Wages to estimate the relationship between experience rating and job flows. I turn first to describing the data used to analyze the effect of experience rating on job flows. I then describe how I quantify the level of experience rating across states and industries for the econometric analysis that follows.

### 2.4.1 QCEW Data

The data used to measure labor market outcomes are from the Quarterly Census of Employment and Wages (QCEW). The QCEW is a census of establishments with employment covered by UI, making it an ideal source of data for the questions at hand. The entire database covers 99.7% of wage and salary employment. Establishments in the QCEW are linked across quarters to create the Longitudinal Database of Establishments from 1990 Q2-2010 Q2.

I have been granted access by the Bureau of Labor Statistics to QCEW micro-data for 40 states, including Puerto Rico and the Virgin Islands (shown in Table 2.15). The remaining states are either excluded due to the legal arrangement or due to incomparable experience rating systems.<sup>14</sup> Establishments in the data are identified by an UI tax account number. I define a firm as an

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<sup>13</sup>Primarily these data come from Section C of the 204 report collected by the DOL from state UI agencies. These data are available in a consistent format between 2001-2010.

<sup>14</sup>Table 2.6 and Section 2.9.3 show a robustness check using additional data from the missing states.

agglomeration of establishments with a common UI account number. This implicitly treats firms as single-state entities and ignores employment decisions across states that may be due to differing marginal tax costs.

There are several additional restrictions in the data that are worth noting. Monthly employment at the establishment is defined as employment in the pay period including the 12th of the month. Following BLS procedure, quarterly employment is defined as the third month of each quarter's employment. I also only consider firms that are continuing between quarters and therefore abstract from openings and closing.<sup>15</sup> In addition, I exclude from the analysis establishments within firms that engaged in a consolidation or breakout between quarters due to difficulties in correctly apportioning the employment change across quarters. These exclusions allow me to extend the QCEW back to the second quarter of 1990.<sup>16</sup>

Multi-establishment firms can potentially have establishments in several industries. In order to examine firm behavior by industry, I assign the industry of largest establishment to the entire firm. Finally, I exclude public sector establishments and NAICS sectors 92 and 99 from the analysis as UI finance differs in the public sector.

After applying these restrictions, I calculate statistics at the 3-digit NAICS-by-state level. This results in 3,377 3-digit NAICS-by-state cells observed for 80 quarters from 1990 Q2 to 2010 Q1. For each cell, I calculate the job creation and job destruction rates as given above in (2.7). Recall that job reallocation is  $JR = JC + JD$  and the net change is  $JC - JD$ . These variables are the primary outcomes examined in the econometric analysis below. I now describe in detail the two primary UI financing systems in order to construct a measure of experience rating across states and industries.

### 2.4.2 Reserve Ratio System

The most common system of UI tax determination is the “reserve ratio” system. In reserve ratio states, firms have an account with the state from which unemployment benefits charged are debited

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<sup>15</sup>The effect of experience rating on openings and closing is an important extension given the concern with SUTA dumping. Estimates of firm birth and death rates on experience rating do not indicate that this is quantitatively important, however.

<sup>16</sup>Faberman (2008) extends the LBD back to 1990 using a careful matching algorithm to account for breakouts and consolidations.

and to which taxes payments are credited. Each year, the firm's reserve ratio is calculated as the ratio of its reserve balance,  $R_t$ , to the average of its payroll over the past three years. The reserve ratio is then converted into a tax rate based on the tax schedule that will be in effect for the next year.<sup>17</sup> Recall that taxes are paid on each employee up to a maximum taxable wage base (between \$7,000 and \$37,000).

The tax schedule in a reserve ratio state is a declining function of the reserve balance,  $R_t$ . Firms with a highly negative account balance are subject to the statutory maximum rate while firms with the most positive balances are subject to the statutory minimum rate. Between the minimum and maximum rates, firms with more negative balances are required to pay higher tax rates. A linear approximation of the tax schedule between the minimum and maximum rates is:  $\tau_t = \lambda_0 - \lambda_1 r_{t-1}$ . The reserve ratio,  $r_t$ , is given by  $r_t = \frac{R_t}{\bar{w}n}$ , where  $\bar{w}n$  is average taxable payroll.

### Calculation of Marginal Tax Cost

Due to the unavailability of individual firm tax rates, I follow Card and Levine (1994) and calculate the marginal tax cost for an average firm in a given state and industry. Let  $n$  be the level of employment and  $1 + g_n$  be the gross annual growth of employment in a given industry within a state at time  $t$ . Further, let  $w$  be the taxable wage base in that state and  $1 + g_w$  be the annual growth in the taxable wage base. In the data, I estimate  $(1 + g_n)$  and  $(1 + g_w)$  as the average annual growth rates from 2001 Q1 to 2007 Q4, the business cycle peaks over the relevant time frame. Consider the reserve balance of an industry in a particular state on the sloped portion of the tax schedule

$$R_t = R_{t-1} + \tau_t w_t n_t - B_t, \quad (2.8)$$

where  $B_t$  is the dollar value of benefits charged to the industry.  $B_t$  is composed of the proportion of benefits that are charged to firms in each state,  $\chi$ , and the value of benefits,  $b_t$ , paid to the those beneficiaries.<sup>18</sup> So,  $B_t = \chi b_t$ . The reserve ratio is the ratio of the reserve balance,  $R_t$ , and the average taxable payroll over a three year period. Due to the assumption of constant growth of  $n$

<sup>17</sup>Computation dates are typically January 1st. Four states use July 1st.

<sup>18</sup> $\chi$  is typically less than 100% since certain types of benefits are not fully charged to firms.

and  $w$ , average payroll is just  $w_{t-1}n_{t-1}$ . Converting to a reserve ratio by dividing both sides by  $w_{t-1}n_{t-1}$  gives the approximate reserve ratio:

$$r_t \approx \frac{R_t}{w_{t-1}n_{t-1}} = \frac{r_{t-1}}{(1+g_n)(1+g_w)} + (1+g_n)(1+g_w)\tau_t - \frac{\chi b_t}{w_{t-1}n_{t-1}}. \quad (2.9)$$

If a firm is at the minimum or maximum tax rate, an addition dollar of benefits charged does not increase the tax rate, so the marginal tax cost is zero. If the industry is on the sloped portion, then the tax rate is linearly related to the reserve ratio as given by

$$r_t = \frac{\lambda_0 - \tau_{t+1}}{\lambda_1}. \quad (2.10)$$

Substituting for  $r_t$  and manipulating gives

$$\lambda_0(1-(1+g_n)(1+g_w))w_t n_t + \tau_t w_t n_t (1-\lambda_1(1+g_n)(1+g_w)) + \lambda_1(1+g_n)^2(1+g_w)^2 \chi b_t = \tau_{t+1} w_{t+1} n_{t+1}. \quad (2.11)$$

The present discounted value of the firm's tax bill, discounted at rate  $i$ , can be written as

$$T_t = \sum_{j=0}^{\infty} \left[ \frac{1}{1+i} \right]^{t+j} w_{t+j} n_{t+j} \tau_{t+j}. \quad (2.12)$$

The marginal tax cost is the derivative of the present discounted value of future taxes, assuming a discount rate  $i$ , with respect to an increase in benefits. Substituting in the left hand side of equation 2.10 in to equation 2.11, we find

$$MTC = \frac{\partial T}{\partial B_t} = \frac{\chi \lambda_1 (1+g_n)^2 (1+g_w)^2}{i + \lambda_1 (1+g_n)^2 (1+g_w)^2}. \quad (2.13)$$

The marginal tax cost is linearly increasing in  $\chi$ , the fraction of benefits charged to firms. The MTC is also decreasing in the interest rate. In a reserve ratio state, due to discounting future tax payments by the discount rate, the marginal tax cost is necessarily below 100%. In the simple case where  $g_n = g_w = 0$ , however, it is easy to verify that the MTC is increasing in the slope of the

tax schedule if  $\lambda_1 > -i$ , which will be satisfied for any positive interest rate. Under reasonable magnitudes of  $g_n$  and  $g_w$ , the MTC is also increasing in the slope of the tax schedule.

### 2.4.3 Benefit Ratio System

The other method of experience rating a firm's tax rate is the benefit ratio system. States charge a tax rate that is proportional to the value of benefits drawn by laid off workers divided by its payroll. The previous three to five years of benefits and payrolls are used in determining the benefit ratio.

#### Calculation of Marginal Tax Cost

Call  $T$  the number of years of benefits and payrolls used in the calculation. Then the benefit ratio is given by

$$BR_t = \frac{\sum_{j=1}^T \chi B_{t-j}}{\sum_{j=1}^T w_{t-j} n_{t-j}}. \quad (2.14)$$

Under the assumption of constant growth of employment and taxable wages as above, the benefit ratio can be approximated by

$$BR_t \approx \frac{\sum_{j=1}^T \chi B_{t-j}}{T \bar{w} \bar{n}}$$

and the tax schedule by

$$\tau_t = \lambda_0 + \lambda_1 BR_t.$$

After some manipulation, the tax bill of a firm can be written as

$$w_t n_t \tau_t = w_t n_t \lambda_0 + \lambda_1 w_t n_t \frac{\sum_{j=1}^T \chi B_{t-j}}{T \bar{w} \bar{n}}.$$

The discounted present value of an additional dollar of benefits is

$$MTC = \chi \lambda_1 (1 + g_n)^2 (1 + g_w)^2 \frac{1 - (1 + i)^{-T}}{Ti}. \quad (2.15)$$

In a benefit ratio system, it is clear that the marginal tax cost can rise above 100% depending upon the slope of the tax schedule. Further, inspecting the equation shows that the marginal tax cost for a benefit ratio state is linearly increasing in the slope of the tax schedule and the fraction of benefits charged to firms. With a bit of algebra, it can be shown that the marginal tax cost is also decreasing in the discount rate.

#### 2.4.4 Accounting for the Minimum and Maximum Tax Rates

The above calculations for the marginal tax cost only apply to firms on the sloped portion of the tax schedule. For firms that are on the flat portion—either assigned the minimum or maximum tax rates—the marginal tax cost of an additional layoff is approximately zero.<sup>19</sup> I use newly available QCEW tabulations on the overall UI tax contributions at the 3-digit industry and state cell to place an average firm in each cell on the sloped or flat portion of the tax schedule.

Using these data, I calculate for each state and industry cell the average tax rate for each quarter from 2001 forward. If the industry’s tax rate is above the maximum or below the minimum, therefore, I set the marginal tax cost to zero. Requiring the average tax rate in a cell to be at the minimum or maximum is a very restrictive assumption which is infrequent in the sample. Therefore, I implement this in the following way. If an industry is ever at the minimum or maximum, I set the marginal tax cost to zero in all years. Depending on the distribution of firms across tax rates within each industry, this is a conservative method of assigning cells to the sloped portion which would tend to attenuate regression coefficients since some firms on the sloped portion are assigned the zero marginal cost. As a robustness check, I also assign zeros only in those quarters in which the tax rate is at the statutory minimum or maximum rates. The results are robust to the different methods.

These newly available data on tax rates provide a significant improvement over the previous literature. In previous studies, it is commonly assumed that over a long period of time, tax contributions must equal benefits paid. Given this assumption, researchers used the average unemployment rate

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<sup>19</sup>As pointed out in the model above, the marginal tax cost for a firm that approaches the sloped portion is non-zero. I follow the literature and assign the marginal tax cost as zero at the minimum rate as well. Importantly, imposing this assumption biases the results against finding a significant effect of experience rating. This is because some cells are assigned the zero marginal tax cost when in fact they face the sloped portion of the schedule. This will reduce the variation caused by the marginal tax cost on the job flow estimates and therefore attenuate the coefficients.

within each cell to determine the level of taxes required to fund those benefits in steady state. If these steady state tax rates were below the minimum or above the maximum, the marginal tax cost was set to zero.

There are several problems encountered with this method. First, as Pavosevich (2009) points out, over the time period of this study, tax contributions fell far short of benefits paid, causing large deficits in many state trust funds. Therefore, the steady state tax assumption is less appropriate in recent years. Indeed, over the recent period, the steady state tax rates implied by this method swamp the maximum tax rate in nearly all cells. Second, while a state must eventually equate contributions with benefits, it is not necessarily true that this must hold for each industry within a state, especially since persistent industry cross-subsidies are inherent in the system. Third, assigning the marginal tax cost to zero as a function of each state-by-industry unemployment rate induces a simultaneity in the dependent variable—the temporary unemployment probability in Card and Levine (1994)—with the calculated marginal tax cost. The method in this chapter, therefore, reduces misclassification of zero marginal tax cost cells as well as avoids the simultaneity problem inherent in previous studies.

#### **2.4.5 Discount Rate Calculation**

In both experience rating systems, the nominal interest rate is an important parameter since previous benefits are charged to the firm in nominal terms. I apply several different values for the interest rate. First, I follow the literature and set the nominal interest rate to 10%. Second, I calculate the interest rate as the sum of a nominal interest rate on corporate paper and add to that the quarterly probability of firm closure in the QCEW micro data.<sup>20</sup> This discount rate varies over states and industries but is only available from the detailed micro data from the QCEW in this study. Third, as a robustness check, I use interest rates of 5% and 15% as well (see Table 2.4). Overall, the results with different interest rates are qualitatively similar.

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<sup>20</sup>I use the 3 month AA non-financial corporate paper rate from the FRED database (DCPN3M).

### 2.4.6 Econometric Analysis

Table 2.1 shows summary statistics for several of the variables for the states listed in Table 2.15. First, the average marginal tax cost using the exogenous interest rate is 54% with a maximum of 217%. The average is slightly lower than the 68% in Card and Levine (1994) whereas the maximum in their sample was 1.6.<sup>21</sup> The lower average MTC over the recent period accords with Pavosevich (2009) who shows that states are charging firms too little to finance their UI trust funds. Figure 2.7 graphs the marginal tax cost by 2-digit industry. Variation within each 2-digit industry is across state and also 3-digit industries within the 2-digit sector. From this graph we can see that the largest spikes at zero marginal tax cost (either from the minimum or maximum rate) are in mining, construction, and arts and entertainment. I find that retail trade is less likely to be at the maximum tax rate than is found in Card and Levine (1994).

The average marginal tax cost with the estimated interest rate is similar to the exogenous interest rate. The average is a 61% MTC with the same standard deviation and a slightly higher maximum value of 220%. Over the entire sample, the job destruction rate averaged 6.48 and job creation averaged 6.23 for a mean net creation rate of -.25 over the entire period. Total flows in the labor market, measured by the job reallocation rate, was 12.5% per quarter.

The baseline specification is a standard fixed effects model with the job destruction rate, job creation rate, net creation rate, or the reallocation rate as outcomes. I follow the literature and average the marginal tax cost over all of the observations within each 3-digit industry and state cell and apply that average to all quarters of data. Therefore, the variation that is exploited in this regression is the *between* variation in the level of the marginal tax cost. This requires assuming that there are fixed differences at the 3-digit industry across states as well as fixed state effects (constant across industries). The full specification is

$$Y_{isyq} = \varsigma + \varsigma_i + \varsigma_s + \varsigma_y + \varsigma_q + \beta MTC_{is} + x'_{isyq} \kappa + \epsilon_{isyq} \quad (2.16)$$

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<sup>21</sup>Regressions omitting  $MTC > 1.5$  yielded substantially similar results.



The  $\zeta$ 's are fixed effects for 3-digit industry, state, year, and quarter.<sup>22</sup>  $x_{isyq}$  includes the level of employment and the number of firms in each cell for each quarter to control for the size of the cell and  $\kappa$  are the associated coefficients. The dependent variable,  $Y$ , will be either job creation, job destruction, job reallocation, or net job creation.  $\beta$  is the coefficient of interest and gives the effect of going from 0% to 100% MTC on the dependent variable. The interpretation of the coefficient is that going from 0 to 100% marginal tax cost reduces the job flow rate by the magnitude of the coefficient.

Table 2.2 shows results from the regression with the averaged marginal tax cost using the exogenous interest rate of 10%. The coefficient on the marginal tax cost is -2.4 implying that a change from the mean of 54% to 100% marginal tax cost would reduce job destruction by 17%. The coefficient on job creation is -1.86. The point estimate suggests that implementing perfect experience rating would reduce job creation by 13.7%. Moreover, an average state instituting a 100% MTC would reduce job reallocation by 10%. The right panel is the same analysis conducted using on the period 2001-2010, as these are the actual years that I measure marginal tax costs. The results are qualitatively similar with larger coefficients for job destruction and job reallocation.

Table 2.3 presents estimates using two different marginal tax cost measures. The left panel shuts down employment growth in the marginal tax cost calculation, i.e.  $g_n = 0$ .<sup>23</sup> In this specification, job destruction would fall by 15.8% and job creation by 15.4% after instituting 100% experience rating. As another robustness check, I calculate the marginal tax cost as in Topel (1983) which amounts to setting  $g_n = g_w = 0$  and  $\chi = 1$ , shown in the right panel of Table 2.3. Note that this regression only exploits variation in the slope of the tax schedule across states. The results are much the same with a slightly larger decrease in job creation than job destruction (13.4% vs. 16.5%).

Table 2.4 presents estimates using alternative discount rates. The first two panels use alternative exogenous interest rates. The coefficients on the marginal tax cost in each of these regressions are significant. Using a 5% interest rate, job destruction is predicted to fall by 12.2% if perfect experience was instituted. With a 15% interest rate, job destruction would fall by 22%. Results for

<sup>22</sup>Specifications with year  $\times$  quarter dummies are nearly identical.

<sup>23</sup>I also try specifications including  $g_n$ ,  $g_w$ , and  $\chi$  as regressors. Results are similar.

the other outcomes are similar to those found in Tables 2.2 and 2.3. The right-most panel uses an estimated interest rate adding the estimated death rate in the QCEW to the corporate paper rate for each quarter.<sup>24</sup> I estimate this on the subsample over which I calculate the marginal tax costs from 2001-2010. The results are even stronger in this specification. Going from average to perfect experience rating would reduce job destruction by 29% while reducing job creation by 23% (both significant). Job reallocation would be reduced by about 20% and net creation is economically and statistically significantly positive.

In the next set of estimates in Table 2.5, I regress the job destruction and creation rates including several additional measures of the tax schedule as controls. In the left column of each panel (labeled (1)), I include the proportion of the state's accounts that are on the sloped portion of the schedule as well as its interaction with the marginal tax cost. The motivation for this is that the higher the fraction on the sloped portion, the more likely the marginal tax cost will be to bind. Therefore, we should expect a negative sign on the interaction.<sup>25</sup> As expected, the interaction effect is significantly negative, showing that if the slope is binding for more firms, there is a larger negative effect of increasing experience rating on job flows.<sup>26</sup>

Column (2) of each panel includes the proportion on the slope (not interacted) as well as the percent of benefits charged, and the minimum and maximum statutory rates. These turn out to be insignificant with the exception of the maximum rate on job destruction. The coefficient on the marginal tax cost remains large and significant.<sup>27</sup>

One caveat to the analysis above is the definition of the firm. Recall that I define a firm as the collection of establishments under the same UI account number, which is unique to each state's unemployment insurance system. Some firms, of course, have establishments across several states. It is therefore possible that firms might shift employment to low marginal tax cost states and concentrate its turnover in that state, thereby generating a negative relationship between layoffs and the marginal tax cost. While the incentive from the firm's perspective is to avoid the layoff cost,

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<sup>24</sup>Corporate paper rate is from the Fred database. See Section 2.4.5

<sup>25</sup>Admittedly, this suggests that the method of assigning a zero MTC as described in Section 2.4.4 does not fully disentangle firms on the sloped portion from the flat portions.

<sup>26</sup>Additionally, estimating job creation and job destruction as a system of equations yields quantitatively similar results.

<sup>27</sup>See Section 2.9.3 and Table 2.5 for an additional robustness check with missing states.

the question remains as to whether higher experience rating in one state actually reduces overall job flows.

It is difficult to identify multi-state firms and their associated job flows in the QCEW. Instead, I focus on firms with only one establishment within each state and discard firms with multiple establishments under the same UI accounts as a sensitivity check. It is more likely that these firms only have one establishment and are not multi-state firms. The results from the baseline specification for JC and JD are shown in Table 2.7. Again, the results are significant and quantitatively similar—job destruction would fall by 14% and job creation by 10% if an average marginal tax cost state implemented 100% repayment.

Finally, it is possible that the anticipation of the marginal cost of a layoff affects the firm entry and exit decision. So far, the model of labor demand and the empirical study has just considered continuing firms. In principle, firm's might decide to exit the market rather than lay off a large fraction of its workforce to avoid the tax hike. Analysis of the firm birth and death rates calculated from the QCEW data do not show that this is a substantial concern. Table 2.8 shows the effect of the marginal tax cost on the fraction of firms that die or are born within a quarter in a 3-digit state-by-industry cell. From these regressions, it appears that experience rating does not have a large effect on the entry and exit decision as the coefficients on both the birth and death rates are small and insignificant.

The empirical evidence presented in this section strongly confirms the prediction that higher experience rating reduces the firm's incentives to both create and destroy jobs. I now turn back to a fully-specified macroeconomic model to understand the effect of experience rating on long-run and short-run aggregate labor market outcomes.

## **2.5 Macroeconomic Equilibrium and Dynamics with Tax Experiments**

In this section, I develop a search model of unemployment with heterogeneous firms that face UI taxes based on endogenously-determined, individual layoff histories. I analyze this model to understand the effect of experience rating on the dynamics of the labor market and to consider

counterfactual UI financing. The model is an extension of Elsby and Michaels (2011) who develop a search and matching model of the labor market with large firms and endogenous job destruction.

The economy is populated by a measure one of firms and measure  $\mathbb{L}$  of workers. Aggregate productivity at a given time is  $p_t$  and follows an autoregressive process in logs:  $\ln p_t = \rho_p \ln p_{t-1} + \epsilon_t^p$ . Idiosyncratic productivity is also assumed to follow an AR(1) process in logs:  $\ln x_t = \rho_x \ln x_{t-1} + \epsilon_t^x$ . Firms have access to identical production functions and workers are ex-ante homogeneous. Productivity at the firm level is merely the product of the level of each,  $px$ . Firms observe aggregate and idiosyncratic productivity and workers observe aggregate productivity and the idiosyncratic productivity of its employer or potential match.

Workers and firms meet through a process of search and matching governed by an aggregate matching function. The rates of job finding and job filling are determined by the aggregate number of vacancies,  $V$ , and the aggregate number of searchers,  $U$ . As is standard in the literature, the matching function is assumed to be constant returns to scale:  $M(U, V) = M(1, \frac{V}{U})$ . Define labor market tightness,  $\theta \equiv \frac{V}{U}$ . The higher is  $\theta$ , the more job openings per searching worker and, therefore, the tighter the labor market.

Unemployed workers meet a job posting at the job finding rate,  $f(\theta) \equiv \frac{M(U, V)}{U}$ . The standard assumptions apply:  $f'(\theta) > 0$  and  $f(0) = 0$ . A posted vacancy is filled at the job queueing rate,  $q(\theta) \equiv \frac{M(U, V)}{V}$ ;  $q'(\theta) < 0$  and  $q(\infty) = 0$ .

Unemployment insurance benefits,  $b$ , are financed through two forms of taxes. (1) firm specific payroll taxes,  $\tau$ , based on individual firm's history of layoffs; (2) lump sum taxes,  $T$ , on firms and all workers (whether unemployed or not). These taxes are set each period to balance the government budget constraint. Since they are equally levied and non-distortionary, they do not affect the optimal decisions of the agents. Thus, they are ignored in exposition of the model below.<sup>28</sup>

The timing of events in the model is as follows. At the beginning of each period, firms evaluate the idiosyncratic and aggregate state of the economy and decide to post vacancies or lay off workers. Unemployed workers meet firms and bargain over wages while laid off workers cycle into unemploy-

<sup>28</sup>In reality, firms pay taxes on a capped portion of payroll. I abstract from this for simplicity.

ment. After all job flows are complete, production occurs and wages are paid, which completes a time period.

The model's key endogenous variables are determined mainly by the labor demand decision of individual firms, to which I now turn.

### 2.5.1 Firm's Problem

The firm's labor demand problem is similar to that presented in Section 2.3. Recall that the firm has a stock of workers,  $n_{-1}$ , and a stock of layoffs,  $\ell_{-1}$ . Of the laid off, a fraction  $\delta$  no longer determine the firm's UI tax. Previous layoffs are no longer counted in a firm's stock if the laid off find other jobs or there are statutory benefit liability time limits. Therefore, depreciation of layoffs is a function of the job finding rate,  $f$ .<sup>29</sup>

The firm observes idiosyncratic productivity,  $x$ , and aggregate productivity,  $p$ , and decides to hire or fire. Let the number of hires be denoted by  $h$  and the number of fires as  $s$ . As opposed to the costless hiring in Section 2.3, the firm must post vacancies at a cost of  $c$  per vacancy. Each vacancy meets a worker with probability  $q$  so that a firm hiring  $h$  workers must post  $\frac{h}{q}$  vacancies. If it fires  $s$  workers, it sends those workers into the layoff pool,  $\ell$ . Therefore, the equations of motion for the firm's state variables are

$$n = n_{-1} + h - s$$

$$h = qv$$

$$\ell = (1 - \delta)\ell_{-1} + s.$$

Since  $s \equiv -\mathbb{1}^- \Delta n > 0$ , it is possible to rewrite the equation of motion for layoffs as:  $\ell = (1 - \delta)\ell_{-1} - \mathbb{1}^- \Delta n$ . In addition,  $h \equiv \mathbb{1}^+ \Delta n = qv$ . Total hiring costs are given by  $cv \equiv \frac{c}{q} \mathbb{1}^+ \Delta n$ . The firm's optimization problem is written entirely in terms of  $n$  and  $\Delta n$  according to these equations.

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<sup>29</sup>Geometric depreciation of layoffs through  $\delta$  is a parsimonious reduced form method to model laid off workers finding new jobs without tracking their employment history. In addition, it captures the statutory maximum amount of time that previous benefits are charged to a firm. Even in reserve ratio states in which previous benefits are forever counted, previous layoffs are diminished through tax contributions over time that restore a firm's balance. It is also worth noting that  $\delta$  will also be integral in matching the distribution of firms across tax rates.

In addition to idiosyncratic state variables, the firm must take account of several aggregate states. Along with the level of aggregate productivity, the firm must predict future queuing rates to make optimal intertemporal vacancy posting decisions. In this model, that amounts to forecasting future labor market tightness,  $\theta'$ . The reason for this is fairly intuitive. Suppose that aggregate productivity was in a long drought so that many firms had shed workers. After aggregate productivity recovers, firms will be looking to hire a large number of workers and labor market tightness will be high. On the other hand, suppose that aggregate productivity had realized a series of positive shocks. Firms will have a larger than typical stock of workers; in response to the same positive shock, firms will hire fewer workers and so tightness will be relatively lower. Therefore, aggregate productivity is not sufficient for firms to determine the price of hiring.

In order to forecast labor market tightness, the firm must keep track of the type distribution of firms across state variables,  $\{n, \ell, x\}$ . Call this distribution  $\Xi$  and the transition equation  $\Xi' = \Gamma(p, \Xi)$  which is a function of aggregate productivity as well. It is important to note that endogenous aggregate variables depend on aggregate productivity and the type distribution of firms:  $\theta = \theta(p, \Xi)$ ,  $f = f(\theta(p, \Xi))$ ,  $q = q(\theta(p, \Xi))$ , and  $\delta = \delta(f(\theta(p, \Xi)))$ . In what follows, the dependence of these variables on the aggregate state is suppressed. Therefore, the following is the firm's Bellman equation

$$\begin{aligned} \Pi(n_{-1}, \ell_{-1}, x, p, \Xi) = \max_n \left\{ pxF(n) - wn - \tau(\ell)wn - \frac{c}{q}\mathbb{1}^+\Delta n \right. \\ \left. + \beta \int \int \Pi(n, \ell, x', p', \Xi') dG(x'|x) dP(p'|p) \right\} \end{aligned} \quad (2.17)$$

such that

$$\ln x' = \rho_x \ln x + \epsilon^x \quad (2.18)$$

$$\ell = (1 - \delta)\ell_{-1} - \mathbb{1}^-\Delta n \quad (2.19)$$

$$\mathbb{1}^+\Delta n = qv \quad (2.20)$$

$$\ln p' = \rho_p \ln p + \epsilon^p \quad (2.21)$$

$$\Xi' = \Gamma(p, \Xi). \quad (2.22)$$

### 2.5.2 Wage Setting

For tractability, the workers side of the model is kept extremely simple. I abstract from the situation in which laid off workers remain on call with their previous firm. If firms could recall (as Section 2.9.2 shows), this would give rise to an option value of remaining on recall with that firm versus searching in the general labor market. I leave this interesting extension for future research.

Workers can either be employed at a firm with  $n$  employees,  $\ell$  laid off workers, and productivity  $x$ , or unemployed. An unemployed worker earns a flow unemployment benefit of  $b$ . Unemployed workers find a job with probability  $f$ . The Bellman equation for an unemployed worker is given by

$$W^u(p, \Xi) = b + \beta E[f'W^e(n', \ell', x', p', \Xi') + (1 - f')W^u(p', \Xi')]. \quad (2.23)$$

An employed worker in the current period earns wage  $w$  and is fired with probability  $\tilde{s}$  into the layoff pool.

$$W^e(n, \ell, x, p, \Xi) = w + \beta E [\tilde{s}' W^u(p', \Xi') + (1 - \tilde{s}') W^e(n', \ell', x', p', \Xi')]. \quad (2.24)$$

For additional simplicity, I will assume that wages are simply the weighted average, with bargaining power  $\eta$ , of the average flow surplus from working and the average flow surplus from employing  $n$  workers, gross of adjustment costs.<sup>30</sup> <sup>31</sup> The flow surplus from working is just  $w - b$ . The average flow surplus from employing  $n$  workers is

$$\frac{pxF(n) - (1 + \tau(\ell))wn}{n}. \quad (2.25)$$

The assumed bargain is, therefore,

$$\eta \left[ \frac{pxF(n) - (1 + \tau(\ell))wn}{n} \right] = (1 - \eta) [w - b]. \quad (2.26)$$

Solving for the wage gives

$$w = \frac{\eta \frac{pxF(n)}{n} + (1 - \eta)b}{1 + \eta\tau(\ell)} = \frac{\eta pxn^{\alpha-1} + (1 - \eta)b}{1 + \eta\tau(\ell)}. \quad (2.27)$$

There are several important features of the wage in comparison to the standard bargained wage that should be noted. First, as is standard, conditional on labor productivity, the wage is declining in  $n$  due to diminishing marginal productivity. Second, as expected, the wage is (weakly) decreasing in the UI tax rate. In the standard model, the wage is typically a function of future labor market productivity—firms must compensate workers when the labor market is tighter as the outside of option of finding another job is easier.<sup>32</sup> Therefore, the wage will co-vary with productivity substantially less without this additional term. As is well known, this will lead to substantial amplification of shocks relative to comparable models.

<sup>30</sup>Several papers make this assumption such as Barlevy (2002), Shimer (2001), and others.

<sup>31</sup>Stole and Zwiebel (1996a) bargaining is intractable in this model due to the interaction of the layoff cost and the unknown policy function in the continuation value of the firm's problem. Numerical derivatives of value functions are subject to substantial error at early stages of value function iteration. This makes numerically solving the full bargaining problem intractable.

<sup>32</sup>Mechanically, this term is the only remaining term from the continuation values of the firm and worker.



### 2.5.3 Aggregation and Equilibrium

Let the policy function for the firm be denoted as

$$n^* \equiv \Phi(n, \ell, x, p, \Xi), \quad \Delta_p(n, \ell, x, p, \Xi) \equiv \Phi(n, \ell, x, p, \Xi) - n. \quad (2.28)$$

and

$$\ell^* = (1 - \delta)\ell - \mathbb{1}^- \Delta_p(n, \ell, x, p, \Xi). \quad (2.29)$$

where  $\mathbb{1}^{\{+, -\}}$  is an indicator for positive or negative employment adjustment. Total separations are given by

$$S = \int_n \int_\ell \int_x \mathbb{1}^- \Delta_p(n, \ell, x, p, \Xi) d\Xi(n, \ell, x), \quad (2.30)$$

Total hires are described by

$$H = \int_n \int_\ell \int_x \mathbb{1}^+ \Delta_p(n, \ell, x, p, \Xi) d\Xi(n, \ell, x). \quad (2.31)$$

Employment is simply the average employment level across firms

$$\bar{N} = \int_n \int_\ell \int_x \Phi(n, \ell, x, p, \Xi) d\Xi(n, \ell, x). \quad (2.32)$$

Employment evolves according to the following difference equation

$$\bar{N} = \bar{N}_{-1} + H - S. \quad (2.33)$$

Finally, the evolution of the aggregate stock of layoffs is

$$\bar{L} = (1 - \delta)\bar{L}_{-1} - \int_\ell \int_n \int_x [\mathbb{1}^- \Delta_p(n, \ell, x, p, \Xi)] d\Xi(n, \ell, x). \quad (2.34)$$

These accounting rules allow me to define an equilibrium of the model.<sup>33</sup> A *recursive stationary equilibrium* is a set of functions

$$\{\Pi, \Phi, H, S, \bar{N}, \bar{L}, W^e, W^u, w, \theta, f, q, \delta, \bar{s}, \Gamma\}$$

such that:

1. Firm's problem: taking  $\theta$  as given, firms maximize  $\Pi$  subject to the bargained wage,  $w$ , and the optimal choice is consistent with  $\Phi$ .
2. Wage bargaining and worker flows: the wage function,  $w$ , splits the flow surplus between the worker and firm. The finding and separation rates along with the wage bargain and the value of leisure satisfy the worker's Bellman equations
3. Hiring and separations consistent with  $f$  and  $\bar{s}$ :
  - Hiring,  $H$ , is consistent with  $\Phi$  and  $f = \frac{H}{\bar{L} - \bar{N}}$
  - Separations,  $S$ , are consistent with  $\Phi$  and imply  $\bar{s} = \frac{S}{\bar{N}}$
  - $\theta$  is given by the matching function and is consistent with  $f$ .
4. Employment Dynamics:  $\bar{N} = \bar{N}_{-1} + H - S$
5. Model Consistent Dynamics: The evolution of aggregate employment and layoffs given by  $\Gamma$  is consistent with  $\Phi$  and the processes for  $p$  and  $x$ .

#### 2.5.4 Solution Method

The solution to the dynamic labor demand problem stated above is analytically intractable, therefore I use numerical methods to solve the model. The crux of the solution is to pin down the policy function for the firm,  $\Phi$ . To accomplish this, I use value function iteration on the firm's recursive problem stated in equation (2.17).

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<sup>33</sup>Note that the government fills any holes in UI financing through a lump sum tax that does not distort the optimal choices of any of the agents. It is therefore abstracted from here.

Specific details of the algorithm are described in Section 2.9.1. I briefly describe the computational method to solve for the steady state allocation here. First, I discretize the state space which consists of  $\{n, \ell, x\}$ . I discretize the shock process  $x$  using the method in Tauchen (1986). I discretize  $n$  on an equally spaced grid between one-half of the minimum frictionless employment level and two times the maximum frictionless employment level. In order to reduce computation time, I restrict the firm to choose points on the discrete grid for  $n$ .

I then discretize the grid for layoffs: the maximum of the layoff grid is chosen as the maximum employment change in the frictionless model. Since the firm chooses an employment level which pins down the layoff stock next period, I linearly interpolate at points off the layoff grid. In practice, firms in equilibrium do not reach the highest point of the layoff grid. Therefore, I use an unequally spaced grid with more points at the bottom two-thirds of the grid. Finally, in the simulations, I ensure that firms do not hit the end points of either the employment or layoff grids.

After I solve the firm's policy function, I simulate the model for 10,000 firms and 3,000 periods, discarding the first 1,000 observations as the burn-in period. I simulate the continuous shock process in logs and piece-wise linearly interpolate between points on the grid.<sup>34</sup> The aggregation of the simulation across all time periods and agents following equations (2.29)-(2.33) constitutes the solution to steady state equilibrium.

### Approximate Aggregation

In each period, firms decide on vacancy posting given their idiosyncratic state vector and the aggregate state of the economy. In order to predict future levels of labor market tightness (and therefore vacancy posting costs), firms must forecast the entire type distribution of firms across the state space. This dependence is shown in the inclusion of  $\Xi$  in the firm's optimization problem. Since  $\Xi$  is an infinite-dimensional object, the exact equilibrium is not computable. I follow the Krusell and Smith (1998) approximate equilibrium approach.<sup>35</sup>

<sup>34</sup>I experiment with log-linearly interpolating along the  $x$  and  $n$  dimensions, but the results are similar in the steady state.

<sup>35</sup>See Bils et al. (2011), Elsby and Michaels (2011), and Fujita and Nakajima (2009) for examples of using this method in similar contexts.

The approach is as follows. Instead of forecasting the entire distribution of firms across states, I assume the firm is boundedly rational and only keeps track of a finite set of moments of the distribution. Suppose that the set of moments chosen is called  $\xi$  and the transition of these moments is governed by  $\gamma$ . Therefore,  $\Xi$  is replaced by  $\xi$  in the dynamic programming problem to make the problem computable.

$$\begin{aligned} \Pi(n_{-1}, \ell_{-1}, x, p, \xi) = \max_n \left\{ pxF(n) - wn - \tau(\ell)wn - \frac{c}{q}\mathbb{1}^+ \Delta n \right. \\ \left. + \beta \int \int \Pi(n, \ell, x', p', \gamma(\xi)) dG(x'|x) dP(p'|p) \right\}. \end{aligned} \quad (2.35)$$

The task is to solve for the transition equation:  $\xi' = \gamma(p, \xi)$ . I assume the moments are the mean of the employment distribution,  $\bar{N}$ , and the mean of the layoff distribution,  $\bar{L}$  and conjecture log-linear transition equations

$$\begin{aligned} \ln \bar{L}' &= \gamma_{\ell 0} + \gamma_{\ell 1} \ln \bar{L} + \gamma_{\ell 2} \ln \bar{N} + \gamma_{\ell 3} \ln p \\ \ln \bar{N}' &= \gamma_{N 0} + \gamma_{N 1} \ln \bar{L} + \gamma_{N 2} \ln \bar{N} + \gamma_{N 3} \ln p. \end{aligned}$$

Note that the firm takes these forecasts for the aggregate state and estimates labor market tightness in order to calculate expected future vacancy posting costs. That is the last equation

$$\ln \theta' = \gamma_{\theta 0} + \gamma_{\theta 1} \ln \bar{L}' + \gamma_{\theta 2} \ln \bar{N}' + \gamma_{\theta 3} \ln p'.$$

The solution algorithm is to find the parameters,  $\gamma$ , that accurately forecast aggregate variables. I discretize  $p$  via the method of Tauchen (1986) and solve the value function on the state space:  $\{n, \ell, x, p, \bar{N}, \bar{L}, \theta, \xi\}$ . I simulate the model for 10,000 firms and 2,000 periods and estimate the coefficients via OLS on the simulated data. Further details are in Section 2.9.1.

In practice, the means of the distribution provide adequate information for the firm to forecast the distribution of firms across states as measured by the sufficiently high  $R^2$ 's in the regressions for the forecast coefficients. Higher  $R^2$ 's would be obtained through either larger simulation sizes

or with additional terms in the forecasting equations. Further details as well as the  $R^2$ 's from the solution of the baseline model are given in Section 2.9.1.

In the present model, market clearing every period is defined through an equilibrium labor market tightness that coincides with the flows of workers into and out of unemployment. In the standard Krusell and Smith (1998) model, market clearing is insured by the set up of the model—the labor market clears in every period as unemployment is exogenously determined. In the present model, however, the equilibrium for the labor market must be determined in every stage of the simulation.

In principle, firms know the aggregate state of the economy  $\{p, \bar{N}, \bar{L}\}$  and can therefore predict equilibrium  $\theta$ . However, forecast errors can lead to a situation in which the true market clearing level of  $\theta$  is different from the forecasted level. Therefore, I forecast  $\theta$  from the equation using the guess for  $\gamma_\theta$ , but I solve the value function on a grid of  $\theta$ 's. Then, in every time period of the simulation, I iteratively solve for the market clearing  $\theta$ ,  $\bar{N}$ , and  $\bar{L}$ . Further details of the solution algorithm are in Section 2.9.1.

### 2.5.5 Calibration

A model period is calibrated to be one month in length. There are several parameters that are set externally before determining other parameters. I set  $\beta = .996$  corresponding to an annual interest rate of 5%. The curvature of the production function,  $\alpha$ , is set at .59 to target a labor share of about two thirds. Average productivity is normalized to one in steady state. The elasticity of the matching function,  $\phi$ , is set to .6 following Petrongolo and Pissarides (2001) and the bargaining parameter,  $\eta$  is set to .4, which is in the range used in the literature. I now turn to the calibration of the other parameters of the model. The calibration strategy of the standard parameters borrows from Elsby and Michaels (2011). Table 2.9 contains a full list of the calibrated parameters, their meaning, and the moment they target.

Fourteen parameters remain to be calibrated:  $\mathbb{L}$ , the size of the labor force;  $\sigma^x$  and  $\rho_x$ , the parameters of the idiosyncratic shock process;  $\sigma^p$ ,  $\rho_p$ , the parameters of the aggregate shocks process;  $b$ , the flow value of unemployment;  $c$ , the flow cost of vacancy posting;  $\mu$ , the level of matching

efficiency;  $\delta$ , the depreciation of layoffs;  $\underline{\tau}$ ,  $\bar{\tau}$ , the minimum and maximum tax rates;  $\underline{\ell}$ ,  $\bar{\ell}$ , the tax schedule thresholds;  $MTC$ , the marginal tax cost.

The job finding rate for the United States is targeted at 45% per month on average (Shimer (2005)). In addition, I follow Pissarides (2007) and target labor market tightness in steady state at .72. These two targets pin down matching efficiency,  $\mu$ , according to the following relationship

$$f = \mu\theta^{1-\phi} \Rightarrow \mu = \frac{.45}{.72^{1-.6}} = .5132.$$

Firms take aggregate labor market tightness,  $\theta$ , as given when determining optimal labor demand. In order to set steady state tightness at .72, I fix the labor force so that aggregate hiring implies a labor market tightness of .72. In other words, I set  $\mathbb{L}$  according to the following steady state relationship

$$H = (\mathbb{L} - \bar{N})f \Rightarrow \mathbb{L} = \frac{H}{f} + \bar{N} \Rightarrow \mathbb{L} = \frac{H}{m\theta^{1-\phi}} + \bar{N}.$$

The shock process for idiosyncratic productivity consists of two parameters: the standard deviation of innovations to  $\ln(x)$ ,  $\sigma^x$ , and the persistence of  $\ln(x)$ ,  $\rho^x$ . In order to pin these parameters down, I target two moments from the QCEW data. First, the persistence of shocks, conditional on other parameters, will determine the extent of employment changes in equilibrium. If shocks are long-lived, firms will adjust less frequently. I follow Elsy and Michaels (2011) and target the fraction of employment adjustments that are less than 5% at a quarterly frequency. In the QCEW, this moment is 54.5% at a quarterly frequency.

The standard deviation of innovations controls the degree of job creation and job destruction in the model. The intuition for this is that the higher the standard deviation of shocks, the larger is the fraction of workers that are shed and hired in steady state. In the QCEW, the job reallocation rate, the sum of job creation and job destruction, is 12.5% per quarter. Therefore, I target the model job reallocation rate to pin down  $\sigma^x$ .

For a given set of parameters, further, the reservation productivity for shedding workers is

decreasing in the value of leisure,  $b$ , due to the wage bargain. Therefore, a higher  $b$  will lead to a higher separation rate. I target a monthly separation rate of 3.12%. Along with a finding rate of 45%, this implies a steady state unemployment rate of 6.48%.

The flow cost of posting a vacancy imposes a hiring cost on the firm to the extent that each vacancy takes time to be filled. I target an estimate of hiring costs in Silva and Toledo (2005). They find that hiring costs are roughly 14% of average quarterly wages. Hiring costs in the model are given by  $\frac{c}{q(\theta)}$ , so I choose  $c$  to make this hiring cost 14% of quarterly wages.

I target the persistence of average labor productivity of  $\rho^p = .983$  to coincide with a persistence of output per hour of about .95 quarterly. In addition, I choose the standard deviation of aggregate productivity shocks of  $\sigma^p = .005$  to generate a standard deviation of average labor productivity at roughly 2%.

### UI finance calibration and calculation of MTC

I now turn to calibration of the UI experience rating tax system. Recall that the marginal tax cost is the present discounted value of a dollar in benefits paid back in taxes. The marginal tax cost is calculated in the data for a firm always on the sloped portion of the schedule. I calculate the analogous measure in the model. Consider exogenously increasing a firm's layoff stock by one. This laid off worker receives unemployment benefits,  $b$ , for each period he is unemployed. In expectation, therefore, he receives  $\frac{b}{1-\beta(1-f)}$  in present discounted value of unemployment benefits. On the other hand, the firm pays increased taxes of  $\tau_c w n$  for this worker with a depreciation rate of  $(1 - \delta)$  each period. Therefore, the proportion of increased taxes paid back by the firm is the analogue to the empirical marginal tax cost. It is given by

$$MTC = \zeta \frac{\tau_c \bar{w} n}{b},$$

where  $\zeta = \frac{1-\beta(1-f)}{1-\beta(1-\delta)}$ .<sup>36</sup> In this formula, the average wage bill,  $\bar{w} n$  is from the simulation for firms on the sloped schedule. From this equation, it is clear that the marginal tax cost is proportional

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<sup>36</sup> $\chi = 1$  in the model.

to slope of the tax schedule, as it is in the data. In addition,  $\delta$  helps determine the steady state distribution of firms across UI tax rates. In turn,  $\underline{\ell}$  and  $\bar{\ell}$  determines the slope of the tax schedule, given minimum and maximum tax rates.

I set the minimum and maximum statutory rates as the average minimum and maximum rates across states in 2010 (weighted by employment). This implies values of  $\underline{\tau} = .042\%$  and  $\bar{\tau} = 8.44\%$ . It is important to discuss these tax rates in more detail. As discussed above, firms pay these payroll taxes only a capped portion of payroll, ranging between \$7,000 and \$37,000. I abstract from the capped payroll in the model for simplicity. Using a tax rate proportional to total payroll is another potential calibration strategy. Since I target a marginal tax cost to the data, the level of the tax rates should not affect the quantitative results given an appropriately re-calibrated marginal tax cost.

All things equal, the parameter  $\delta$  helps to pin down the distribution of firms across tax rates. Across states in 2010, an average of 17.7% and 6.7% of firms paid the minimum and maximum tax rates, respectively (again using the employment-weighted average). I choose  $\delta$  to mimic this distribution of tax rates.

## Model outcomes

The target moments along with their calibrated outcomes are listed in Table 2.10. Overall, the model moments are relatively close to their targets. In the worst case, I undershoot the fraction of employment changes that are small as well as the average quarterly job flow rate. In particular, the fraction of adjustments less than 5% is only 45% in the model as opposed to 54% in the data. In addition, the equilibrium job reallocation rate is 7.05% which is substantially lower than 12.5% in the QCEW data. The reason for the low model moments for each is that increasing the standard deviation of the idiosyncratic productivity reduces the fraction of small adjustments. In order to more accurately capture the cross-sectional distribution of employment growth, a richer model of persistent differences across firms is likely necessary.<sup>37</sup>

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<sup>37</sup>Elsby and Michaels (2011), for instance, consider the Pareto distribution for idiosyncratic shocks and include persistent firm fixed effects to better match the cross-section of firms.



In addition, the separation rate in steady state is slightly higher than the targeted rate at 3.5% vs. 3.1%. This implies a steady state unemployment rate of 7.27% vs. a target of 6.5%. Hiring costs as a fraction of quarterly wages is near its target at 14.7%. The simulated process for average labor productivity is slightly less persistent (.94) and slightly less volatile (.0172).<sup>38</sup> The distribution of firms across taxes is very close to the data, as shown in Figure 2.8. Roughly 17.43% (compared to 17.7% in the data) of firms are subject to the minimum rate while 6.76% (compared to 6.6%) are subject to the maximum rate.

## 2.6 Experience Rating Experiments

### 2.6.1 Steady State Comparative Statics

In this section, I show comparative statics from changes to the marginal tax cost. These results shed light on the effect of different possible sources of increasing experience rating. The previous literature which treated experience rating as a simple linear firing cost could not address these experiments. The reason for this is two-fold. First, modeling the institution as a linear firing cost ignores the fundamental fact that firms must pay a payroll tax. Any level increase in payroll taxes reduces labor demand and therefore potentially offset the benefits of a higher layoff cost. Second, the simple linear firing cost ignores important firm heterogeneity across the tax schedule. This is important to accurately measure the revenue effects of tax changes. Suppose that all firms were at the minimum rate. Then increasing the maximum tax rate would have very little, if any, effect on tax revenues while still possibly changing layoff incentives.

The marginal tax cost in the model is calculated as in the data: it is the fraction of benefits paid back in taxes. Recall that in the model and the data, the marginal tax cost is proportional to the slope of the tax schedule. In the model, that implies the following relationship to the parameters of the tax schedule

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<sup>38</sup>Due to the computational intensity of solving the approximate equilibrium, converging on the precise process for average labor productivity in simulated data is impractical.

$$MTC \propto \tau_c \equiv \underbrace{\left( \frac{\bar{\tau} - \underline{\tau}}{\bar{\ell} - \underline{\ell}} \right)}_{\text{slope}}.$$

Different possible changes to the slope are shown in Figure 2.9—they include an increase in the lower threshold,  $\underline{\ell}$ ; a decrease in the minimum tax rate,  $\underline{\tau}$ ; a decrease in the upper threshold,  $\bar{\ell}$ ; or an increase in the maximum tax rate,  $\bar{\tau}$ . The experiments are run as follows. I adjust each parameter so as to increase the marginal tax cost by 5%. I then find the new equilibrium steady state (i.e., the equilibrium tightness) with the higher marginal tax cost. The results are shown in Table 2.11.

For each of the changes to the slope of the tax schedule, job creation and job destruction fall, with magnitudes quantitatively similar to the empirical results. Job creation and job destruction rates fall between 1.1% to 1.9% due to a 5% increase in MTC in the model. To compare, Table 2.2 shows that a 5% increase in MTC decreases job creation by 1.5% and job destruction about 2% in the baseline specification.<sup>39</sup> The effect on the unemployment rate is also negative in each of these specifications, but the magnitude depends on the relative effect on the change in tax revenues.<sup>40</sup>

The reason that unemployment falls between 1.8% and 4.5% is due to the associated change in the tax burden on firms. For experiments in which the average tax burden on firms rises, overall labor demand falls, mitigating the effect of lower job destruction. Overall, unemployment still falls for each of this experiment regardless of the change in tax receipts. Larger decreases in unemployment are consistent, however, with reducing taxes. Moving the upper threshold to the left or increasing the maximum tax rate *increases* the tax rate on many firms. For instance, moving the lower threshold to the right or the minimum tax down *reduces* the tax revenue by 8.6% in each case. On the other hand, decreasing the upper threshold or raising the maximum rate actually increases revenue by 2.3%.

Increasing taxes while reducing unemployment might appear at first to constitute a Pareto improvement. In column 6 of Table 2.11, however, I find that the average enterprise value of firms falls in experiments in which taxes are increased. I calculate this comparative static by taking the

<sup>39</sup>These calculations are done by multiplying the coefficient on JD (-2.4) by .05 and dividing by 6.48, for instance.

<sup>40</sup>The job finding rate increases by small percentages in the second and fourth columns (.8% and 1.2% respectively, not shown). In the first and third row, the job finding rate increases by 3.6% and 5.3%.

average of the firm's value function in equation 2.17.<sup>41</sup> Row four is the experiment that decreases unemployment the most while still raising tax revenue. In this case, profits fall by about .4%. In the case that both taxes fall and unemployment falls by the most (three tenths of a percent, row 3), profits increase by about .07%. Therefore, there is an offsetting effect of lower firm profits when tax revenues are increased.

Given that the unemployment rate falls in both experiments in which tax revenue is increased, it is possible to alter experience rating in a revenue neutral fashion and still decrease unemployment. As an example, I conduct the following experiment. I start from the experiment of raising the maximum tax rate in the fourth row of Table 2.11. In that experiment, I increased  $\bar{\tau}$  by .4 percentage points to raise the marginal tax cost by 5%, which raised tax revenues by 2.3% in the new steady state. In this experiment, I then iteratively lower the minimum tax rate to achieve revenue neutrality in steady state. This will further increase the slope of the tax schedule and therefore slightly increase the marginal tax cost.

In order to remain revenue neutral in steady state, the lower tax rate must fall by 10% (or .04 percentage points) as shown in Table 2.12. The marginal tax cost in the revenue neutral experiments is ultimately 56.7%, a 5.5% increase. In this new equilibrium, job creation and job destruction fall by 1.6% and the unemployment rate is 7.06%, down from 7.27% in the calibrated model, a drop of 2.9%. The fraction of firms at the minimum tax rate increases by 2.8% due to the higher slope and lower tax rate. More importantly, the fraction of firms at the maximum tax rate falls by almost 6% due to the higher tax rate firms face for high layoff histories. While tax revenues remain constant, average firm value falls by .2%, which is less than it fell in the revenue enhancing experiments of Table 2.11. Of course, firm profit falls because they are made to internalize a larger share of the cost of unemployment benefits through a higher marginal tax cost.

Finally, it is worth noting that these experiments highlight the necessity of modeling the cross-sectional distribution of firms across tax rates. The large differences in tax revenue from equal changes to the measured marginal tax cost is an important aspect of evaluating the efficacy of

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<sup>41</sup>The results are quantitatively similar by comparing flow profits.

proposals to increase experience rating.

### **Implications for UI Financing**

Net UI reserves as a fraction of payroll stood around -.5% at the end of 2011, making it the third consecutive year of negative reserves and the longest streak of negative reserves since at least the 1960's. Vroman (2012) notes that UI reserves as a fraction of payrolls were particularly hard hit during the Great Recession due to the lowest run-up of reserves in the expansion prior to the 2007 recession. Vroman (2012) recommends all states index the cap to taxable payroll to wage growth at the state level, as is currently done in sixteen states.

The results of the previous section show that different changes to the UI tax schedule imply differing effects on tax revenues and the labor market. These experiments naturally have important policy implications for reforming UI trust fund financing, a topic that is currently on the legislative agenda at both the national and state levels. While indexation is a very important channel for UI financing reform, this chapter has abstracted from the taxable cap on wages and has focused on the shape of the tax schedule and the experience rating formula in determining UI financing.

Apart from changing the wage base, changes to the tax schedule are being considered by many states in order to ensure more adequate UI financing in the future. Some states, such as New York and New Jersey have considered levying flat rate fees on all employers—equivalent to raising both the minimum and maximum tax rates in my model. States have not considered increasing the degree of experience rating on high-rated employers, however. Alan Krueger has proposed increasing the degree of experience rating, saying

Experience rating is the practice of charging a higher UI contribution rate from employers with a worse history of laying off workers...Unfortunately, the degree of experience rating has severely lapsed. Improved experience rating would discourage employers from laying off workers, and help to internalize the externalities layoffs impose on society. Krueger (2008)

In this section, I study two different methods for shoring-up UI financing to close half of the net

reserve deficit (an increase of revenue equivalent to .25% of payroll). This amounts to an increase of 9.1% of revenue in the baseline, calibrated model. I will compare the labor market effects of a level shift to the tax schedule versus an revenue-equivalent increase in the slope of the tax schedule by shifting  $\bar{\ell}$  to the left. The level shift of the tax schedule is of the type being considered in many states, either as an increase in the tax rates or as flat levies on all firms. The increase in the maximum tax rate constitutes a concurrent increase in experience rating on the highest layoff firms.

In order to raise revenue by 9.1% in a level-shift of the tax schedule, the intercept of the schedule needs to be increased by .2 percentage points, making the minimum tax rate .617% and the maximum rate 8.64%. In the second experiment, I reduce the upper threshold,  $\bar{\ell}$  by 12.4%. Table 2.13 shows the new labor market outcomes under these two experiments.

In the first row, under the experiment in which the tax schedule is raised uniformly, the labor market is negatively affected: unemployment increases by about a tenth of a percentage point in order to raise revenue 9.1%. Under the experiment in which the slope is increased, the marginal tax cost increases by 19%. In this experiment, states would raise revenue by 9.1% again while actually improving labor market conditions in steady state by reducing unemployment by .13 percentage points.

While the previous experiments were two examples of equal revenue-enhancing policy changes, they are not “reserve equivalent.” The first experiment increases unemployment, thereby increasing payments of unemployment benefits by 1.5%. The net change in reserves is therefore 7.6% while in the second experiment, the net change in reserves is 10.9%.<sup>42 43</sup>

## 2.6.2 Aggregate Dynamics

The previous section showed the steady state effects of a change in experience rating. In this section, I analyze the dynamics of the labor market in response to aggregate shocks. Due to experience-rated taxes, firms are reluctant to lay off workers and face higher tax rates. The layoff cost therefore

<sup>42</sup>Unemployment benefits simply equal  $u \times b$  so the percentage increase (decrease) in benefits is just the percentage increase (decrease) in the unemployment rate given in the last column. Therefore, the change in reserve is just the change in revenues (column 5) minus column 8.

<sup>43</sup>The same is true, of course, of the revenue neutral experiment in Table 2.12. Unemployment rolls fall by 2.9% while revenue is constant, leading to a 2.9% improvement in the reserve position.

dampens the response of the labor market to aggregate shocks. Due to accumulated layoffs and the resulting higher tax burden, the model also exhibits non-linearities and asymmetries in the unemployment response to aggregate shocks.

I now turn to understanding the effect of experience rating on the labor market after an aggregate productivity shock. I construct impulse responses to a decline in aggregate productivity under different tax schedules. For each tax experiment, I re-solve the approximate aggregate equilibrium forecast equations. I then simulate the path of endogenous variables following a temporary 1% decline in aggregate productivity.

In Figure 2.10, I plot the impulse responses of productivity, unemployment, the separation rate, and the finding rate for two different marginal tax costs, 51% and 56.7% (5% above and below the baseline of 54%). Examining the dashed lines first, in response to a 1% aggregate shock, the unemployment rate increases on impact and peaks after two quarters, increasing to about 11% above its steady state.<sup>44</sup>

The increase in unemployment is driven by a spike in separations on impact. This is shown in the bottom left panel of Figure 2.10. Here we see that the separation rate increases by just over 10% on impact but declines quickly, as is standard in endogenous separation models. In addition, the job finding rate falls as workers exit to unemployment and vacancy posting falls. The job finding rate falls by just over 6% and also takes two quarters to reach its nadir. In contrast to similar models without experience rating, the job finding rate (and labor market tightness) does not peak on impact. This is seen in the fact that the job finding rate reaches its trough in the second quarter after the shock. The inclusion of experience rating appears to add modest propagation of shocks since it takes time for firms to recover from the higher tax rates.

Comparing the impulse responses under the two marginal tax costs shows that a higher marginal tax cost reduces the amplitude of recessions. The higher marginal tax cost impulse responses are depicted by the solid lines. Instead of unemployment increasing by 11%, unemployment increases by 6.8% less, a difference of about .045 percentage points. In addition, the separation rate increases

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<sup>44</sup>It is worth noting that the impulse response of unemployment is similar in magnitude to a 1% drop in productivity as those shown in similar models such as Fujita and Nakajima (2009).

by 7.8% more and the job finding rate falls by 3.3% more under lower experience rating. The results in this section show that experience rating can in fact tend to stabilize employment by reducing separations and mitigating the effect of recessions on unemployment.

Since the layoff cost in UI financing is on the *stock* of accumulated layoffs, it is possible that this system induces non-linearities in the response of the labor market to larger shocks. In order to examine this further, I show the impulse response of unemployment to a two and three percent negative shock to productivity. I plot the impulse responses keeping the marginal tax cost constant at 56.7% from the previous experiment (solid blue lines). In order to make the one, two, and three percent shock responses comparable, I halve and third the responses to the two and three percent shocks given by red-dashed line and black line with circles shown in Figure 2.11. From this figure, we can see that there is more non-linearity in the impulse responses than is typically found in similar models such as Fujita and Nakajima (2009). Since firms have accumulated a larger stock of layoffs, unemployment does not decline as quickly from the larger shock; the largest difference between these two responses is, in fact, in the 6th quarter after the shock. Because firms are still coping with higher taxes from the recession-induced shock to layoffs, the path of recovery of unemployment is relatively slower. Comparing the two and three percent shocks, the model also generates additional propagation in response to larger shocks—the unemployment rate only peaks after the third quarter in response to the three percent shock whereas the peak was at two quarters in response to the smaller shocks.

In addition to non-linearities, experience rating introduces important asymmetries between positive and negative shocks. First, comparing the solid lines in Figures 2.10 and 2.12, it is clear that the impulse response to the negative shock induces a much larger recession than the positive shock causes a boom. This is due mostly to the asymmetric affect on the separation rate which rises by 10% from a negative shock but only falls by 4.5% after a positive shock. There is also asymmetry in the effect of experience rating. In Figure 2.10, the finding rates react similarly regardless of the marginal tax cost. In response to the boom, higher experience rating has a substantial effect on the finding rate behavior. The higher marginal tax cost causes the finding rate to rise by almost

10% less (.3 percentage points) and stays about 15% lower for twelve quarters relative to the lower marginal tax cost economy. The strong effect on the finding rate in the higher marginal tax cost example is due to the fact that firms anticipate that the boom times are temporary. If they hire a lot of workers but subsequently must lay them off as shock dissipates, they will owe a substantial fraction in increased UI taxes. Therefore, higher experience rating dampens the effects of a positive shock when firms expect to lay off workers as the boom fades.

Moreover, the experience rating system does not induce the same type of non-linear response of unemployment to positive shocks. In Figure 2.13, I plot the impulse response of unemployment to positive one, two, and three percent positive shocks, and scale the impulse responses accordingly (as in Figure 2.11). Here, we do not see the same type of proportionally larger responses to larger shocks. While the two and three percent impulse responses are somewhat larger than the one percent, the two and three percent lines lie one top of each other. This is due to the fact that in response to booms, layoffs fall and there is no added effect of large stock of layoffs raising taxes concurrently with the business cycle.

### 2.6.3 Endogenous Depreciation of Layoffs

Up until this point, the depreciation rate of layoffs has been assumed to be a constant. Recall that layoffs depreciate for two reasons: (1) due to statutory limits on the duration of time that benefits are counted on a firm's books and (2) because laid off workers find other jobs. This suggests, therefore, that the rate of depreciation of layoffs should be a function of the exit rate from unemployment,  $\delta \equiv \delta(f(\theta))$ . Data on this variation, however, is unavailable. I make the assumption that the depreciation rate differs from its baseline steady state level in proportion to the deviation of the job finding rate from the calibrated steady state value of .45. The equation for the log depreciation rate is therefore

$$\ln(\delta_t) = \ln(\bar{\delta}) + \kappa_\delta [\ln(f_t) - \ln(\bar{f})], \quad (2.36)$$

where  $\kappa_\delta \in [0, 1]$ .

In this section, I conduct the same tax experiments allowing for varying depreciation of layoffs.



Note that this captures the important features of a varying depreciation rate: when the finding rate is higher than normal, laid off workers find jobs at a quicker rate and therefore remain on the firm's book for less time, implying a higher depreciation rate. For the purposes of this section, I show results setting  $\kappa_\delta = 25\%$  to demonstrate that the qualitative results of the previous section are bolstered when allowing endogenous depreciation.<sup>45</sup>

The depreciation rate varies both in the steady state experiments of Table 2.11 as well as over the course of the business cycle. In the steady state experiments, allowing the depreciation rate to vary with the finding rate amplifies the effect of each of the experiments on the unemployment rate. The reason for this is that in each experiment, the finding rate rises and therefore the depreciation rate increases. This in turn shifts the distribution of layoffs in equilibrium to lower tax rates and reduces total tax revenues collected.

Table 2.14 shows the results from each of the four experiments with endogenous depreciation. In each of the four experiments, the drop in the unemployment rate is amplified due to fall in the depreciation rate as the distribution of layoffs shifts to lower tax rates in the new steady state. Job flows fall between three-tenths of a point and 1.1 points more with varying depreciation. Unemployment now falls between .2 points up to almost .6 points from .13 and .33 with a fixed depreciation, respectively.

The reason for these larger effects is the reduction in revenues can be large. In the first and third rows, the drop of 8.6% in revenues is amplified to about an 18% drop with varying depreciation. In the second row, the change in revenue remains almost the same since the increase in the depreciation rate is small (1.5%). Figure 2.14 plots the cross-sectional distribution of layoffs under the low  $\tau$  experiment, fixing  $\delta$  and allowing  $\delta$  to vary with the finding rate. Here, we can see a substantial increase in the mass at the lower tax rate. This shift of mass to the lower tax rate accounts for the large drop in revenues in rows 1 and 3 of Table 2.14. From a policy perspective, the loss in revenue from the endogenous depreciation of layoffs can be counteracted by extending the amount of time

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<sup>45</sup>One reason that I did not choose  $\kappa_\delta$  is that the grid used in numerical simulations with fixed depreciation are not well suited when  $\delta$  can vary widely. In addition, some states restrict the degree to which your tax burden can rise or fall over the business cycle, potentially mitigating the effect of the finding rate on the firm's stock of benefits on which it owes taxes.

that benefits are charged to the firm. In essence, the experiments in Table 2.11 assumed that the state re-adjusts the depreciation rate back to 2.6%.

As the finding rate varies over the business cycle, the rate at which previous layoffs find new jobs varies substantially. In this case, during a recession when the finding rate falls, a firm's stock of layoffs should be expected to remain higher for longer. Endogenous depreciation, therefore, can reduce the firm's incentive to lay off workers in response to a negative shock. In order to examine this effect of the experience rating system, I solve a version of the model in which the depreciation rate varies according to equation 2.36. Since the endogenous depreciation rate is determined by the finding rate, and in turn, labor market tightness, I do not need to add a forecast equation to the Krusell & Smith algorithm. Forecasting tightness is sufficient for the firm to forecast deviations in depreciation.<sup>46</sup> I then plot impulse responses to a 1% negative aggregate productivity shock.

In Figure 2.15, I compare three different impulse responses: (1) under high experience rating and fixed depreciation (crossed green line), (2) under high experience rating and varying depreciation (solid blue line), and (3) under low experience rating and varying depreciation (dashed red line). The crossed green line is identical to the solid blue line in Figure 2.10. The bottom left panel plots the response of the depreciation rate—the green line remains as the steady state while the depreciation rate falls with the finding rate in the other two economies.

Figure 2.15 shows that varying depreciation also amplifies the effect of experience rating over the business cycle. First, consider the difference in the blue line with the marginal tax cost of 56.7% and varying depreciation and the green line with the  $MTC = 56.7\%$  and fixed depreciation. We can see that unemployment rate spikes by less under varying depreciation since the separation rate (middle left panel) spikes by less.

In addition, the unemployment impulse response exhibits additional propagation in two ways. First, it takes unemployment in the economy with varying depreciation three quarters as opposed to two to peak from the shock. Then the shock dissipates more slowly—the green line catches up to the blue line at around 11 quarters. The reason for this is the faster depreciation of layoffs and

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<sup>46</sup>The goodness of fit of the Krusell & Smith regressions with varying depreciation is quantitatively similar to those in the baseline solution.

thus lower taxes after the shock fades away. In the middle right panel, we can see that the layoff stock without varying depreciation is substantially lower than with varying depreciation, *even though* there was a larger bout of job destruction.

## 2.7 Related Literature

Brechling (1975) and Feldstein (1976) were two of the earliest examinations of the theoretical implications of experience rating. Feldstein (1976) found that imperfect experience rating accounted for a large portion of temporary layoffs and the resulting unemployment from an economic downturn. In a series of seminal papers, Topel (1983, 1984) first studied the empirical effects of imperfect experience rating. Exploiting state variation in the marginal tax cost, Topel found that firms only pay around 75% of benefits charged. Using Current Population Survey (CPS) data along with state UI tax schedules, he shows that layoffs could be reduced by 20% with perfect experience rating. Card and Levine (1994) also study the effect of higher marginal tax costs on layoff rates. They find that full experience rating would reduce layoffs at a higher rate in recessionary periods.

Anderson and Meyer (1993) and Anderson and Meyer (2000) study the effect of experience rating in the context of a linear layoff cost model. Anderson and Meyer (1993) is one of the only papers to use micro-level data to study the effect of experience rating. Anderson finds that the presence of the linear adjustment cost due to experience rating decreases the response of employment changes to seasonal variation—the labor market is less volatile because of the experience rating. In addition, she finds that the level of employment is slightly higher on average. In fact, moving to perfect experience rating would increase employment by 4.3% over the seasonal cycle.

The general equilibrium effects of layoff costs on employment depend crucially on the structure of the labor market, as shown by Ljungqvist (2002). Albrecht and Vroman (1999) further show in an efficiency wage model, experience rating reduces unemployment relative to a model with privately financed unemployment insurance. On the other hand, Hopenhayn and Rogerson (1993) find that linear layoff costs reduce employment, although their model abstracts from search frictions and instead considers employment determined by lotteries. In the context of search models, Millard and

Mortensen (1996) show that layoff costs unambiguously reduce both job creation and job destruction but the overall effect on employment is ambiguous depending on which effect dominates. Lower unemployment in search and matching models with endogenous job destruction is driven by reduced job reallocation externalities at the cost of a potentially less efficient allocation of labor.

This chapter finds that higher layoff costs reduces unemployment. In a labor market without search frictions, such as in Hopenhayn and Rogerson (1993), there is no externality caused by layoffs. Lower employment is generated by workers substituting towards leisure since the private gain from employment is reduced due to lower wages. In search models, the search externalities arise since each layoff clogs the market for all searchers through lower finding and filling rates. Therefore, it can be the case that in equilibrium, layoff costs reduce the rate of reallocation in the labor market and therefore reduce the unemployment rate.

Several additional papers explore experience rating in the context of search models. First, l'Haridon and Malherbet (2009) study UI finance in a standard job search model. The firing cost from experience rating, unlike in this chapter, is exogenously determined. They also find that higher experience rating reduces the unemployment rate. In more recent theoretical work, Albertini (2011) studies the reserve ratio experience rating system in a search model. Albertini (2011) is the only other paper to tie the firm's tax rate to its experience. Similarly, he finds that higher experience rating reduces the amplitude of recessions. This chapter, however, does not model heterogeneity in firms and instead uses a representative agent framework. The model, therefore, is less suited to study the tax incidence from changes in experience rating as a richer model with heterogeneity allows.

## 2.8 Conclusion

The United States finances unemployment insurance by imposing a tax schedule that penalizes firms for layoffs with higher tax rates. In this chapter, I study the labor market effects of experience rating empirically and theoretically. I show that a model of labor demand under experience-rated taxes predicts that both the rates of job creation and job destruction fall with higher experience

rating. The intuition for this is that firms face a positive marginal cost of a layoff and therefore have an incentive to minimize layoffs. Because of the possibility of laying off a newly-hired worker, experience rating can also act as a hiring deterrent.

This chapter is the first to examine the relationship between experience rating and job flows. I confirm the model prediction using firm-level data from the Quarterly Census of Employment and Wages. I find robust evidence that higher experience rating reduces job destruction and job creation, leading to a decrease in total job reallocation in the labor market. In the baseline specification, I find that going from average marginal tax cost to 100% marginal tax cost would reduce job destruction by 17%, job creation by 13.7%, and job reallocation by about 10%.

I then embed the model of firm labor demand into a DSGE model with search unemployment. Using this model, I conduct steady state tax experiments. I find that higher experience rating reduces job flows as well as reduces unemployment. Quantitatively, the model predicts that job flows fall by roughly the same amount as is predicted by the empirical results. The relative effect on unemployment depends on the type of tax change. Those that reduce tax revenues have a larger effect on unemployment while those that raise revenues reduce unemployment by far less. In experiments that raise revenue, I also find that there is a small decrease in firm profits. Since state tax schedules are not set optimally, I also show that it is possible to increase experience rating while maintaining revenue neutrality and reducing unemployment.

Finally, I solve the model with aggregate uncertainty using the method of Krusell and Smith (1998). I find that the labor market response to an aggregate shock is dampened by higher experience rating as firms do not shed as many workers in response to the shock. Unemployment peaks by 6.8% less upon impact of the shock due to a smaller increase in separations. Since the layoff cost is a function of the accumulated stock of layoffs, experience rating introduces non-linear effects from larger shocks. It takes unemployment longer to recover from larger shocks since firms must shed the relatively larger overhang of accumulated layoffs. I also find that higher experience rating has an asymmetric effect on firms hiring behavior from a positive shock relative to a negative shock. Since firms expect the boom to be temporary, any current hires will have to be laid off as the economy

returns to steady state. Therefore, the job finding rate spikes substantially less from a positive shock relative to a negative one.

For the present study, the welfare analysis of these changes is not addressed. There are at least two caveats to inferring welfare gains from the results in this chapter. Since the model above abstracts from on-the-job search and heterogeneity in workers, there may be reasons that workers benefit from reallocation, such as finding better job matches. If this is the case, then it is not clear reducing job flows is welfare enhancing.

Moreover, I have assumed that the government does not impose distortionary taxes to fill any holes in UI financing. In practice, states and the federal government typically use general revenue funds to fill gaps in UI funding. If changing experience rating imposes an additional burden of distortionary taxes, the effects on the labor market and welfare may be different. However, this chapter suggest that states might alter tax schedules to help plug UI trust fund deficits without harming the economic recovery in the labor market.

## 2.9 Appendix

### 2.9.1 Numerical Algorithm

This section describes in detail the steps to solve the steady state and aggregate uncertainty versions of the model. I start by describing the solution to the steady state model.

I solve the firm’s problem by standard value function iteration on a discretized grid of its state variables. The firm’s state variables are  $n, \ell, x$ . I discretize the continuous choice variables  $n$  and  $\ell$  into  $E_p$  and  $L_p$  points, respectively. The firm’s optimal decision for employment, conditional on its states, determines  $\ell$ . I discretize  $\ell$  independently of  $n$ , however, and piecewise linearly interpolate the value function at points off the  $\ell$  grid. I restrict the firm to choose employment on the discretized grid. By virtue of choosing a fairly fine number of grid points (minimum of 75), this restriction does not substantially effect the firm’s policy functions. Robustness checks using polynomial interpolation off the employment grid yield similar results.

Idiosyncratic shocks are assumed to be log-normally distributed. I therefore discretize the space of idiosyncratic shocks using Tauchen’s method described in Carroll (2011).<sup>47</sup> Due to the highly non-linear nature of the policy function from experience rating, I use at least 11 equiprobable points in the grid.

I start with a guess of  $\Pi^j$ . At each iteration I evaluate the optimal choice conditional on not adjusting, hiring, or firing. I then take the max over those three possible choices as the updated guess for  $\Pi^{j+1}$ . If the maximum percentage deviation of  $\Pi^j$  and  $\Pi_{j+1}$  is less than a pre-specified tolerance, the value function has converged. I use the optimal choice at each grid point to define  $n^* = \Phi(n, \ell, x')$ , the policy function.

Armed with the policy function, I generate a simulated panel dataset of firms over  $T$  periods. I simulate the continuous log-AR(1) shock process and linearly interpolate the policy function to points off each grid. I ensure that during the simulation (after the system has settled into steady state) that each state variable remains on the grid so that no extrapolation procedure is needed. Extrapolating is subject to large approximation error as well as computational intensity. I restrict

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<sup>47</sup>I thank Ryan Michaels for the Matlab code to produce this discretization.

the points for  $x$  to remain on the grid. Due to the equiprobable choice of the grid, this happens with probability  $\frac{1}{N_x+1}$ . Experimentation with polynomial interpolation and linear interpolation in the logs (as opposed to levels) did not change the results substantially.

Calibration of the model is performed using a coarse grid search across the relevant state space and then a numerical minimization of the sum of squared residuals from the target moments. For this, I use the package *fminsearchbnd* which implements a simplex search method optimization routine. This method is often preferable to a gradient based method as it is more robust to discontinuities in the objective function.

Finally, I conduct the steady state tax schedule experiments as follows. A new steady state of the model consists of finding a fixed point in  $\theta$ —firms take the conjectured  $\theta$  as given and this must be consistent with the labor market tightness of the simulated panel of firms. To save time on solving the firm’s problem repeatedly, I solve the firm’s value function on an additional grid of  $\theta$ ’s including 25% above and 25% below the steady state values. For conjectured  $\theta$ ’s off the grid, I use linear interpolation on the policy functions. I then iterate on  $\theta$  until the aggregated micro behavior of a panel of firms generates the conjectured  $\theta$ , updating  $\theta$  using a convex combination of the conjecture and the simulated tightness with a relatively low damping parameter.

### Approximate Equilibrium Algorithm

The solution to the approximate aggregate equilibrium is as follows. As stated above, I conjecture log-linear equations of motion for the aggregate “states”:

$$\begin{aligned}\ln \bar{L}' &= \gamma_{l0} + \gamma_{l1} \ln \bar{L} + \gamma_{l2} \ln \bar{N} + \gamma_{l3} \ln p \\ \ln \bar{N}' &= \gamma_{N0} + \gamma_{N1} \ln \bar{L} + \gamma_{N2} \ln \bar{N} + \gamma_{N3} \ln p \\ \ln \theta' &= \gamma_{\theta0} + \gamma_{\theta1} \ln \bar{L}' + \gamma_{\theta2} \ln \bar{N}' + \gamma_{\theta3} \ln p'\end{aligned}$$

Again, the forecast equation for  $\theta$  is used by the firm to form expectations of hiring costs today



and in the future period. The task is to solve for the coefficients  $\{\gamma_L, \gamma_N, \gamma_\theta\}$ .

Implementing this procedure is computationally burdensome as it requires an additional four state variables for the firm's problem:  $p, \bar{N}, \bar{L}, \theta$ . It is important to discuss why  $\theta$  must be a state variable for the firm. In principle, firms know the aggregate state of the economy and can therefore predict  $\theta$  from  $\bar{N}, \bar{L}, p$ . However, forecast errors can lead to a situation in which the true market clearing level of  $\theta$  is different from the forecasted level. Therefore, I forecast  $\theta$  from the equation above but I solve the value function on a grid including 75% and 125% of that forecasted  $\theta(\bar{N}, \bar{L})$ . I use a coarse grid of 5 points in both  $\bar{N}$  and  $\bar{L}$  and three points for  $\theta$ .

While the forecast equations ultimately are very accurate, it is not enough to use the forecasted aggregate variables  $\bar{N}, \bar{L}, \theta$  as the equilibrium aggregate state at each stage of the simulation. Instead, in each period of the simulation, I iterate on  $\bar{N}, \bar{L}, \theta$ , using the firm's optimal policy for each guess of the aggregate state, until the micro behavior is consistent with the aggregate state.

In summary, the algorithm proceeds as follows:

1. Guess  $\Pi^0(n, \ell, x, p, \{\bar{N}, \bar{L}, \theta\}; \gamma^j)$  and  $\gamma^j$
2. Solve for the value function,  $\Pi^j$ , and associated policy function,  $\Phi^j$
3. Simulate the model for 2,000 periods and 10,000 agents per period starting each firm at the steady state level of the idiosyncratic states. I discard the first 200 periods.
4. In each period,  $t$ , of the simulation, solve for the market clearing aggregate state. I start with last period's aggregate state as a guess. I iterate on  $\{\bar{N}, \bar{L}, \theta\}$  until the aggregate micro behavior is consistent with the guessed state.
5. Run OLS regressions to obtain simulated  $\gamma_{\text{OLS}}$  coefficients. If the difference between the  $\gamma^j$  and  $\gamma_{\text{OLS}}$  is smaller than a pre-specified tolerance, stop.
6. Otherwise, set the conjecture for  $\gamma^{j+1} = \lambda \gamma^j + (1 - \lambda) \gamma_{\text{OLS}}$ ,  $\lambda \in (0, 1)$  and start at 1.

For the calibrated parameters, the equilibrium forecast equations are as follows:

$$\ln \bar{L}' = .0062 + .9724 \ln \bar{L} + .0167 \ln \bar{N} - .0823 \ln p, R^2 = .997 \quad (2.37)$$

$$\ln \bar{N}' = -.0315 + .0118 \ln \bar{L} + .8692 \ln \bar{N} + .1303 \ln p, R^2 = .971 \quad (2.38)$$

$$\ln \theta' = 3.2596 + .6804 \ln \bar{L}' + 15.4623 \ln \bar{N}' + 8.6422 \ln p', R^2 = .988 \quad (2.39)$$

The  $R^2$  for this solution are similar to those in Bils et al. (2011). It is worth mentioning that since I use a simple stochastic simulation with only 10,000 agents and 2,000 periods, the  $R^2$  are low due to simulation error. Increasing the size of the panel and the length of the panel would increase the  $R^2$  but with the loss of a large increase in computational time. I simulate aggregate data and impulse responses using the optimal decision policy of the firm as solved above.

### Larger Stochastic Simulations

For the baseline results, I used a stochastic simulation size of 10,000 firms over 2,000 periods, discarding the first 200 observations for a burn-in period. Here, I show the results of solution to the baseline model with a larger panel of firms. I expand the number of firms from 10,000 to 30,000 while keeping the number of periods constant. The  $R^2$  from these regressions are as follows. From the regression for  $\ln L'$  it is .9973, for  $\ln N'$  it is .9738, and for  $\ln \theta'$  it is .9928. Just adding additional firms to the simulation increases the goodness of fit in each regression. Additional agents would further increase the precision, but the results are quantitatively similar.

#### 2.9.2 Firm's Problem with Recall

In this section, I generalize the model to allow firms to rehire some of its laid off workers. I assume that laid off workers are recalled without the flow cost  $c$ . To maintain hiring from both the general pool of unemployed and the temporarily laid off, I assume that if a firm wanted to hire  $h$  workers, it may hire up to the proportion  $p^T$  from its stock of lay offs. I assume for simplicity that firms still post "vacancies" for each recall and meets those vacancies with rate  $q$ . Of those hired from outside its layoff pool, the firm posts a vacancy,  $v_r$  at a flow cost  $c$ . This allows me define the

finding and queueing rates in the same manner as above.

The equations of motion and costs of hiring will depend on the size of the stock of layoffs relative to the desired level of hiring. I now describe these in more detail. Suppose that the firm considers hiring  $\mathbb{1}^+\Delta n$  workers. If the fraction it will recall from  $\ell$  is less than its stock available for recall, i.e.  $p_T\mathbb{1}^+\Delta n < \ell_{-1}(1 - \delta)$ , then

$$(1 - p^T)\mathbb{1}^+\Delta n = qv_r \rightarrow v_r = (1 - p^T)\frac{\mathbb{1}^+\Delta n}{q}.$$

On the other hand, suppose that it wants to hire so many workers such that it depletes its stock of layoffs. Then,  $p_T\mathbb{1}^+\Delta n \geq \ell_{-1}(1 - \delta)$  and

$$\mathbb{1}^+\Delta n = \ell_{-1}(1 - \delta) + qv_r \rightarrow v_r = \frac{\mathbb{1}^+\Delta n - \ell_{-1}(1 - \delta)}{q}.$$

Notice that if  $p_T = 0$ , the first condition— $p_T\mathbb{1}^+\Delta n \leq \ell_{-1}(1 - \delta)$ —always holds and  $v = \frac{\mathbb{1}^+\Delta n}{q}$ , as in the standard model. We can now state the general equations of motion for the stock of layoffs for a firm

$$\ell = (1 - \delta)\ell_{-1} - \underbrace{\mathbb{1}^-\Delta n}_{\text{layoffs}} - \underbrace{\min\{\mathbb{1}^+\Delta n p_T, (1 - \delta)\ell_{-1}\}}_{\text{recalls}}, \quad \ell \geq 0.$$

Note that total vacancies are  $v_r$  plus the amount of recalls because of my assumption that each hire must be associated with a vacancy.

$$v = v_r + p^T\mathbb{1}^+\Delta n.$$

The addition of recalls reduces the cost of laying off a worker since you can rehire that worker without cost in the future. Consider the case where  $p^T = 1$ . In this case, firms can costlessly rehire from its stock of layoffs up to the point that it depletes its entire stock. Assuming a large enough stock, this reduces the firm's problem to the frictionless one. To see this, the equation of motion for  $\ell$  becomes

$$\ell = (1 - \delta)\ell_{-1} - \mathbb{1}^-\Delta n - \mathbb{1}^+\Delta n \rightarrow \ell = (1 - \delta)\ell_{-1} - \Delta n.$$

In this case, there is no kink in the adjustment cost. At the point at which the firm recalls all of its workers, the marginal hire will cost  $c$  per vacancy and thus the firm behaves as in the standard linear hiring cost model. For  $p^T < 1$ , there remains a linear layoff cost, but its magnitude falls with  $p^T$ . The band of inaction shown in the policy functions in Figures 2.4 and 2.5 will correspondingly shrink with  $p^T$ .

I take the calibrated model of Section 2.5 and allow the firm to rehire up to 10% of its hires from its layoffs.<sup>48</sup> The steady state effects are as expected: the fraction of firms at both the low and high tax rates are higher. At the low tax rate, the mass increases from 17.43% to 18.27% and the low tax rate the perfect of firms changes from 6.76% to 7.75%. This is because firms are more likely to hold higher layoff stocks as the cost of that stock is lower due to the recall possibility. In addition, firms recall more of their layoffs and so more firms are at the low tax rate.

### 2.9.3 Data Analysis with Missing States

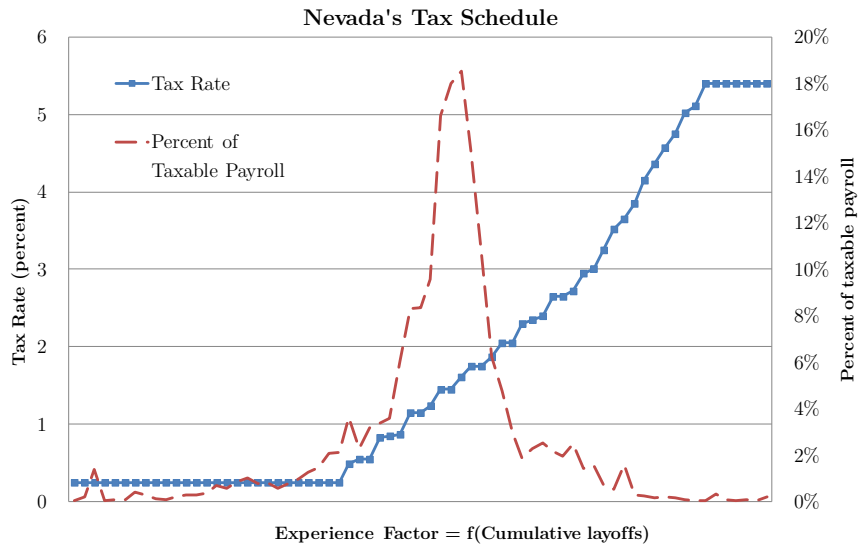
Table 2.15 denotes states that I was restricted from accessing due to legal restrictions between the state and the BLS. The BLS provided a dataset of job flow statistics calculated at the establishment level for all states at the 2-digit NAICS level. With these data, I provide an additional robustness check to ensure that the missing states do not materially affect the econometric results.

The main difference between these data and the firm-level data is that job flows are calculated at the establishment level. In addition, they include opening and closing establishments in the job creation and job destruction measures. Nonetheless, the regressions in Table 2.6 provide a useful check on the empirical results. Table 2.6 shows that including the additional states does not change the main results that higher experience rating reduces both job destruction and job creation rates. With these data, I find that increasing the marginal tax cost to 100% would reduce job destruction by 12.7% and job creation by 13.3% (Table 2.6).

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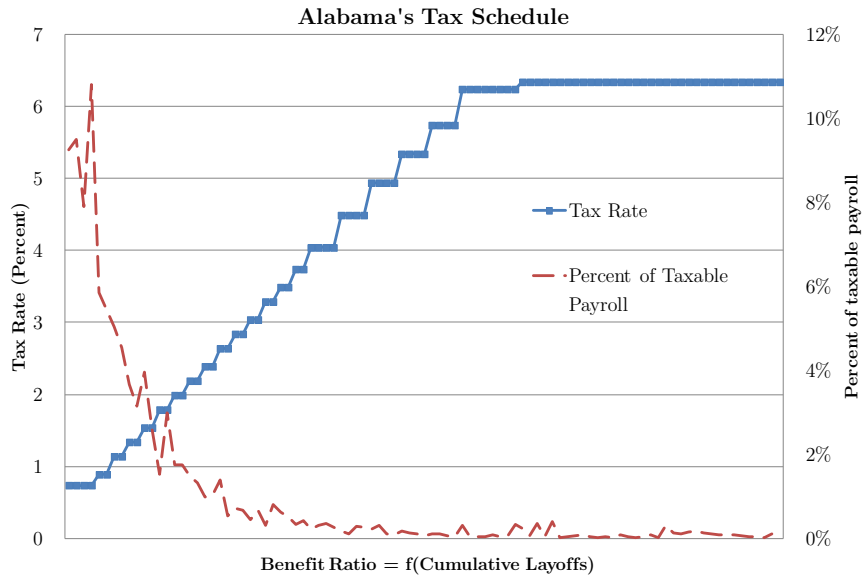
<sup>48</sup> $p^T$  is an unobservable parameter from standard sources of data on the labor market. Data from the CPS suggest that 17% is an upper bound on the fraction of hires that are from temporarily laid off workers. This fraction assumes that *all* temporarily laid off workers who are hired are hired by the firm that laid them off. Therefore, 10% is in the range of plausible values for  $p^T$ .

**Figure 2.1:** Typical Tax Schedule, Reserve Ratio



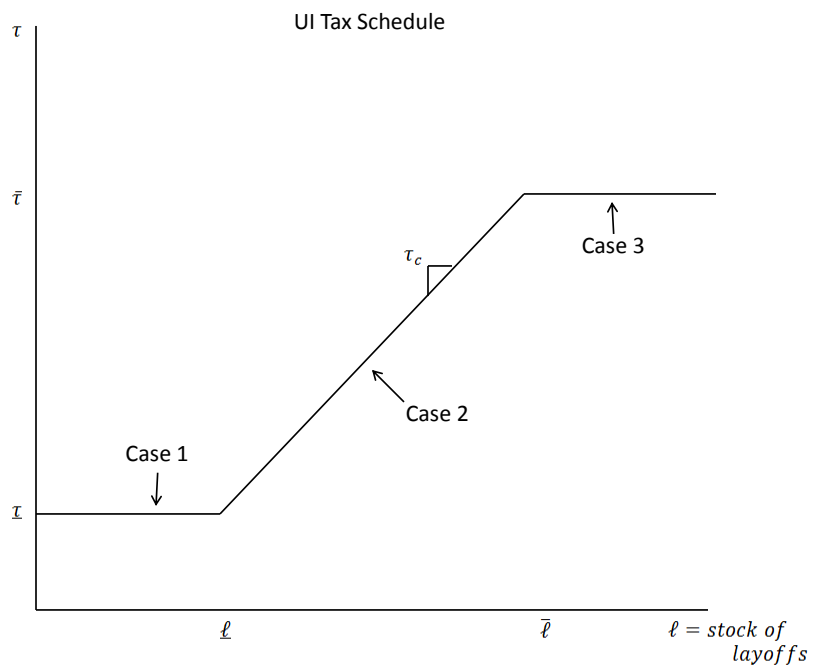
Source: Department of Labor.

**Figure 2.2:** Typical Tax Schedule, Benefit Ratio

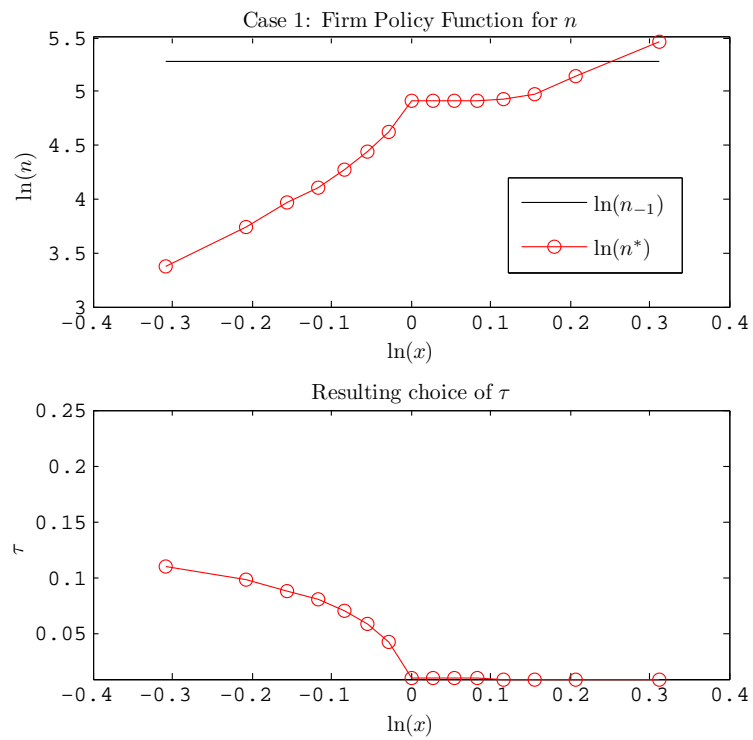


Source: Department of Labor.

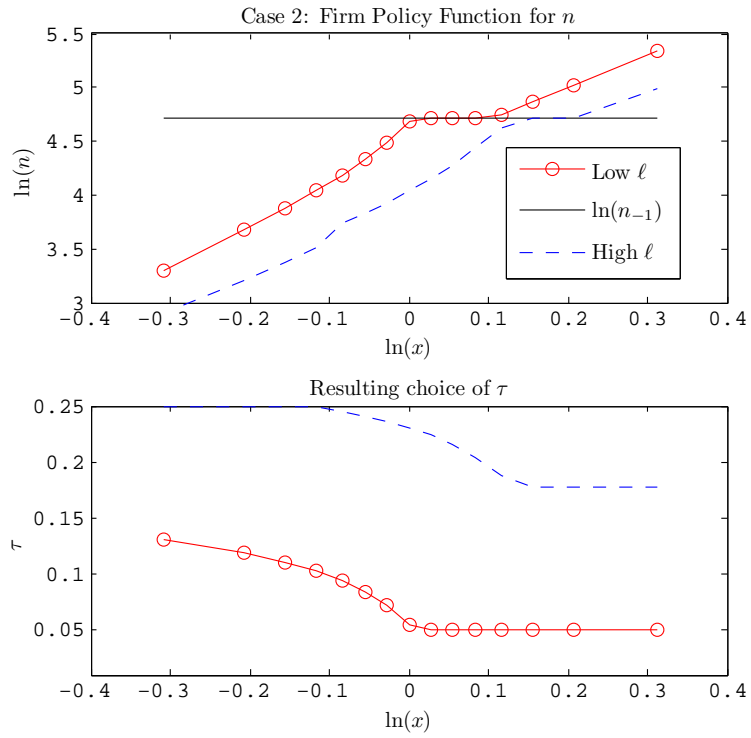
**Figure 2.3:** Parameterized Tax Schedule



**Figure 2.4:** Policy Function, Case 1



**Figure 2.5:** Policy Function, Case 2



**Figure 2.6:** Experience Rating and Job Flows

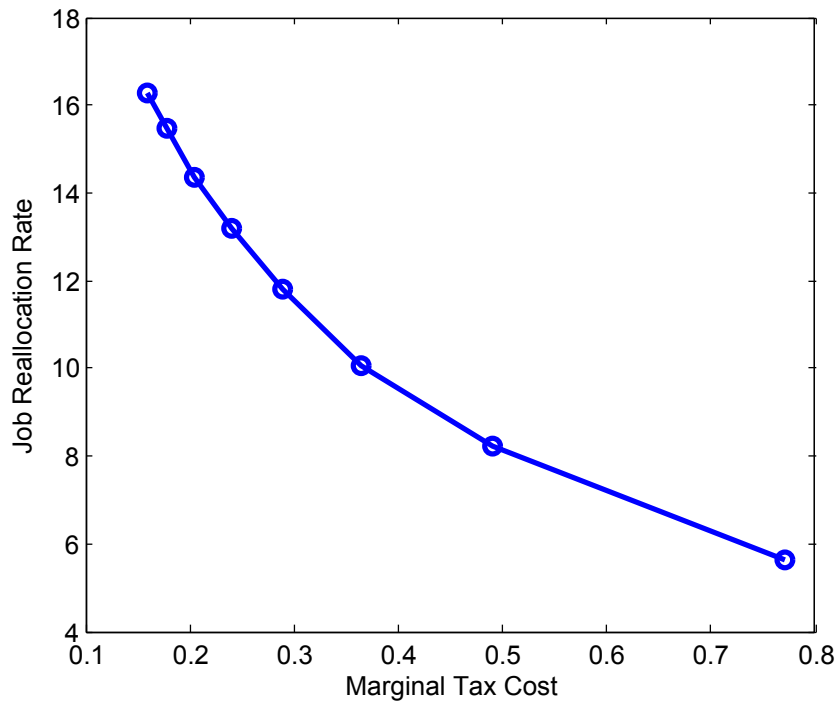
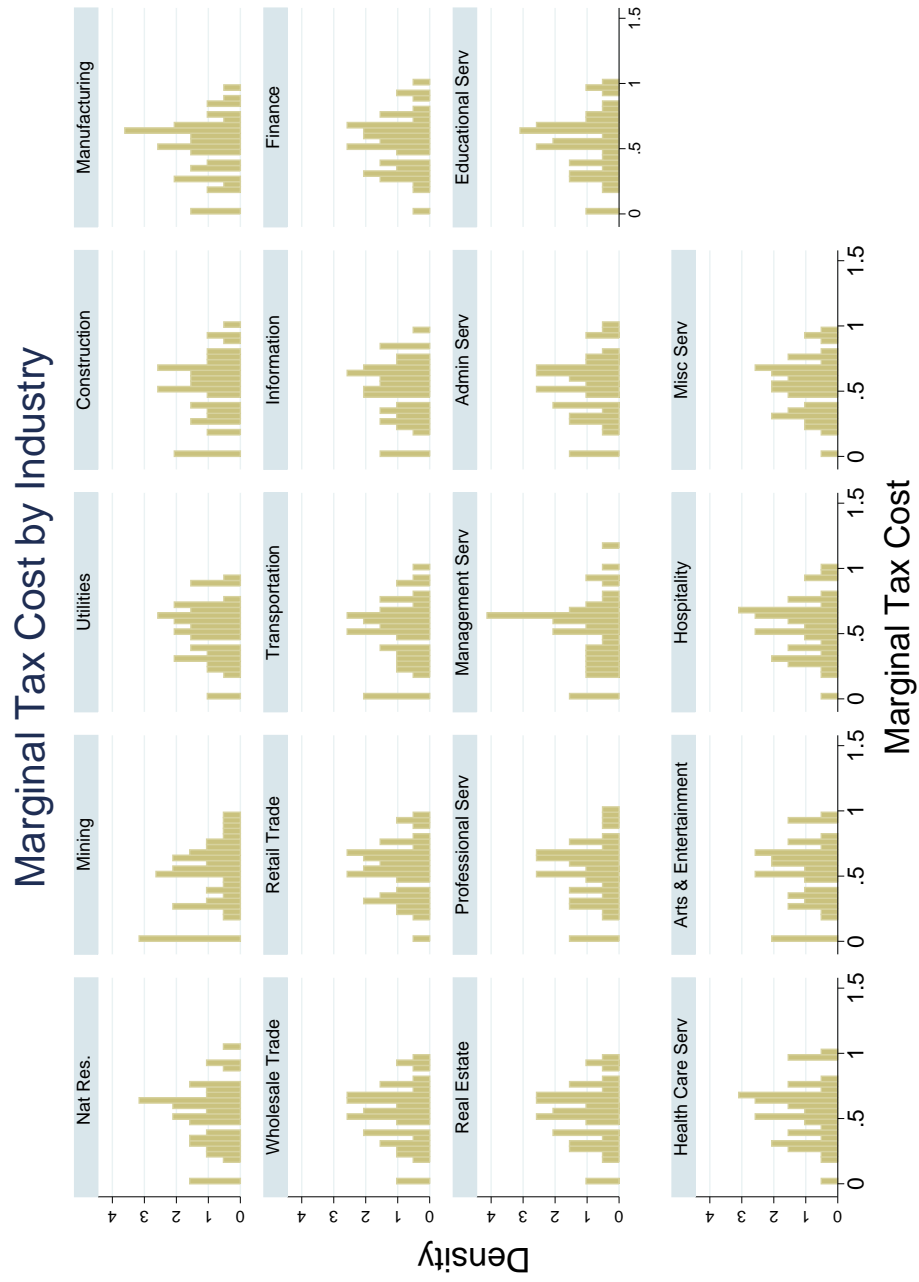


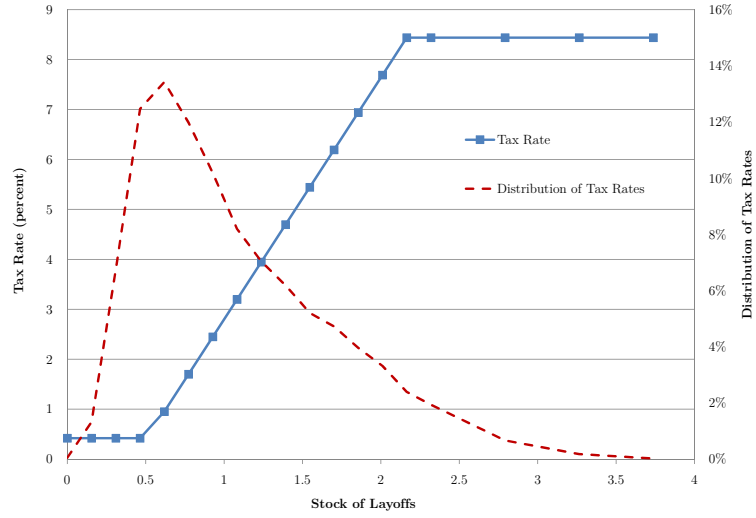


Figure 2.7: Distribution of Marginal Tax Costs

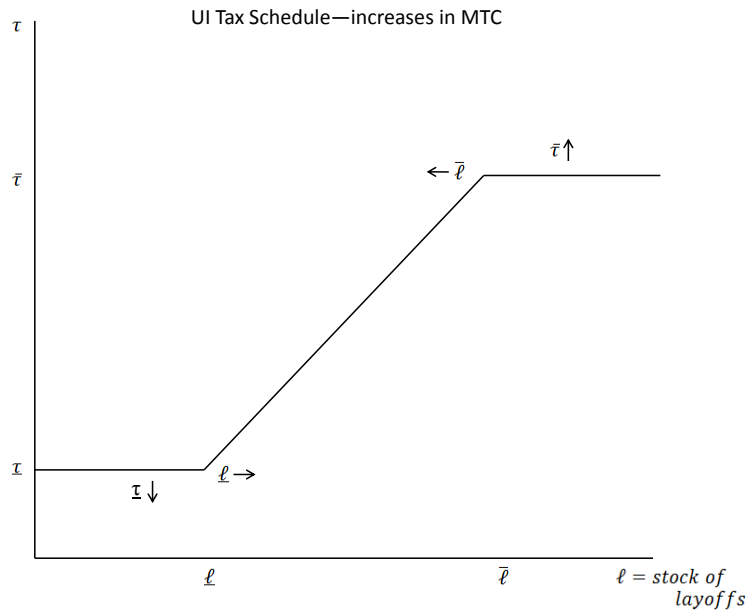


Author's analysis of QCEW data

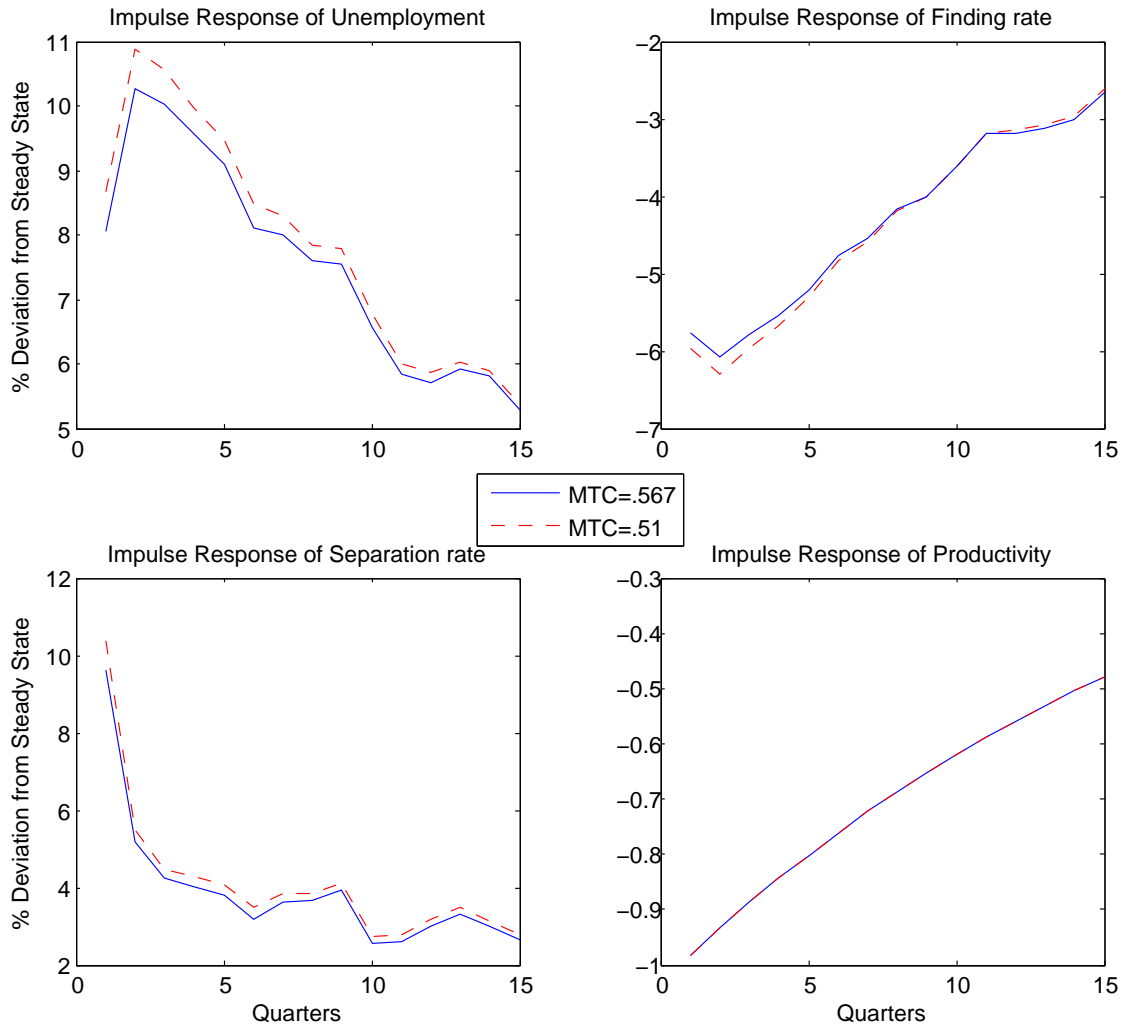
**Figure 2.8:** Distribution of Taxes in Model



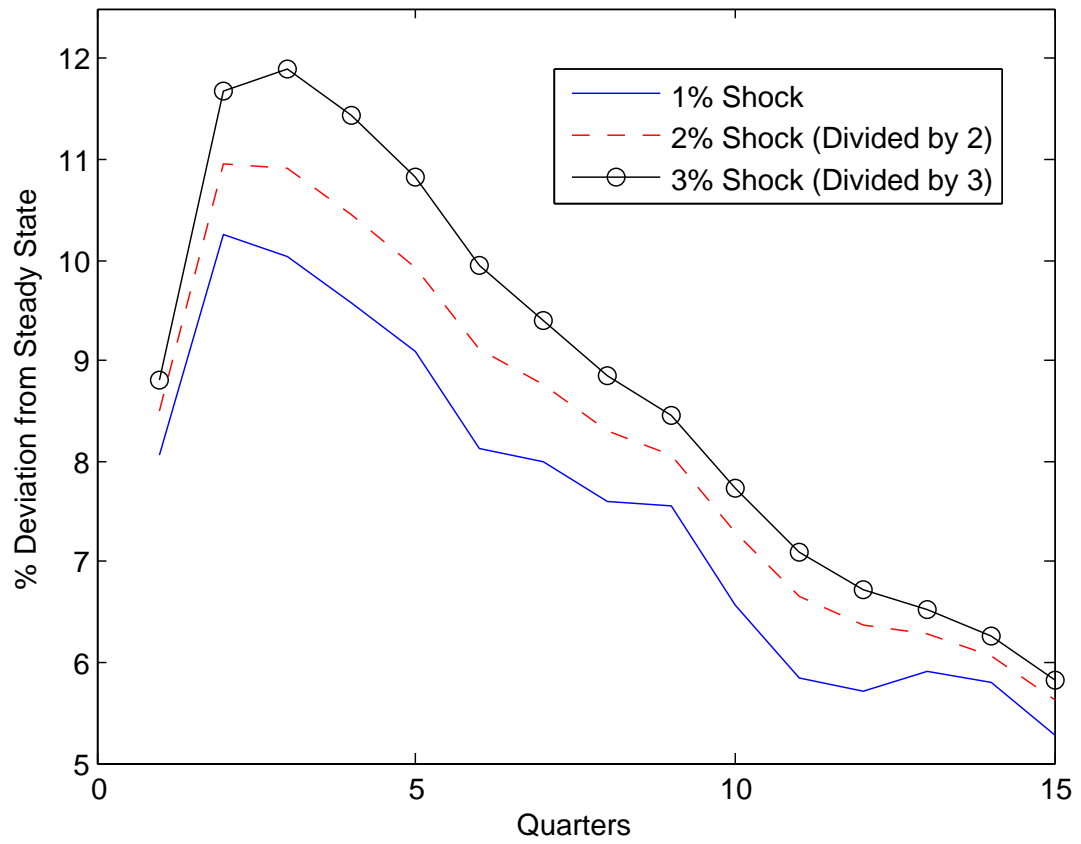
**Figure 2.9:** Types of Tax Changes



**Figure 2.10:** Impulse Response to Negative 1% Aggregate Shock



**Figure 2.11:** Nonlinear Response of Unemployment



**Figure 2.12:** Impulse Response to Positive 1% Aggregate Shock

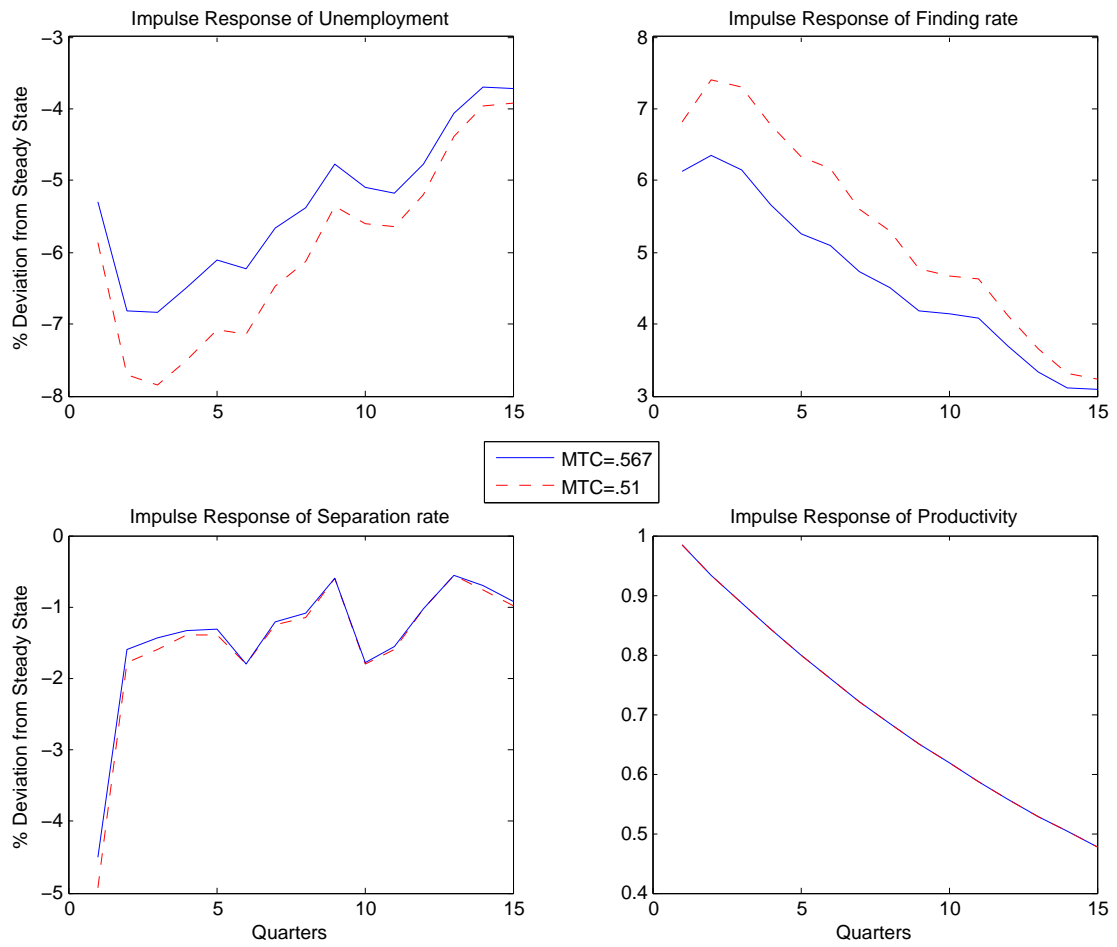
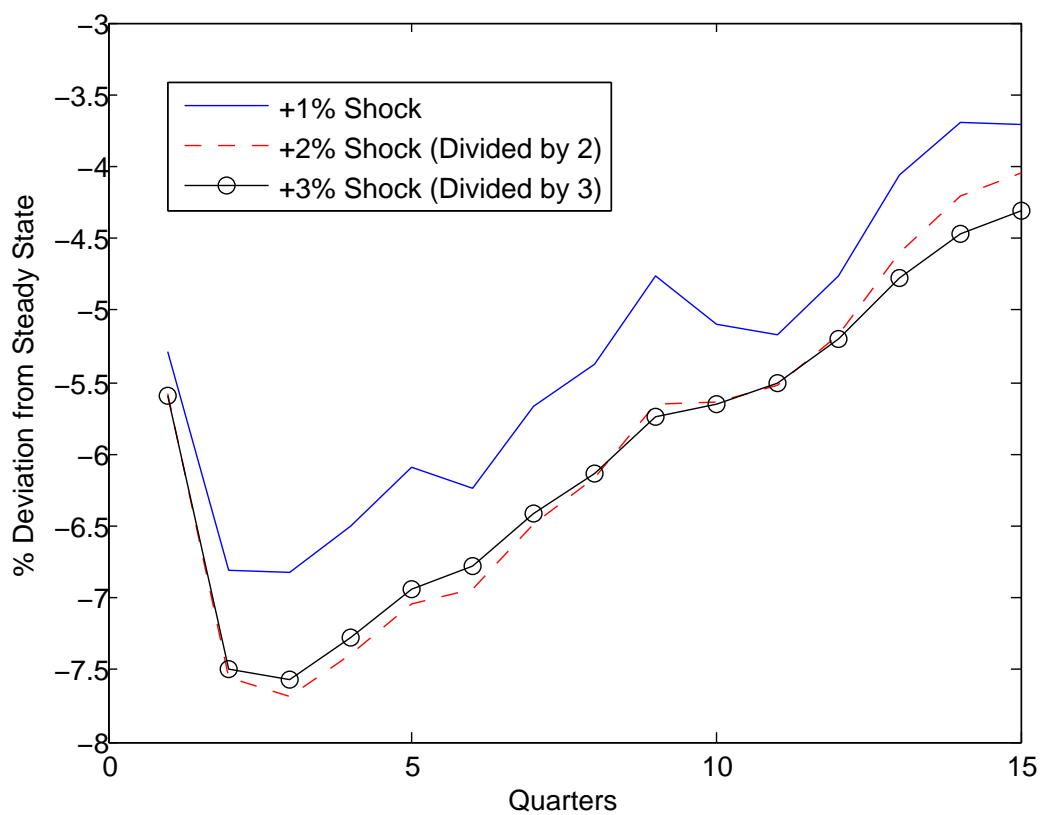
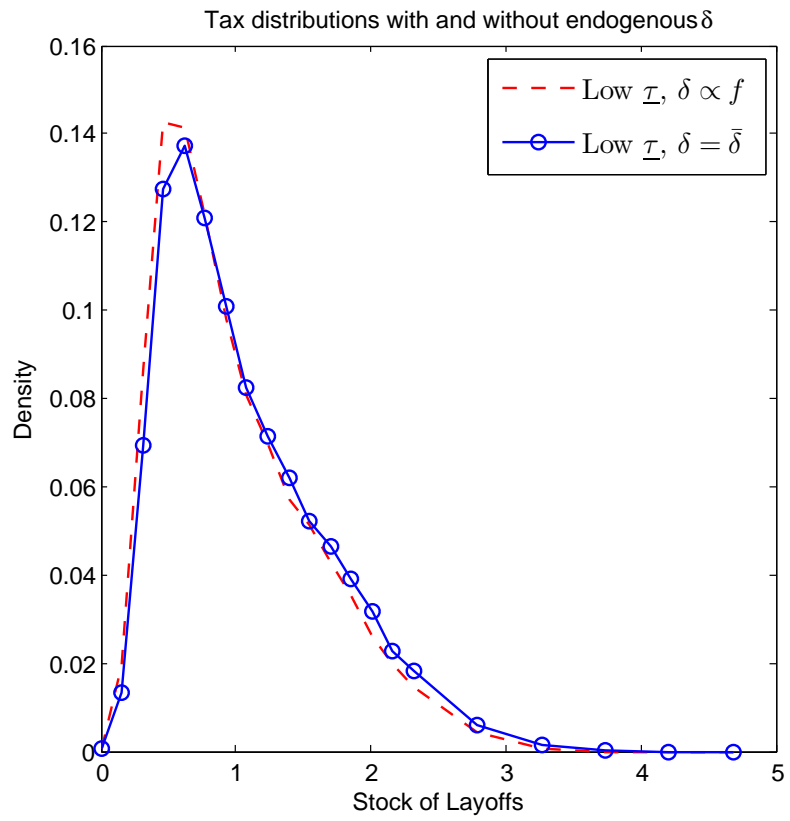


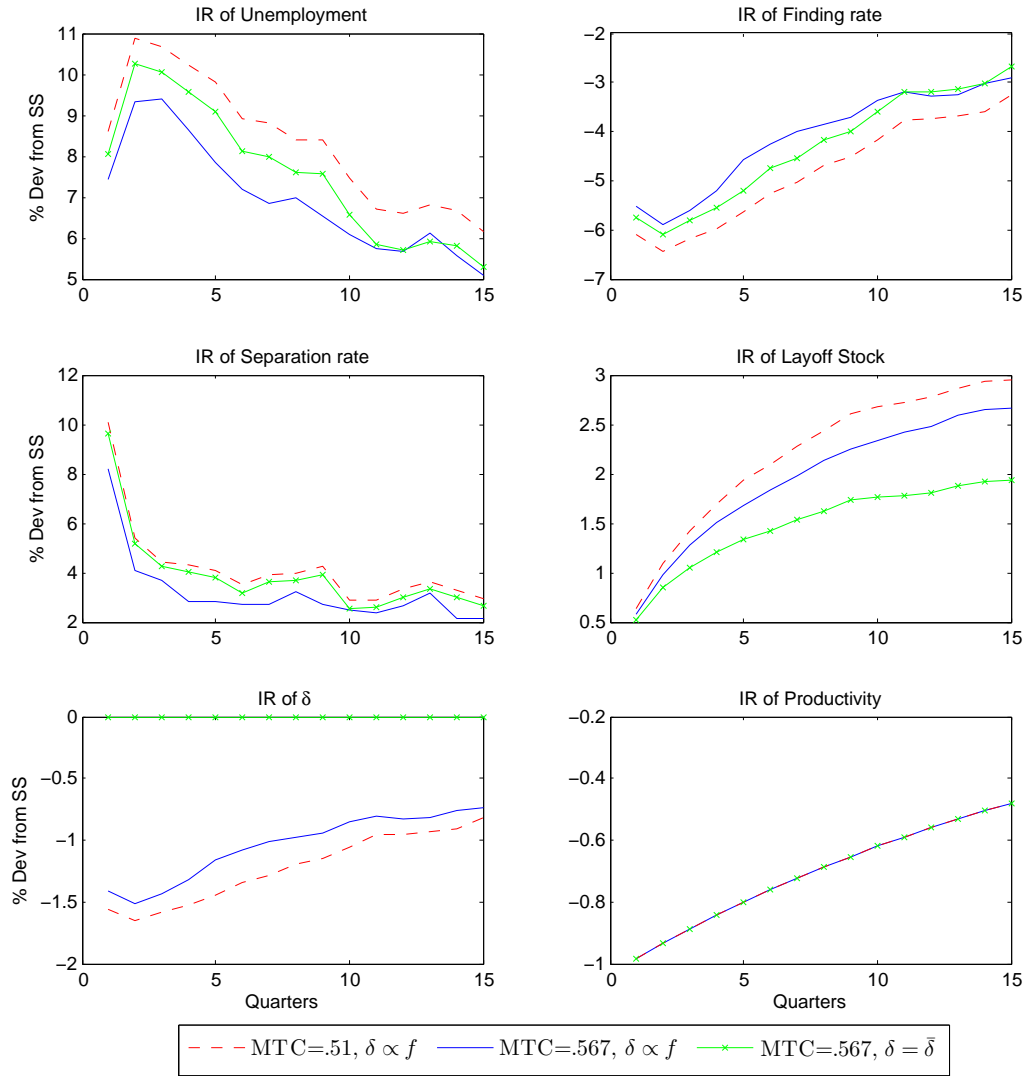
Figure 2.13: Nonlinear Response of Unemployment



**Figure 2.14:** Tax Distributions



**Figure 2.15:** Impulse Response to Negative 1% Aggregate Shock, endogenous  $\delta$





**Table 2.1:** Summary Statistics

	Mean	Std. Dev	Min	Max
Averaged MTC, i=.1, All Years	0.54	0.21	0.00	2.17
Average MTC, i=estimated, 2001-2010	0.61	0.22	0.00	2.20
Average MTC, i=.1, All Years. $g_n=0$	0.63	0.24	0.00	1.16
Average MTC, i=.1. All Years. Topel	0.62	0.23	0.00	1.09
Job Destruction	6.48	7.40	0.02	185.71
Job Creation	6.23	7.61	0.02	191.11
Net Creation Rate	-0.25	8.73	-176.71	175.85
Job Reallocation	12.49	9.92	0.17	182.27
Total Employment	21599	51694	1	1039293
Total Firms	1145	4785	1	274690
Number of 3-digit industry X state cells			3,377	
Number of 3-digit industry X state cells, 2001-2010			123,086	
Number of 3-digit industry X state cells, All Years			264,932	

Source: Author's analysis of QCEW data.

**Table 2.2:** Regression Analysis. Marginal Tax Cost and Job Flows

Dependent Variable	Regressor: Averaged MTC. $i=.10$			Regressor: Averaged MTC. $i=.10$		
	All Years			2001-2010		
	Coefficient	Mean LHS	Change from average MTC to 1	Coefficient	Mean LHS	Change from average MTC to 1
JD Rate	-2.4** (0.98)	6.48	-17.0%	-3.05*** (1.01)	6.16	-22.7%
JC Rate	-1.86** (0.87)	6.23	-13.7%	-1.73** (0.86)	5.87	-15.6%
JR Rate	-2.69** (1.29)	12.5	-10.0%	-3.27** (1.32)	11.58	-13.0%
Net Creation Rate	.81** (0.25)	-0.25		1.53*** (0.34)	-0.29	
N	264,932			101,301		

Author's analysis of QCEW data. Covariates: State, 3-digit NAICS, year, quarter fixed effects, total employment and total number of firms. Standard errors are clustered at the 3-digit industry X state cell. (\* $p < .10$ , \*\* $p < .05$ , \*\*\* $p < .01$ )

**Table 2.3:** Regression Analysis. Marginal Tax Cost and Job Flows. Alternate Marginal Tax Costs

Dependent Variable	Regressor: Averaged MTC. No $g_n$			Regressor: Averaged Topel MTC. $i=.1$		
	All Years			All Years		
	Coefficient	Mean LHS	Change from average MTC to 1	Coefficient	Mean LHS	Change from average MTC to 1
JD Rate	-2.76*** (1.04)	6.48	-15.8%	-2.29*** (0.79)	6.48	-13.4%
JC Rate	-2.59*** (0.98)	6.23	-15.4%	-2.71*** (0.87)	6.23	-16.5%
JR Rate	-3.36** (1.37)	12.5	-9.9%	-3.94*** (1.29)	12.5	-11.9%
Net Creation Rate	.41 (0.28)	-0.25		-.44*** (0.25)	-0.25	
N	264,932			264,932		

Author's analysis of QCEW data. Covariates: State, 3-digit NAICS, year, quarter fixed effects, total employment and total number of firms. Standard errors are clustered at the 3-digit industry X state cell. (\* $p < .10$ , \*\* $p < .05$ , \*\*\* $p < .01$ )

**Table 2.4:** Regression Analysis. Marginal Tax Cost and Job Flows  
Alternative Marginal Tax Costs II

Dependent Variable	Regressor: Averaged MTC. $i=.05$			Regressor: Averaged MTC. $i=.15$			Regressor: Averaged MTC. $i=estimated$		
	All Years			All Years			2001-2010		
	Coefficient	Mean LHS	Change from average MTC to 1	Coefficient	Mean LHS	Change from average MTC to 1	Coefficient	Mean LHS	Change from average MTC to 1
JD Rate	-2.19** (0.84)	6.48	-12.2%	-2.65*** (1.12)	6.48	-21.7%	-4.5*** (0.84)	6.16	-28.5%
JC Rate	-1.79** (0.75)	6.23	-10.3%	-1.93** (0.98)	6.23	-16.4%	-3.4*** (0.78)	5.87	-22.6%
JR Rate	-3.36** (1.37)	12.5	-9.7%	-2.85* (1.47)	12.5	-12.1%	-6.1*** (0.29)	11.58	-20.50%
Net Creation Rate	.62*** (0.20)	-0.25		.965*** (0.29)	-0.25		1.18* (1.19)	-0.29	
N	264,932			264,932			123,898		

Author's analysis of QCEW data. Covariates: State, 3-digit NAICS, year, quarter fixed effects, total employment and total number of firms. Standard errors are clustered at the 3-digit industry X state cell. (\* $p < .10$ , \*\* $p < .05$ , \*\*\* $p < .01$ )

**Table 2.5:** Regression Analysis. Marginal Tax Cost and Job Flows. Additional covariates

	Dependent Variable: JD Rate		Dependent Variable: JC Rate		
	(1)	(2)	(1)	(2)	
Averaged MTC $i=.1$	1.34 (1.07)	-3.31*** (0.33)	Averaged MTC $i=.1$	2.82*** (0.99)	-1.23*** (0.29)
Proportion on slope	1.94** (0.78)	0.67 (0.26)	Proportion on slope	3.4*** (0.76)	1.01*** (0.25)
Prop Slope*MTC	-3.31** (1.39)		Prop Slope*MTC	-5.1*** (1.30)	
% Benefits Charged		-0.36 (0.50)	% Benefits Charged		-0.63 (0.47)
Minimum Rate		0.12 (0.09)	Minimum Rate		0.04 (0.09)
Maximum Rate		.05* (0.03)	Maximum Rate		0.04 (0.03)
Years	2001-2010	2001-2010	Years	2001-2010	2001-2010
N	103,306	101,011	N	103,244	100,955

Author's analysis of QCEW data. Covariates: State, 3-digit NAICS, year, quarter fixed effects, total employment and total number of firms. Standard errors are clustered at the 3-digit industry X state cell (\* $p<.10$ , \*\* $p<.05$ , \*\*\* $p<.01$ )

**Table 2.6:** Regression Analysis. Marginal Tax Cost and Job Flows  
Two Digit Data with Excluded States

Dependent Variable	Regressor: Averaged MTC. $i=.10$ 1992 Q2-2010 Q1		
	Coefficient	Mean LHS	Change from average MTC to 1
JD Rate	-2.12** (0.85)	7.95	-12.7%
JC Rate	-2.27*** (0.86)	8.13	-13.3%
JR Rate	-4.39*** (1.68)	16	-13.0%
Net Creation Rate	-.15 (0.27)	0.18	
Clusters	891		
N	98,010		

Author's analysis of QCEW data. Covariates: State, 2-digit NAICS, year, quarter fixed effects, total employment and total number of firms. Standard errors are clustered at the 2-digit industry X state cell. (\* $p<.10$ , \*\* $p<.05$ , \*\*\* $p<.01$ )

**Table 2.7:** Regression Analysis. Marginal Tax Cost and Job Flows  
Single Establishment Firms Only

Regressor: Averaged MTC. $i=.10$			
1992 Q2-2010 Q1			
Dependent Variable	Coefficient	Mean LHS	Change from average MTC to 1
JD Rate	-2.16** (0.95)	7.06	-14.0%
JC Rate	-1.58* (0.86)	7.30	-10.0%
Clusters	3377		
N	264,094		

Author's analysis of QCEW data. Covariates: State, 3-digit NAICS, year, quarter fixed effects, total employment and total number of firms. Standard errors are clustered at the 3-digit industry X state cell (\* $p<.10$ , \*\* $p<.05$ , \*\*\* $p<.01$ )

**Table 2.8:** Regression Analysis. Marginal Tax Cost and Extry/Exit

Regressor: Averaged MTC		
All Years		
Dependent Variable	Coefficient	Mean LHS
Birth Rate	-.15 (0.25)	2.20%
Death Rate	-.06 (0.20)	3.40%
Clusters	3347	
N	218,836	

Author's analysis of QCEW data. Covariates: State, 3-digit NAICS, year, quarter fixed effects, total employment and total number of firms. Standard errors are clustered at the 3-digit industry X state cell. (\* $p<.10$ , \*\* $p<.05$ , \*\*\* $p<.01$ )

**Table 2.9:** Calibrated Parameters

	Parameter	Meaning	Value	Reason
“External”	$\beta$	Discount factor	.996	Annual interest rate of 5%
	$\alpha$	Scale parameter	.59	Labor’s share $\approx .72$
	$\eta$	Bargaining power	.4	
	$\phi$	Matching elasticity	.6	Petrongolo & Pissarides (2001)
	$p$	Steady state productivity	1	Normalization
	$\rho_p$	Persistence of $p$	.983	Persistence of ALP .95 quarterly
	$\sigma^p$	Std. dev. of $\epsilon^p$	.005	$\sigma(APL) = .02$
	$\mathbb{L}$	Labor force	.8553	Tightness= .72
	$\mu$	Matching efficiency	.5132	Finding rate= .45
	$\underline{\tau}$	Minimum tax rate	.417%	Average minimum tax rate in data
	$\bar{\tau}$	Maximum tax rate	8.44%	Average maximum tax rate in data
“Internal”	$b$	Leisure value	.7934	Sep. rate=3.1%
	$c$	Flow cost vacancy	.2828	Hiring cost= 14% quarterly wage
	$\rho_x$	Persistence of $x$	.9504	$P( \% \Delta n  < .05) = 54.5\%$
	$\sigma^x$	Std. dev. of $\epsilon^x$	.1721	$JR = 12.5\%$
	$\delta$	Depreciation of layoffs	.026	$P(\tau = \underline{\tau}) = 17.7, P(\tau = \bar{\tau}) = 6.6\%$
	$\underline{\ell}$	Lower tax threshold	.5085	$MTC = 54\%$
	$\bar{\ell}$	Upper tax threshold	2.16	

**Table 2.10:** Calibrated Targets and Moments

Moment	Symbol	Target	Value
Separation Rate ( $b$ )	$s$	3.1%	3.53%
Hiring Cost ( $c$ )	$\frac{c/q}{w_q}$	14%	14.74%
Non-adjustment Prob. ( $\rho_x$ )	$P( \% \Delta n  < .05)$	54.5%	45%
Job reallocation ( $\sigma^x$ )	$JR$	12.5%	7.05%
Tightness ( $\mathbb{L}$ )	$\theta_{ss}$	.72	.72
Finding Rate ( $\mu$ )	$f_{ss}$	45%	45%
Minimum Rate ( $\underline{\ell}$ )	$P(\tau = \underline{\tau})$	17.7%	17.43%
Maximum Rate ( $\bar{\ell}$ )	$P(\tau = \bar{\tau})$	6.6%	6.76%
Marginal Tax Cost ( $\delta$ )	MTC	54%	53.7%

**Table 2.11:** Steady State Tax Experiments. Percentage changes unless noted

Change in:	Param	MTC	JC,JD	Revenue	$\Pi$	$u$ % pts.	$\% \Delta u$
$\rightarrow \underline{\ell}$	15.5%	5%	-1.1%	-8.6%	.06%	-.31	-4.3%
$\leftarrow \bar{\ell}$	-3.6%	5%	-1.1%	2.3%	-.38%	-.13	-1.8%
$\downarrow \underline{\tau}$	-.2% pts	5%	-1.9%	-8.6%	.07%	-.33	-4.5%
$\uparrow \bar{\tau}$	.4% pts	5%	-1.5%	2.3%	-.26%	-.18	-2.5%
Steady State		54%	3.53%	.022	76.65		7.27%

**Table 2.12:** Revenue Neutral Experiment. Percentage changes unless noted

Change in:	Param	MTC	JC,JD	Revenue	$\Pi$	$u$ % pts.	$\% \Delta u$
$\uparrow \bar{\tau}, \downarrow \underline{\tau}$	+.4%, -.04% pts	5.5%	-1.6%	0%	-.2%	-.21	-2.9%
Steady State		54%	3.53%	.022	76.65		7.27%

**Table 2.13:** Closing 50% of Net Reserve Gap. Percentage changes unless noted

Change in:	Param	MTC	JC,JD	Revenue	$\Pi$	$u$ % pts.	$\% \Delta u$
$\uparrow \underline{\tau}, \uparrow \bar{\tau}$	+.2%, +.2%	0%	.85%	9.1%	-.29%	.11	1.5%
$\leftarrow \bar{\ell}$	-12.4%	19.4%	-1.1%	9.1%	-.6%	-.13	-1.8%
Steady State		54%	3.53%	.022	76.65		7.27%

**Table 2.14:** Steady State Tax Experiments,  $\delta \propto f$ . Percentage changes unless noted

Change in:	Param	MTC	JC,JD	Revenue	$\Pi$	$u$ % pts.	$\% \Delta u$
$\rightarrow \underline{\ell}$	15.5%	5%	-1.9%	-17.7%	—	-53	-7.3%
$\leftarrow \bar{\ell}$	-3.6%	5%	-1.4%	2.3%	-4%	-2	-2.75%
$\downarrow \tau$	-.2% pts	5%	-3.1%	-18%	-.01%	-.58	-7.9%
$\uparrow \bar{\tau}$	.4% pts	5%	-1.7%	-1.36%	-.27%	-.23	-3.2%
Steady State		54%	3.53%	.022	76.65	7.27%	



**Table 2.15:** List of States

State	States Excluded from QCEW. Included in Table 6	State	States Excluded from QCEW. Included in Table 6
Reserve Ratio		Benefit Ratio	
Arkansas		Alabama	
Arizona		Connecticut	
California		Florida	X
Colorado		Iowa	
DC		Illinois	X
Georgia		Maryland	
Hawaii		Minnesota	
Idaho		Mississippi	X
Indiana		Oregon	X
Kansas		Texas	
Kentucky		Utah	
Louisiana		Virginia	
Massachusetts	X	Vermont	
Maine		Washington	
Missouri		Wyoming	X
Montana			
North Carolina			
North Dakota			
Nebraska			
New Hampshire	X		
New Jersey			
New Mexico			
Nevada			
New York	X		
Ohio			
Puerto Rico			
Rhode Island			
South Carolina			
South Dakota			
Tennessee			
Wisconsin	X		
West Virginia			
Number of Reserve Ratio States: 32		Number of Benefit Ratio States: 15	

Note: Author's analysis of DOL and QCEW data. States with an 'X' were excluded in Tables 1-5 due to restrictions in QCEW data. Table 6 includes these states using analysis of 2-digit aggregated data of the QCEW provided by the BLS.

## CHAPTER III

# Capital Adjustment and Aggregate Labor Market Fluctuations

### Introduction

What role does capital adjustment play in the dynamics of the aggregate labor market? A large literature has examined the ability of macroeconomic models of the labor market to match salient features of the empirical business cycles. Despite the large literature on this topic, most models of the labor market abstract from realistic capital adjustment. This chapter considers the quantitative effect of capital adjustment costs on the dynamics of the labor market.

Shimer (2005) found that the standard search and matching model of unemployment fails to capture two important features of the adjustment of the labor market to aggregate shocks. First, unemployment in these models does not vary as substantially as it does in US time series data. Second, the model does not generate sufficient endogenous propagation of shocks so that the dynamics of some aggregate variables are determined by the dynamics of the exogenous shock process. For instance, after a shock is realized, the response of labor market tightness in the model is immediate; in contrast, in the data, the tightness of the labor market takes time to respond and return to normal levels.

The Mortensen-Pissarides and subsequent models abstract from a firm's capital decision by making one of two extreme assumptions. Either a firm can immediately and costlessly adjust its

productive capital, or, as in Elsby and Michaels (2011), the firm's capital stock is fixed.<sup>1</sup> This chapter argues that frictions in capital adjustment affect aggregate labor market fluctuations to an important degree. In particular, costly capital adjustment slows down the responses of the labor market tightness due to the interrelated adjust of capital and labor.

I first derive a set of stylized facts for the response of the labor market to an aggregate shock. Following the methodology of Fujita and Ramey (2007), I identify shocks to multi-factor productivity that are uncorrelated with innovations to the labor market or investment. Using this exogenous series for productivity, I estimate vector autoregressions from US macroeconomic data on the labor market and investment from 1950-2004. Estimated impulse responses show a substantial degree of propagation of productivity shocks. Investment responds to the aggregate shock with a lag, reaching its peak after four quarters. Importantly, labor market tightness increases upon impact by 4.8% but only reaches its peak of 12.8% above steady state four quarters after the realization of the shock. The full effects of the productivity shocks are felt after about one year and die off completely after about 2.5 years.

In the next section, I consider three types of capital adjustment frictions. To build intuition, I analyze a simplified model with one period time-to-build timing frictions to show qualitatively that capital frictions alter the dynamic behavior of the labor market. Quite simply, the delay in operational capital investment causes the firm to reduce vacancy posting until the capital will come online. This causes labor market tightness to react slowly after the aggregate shock.

Next, I show that under both capital or investment adjustment costs, the dynamics of labor adjustment exhibit different cyclical properties than in the flexible model. I calibrate the model with convex adjustment costs to match features of the US labor market. I set the parameters of the quadratic adjustment cost functions to match the contemporaneous correlation between productivity and investment. Model impulse responses from the adjustment cost models versus the standard, frictionless model show that the joint dynamics of labor and capital are important to accurately capture the dynamics of the labor market over the business cycle. In the convex adjustment cost

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<sup>1</sup>See Pissarides Ch. 3 for a textbook treatment of the flexible capital case.

models, labor market tightness takes four quarters to peak and employment five quarters to peak, in line with the empirical results.

The chapter is organized as follows: Section 3.1 presents empirical evidence that constitutes the stylized facts to which the model will be compared. Section 3.2 lays out the model and Sections 3.3 through 3.4 analyze different specifications of capital adjustment. Section 3.5 discusses related literature and Section 3.6 concludes.

### 3.1 Empirical Stylized Facts

First, it is important to understand the stylized facts to which a model of the aggregate labor market should be compared. In order to examine the response of variables to the empirical analogue of a shock in the model, I attempt to identify shocks to the level of productivity not explained by other labor market variables. Implicitly, however, this is not the same as identifying “technology” shocks per se as in Gali (1999) or Basu, Fernald, and Kimball (2006). For the purposes of this exercise, it is not important to identify technology shocks but rather shocks to multifactor productivity that are cleansed of feedback effects from either investment or the labor market. In other words, demand shocks, shocks to preferences, utilization or composition, or money shocks are all abstracted from in the model; the use of a regression-adjusted Solow residual comes closest to the type of exogenous productivity sequence assumed in the model.

Following Fujita and Ramey (2007), productivity shocks are defined as innovations to multifactor productivity that are not explained by the past or by current innovations in employment or investment. In particular, multifactor productivity is first estimated by regressing log output on share weighted log of inputs, capital and labor by the following regression (imposing constant returns to scale)

$$\ln \left( \frac{y_t}{N_t} \right) = \alpha \ln \left( \frac{k_t}{N_t} \right) + \epsilon_t.$$

Output is measured as real GDP and employment is civilian employment. The capital stock is taken from Gomme and Rupert (2007) who construct the series by using annual capital stock levels

and quarterly investment rates to impute quarterly capital stocks. Next, multifactor productivity is defined as log output minus the share-weighted log inputs (the Solow residual, essentially),  $\ln p_t = \ln y_t - \hat{\alpha} \ln k_t - (1 - \hat{\alpha}) \ln N_t$ . The imposition of constant returns did not substantially change the baseline results reported.

The next step is to isolate productivity shocks in this Solow residual series. Again, productivity shocks are those innovations to productivity not explained by past values of investment or labor market conditions, nor current innovations in those variables. To accomplish this, the following reduced form regression is estimated:

$$\ln p_t = A_1(L) \ln p_t + A_2(L) \ln i_t + A_3(L) \ln \theta_t + A_4(L) \ln n_t + \epsilon_t^p, \quad (3.1)$$

where  $A_k(L)$  is a lag order polynomial with  $L = 1, 2, 3$ .<sup>2</sup>  $\theta_t$  is a measure of labor market tightness,  $i_t$  is investment, and  $n_t$  is the employment to population ratio, at the quarterly frequency, over the period 1951:Q1-2004:Q2. The data are described fully in section 3.7.1. Labor market tightness is measured by the ratio of a help wanted index to the number of unemployed workers. Investment is real US private fixed investment. All variables are detrended by regressing each series on a constant and cubic time trend and retaining the residuals. It is worth noting that the results are quantitatively similar if the data are detrended using an HP filter (see Figure 3.8).

Due to the identification assumption, the reduced form errors of this equation are the structural innovations to multifactor productivity. The exogenous productivity series is estimated by recursively calculating  $\ln p_t$  and imposing that  $A_2(L) = A_3(L) = A_4(L) = 0$ . Intuitively, this generates an AR(3) process for exogenous productivity that is purged of feedback effects from past values of investment, tightness, and employment. Denote the exogenous productivity series as  $\ln \hat{p}_t$ . The implied AR(3) process for  $\ln \hat{p}_t$  is shown in the bottom right hand panel of Figure 3.1. It shows that productivity is a highly persistent, yet mean-reverting process. The error bands, however, imply that the unit root cannot be rejected in this, which is consistent with Basu, Fernald, and Kimball's

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<sup>2</sup>Note that this is equivalent to running the reduced form 4 variable VAR with productivity first in the ordering. This implies that the reduced form innovations are the structural innovations.

technology process. Note, however, that using HP-filtered data yields a productivity process that is less persistent (Figure 3.8).

First, it is instructive to examine the data before investigating the impulse responses to a productivity shock. Table 3.1 gives the quarterly standard deviations, and cross- and auto-correlation functions for the four variables of interest; Table 3.2 gives the cross correlations of the four variables with productivity at various dates. Labor market tightness is the most volatile of the five variables with a standard deviation of .42, almost 12 times the standard deviation of productivity. Unemployment is more volatile than the employment ratio with standard deviations of .22 and .015 respectively. In addition, investment has a quarterly standard deviation of .08, or 2.3 times productivity's volatility.

Looking next at the autocorrelations in the right-most panel of Table 3.1, it is clear that all of the detrended series are highly autocorrelated. The first quarter autocorrelations are between .94 and .96 for all of the variables. At 3 quarters, productivity is still highly persistent with a correlation of .86 with date  $t$  productivity, while investment and the labor market variables have autocorrelations of about .7. The middle panel of Table 3.1 reports the contemporaneous cross correlations; unemployment is highly negatively correlated with productivity (-.79) and labor market tightness is highly positively correlated at .76 (the employment rate is positively correlated but less so with a coefficient of .45). Investment is positively correlated as well, albeit with a lower correlation coefficient of .53. As compared to Shimer's table, these variables are more highly correlated with my measure of productivity.

Finally, Table 3.2 shows the correlations of each variable with productivity as it varies over time. All of the variables are correlated with productivity at each lag and lead. The important variable to examine in this table is tightness because, as will be explained later, this variable is a "jump" variable in the standard model and is not backwards looking. Empirically, the correlation coefficient between tightness at date  $t$  and productivity three periods before, for example, is .72. In addition, the correlation between tightness at date  $t$  and productivity in the future falls off more quickly than tightness with past productivities.

To examine the dynamic responses of the variables to a productivity shock, I again follow Fujita and Ramey and estimate a four variable VAR using the exogenous productivity series,  $\ln \hat{p}_t$ . The VAR includes three lags of investment, tightness, employment, and exogenous productivity.<sup>3</sup> This VAR(3) has the form

$$\begin{bmatrix} \ln \hat{p}_t \\ \ln \theta_t \\ \ln n_t \\ \ln i_t \end{bmatrix} = B(L) \begin{bmatrix} \ln \hat{p}_t \\ \ln \theta_t \\ \ln n_t \\ \ln i_t \end{bmatrix} + \begin{bmatrix} \epsilon_t^p \\ \epsilon_t^\theta \\ \epsilon_t^n \\ \epsilon_t^i \end{bmatrix}. \quad (3.2)$$

Due to previous “cleansing” of employment, investment, and tightness from the productivity series, the coefficients on those variables are zero in the  $B(L)$  matrix of coefficients. Impulse responses to a one standard deviation shock to productivity,  $\hat{\epsilon}_t^z$ , are plotted in Figure 3.1. These impulse responses are the stylized facts that will be compared to the model impulse responses.<sup>4</sup>

The important features of the impulse responses generate a set of stylized facts that standard models of the labor market have had difficulty matching. In particular, the humped shaped responses of each of the variables is starkly different from those implied by the model with perfectly flexible capital. The impulse responses for investment and labor market tightness peak after four quarters whereas employment takes an additional quarter to reach its maximum level. The point estimates of investment and tightness remain above zero until around 13 quarters, when investment goes slightly below zero and tightness remains slightly above zero; the point estimate for employment takes about 15 quarters to return to zero. The point estimates are insignificant, however, after 9 quarters for investment, 10 quarters for labor market tightness, and 11 quarters for employment. Thus, the full effects of the productivity shocks are felt after about one year and die off completely after about 2.5 years.

In addition to the duration of the shocks, it is important to examine the amplitude of the impulse responses to understand business cycle properties of investment and labor market variables. First,

<sup>3</sup>Technically I estimate this system using a “quasi-VAR” as in Fujita and Ramey (2007) without productivity as a left hand side variable. The results are numerically identical

<sup>4</sup>The impulse responses are qualitative similar using employment as a fraction of the labor force or the unemployment rate. In addition, they are similar when using only labor productivity as used in Fujita and Ramey.

on impact, in response to a one standard deviation shock to productivity, investment rises about .8% and continues to rise to about 1.7% above trend by the fourth quarter. Next, labor market tightness also jumps upon impact after a shock by 4.5% and then continues to rise to 12.8% after four quarters before returning to its trend level. In addition, the empirical elasticity of contemporary tightness and productivity is about 8, a fact to which will be discussed later. The employment ratio is unchanged on impact of the shock but monotonically rises to .73% above its trend after five quarters before returning to normal. The persistence and amplitude of these impulse responses will be compared to the analogous impulse responses from the model, to which I now turn.

### 3.2 Search and Matching Model of the Labor Market

The model setup is parallel to the standard MP matching model with exogenous job destruction.<sup>5</sup> The economy is populated by a measure one continuum of workers who are all identical and firms which have access to the same technology. Firms and workers meet through a matching process that is summarized by a matching function which registers the number of matches that occur for a given number of unemployed workers,  $u$ , and a given number of vacancies,  $v$ . The number of matches,  $M$ , therefore, is given by  $m(u, v)$ . As is standard,  $m$  is taken to be homogeneous of degree one in  $u$  and  $v$  so that  $M = m(u, v) = m(1, \frac{v}{u})$ .

Define  $\theta \equiv \frac{v}{u}$ , which can be thought of as the degree of market tightness. If  $v = 0$ , then the market is perfectly slack and there are no job openings for an unemployed worker; where there are relatively few unemployed workers per job opening,  $\theta$  is large and the labor market is relatively tight. Due to the homogeneity assumption, the number of matches can be summarized by  $M = m(1, \theta)$ . In addition, the matching function is assumed to take the standard form  $m(u, v) = \mu u^\gamma v^{1-\gamma}$ , where  $\mu$  is the matching efficiency parameter, assumed to be time-invariant, and  $\gamma$  is the elasticity of matches with respect to unemployment.

The timing of the model is as follows. Workers arrive in a period either employed or unemployed and begin to search for work. Workers find jobs with probability  $f(\theta) \equiv \frac{M}{u}$ , called the job finding

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<sup>5</sup>See Pissarides (2000) for a complete treatment of the model.



probability. Firms, endowed with a stock of labor and capital held over from the period before, decide on the level of capital investment and the number of vacancies to post. For each vacancy posted there is a probability,  $q(\theta) \equiv \frac{M}{v}$ , the job-filling probability, that a worker will be found.

After all the of the matches are complete, firms and workers produce output according to the production function  $y = pF(n, k)$ . For the duration of the chapter, I impose the functional form assumption that the production function is Cobb-Douglas:  $pF(n, k) = pk^\alpha n^{1-\alpha}$ . Aggregate productivity,  $p$ , is realized at the beginning of every period and follows an AR(1) process in logs:  $\ln p_t = (1 - \rho) \ln p + \rho \ln p_{t-1} + \epsilon_t$ . The autoregressive parameter,  $\rho$  and the distribution of  $\epsilon$  are assumed to be common knowledge. Further,  $\epsilon \sim i.i.d. N(0, \sigma^2)$ .

After production is complete, workers are separated from their firms with probability  $\lambda$ . In addition, it is assumed that a proportion  $\delta$  of the firm's capital stock depreciates before the beginning of next period. The stock of unemployed workers evolves according to the following aggregate equation of motion (recall the labor force is normalized to 1 so  $n_t = 1 - u_t$ )

$$u_{t+1} = \frac{\lambda + (1 - \lambda)u_t}{1 + f(\theta_{t+1})}. \quad (3.3)$$

The next section considers the firm's optimal behavior in this environment followed by a section on the worker's problem.

### 3.2.1 Firm's Problem

The firm's objective is to maximize the expected present discounted value of its profits, subject the equations of motion for its state variables, by choosing an optimal path of investment and vacancies. First, it is worth noting that all firms have access to identical production technology and face the same labor market conditions; thus, for the representative firm's problem, all firm subscripts are omitted. Further, this implies that, in any equilibrium, all firms will post some positive amount of vacancies; since the cost of filling a job limits to zero, if this was not the case, a firm will be induced to post vacancies if the aggregate vacancy rate approaches zero.<sup>6</sup>

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<sup>6</sup>One might be worried that firm will want to post negative vacancies; in other words, firms will want to fire workers. Consider the equilibrium in which aggregate  $v < 0$ . This, however, will turn the job-filling cost negative and

As outlined above, the firm enters a period with a stock of capital and labor held over from the period before. A firm's workforce is subject to exogenous separations and the stock of capital depreciates at the end of each period. The equation of motion for capital is thus:

$$k = \Gamma(i) + (1 - \delta)k_{-1} \quad (3.4)$$

The investment technology will vary in the following analyses, so it is left general in the preceding equation. Note, for instance, that if  $\Gamma(i) = i$ , then a firm's capital is adjustable within any period. In the following,  $\Gamma$  may build in timing frictions depending on the setup.

The equation of motion for  $n$  is the following:

$$n = (1 - \lambda)n_{-1} + q(\theta)v \longrightarrow \frac{n - (1 - \lambda)n_{-1}}{q(\theta)} = v \quad (3.5)$$

A firm's employment is determined by the workers who are still employed from last period plus the workers who successfully match out of the  $v$  vacancies the firms posts.

Let  $\Omega$  be the set of state variables for the firm, aside from aggregate productivity,  $p$ .  $\Omega$  will always contain at least the maintained capital stock,  $k_{-1}$  and employment stock,  $n_{-1}$ , but may also include past investments or capital as well, depending on the assumed capital frictions. The Bellman equation for the firm is given by (subject to the equations of motion for capital and labor):

$$\Pi(\Omega, p) = \max_{v, i} \{pF(n, k) - w(\Omega, p)n - C(i_{-1}, i, k_{-1}, k) - cv + \beta E\Pi(\Omega', p')\} \quad (3.6)$$

The function,  $C(i_{-1}, i, k_{-1}, k)$ , gives the flow cost of investment either in the form of a per-unit purchase price or internal adjustment costs, where applicable.

$$C(i_{-1}, i, k_{-1}, k) = p^k(i) + \frac{\phi_k}{2} \left(\frac{i}{k_{-1}}\right)^2 k_{-1} + \frac{\phi_i}{2} \left(\frac{\Delta i}{i_{-1}}\right)^2 i_{-1} \quad (3.7)$$

$\beta$  is the firm's real rate of time discount.  $\phi_k$  governs the degree of convex adjustment costs in firms will be rewarded for posting vacancies; this will put a lower bound on vacancies.

changing the firm's capital stock;  $\phi_i$  similarly denotes the degree of adjustment costs the firm faces when changing its investment, following the Christiano et al. (2005) setup.  $p^k$  is the per unit cost of capital that the firm pays in the capital goods market. In addition, firms can resell its capital in a secondary market without penalty (i.e., at the going rate,  $p^k$ ).

The first order condition for vacancies yields a difference equation in  $\theta$  of the following form:

$$\frac{c}{q(\theta)} = pF_1(n, k) - w_n(\Omega, p)n - w(\Omega, p) + \beta E \left[ (1 - \lambda) \frac{c}{q(\theta')} \right] \quad (\text{FOC}_n)$$

Finally, the first order condition for the optimal capital stock will depend on the type of adjustment costs or the timing frictions imposed below. The investment first order condition is shown during the discussion of each setup.

### 3.2.2 Worker's Problem

Since I abstract from variable search intensity, the intensive margin of labor supply (i.e., hours), and idiosyncratic productivity, the labor supply decision is trivial; all wage offers in equilibrium will be above the worker's reservation wage and, therefore, any matched worker and firm pair will agree to the terms of a contract.<sup>7</sup> Because of this, the supply side of the model is used only to pin down equilibrium wages. The level of employment, conditional on the wage setting curve, is determined on the demand side.

The worker's problem is characterized by two Bellman equations, one for an employed worker and one for an unemployed worker. The value of working at a firm depends not only on the number of employees at that firm and also its current and future capital stocks. Therefore, the value of employment to a worker at a firm will depend on all of the state variables in  $\Omega$ .<sup>8</sup>

The value of being unemployed in a period is given by:

$$U(p) = b + \beta E [f(\theta')W(\Omega', p') + (1 - f(\theta'))U(p')], \quad (3.8)$$

<sup>7</sup>The asset values for an unemployed and employed workers anticipate this result.

<sup>8</sup>In the end, because of the continuous renegotiation of wages, the wage will only depend on  $n, k$ , and  $p$ .

where  $b$  is the flow benefit of unemployment. The value of  $b$  is taken to be exogenous and can reflect the value of unemployment benefits, non-labor income, and/or leisure to a worker. The value of working at a firm with state variables  $\Omega$  in a period is then given by:

$$W(\Omega, p) = w(\Omega, p) + \beta E[\lambda U(p') + (1 - \lambda)W(\Omega', p')] \quad (3.9)$$

Given the firm's problem and the worker's Bellman equation, the equilibrium wage can be determined.

### 3.2.3 Wage Setting

In the standard MP model, firms have perfectly elastic demand schedules, a consequence of the constant returns assumption in the standard model. As a result, the marginal productivity of an additional worker is equal to the average productivity.<sup>9</sup> This greatly simplifies the analysis because the Nash bargain with an additional work does not affect the productivity, and therefore, wage, of any other worker.

In the following analyses, however, the firm faces adjustment costs or a timing friction. This will result in downward-sloped demand schedules for labor in which the surplus to employment of the marginal worker is less than that of the average worker. Thus, I adopt the Stole and Zweibel (1996) bargaining solution which generalizes the Nash bargain to one over the marginal surplus.<sup>10</sup> The underlying game is one in which the firm continuously negotiates with the marginal worker over the marginal surplus. The bargain leads to a surplus sharing rule such that the wage is given by:

$$(1 - \eta) [W(\Omega, p) - U(p)] = \eta [J(\Omega, p)], \quad (3.10)$$

where  $J(\Omega, p)$  is the marginal value of an additional worker to the firm,  $\frac{\partial \Pi(\Omega, p)}{\partial n}$ . From the derivative

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<sup>9</sup>In the standard model, every worker produces  $p$ . Adding perfectly flexible capital is irrelevant as long as the production function is assumed to be CRS, in which case the marginal product is in terms of an efficiency unit of labor.

<sup>10</sup>Krause and Lubik (2007), Cahuc and Wasmer (2001), Delacroix (2006), and Elsby and Michaels (2011) have analogous solutions for the wage equation.

of the Bellman equation with respect to the state variable,  $n$ ,  $J(\Omega, p) = \frac{c}{q(\theta)}$  and

$$J(\Omega, p) = pF_1(n, k) - w_n(n, k, p)n - w(n, k, p) + \beta(1 - \lambda)EJ(\Omega', p')$$

Substituting in for the Bellman equations as given above and the condition on  $J(\Omega, p)$ , the wage bargain yields a differential equation of the form (imposing the functional form for  $F(\cdot, \cdot)$ ):

$$\eta w_n(n, k, p)n + w(n, k, p) - \eta E \left[ p(1 - \alpha) \left( \frac{k}{n} \right)^\alpha - \beta c \theta' \right] - b(1 - \eta) = 0$$

Solving this differential equation (see Section 3.7.2 for solution method), the wage is given by:

$$w(n, k, p) = \eta \left[ \frac{p(1 - \alpha) \left( \frac{k}{n} \right)^\alpha}{1 - \alpha \eta} + E \{ \beta c \theta' \} \right] + b(1 - \eta) \quad (\text{WE})$$

This equation, along with the first order conditions for investment and vacancies and the aggregate equation of motion for employment, constitute the system of equations that defines the equilibrium of the model. Now that the employment side of the market has been determined, it remains to solve the firm's investment policy under various capital adjustment structures.

### 3.3 Capital Adjustment with Time-to-Build

To gain some intuition, it is useful to examine a version of the model in which the firm faces a one period time lag between investment in capital goods and an increase in its productive capacity. Intuitively, the delay in investment will cause the firm to invest so that, in expectation, it achieves a certain capital-labor ratio. When the shock is realized next period, the capital stock is fixed in that period and so the firm is stuck choosing the level of vacancies with a potentially suboptimal level of capital. Specifically, let  $\Gamma(i) = i_{-1}$  so that the equation of motion for capital now becomes

$$k = i_{-1} + (1 - \delta)k_{-1}$$

Aside from timing frictions, there are no adjustment costs to capital,  $\phi_k = \phi_i = 0$ . Moreover, the model is closed by assuming the per-unit purchase price of capital,  $p_t^k$ , is constant over time at  $p^k$ .

This setup is only slightly different from the perfectly flexible capital equation, but it will lead to a dynamic relationship between shocks and the labor market. In this case, the first order condition of the firm's problem for investment is:

$$(1 - (1 - \delta)\beta)p^k = \beta E [p' F_2(n', k') - w_k(\Omega' p')n'] \quad (FOC_{k_{tt}})$$

Therefore, the system of equations that define the equilibrium in this model become (turning to time subscripts):

$$n_{t+1} = \frac{(1 - \lambda)n_t + f(\theta_{t+1})}{1 + f(\theta_{t+1})} \quad (TTB_1)$$

$$\frac{c}{q(\theta_t)} = p_t(1 - \alpha) \left(\frac{k_t}{n_t}\right)^\alpha \frac{1 - \eta}{1 - \alpha\eta} - b(1 - \eta) + E_t \left[ \beta(1 - \lambda) \frac{c}{q(\theta_{t+1})} - \eta\beta c\theta_{t+1} \right] \quad (TTB_2)$$

$$p^k = \left( \frac{\beta}{1 - (1 - \delta)\beta} \right) E_{t-1} \left[ \left(\frac{k_t}{n_t}\right)^{\alpha-1} p_t \alpha \frac{1 - \eta}{1 - \alpha\eta} \right] \quad (TTB_3)$$

The solution method for this system of nonlinear difference equations is given in Section 3.7.3. The equilibrium will be a set of  $\{n, k, \theta\}$  which satisfy the firm's first order conditions for vacancies (TTB2) and investment (TTB1) and the aggregate equation of motion for employment. Moreover, in equilibrium,  $\theta$  will depend on current and past aggregate productivities due to the lagged expectational operator. To summarize the algorithm, I discretize the process for  $p$  into a Markov chain using the method of Tauchen (1986). Then, for every possible pair of shocks in consecutive periods,  $\theta$  and capital labor ratios are found that satisfy the above equations. These together imply a value for employment. Then, for an arbitrary starting tuple of  $k, n$ , and  $p$ , I can solve the model and generate simulated data.

It is important to note that the standard, perfectly flexible, MP model is nested in the above equations if  $\alpha = 0$ . This would simplify the second equation above to

$$\frac{c}{q(\theta_t)} = (1 - \eta)(p_t - b) + E_t \left[ \beta(1 - \lambda) \frac{c}{q(\theta_{t+1})} - \eta\beta c\theta_{t+1} \right], \quad (3.11)$$

which is exactly the discrete time analogue to Equation (6) in Shimer (2005). The key feature of equation (3.11) is that  $\theta_t$  is a purely forward looking, and thus, “jump” variable. It reacts to future expectations of productivity but not past innovations. For the case when  $\alpha > 0$ , on the other hand, the key is the lagged expectational operator. This says that the firm must target an expected capital-labor ratio in the next period, forming expectations over future productivity levels given its current state variables. To the extent that the firm forecasts incorrectly and productivity is different from its expected value, the firm’s level of capital will be suboptimal vis-à-vis the perfectly flexible model.

The result of the fixed capital stock is that the that the firm’s current choice of vacancy posting—and, thus,  $\theta$ —will be tied to last period’s productivity shock and date t-1 expectations. To see this, calibrated impulse responses are shown after a one period shock to productivity (see Section 3.7.4 below for calibration discussion.). For comparison, the impulse response of the perfectly flexible model is plotted along side the time-to-build responses.

Figure 3.2 shows the effect of the timing lag as discussed above. In particular, after the shock hits the system in period 3,  $\theta$  rises by about 12% in both the flexible and time-to-build models. In the standard model, however, once the shock disappears,  $\theta$  returns back to its steady state immediately. In the time-to-build setting, however, because of the expectational error that persists,  $\theta$  remains above its steady state for an additional period resulting in the bowed-out impulse response seen in the left panel and the more persistent effects on employment in the right panel.

### 3.4 Convex Adjustment Costs

A more general version of the time-to-build model, such as in Kydland and Prescott (1982), would yield quantitatively important labor dynamics in response to an aggregate shock. Time-to-build investment lags, however, generate a large number of extra state variables for the firm since potentially many past investment rates and capital stocks affect future decisions of investment. In addition, time-to-build capital adjustment, while intuitively appealing, leads to somewhat unappealing time series behavior of investment. Christiano and Todd (1996) investigate several specifications of time-to-build and show that investment and, as a result, other aggregate variables, take on a “saw-tooth” profile in response to a shock (Chart 1-6 in that paper).

Therefore, instead of generalizing the time-to-build model, I adopt the simpler convex adjustment cost structure. This has a few appealing features, as well as some downsides. First, convex adjustment costs are appealing due to the tractability of the firm’s optimal policy. In addition, quadratic adjustment costs, depending on the specification, can do a relatively good job of matching aggregate data on investment and capital (for instance, in Christiano et al. (2005)).

On the other hand, from a firm-level perspective, convex adjustment costs are perhaps less attractive than time-to-build. In particular, the micro evidence on firm level investment shows that investment profiles exhibit “lumpy” behavior in the sense that firms go through periods without investment and then engage in large bouts from time to time. This contrasts a quadratic adjustment cost structure which would predict that a firm constantly make small adjustments to its capital stock. Due to the representative firm model considered here, however, quadratic adjustment costs will be a reasonable approximation to the gradual adjustment of investment as seen in the data and in contrast to that predicted by a flexible model.

Two types of convex adjustment cost structures will be considered. For both, the equation of motion for capital will be the same as that in the perfectly flexible model(i.e.,  $\Gamma(i_{t+1}) = i_{t+1}$ )

$$k_{t+1} = i_{t+1} + (1 - \delta)k_t,$$



so that current investments become productive immediately. First, standard quadratic costs in adjusting the firm's capital stock are examined (referred to as capital adjustment costs). In this case, the firm pays the following adjustment cost for investment with a given capital stock,  $k_{-1}$

$$\frac{\phi_k}{2} \left( \frac{i}{k_{-1}} \right)^2 k_{-1}.$$

Most importantly, this structure implies an increasing marginal cost of investment. In addition, a proportionately bigger investment project, relative to the capital size of the firm, penalizes the firm proportionally more. These costs can be thought of as lost productive capacity during installation of or acclimation to the new capital. Faced with increasing marginal costs of investment, the firm is forced to smooth out investment in response to a shock. This formulation of adjustment costs does require that the firm pays costs in steady state since it costs firms to replace depreciated capital. The model can easily be recast so that repairs are not costly in this sense, but the main results of the chapter are unchanged. In equilibrium, to maintain the same capital-labor ratio, however, the price of capital will have to be somewhat lower.

As Christiano et al. point out, however, these adjustment costs still produce counterfactual investment impulse responses. In particular, investment still spikes and monotonically falls as the shock decays. In the data, however, it is clear that investment is still rising after the productivity shock hits and persists in a hump-shaped pattern. CEE suggest, then, quadratic adjustment costs in the change of investment:

$$\frac{\phi_i}{2} \left( \frac{\Delta i}{i_{-1}} \right)^2 i_{-1}.$$

These adjustment costs are typically interpreted as an cost to change the firm's plan of investments in to the future. This causes a firm to make far slower and smaller changes in its capital stock. These costs produce the more accurate hump-shaped pattern of investment as seen in the data. Figure 3.3 shows the investment impulse responses in the calibrated models; the green line shows that with standard capital adjustment, investment spikes with the shock and monotonically decays. On the other hand, the blue line gives investment dynamics in the CEE cost model. Here, investment is a

state variable and thus slow to move. It rises to a hump about five periods after the shock has hit and then returns, in a highly persistent manner, to its steady state.

Finally, it is important to note that the two different adjustment costs have differing effects on the steady state of the model. Capital adjustment costs are realized even in steady state because the firm must pay the cost when maintaining its depreciated capital stock. On the other hand, investment adjustment costs are zero in steady state because the firm has a constant investment rate. Thus, the CEE model shares the same steady state as the flexible model, whereas the steady state of the standard costs is slightly different.

Again, the model is closed by assuming that the price of capital is constant over time so that  $p_t^k = p^k$  at all times.<sup>11</sup>

First, the standard capital adjustment cost model has a first order condition for investment of the following form:

$$p_t \alpha \left( \frac{n_t}{k_t} \right)^{\alpha-1} \left( \frac{1-\eta}{1-\alpha\eta} \right) - p^k + \beta E \left[ p^k (1-\delta) + \phi_k \left( \frac{i_{t+1}}{k_t} \right) \frac{k_{t+1}}{k_t} - \frac{\phi_k}{2} \left( \frac{i_{t+1}}{k_t} \right)^2 \right] = \phi_k \left( \frac{i_t}{k_{t-1}} \right) \quad (3.12)$$

The important feature of this equation is that it is a second-order difference equation in investment. The firm takes into account not only the current capital stock, but also the previous and the future expected capital stock to determine its optimal level of investment. Indeed, a recursive substitution into the above equation reveals that the current capital choice is proportional to the present discounted value of future marginal productivities of capital. In addition, note that if  $\phi_k = 0$ , as in the flexible model, the capital stock is determined solely by the current productivity level and is thus a static decision.

The investment adjustment cost (CEE costs) model yields a similar optimal condition for invest-

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<sup>11</sup>Including an upward sloping inverse supply curve of capital:

$$p_t^k = p^k \left( \frac{i_t}{i_{ss}} \right)^{\frac{1}{\zeta}}$$

caused firms to delay investment for relatively low elasticities of supply. For higher elasticities, firms delay investment almost completely and wait for the shock to decay. See Barsky, House, and Kimball (2006) for an explanation related to the nearly infinite intertemporal elasticity for durable goods.

ment:

$$p_t \alpha \left( \frac{n_t}{k_t} \right)^{\alpha-1} \left( \frac{1-\eta}{1-\alpha\eta} \right) - p^k + \beta E \left[ p^k (1-\delta) + (2-\delta) \phi_i \left( \frac{\Delta i_{t+1}}{i_t} \right) + \beta \frac{\phi_i}{2} \left( \frac{\Delta i_{t+1}}{i_t} \right)^2 \right] = \phi_i \left( \frac{\Delta i_t}{i_{t-1}} \right) \quad (3.13)$$

Now, the firm's condition is a second-order difference equation in the *change* in investment, or a third order equation in the level of investment. In this model, investment is a state variable and the firm considers not only past capital stocks but past investment flows.

Importantly, the model and data have assumed that the workweek of capital is fixed over the business cycle. If the firm can adjust on the utilization margin of capital instead of having to adjust the number of units of capital that it employs, it is possible that adjustment costs to capital will not affect dynamic adjustment of the labor market. Extending the standard model to include the flexible workweek of capital as well as allowing for other flexible inputs is an important avenue for future research.

In order to quantitatively evaluate these models, the models parameters are calibrated in the following section.

### 3.4.1 Calibration

In order to evaluate the fit of the realistic adjustment cost models, the model's parameters are calibrated to compare the model impulse responses to those in the empirical section. The adjustment cost model has 15 parameters, of which nine will be fixed and the other six picked to match several moments in the data. The model time period is one week.

In particular, the discount rate,  $\beta$ , is set at .9991 corresponding to an annual interest rate of 5%. The curvature of the production function,  $\alpha$ , is fixed at .33 as is standard in the literature. Following the estimate in Petrongolo & Pissarides (2001), I set the elasticity of the matching function by fixing  $\gamma = .6$ . To match a quarterly exogenous separation rate of 10%,  $\lambda = .0077$ . In addition, the capital depreciation rate,  $\delta = .002$ , generates an annual capital depreciation rate of 10%, as is standard in

the RBC literature.

The process for productivity is determined by setting  $\rho = .998$  and  $\sigma = .003$  to mimic the empirical process for productivity (but constraining it to be an AR(1)). Finally, I set the worker's share of the surplus,  $\eta$ , to be .4 which is consistent with the range of values used in the literature.

This leaves the following six parameters to be determined:  $[\mu, b, c, p^k, \phi_i, \phi_k]$ . Intuitively,  $\mu$  pins down the efficiency of the matching process; for a given level of  $\theta$ ,  $\mu$  determines the job-finding and job-filling probabilities,  $q$  and  $f$ . This parameter is used to reconcile the empirical job-finding rate and labor market tightness. In particular, I target a steady state value of  $f = .1125$  to correspond to Shimer's finding that the monthly job filling probability is .45 ( $.45/4 = .1125$ ). In addition, the steady state value of labor market tightness will be targeted at .72. Therefore, given  $f$  and  $\theta$ , this implies that  $.1125 = \mu \cdot .72^{(1-.6)} \implies \mu = .1283$ . By the steady state equation for unemployment, this yields a steady state unemployment rate of 6.4%.

The parameters,  $b$  and  $c$ , jointly determine the volatility of the endogenous labor market variables. The calibration of these two parameters is controversial and very important to the performance of the model (See Hagedorn and Manovskii (2008) and Fujita and Ramey (2007), for examples). It is important to note that it is not the level of  $b$  and  $c$  that matters, but rather their proportion of flow profits. So, for any chosen capital-labor ratio, the values of  $b$  and  $c$  will be renormalized to generate the same cyclical properties.

I set  $b$  and  $c$  to target two empirical moments.<sup>12</sup> First,  $b$  is found such that the flow value of unemployment is  $\kappa \in (0, 1)$  times output per worker. Second, the job-filling cost,  $c/q$  is targeted to be about 14% of expected quarterly wages following the estimates in Silva and Toledo (2005). It follows, from the functional forms above, that  $b$  will be determined such that  $b \approx \kappa \left(\frac{k}{n}\right)^\alpha$  and  $\frac{c}{q(\theta)} \approx (.14)(13)(w)$ . Choosing the capital-labor ratio of 2.54 and the fraction,  $\kappa = .61$ , pins down  $b = .8297$ . Then, the value of  $c$  is .3853 which implies a steady state hiring cost equal to 13.81% of quarterly wages, which is very close to the targeted moment. For sensitivity analysis, I will vary  $b$  as a fraction of output per worker to .71 to show that the cyclical properties are very sensitive to

<sup>12</sup>They cannot be jointly satisfied, but the calibration results in moments that are very close to the data. See section 3.7.4 for details.

this parameter. For further details on the calibration see section 3.7.4.

The per-unit price of capital,  $p^k$  will pin down, for a given set of parameters, the steady state capital-labor ratio. This parameter is used to match a capital-labor ratio of 2.54 as found in the data described above. The quadratic adjustment cost parameters  $\phi_k$  and  $\phi_i$  are calibrated to match the contemporaneous correlation between investment and productivity, .54. For the baseline calibration, this implies a value of  $\phi_k = 145$  and  $\phi_i = .28$ .<sup>13</sup> The calibrated parameters are given in Table 3.3.

### 3.4.2 Model Results

In order to solve the adjustment cost models, I log-linearize around the non-stochastic steady state and solve for the rational expectations equilibrium. This method of solution will yield a fairly good approximation of out-of-steady-state dynamics as the model abstracts from endogenous job destruction which causes the firm's policy function to be discontinuous in the shocks. See section 3.7.5 for the log-linearized model.

Examining the flexible model first in Tables 3.4 and 3.5 and Figure 3.4. The model data perform very similarly to Shimer's model in that tightness and employment are not nearly as volatile as they are in the data. The normalized standard deviation of  $\theta$  is 7.45 as opposed to 11.45 in the data; the contemporaneous elasticity of  $\theta$  with respect to  $p$  is about 7.4 (with Shimer's calibration of  $\kappa = .4$ , the elasticity is 3). In the data, the elasticity is around 8, so the model is generating, for a reasonable calibration of  $\kappa$ , a respectable amount of amplification in  $\theta$ . For employment, the scaled standard deviations are .19 in the model and .42 in the data. Investment, due to its flexibility, is too volatile and uncorrelated with its past values. Each of the variables, aside from investment, are highly autocorrelated due to their dependence on productivity and the highly persistent nature of the calibrated productivity process.

In Table 3.4 and Figure 3.4, the dynamic correlations and dynamic responses of the flexible model are shown. First, in Table 3.4, tightness is symmetrically correlated with productivity at different lags. This is an important result that will be contrasted in the adjustment cost case. Tightness

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<sup>13</sup>In the case that capital adjustment costs are net of depreciation, the calibrated  $\phi_k$  is around 10. The results are otherwise quantitatively the same.

is almost perfectly correlated contemporaneously with productivity and even has a .89 correlation coefficient with productivity at  $t-3$ . In addition, employment and unemployment are more highly correlated with past productivity levels than future, indicating the slow-moving nature of those variables, even in the flexible model.

Turning to the dotted lines in Figure 3.4, the investment impulse response is furthest from the empirical impulse response since investment spikes by 47% on impact and immediately returns to zero. Tightness rises by 5.6% on impact and returns monotonically to steady state, with a half-life of about 28 quarters. In a regression of  $\theta$  on current and two lags of productivity, in addition, only current productivity is significant. This shows that  $\theta$  is correlated with past productivities, as in Table 3.4, only to the extent that current productivity is correlated with past productivities. Finally, the impulse response of employment peaks at three quarters with a maximum response of .13%, which is far quicker and smaller than the empirical results. Thus, the flexible model here produces little amplification and propagation.

For comparison, the capital adjustment model data are presented in Tables 3.6 and 3.7 and the solid lines of Figure 3.4. First, investment is much less volatile and more highly persistent in the adjustment cost model; its relative standard deviation is 6.45, which is still more than twice as high as in the data. Tightness is slightly less volatile relative to productivity at 7.09 compared to 7.45 in the flexible model and 11.75 in the data. The contemporaneous elasticity of  $\theta$  with respect to  $p$  is 7, so the model has slightly less amplification than the flexible model. Again, employment volatility is too small at .18 compared to .45 in the data.

Table 3.7, however, shows some important differences compared to the flexible model. Both tightness and employment exhibit more correlation with past productivities than they did in the flexible model which is more in line with the data. For instance, the correlation of tightness with productivity at  $t-3$  is .92, whereas it is .89 in the flexible model—this breaks the symmetric correlation of  $\theta$  with  $p$ , which more closely matches the data. In addition, in a regression of  $\theta$  on current and two past productivities, all are significant and large in magnitude in determining  $\theta$ . This is in contrast to the flexible model in which only current productivity mattered.

The impulse responses are also more realistic in terms of their propagation in Figure 3.4. Tightness rises by 4.2% on impact and increases until five quarters after the shock up to 4.7%, then declines back to steady state. In the data, tightness also peaks at four quarters but its peak is much higher than its initial jump, which is still not captured in the model. Employment rises in the first quarter by .05% and rises to a peak of .12% above its steady state by the sixth quarter. This is about a third of the response as seen in the data, but the dynamics are more similar to those in the data.

The investment adjustment cost model displays very similar results with the given calibration. This is because, for the investment adjustment calibration, both cost structures act in very similar ways when the data are aggregated to quarterly frequency (Figure 3.3 is weekly). The important features, again, are that tightness and employment respond in a hump-shaped pattern to a productivity shock. The same regression of  $\theta$  on past and present  $p$ 's shows that, even after accounting for today's productivity, past values have a significant and large effect on  $\theta$ . Employment still peaks at six quarters and tightness at five quarters after the shock.

The model impulse responses generate relatively larger amplification of shocks than the model with constant returns to labor and no capital as in Shimer (2005). Here I show that the amplification seen in this model is very similar to standard models. First, Section 3.7.6 and Table 3.10 show results from the implied elasticities of both the model with and without constant returns and different scenarios for the ratio of the value of leisure to average productivity. Table 3.8 reconciles the larger elasticities as seen in the impulse responses in Figures 3.4 and 3.5 under differing calibrations.

By virtue of abstracting from capital, the literature has typically reported elasticities with respect to output per worker, not multifactor productivity as in this chapter. Here I show that the amplification properties of the flexible model of this chapter behaves very similarly. Figure 3.6 gives the time path of the change in labor market tightness with respect to the change in output per worker after a 1% increase in multifactor productivity. This picture shows the standard lack of amplification as is typical of MP models. Table 3.11 gives the elasticities of tightness with respect to output per worker in the data (13.2%) versus the two models, which perform similarly (4.9% and

5%).

With a modestly different calibration of  $\kappa$ , however, the value of leisure as a fraction of output per worker, both adjustment cost models obtain very realistic amplification and propagation dynamics. Figure 3.7 shows the impulse responses for the capital adjustment model calibrated as in Table 3.3 but with  $\kappa = .71$ , chosen to match the elasticity of tightness with respect to output per worker in the data (13.2%). Note that .71 implies a ratio of  $b$  to average productivity of .92, which is slightly higher than the .9 in Fujita and Ramey (2007) but still lower than the .96 in Hagedorn and Manovskii (2008). In the adjustment cost model (solid lines),  $\theta$  rises by about 10% and increases to about 11% by five quarters.

Therefore, the addition of capital and investment adjustment costs significantly alters the dynamics of labor adjustment in the MP model. Both cost structures perform very similarly. For a reasonable calibration, the model can produce realistic propagation as found in the data. The amplification properties of the model are not improved by the addition of convex adjustment costs to capital.

### 3.5 Literature Discussion

The canonical search and matching model of the aggregate labor market is due to Pissarides (1984, 2000) and Mortensen and Pissarides (1994) (thus, MP model). Shimer (2005) analyzed the MP model with aggregate productivity shocks to examine the cyclical properties of labor market. He finds that the standard model of the labor market failed to generate both the volatility (amplification problem) and persistence (propagation problem) of shocks as found in the US labor market.

A large literature has examined the sources of the amplification deficiency of the standard MP model. For instance, a track of research has examined the influence of rigid wages on the fluctuation of employment and tightness such as in Hall (2005) and Trigari and Gertler (2009). Another set of papers examines the model with decreasing returns to scale in employment (Cahuc and Wasmer (2001), Krause and Lubik (2007), and Elsby and Michaels (2011)). This amounts to the opposite assumption about capital as made in this chapter—in those models, the capital stock is fixed, whereas



before firms can instantaneously adjust capital and face a perfect second-hand market for its capital goods. Krause and Lubik show that, in the exogenous job destruction model such as the one in this chapter, the business cycle properties of the search and matching model are largely unaffected by the addition of downward-sloped labor demand and large firms.

A smaller literature, however, has been concerned with the propagation aspect of the search model. Fujita and Ramey (2007) focus on quadratic costs to posting vacancies as opposed to the standard linear costs. This serves, as will be seen with similar capital adjustment costs, to smooth out vacancies over the business cycle, leading to more plausible propagation. Hagedorn and Manovskii (2008) use a time-to-build framework in posting vacancies and variable home production and find that the dynamic correlation of tightness and productivity is improved by the time-to-build structure. Epstein (2011) shows that worker-side heterogeneity and search intensity lead to slow-moving adjustment of labor tightness.

den Haan et al. (2001) is one of the only papers to consider the effect of capital frictions in a labor matching model.<sup>14</sup> They find qualitatively that capital frictions are important for the equilibrium of the model and can improve the propagation of aggregate shocks. Their capital friction is of a different form from those considered here. The authors assume that firms choose its capital stock *before* idiosyncratic shocks are realized but may renege on its capital rental if the idiosyncratic shock it receives is bad; they show that capital frictions lead to a delayed response of endogenous variables to the productivity shock.

Finally, it is important for the purposes of this chapter to understand the capital adjustment cost literature.<sup>15</sup> Cooper and Haltiwanger (2006) find that a mixture of convex and non-convex adjustment costs fit the data best, whereas Eberly et al. (2009) argue that a quadratic adjustment cost model can fit the microdata well.

In this chapter's representative firm setup, I argue that, while convex adjustment costs do not match firm-level data particularly well, they are a useful approximation to the time-series properties

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<sup>14</sup>Merz (1995) and Andolfatto (1996) study RBC models with search frictions. They do not, however, examine adjustment costs. The timing of investment is a one period time-to-build but since labor does not become productive for a period as well, this is not a capital friction like those considered in this chapter.

<sup>15</sup>A full literature review is beyond the scope of this chapter. See Hammermesh and Pfann (1996) for a summary.

of aggregate investment. In addition, Christiano, Eichenbaum, and Evans (2005) argue that adjustment costs in the change in the flow of investment produce more realistic properties of investment in response to shocks.

In addition, work by Shapiro (1986) and Bloom (2009) show that capital adjustment matters for labor adjustment. Shapiro (1986) estimates a structural model of the firm's employment and investment decision with quadratic adjustment costs to both capital and labor. He finds that adjustment costs in capital are important for determining firm-level labor demand. Bloom (2009) estimates a model with various adjustment costs—convex, kinked, and fixed—for both capital and labor and finds that the strongest evidence is for fixed costs of labor and capital, large kinked costs of capital adjustment and modest hiring and firing costs on a per-worker basis. Importantly, he argues while studying the dynamics of labor demand, omitting capital adjustment costs yields an ill-fitting model. This is strong evidence that DSGE models of the labor market with search frictions should include non-trivial capital adjustment costs.<sup>16</sup>

### 3.6 Conclusion

This chapter argues that including more realistic models of capital adjustment has important implications for the dynamics of labor adjustment in standard models of the labor market. After Shimer's influential study of the canonical Mortensen-Pissarides search and matching model, a large literature has emerged to generate more quantitatively reasonable amplification and propagation properties of these models. Much of the literature has focused on either the perfectly flexible capital or fixed capital versions of the model.

Examining three types of capital adjustment, I have shown that the timing and costs associated with adjustment of a firm's capital stock can lead to more realistic propagation of aggregate shocks. In addition, for very reasonable parameterizations of the model with plausible values of the flow surplus to a match, the models considered here generate reasonable propagation of shocks. Most importantly, the dynamic responses of labor market tightness and employment (or unemployment)

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<sup>16</sup>Interestingly, he finds that omitting labor adjustment when studying capital dynamics is much less important to the model's fit.

take on hump-shaped patterns so that the largest impact of the shock is not felt until around a year after the arrival of the shock. The two types of convex adjustment costs yield very similar dynamic responses; the CEE investment adjustment costs, however, can provide larger propagation implications due to the very slow-moving nature of investment in that model.

While the extensions to the canonical search and matching model of the labor market in this chapter improve the model's propagation fit, there are still areas that the model can be improved. Aside from well-known issues of wage fluctuation and amplification, the model's investment responses are not realistic. There are two reasons for this. First, agents in the model are risk neutral and so the consumption smoothing incentives in standard business cycle models is not present. This leads to a larger-than-realistic variability of investment and unrealistic investment impulse response functions. Second, while convex adjustment costs are a plausible modeling device for aggregate investment dynamics, they likely do not describe the type of adjustment costs faced by individual firms.

In future work, it is important to build realistic microfoundations of a firm that faces a variety of non-convex adjustment costs. Bloom (2009) and others find that linear adjustment costs to both capital and labor best fit panel data on firm factor demand. A richer model of firm heterogeneity with endogenous job destruction would be able to fully characterize the joint dynamics of capital and labor over the business cycle as well as quantifying the importance of the effects of capital adjustment on labor market dynamics.

In addition, several additions to the model would make for a richer accounting of the joint dynamics of capital and labor. First, understanding how the elasticity of substitution between capital and labor affects the joint dynamics of the labor market is important to understanding how adjustment costs to one factor can affect the adjustment of the other. Second, accounting for flexible adjustment of the workweek of capital in the model and data are important extensions to both the empirical and model analysis. If firms can adjust the use of its current capital stock over the business, then adjustment costs to capital might have less of dynamic effect on the labor market. These are all avenues of future research to understand the interrelated nature of the adjustment of capital and labor.

## 3.7 Appendix

### 3.7.1 Data Description

All variables except the measured capital stock were downloaded from the FRED II database and range between 1951:Q1 and 2004:Q2. The raw labor market variables were downloaded at the monthly frequency and converted to quarterly data by taking simple averages over the relevant months. Civilian Employment, labor force, and the number of unemployed people are defined for those 16 or older and are seasonally adjusted (series CE16OV, CLF16OV, UNEMPLOY respectively). The series CNP16OV is a measure of the civilian noninstitutional population. The measure of vacancies, which is commonly used in the literature, is the help wanted index that comes originally from the Conference Board (this variable restricts the range of dates).

For the empirical analysis shown, employment is defined as the ratio of employment to population; the unemployment rate is ratio of the number of unemployed people to the labor force. Also, the employment rate, constructed by dividing employment by the labor force, is used as a sensitivity check. In addition, labor market tightness is the ratio of the help wanted index to the number of unemployed workers.

Two variables were also downloaded from the National Income and Product Accounts. Real GDP (GDPC96) is used as the measure of output and real private fixed investment as the measure of investment (FPIC96). Each of these variables comes at the quarterly frequency and in billions of chained 2000 dollars.

Finally, in order to construct the multifactor productivity series, I require a measure of the quarterly capital stock. The NIPA only offers these at the annual frequency. I use a measure of the capital stock from Gomme and Rupert's (2007) capital stock 3 which is the sum of market capital and household capital. This series is constructed by using the 1947 capital stock and imputing quarterly data with estimated depreciation rates and a quarterly investment series.

All the data are detrended by regressing the log of each series on a cubic polynomial in time and a constant. The residuals from these regressions are the detrended data. The results are qualitatively the same if an HP filter with a parameter of 1600 is used to detrend the data. The only major

difference is that the productivity series is less persistent. In addition, the results are very similar if the employment rate or the unemployment rate is used instead of the employment to population ratio is used or if the unemployment rate is used.

### 3.7.2 Wage Equation Solution

As stated above, the surplus sharing rule  $(1 - \eta) [W(\Omega, p) - U(p)] = \eta [J(\Omega, p)]$  determines the constantly renegotiated wage between every employee in the representative firm. Examining the right hand side first:

$$W(\Omega, p) - U(p) = w(\Omega, p) - b + \beta E [W(\Omega', p') - U(p') - f(\theta')(W(\Omega', p') - U(p')) - \lambda(W(\Omega', p') - U(p'))]$$

Then, rearranging and plugging in for the Nash sharing rule yields:

$$W(\Omega, p) - U(p) = w(\Omega, p) - b + \beta E \left[ (1 - \lambda) \frac{\eta}{1 - \eta} (W(\Omega', p') - U(p')) - f(\theta') \frac{\eta}{1 - \eta} \frac{c}{q(\theta')} \right]$$

The right hand side of this equation is equal, in equilibrium, to  $\frac{\eta}{1 - \eta} J(\Omega, p)$ :

$$w(\Omega, p) - b + \beta E \left[ (1 - \lambda) \frac{\eta}{1 - \eta} (W(\Omega', p') - U(p')) - f(\theta') \frac{\eta}{1 - \eta} \frac{c}{q(\theta')} \right] = \frac{\eta}{1 - \eta} J(\Omega, p) \implies$$

$$w(\Omega, p) - b + \beta E \frac{\eta}{1 - \eta} c \theta' = \frac{\eta}{1 - \eta} [J(\Omega, p) - \beta(1 - \lambda) J(\Omega', p')]$$

Finally, the right hand side of the above is given by the *FOC* to be  $pF_1(n, k) - w_n(\Omega, p)n - w(n, k, p)$  so it can be shown that:

$$(1 - \eta) (w(n, k, p) - b) + E \beta \eta c \theta' = \eta [pF_1(n, k) - w_n(\Omega, p)n - w(\Omega, p)]$$

Following Delacroix (2006) This can be written as a differential equation of the form

$$\frac{\partial w(\Omega, p)}{\partial n} + F(n)w(\Omega, p) + G(n) = 0$$

to which the solution is

$$w(\Omega, p) = \left( \int_0^n \frac{G(z)}{H(z)} dz \right) H(n),$$

the wage equation in equation WE is the solution to this differential equation.

### 3.7.3 Solution Method for One-period Time-to-build Model

The algorithm to solve the model given in Section 3.3 is as follows. The ultimate goal is to find a solution to the difference equation which gives  $\theta_{ij}(n_{t-1})$ , where  $i$  is last period's aggregate state and  $j$  is this period's aggregate state.

1. Fix  $\{n_{t-1}, k_{t-1}\}$  and  $\{p_{t-1} = p_i, p_t = p_j\}$  for some  $i, j$  in the discretized state space for  $p$ .
2. Guess the function  $\theta'_{ij}(n_t)$ . By the time stationarity of the functional equation for  $\theta$ ,  $\theta_{ij}(n_t) = \theta_{ij}(n_{t-1})$ .
3. Given  $n_{t-1}, k_{t-1}$ , use:

$$n_t = \frac{(1 - \lambda)n_{t-1} + f(\theta_{ij})}{1 + f(\theta_{ij})}$$

which gives  $n_t$  as a function of  $n_{t-1}$  for all possible  $i, j$  histories.

4. Evaluate the forward expectation in equation  $TTB_2$  using the postulated  $\theta'_{ij}(n_t)$  and the appropriate  $n_t(n_{t-1})$ .
5. Use equation  $TTB_3$  (the equation for  $k$ ) to compute  $k_i(n_{t-1})$ . Capital depends on last period's shock and  $n_{t-1}$ .
6. Use equation  $TTB_1$  to solve for  $\hat{\theta}_{ij}(n_{t-1})$  and update.
7. Repeat from step 3 until convergence

8. Loop over all possible pairs,  $\{p_i, p_j\}$ .

Thus, for any arbitrary  $\{n_{t-1}, k_{t-1}\}$  and pair  $\{p_i, p_j\}$ , I can find the equilibrium values of  $n_t$ ,  $\theta_t$ , and  $k_t$ .

### 3.7.4 Calibration

The following are the steady state equations common to both quadratic adjustment cost models:

$$\begin{aligned}\frac{y}{n} &= p \left(\frac{k}{n}\right)^\alpha \\ \frac{c}{\mu} \theta^\gamma (1 - (1 - \lambda)\beta) + \eta\beta c\theta &= p(1 - \alpha) \left(\frac{k}{n}\right)^\alpha \frac{1 - \eta}{1 - \alpha\eta} - b(1 - \eta) \\ n &= \frac{\mu\theta^{1-\gamma}}{\lambda + \mu\theta^{1-\gamma}} \\ w(n, k, p) &= \eta \left[ \frac{p(1 - \alpha) \left(\frac{k}{n}\right)^\alpha}{1 - \alpha\eta} + \beta\theta c \right] + b(1 - \eta)\end{aligned}$$

For the different adjustment costs, the capital-labor ratios are:

$$\begin{aligned}\left(\frac{k}{n}\right)_k &= \left( \frac{p\alpha \frac{1-\eta}{1-\alpha\eta}}{\phi_k \delta (1 - \beta + \frac{\beta\phi}{2}) + p_k (1 - (1 - \delta)\beta)} \right)^{\frac{1}{1-\alpha}} \\ \left(\frac{k}{n}\right)_i &= \left( \frac{p\alpha \frac{1-\eta}{1-\alpha\eta}}{p_k (1 - (1 - \delta)\beta)} \right)^{\frac{1}{1-\alpha}}\end{aligned}$$

Notice, first, that  $\phi_i$  does not alter the steady state of the model in CEE adjustment costs. Here I flesh out the details of finding  $b$  and  $c$  for the calibration. For any given capital-labor ratio, the adjustment cost parameter does not change the choice of these parameters. From the second equation above,  $b$  and  $c$  are related for a given set of parameters and a chosen value of  $\theta (= .72)$ . This equation is of the form:  $c = \psi(\theta)b$  where  $\psi$  is given by:

$$\psi(\theta) = \frac{\frac{p(1-\alpha)}{\kappa} \frac{1-\eta}{1-\alpha\eta} - (1 - \eta)}{\frac{\theta^\gamma}{\mu} (1 - (1 - \lambda)\beta) + \eta\beta\theta}$$

where  $\kappa = \frac{b}{y/n}$ . I proceed by choosing a capital-labor ratio and a  $\kappa$  which gives  $b$ . Using  $\psi(\theta)$  and my choice of  $\theta$ ,  $c$  is pinned down.

It is important to note, though, that doing this makes hiring costs as a fraction of the wage

invariant to the choice of  $b$ . This can be seen as follows. To pin down hiring costs to be 14% of quarterly wages requires:

$$c = .14q(\theta) \left\{ \eta \left[ \frac{p(1-\alpha) \left(\frac{k}{n}\right)^\alpha}{1-\alpha\eta} + \beta\theta c \right] + b(1-\eta) \right\}$$

Substituting in  $b$  for both the capital labor ratio and for  $c$ ,  $b$  is eliminated from this equation. What determines the fraction of wages is  $\theta$  and  $b$  as a fraction of output per worker. Thus, the two moment conditions cannot be jointly satisfied. Table 3.3 shows the results of the calibration.

### 3.7.5 Log-linearized Model

Let a variable,  $\tilde{x}_t = \ln(x_t) - \ln(x_{ss})$ , be the log deviation from the non-stochastic steady-state value of  $x$  ( $x_{ss}$ ). Equations common to standard adjustment costs and CEE adjustment costs:

$$\tilde{p}_t = \rho E[\tilde{p}_{t-1}] \quad (3.14)$$

$$\tilde{k}_t = \delta \tilde{i}_t + (1-\delta)\tilde{k}_{t-1} \quad (3.15)$$

$$\tilde{n}_t = \frac{1-\lambda}{1+\mu\theta_{ss}^{1-\gamma}} \tilde{n}_{t-1} + \tilde{\theta}_t(1-\gamma) \left\{ \left( \frac{1-n_{ss}}{n_{ss}} \right) \left( \frac{\mu\theta_{ss}^{1-\gamma}}{1+\mu\theta_{ss}^{1-\gamma}} \right) \right\} \quad (3.16)$$

$$\tilde{p}_t + \alpha\tilde{k}_t - \alpha\tilde{n}_t = \frac{1}{B_{ss}} E \left[ \left( \tilde{\theta}_t - \beta(1-\lambda)\tilde{\theta}_{t+1} \right) + \eta\beta c\theta_{ss}\tilde{\theta}_{t+1} \right] \quad (3.17)$$

where

$$B_{ss} = \frac{c}{\mu}\theta_{ss}^\gamma - \beta(1-\lambda)\frac{c}{\mu}\theta_{ss}^\gamma + \eta\beta c\theta_{ss} + b(1-\eta)$$

For the standard capital adjustment cost model where  $\phi_k > 0$  and  $\phi_i = 0$ , the final equation is

$$\tilde{p}_t + (1-\alpha)\tilde{n}_t - (1-\alpha)\tilde{k}_t = \frac{1}{C_{k,ss}} E \left[ \phi_k \delta \left\{ \beta^{-1}\tilde{i}_t - (1+\delta)\tilde{i}_{t+1} - \beta^{-1}\tilde{k}_{t-1} + (\delta+2)\tilde{k}_t - \tilde{k}_{t+1} \right\} \right] \quad (3.18)$$

where

$$C_{k,ss} = \beta^{-1}\phi_k\delta + \beta^{-1}p_{ss}^k - p_{ss}^k(1-\delta) + \phi_k\delta^2 - \phi_k\delta$$



For the CEE investment adjustment cost model with  $\phi_i > 0$  and  $\phi_k = 0$ , the final equation is

$$\tilde{p}_t + (1 - \alpha)\tilde{n}_t - (1 - \alpha)\tilde{k}_t = \frac{1}{C_{i,ss}} E [\phi_i \tilde{i}_t (1 + \beta(2 - \delta)) - \phi_i \tilde{i}_{t-1} - \beta(2 - \delta)\phi_i \tilde{i}_{t+1}], \quad (3.19)$$

where

$$C_{i,ss} = p_{ss}^k (1 - (1 - \delta)\beta).$$

Simulated data are drawn for 25,000 periods with the first several hundred discarded. The shocks are the same across models. Then, the model data are aggregated to quarterly frequency and detrended via a regression on a cubic polynomial and constant, as in the empirical section. The final simulated data contain 1867 quarters of data to obtain precise estimates of the data properties.

### 3.7.6 Amplification

Recall that, in steady state, the job creation condition is

$$\frac{c}{\mu} \theta^\gamma (1 - (1 - \lambda)\beta) + \eta \beta c \theta = p(1 - \alpha) \left(\frac{k}{n}\right)^\alpha \frac{1 - \eta}{1 - \alpha \eta} - b(1 - \eta).$$

The capital-labor ratio for flexible version of the model in Section 3.4 ( $\phi_k = 0$  and  $\phi_i = 0$ ) is given by<sup>17</sup>

$$\left(\frac{k}{n}\right)_i = \left(\frac{p\alpha \frac{1-\eta}{1-\alpha\eta}}{p_k(1 - (1 - \delta)\beta)}\right)^{\frac{1}{1-\alpha}}.$$

Plugging this in to the job creation condition yields

$$\frac{c}{\mu} \theta^\gamma (1 - (1 - \lambda)\beta) + \eta \beta c \theta = p(1 - \alpha) \left(\frac{p\alpha \frac{1-\eta}{1-\alpha\eta}}{p_k(1 - (1 - \delta)\beta)}\right)^{\frac{\alpha}{1-\alpha}} \frac{1 - \eta}{1 - \alpha \eta} - b(1 - \eta).$$

---

<sup>17</sup>Note that the results are identical in the investment adjustment cost model since firms do not pay adjustment costs in steady state. They differ only slightly in the capital adjustment cost model.

Taking logs and differentiating gives the following relationship:

$$\frac{d \ln \theta}{d \ln p} = \frac{1}{1 - \alpha} \left[ \frac{p^{\frac{\alpha}{1-\alpha}} \left[ \frac{(1-\alpha)}{1-\eta\alpha} \right] \left[ \frac{\alpha \frac{1-\eta}{1-\eta\alpha}}{p_k(1-(1-\delta)\beta)} \right]^{\frac{\alpha}{1-\alpha}}}{p^{\frac{\alpha}{1-\alpha}} \left[ \frac{(1-\alpha)}{1-\eta\alpha} \right] \left[ \frac{\alpha \frac{1-\eta}{1-\eta\alpha}}{p_k(1-(1-\delta)\beta)} \right]^{\frac{\alpha}{1-\alpha}} - b} \right] \frac{\frac{\theta^\gamma}{\mu} (1 - (1 - \lambda)\beta) + \eta\beta\theta}{\frac{\gamma\theta^\gamma}{\mu} (1 - (1 - \lambda)\beta) + \eta\beta\theta}. \quad (3.20)$$

If  $\alpha = 0$ , as in the standard Mortensen-Pissarides model, this reduces to the elasticity derived in Mortensen and Nagypal (2005) equation (10). With the same parameter values, I replicate, of course, the elasticities in their results. Let

$$\tilde{p} \equiv p^{\frac{\alpha}{1-\alpha}} \left[ \frac{(1-\alpha)}{1-\eta\alpha} \right] \left[ \frac{\alpha \frac{1-\eta}{1-\eta\alpha}}{p_k(1-(1-\delta)\beta)} \right]^{\frac{\alpha}{1-\alpha}}$$

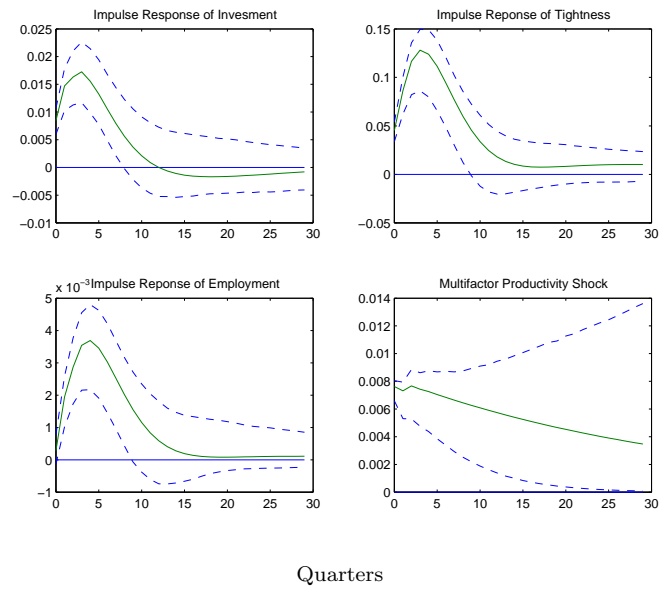
then

$$\frac{d \ln \theta}{d \ln p} = \frac{1}{1 - \alpha} \left( \frac{\tilde{p}}{\tilde{p} - b} \right) \frac{\frac{\theta^\gamma}{\mu} (1 - (1 - \lambda)\beta) + \eta\beta\theta}{\frac{\gamma\theta^\gamma}{\mu} (1 - (1 - \lambda)\beta) + \eta\beta\theta}. \quad (3.21)$$

Note that if  $\alpha = 0$ , the  $\tilde{p} = p$ . Table 3.8 calculates implied elasticities for three different calibrations. The first column gives the calibration target for the ratio of the flow benefit to unemployment to output per worker. The second translates this into  $b$ 's ratio to  $\tilde{p}$ . I report this since the calibration strategy in Shimer (2005) and Hagedorn and Manovskii (2008) both target this fraction.

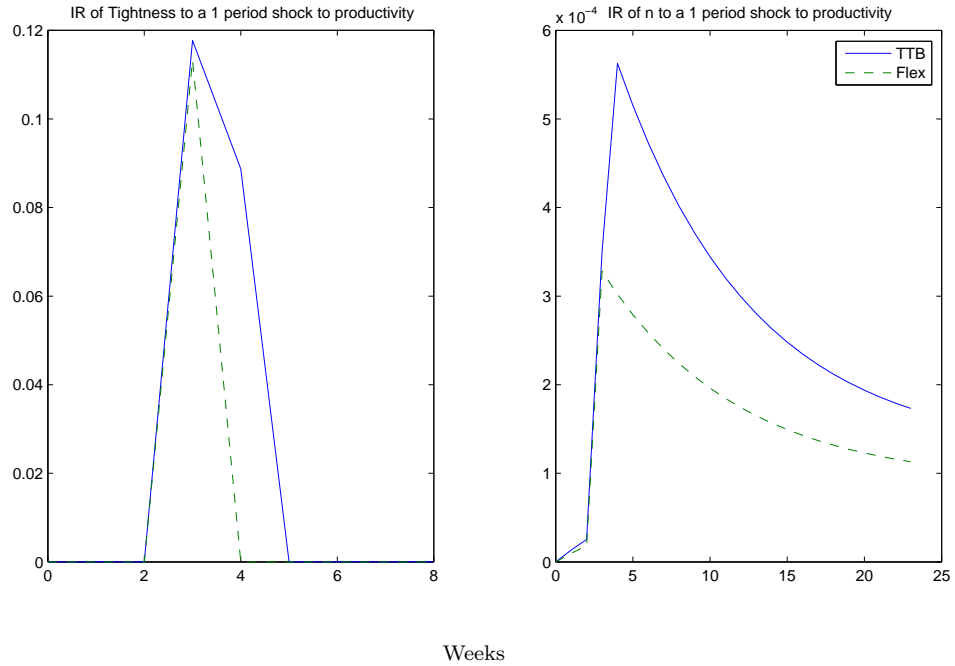
Shimer (2005) sets  $b = .4$  so that the ratio of  $b$  to the marginal product of labor was 40%. We see that under this calibration strategy, I get an elasticity of 2.65 in the model with diminishing returns to labor while an elasticity of 1.75 with constant returns. The second row reports the calibration in Hagedorn and Manovskii (2008) who set  $b$  to be 95.5% of the marginal product of labor. In the diminishing returns to labor model, this implies an elasticity of more than 35%. The elasticity for the baseline calibration in this chapter, I find an elasticity of 7.6%. Due to diminishing returns, this is larger than expected with a modest ratio of  $b$  to  $y/n$ , however the elasticity is in line with what is expected in the literature. It is also almost identical to the elasticity estimated of 7.44% from the regression of  $\ln(\theta)$  on  $\ln(p)$  in the simulated data.

**Figure 3.1:** Empirical Impulse Responses to a 1 Standard Deviation Shock to Productivity  
Percent Deviation



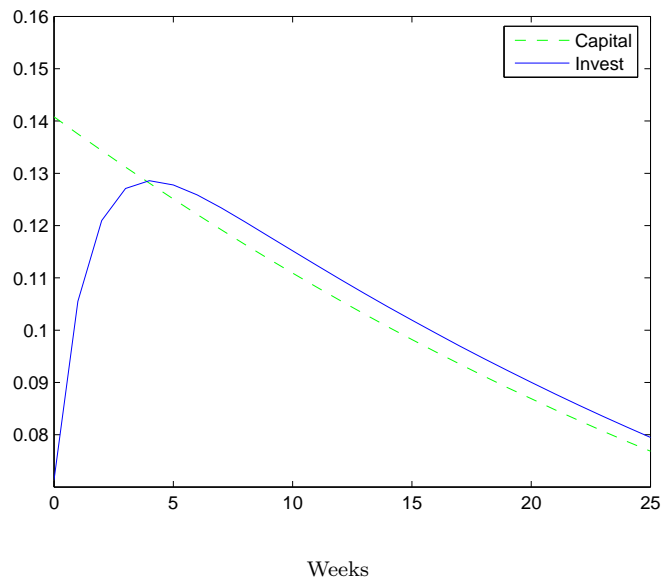
Note: Point estimates are solid lines. Dotted lines constitute 95% confidence intervals estimated by 2,500 bootstrap replications. See Section 3.7.1 for data description.

**Figure 3.2: Time-to-build Stylized Impulse Responses**  
Percent Deviation from Steady State



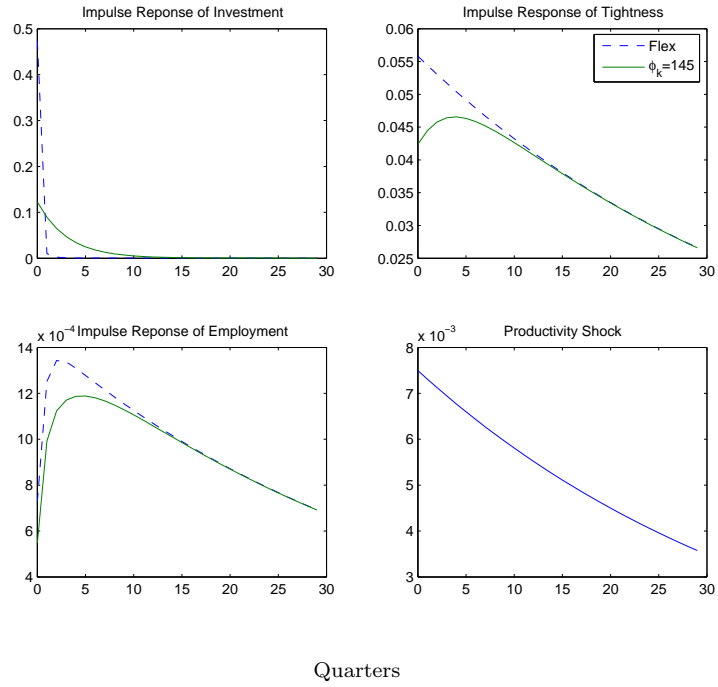
Note: Parameters are calibrated to those in Table 3.3 aside from two.  $b$  is chosen to equate the first period effect on vacancies in both models. The productivity process, however, is based on 5 grid points with a  $\rho = .75$  for expository purposes.

**Figure 3.3: Investment Responses Under Different Adjustment Costs**  
Percent Deviation from Steady State



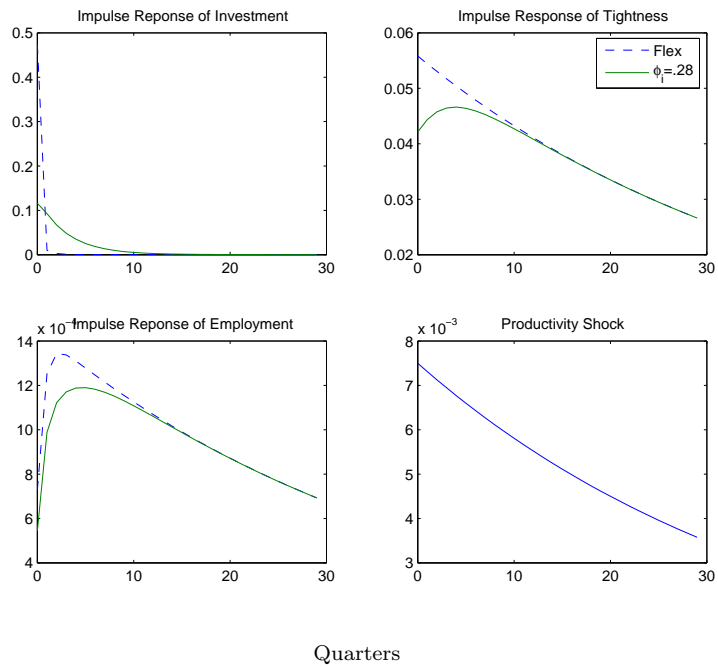
Note: Baseline calibration as in Table 3.3

**Figure 3.4:** Capital Adjustment Cost IRs to a 1 Sd Shock to Productivity  
Percent Deviation from Steady State



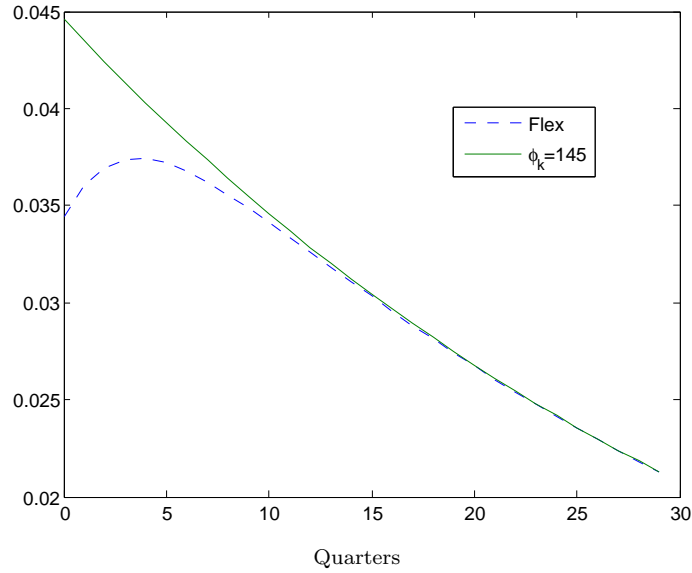
Note: Baseline calibration as in Table 3.3

**Figure 3.5:** Investment Adjustment Cost IRs to a 1 Sd Shock to Productivity  
Percent Deviation from Steady State



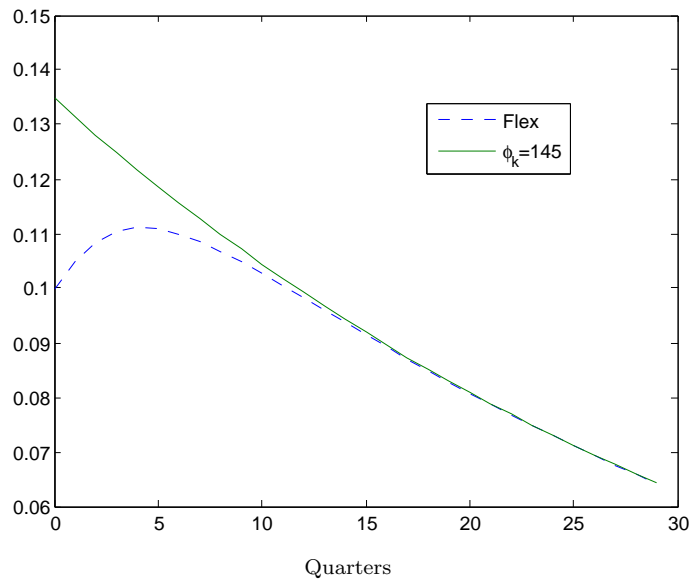
Note: Baseline calibration as in Table 3.3

**Figure 3.6:** Time Path of  $\frac{d \ln(\theta)}{d \ln(y/n)}$   
Percent Deviation from Steady State



Note: Baseline calibration as in Table 3.3

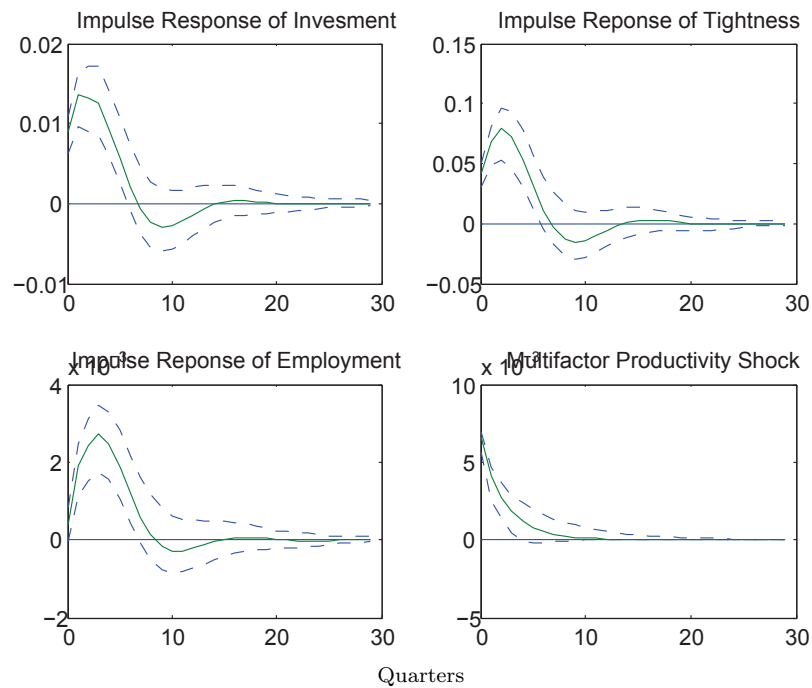
**Figure 3.7:** Time Path of  $\frac{d \ln(\theta)}{d \ln(y/n)}$ , Higher  $\frac{b}{y/n}$   
Percent Deviation from Steady State



Note: Baseline calibration as in Table 3.3 except  $\kappa = .67$ , which implies  $\frac{d \ln(\theta)}{d \ln(y/n)} = 13.2$

**Figure 3.8:** Impulse Responses with HP filtered data

Percent Deviation from Steady State



Point estimates are solid lines. Dotted lines constitute 95% confidence intervals estimated by 2,500 bootstrap replications. See Section 3.7.1 for data description.

**Table 3.1:** Empirical Standard Deviations and Cross- and Auto-correlations

	Sds		Cross					Auto		
	$\sigma$	$\frac{\sigma}{\sigma_p}$	$p$	$i$	$\frac{v}{u}$	$n$	$u$	t-1	t-2	t-3
Productivity	0.038	1	1	0.53	0.76	0.45	-0.79	0.96	0.92	0.86
Investment	0.08	2.30		1	0.70	0.53	-0.60	0.95	0.86	0.75
Tightness	0.419	11.75			1	0.85	-0.98	0.95	0.84	0.71
Employment Rate	0.015	0.42				1	-0.83	0.94	0.83	0.69
Unemployment Rate	0.219	6.12					1	0.95	0.85	0.72

See Section 3.7.1 for data description

**Table 3.2:** Empirical Cross Correlations with time t+i Productivity

Variable	$i = -3$	$i = -2$	$i = -1$	$i = 0$	$i = 1$	$i = 2$	$i = 3$
Productivity	0.86	0.92	0.96	1.00	0.96	0.92	0.86
Investment	0.50	0.53	0.54	0.53	0.46	0.38	0.29
Tightness	0.72	0.76	0.78	0.76	0.69	0.61	0.54
Employment Rate	0.51	0.52	0.50	0.45	0.38	0.30	0.23
Unemployment Rate	-0.76	-0.80	-0.81	-0.79	-0.72	-0.64	-0.58

See Section 3.7.1 for data description

**Table 3.3:** Baseline Calibration

Parameter	Model			Reason
	Flex	$k$ adj	$i$ adj	
$\beta$	.9991	.9991	.9991	5% Ann interest rate
$\alpha$	.33	.33	.33	Elsby and Michaels (2011)
$\gamma$	.6	.6	.6	Pissarides (2007)
$\lambda$	.0077	.0077	.0077	Quarterly Sep of 10%
$p$	1	1	1	Normalization
$\rho$	.998	.998	.998	Quarterly $\rho_q = .9748$
$\sigma$	.003	.003	.003	Quarterly $\sigma_q = .038$
$\eta$	.4	.4	.4	Elsby and Michaels (2009)
$\theta$	.72	.72	.72	Petrongolo & Pissarides (2001)
$\mu$	.1283	.1283	.1283	Monthly job-finding of .45 (Shimer, 2005)
$b$	.8297	.8297	.8297	See section 3.7.4. $\kappa = .61$
$c$	.3853	.3853	.3853	See section 3.7.4. $\frac{c}{q} \approx .14w_q$
$p^k$	41.27	41.07	41.27	$\frac{k}{n} = 2.54$ in data
$\phi_k$	0	145	0	$corr(i, p) \approx .54$
$\phi_i$	0	0	.28	$corr(i, p) \approx .54$



**Table 3.4:** Flexible Model,  $\phi_k = \phi_i = 0$ . Standard Deviations and Cross- and Auto-correlations

	Sds		Cross					Auto		
	$\sigma$	$\frac{\sigma}{\sigma_p}$	$p$	$i$	$\frac{v}{u}$	$n$	$u$	t-1	t-2	t-3
Productivity	0.037	1	1	0.11	0.9997	0.99	-0.99	0.97	0.93	0.89
Investment	0.653	17.65		1	0.11	0.02	-0.02	0.03	0.00	0.02
Tightness	0.276	7.45			1	0.99	-0.99	0.97	0.93	0.89
Employment Rate	0.007	0.19				1	-0.997	0.98	0.94	0.90
Unemployment Rate	0.103	2.79					1	0.98	0.94	0.90

See Section 3.7.1 for data description

**Table 3.5:** Flexible Model,  $\phi_k = \phi_i = 0$ . Cross Correlations with time t+i Productivity

Variable	$i = -3$	$i = -2$	$i = -1$	$i = 0$	$i = 1$	$i = 2$	$i = 3$
Productivity	0.888	0.929	0.971	1	0.971	0.929	0.888
Investment	-0.058	-0.055	-0.049	0.114	0.243	0.231	0.229
Tightness	0.888	0.929	0.971	1.000	0.971	0.929	0.888
Employment Rate	0.921	0.960	0.992	0.992	0.954	0.912	0.871
Unemployment Rate	-0.920	-0.959	-0.991	-0.991	-0.952	-0.910	-0.869

See Section 3.7.1 for data description

**Table 3.6:**  $k$  adjustment costs. Standard Deviations and Cross- and Auto-correlations

	Sds		Cross					Auto		
	$\sigma$	$\frac{\sigma}{\sigma_p}$	$p$	$i$	$\frac{v}{u}$	$n$	$u$	t-1	t-2	t-3
Productivity	0.037	1	1	0.534	0.996	0.983	-0.982	0.97	0.93	0.89
Investment	0.239	6.45		1	0.460	0.378	-0.378	0.81	0.59	0.42
Tightness	0.262	7.09			1	0.995	-0.992	0.98	0.95	0.91
Employment Rate	0.007	0.18				1	-0.997	0.99	0.96	0.92
Unemployment Rate	0.098	2.66					1	0.99	0.96	0.92

See Section 3.7.1 for data description

**Table 3.7:**  $k$  adjustment costs. Cross Correlations with time t+i Productivity

Variable	$i = -3$	$i = -2$	$i = -1$	$i = 0$	$i = 1$	$i = 2$	$i = 3$
Productivity	0.888	0.929	0.971	1	0.971	0.929	0.888
Investment	0.130	0.236	0.380	0.534	0.555	0.541	0.525
Tightness	0.919	0.952	0.981	0.996	0.964	0.921	0.880
Employment Rate	0.944	0.973	0.992	0.983	0.943	0.901	0.860
Unemployment Rate	-0.943	-0.972	-0.991	-0.982	-0.943	-0.900	-0.858

See Section 3.7.1 for data description

**Table 3.8:**  $i$  adjustment costs. Standard Deviations and Cross- and Auto-correlations

	Sds		Cross					Auto		
	$\sigma$	$\frac{\sigma}{\sigma_p}$	$p$	$i$	$\frac{v}{u}$	$n$	$u$	t-1	t-2	t-3
Productivity	0.037	1	1	0.538	0.996	0.942	-0.982	0.97	0.93	0.89
Investment	0.240	6.495		1	0.463	0.226	-0.384	0.81	0.59	0.42
Tightness	0.263	7.100			1	0.968	-0.992	0.98	0.95	0.91
Employment Rate	0.007	0.181				1	-0.982	0.99	0.96	0.92
Unemployment Rate	0.098	2.659					1	0.99	0.96	0.92

See Section 3.7.1 for data description

**Table 3.9:**  $i$  adjustment costs. Cross Correlations with time  $t+i$  Productivity

Variable	$i = -3$	$i = -2$	$i = -1$	$i = 0$	$i = 1$	$i = 2$	$i = 3$
Productivity	0.888	0.929	0.971	1	0.971	0.929	0.888
Investment	0.134	0.242	0.390	0.538	0.553	0.539	0.523
Tightness	0.920	0.952	0.981	0.996	0.963	0.921	0.879
Employment Rate	0.944	0.973	0.992	0.983	0.943	0.901	0.859
Unemployment Rate	-0.944	-0.973	-0.991	-0.982	-0.942	-0.900	-0.858

See Section 3.7.1 for data description

**Table 3.10:** Elasticities of Labor Market Tightness, varying  $b$ 

$b/\frac{y}{n}$	$b/\tilde{p}$	$\frac{d \ln \theta}{d \ln p}$		Calibration
		$\alpha > 0$	$\alpha = 0$	
0.31	0.40	2.7	1.8	Shimer (2005)
0.61	0.79	7.6	4.9	Baseline Calibration
0.74	0.96	35.4	22.7	Hagedorn and Manovskii (2008)

**Table 3.11:** Elasticities of Labor Market Tightness With Output Per Worker

$\frac{d \ln(\theta)}{d \ln(y/n)}$	Empirical	Flexible Model	Adjustment Cost Model
		$\phi_k = 0$	$\phi_k = 145$
	13.2	4.9	5.0

## CHAPTER IV

# The Wages of Nonemployment

### 4.1 Introduction

Rates of joblessness among males in the United States have risen dramatically in recent decades. Aggregate rates of nonemployment—the fraction of the year spent in unemployment or out of the labor force—have doubled since the late 1960’s. This rise in joblessness has been concentrated particularly among the low-skilled: nonemployment rates among high school dropouts have reached as high as 25% in recent years (see Figure 4.1). These trends have been shaped by historic declines in the labor market attachment of low-skilled men, and associated increases in long-term joblessness (see the seminal work of Juhn et al. (1991); Juhn (1992); Juhn et al. (2002)).

In this chapter, we investigate the origins of this secular increase in nonemployment. Motivated by the decline in labor market attachment, we focus on incentives to supply labor over the course of a working life. This labor supply choice boils down to a comparison of the lifetime returns to working versus not working.

In Section 4.2, we develop a model that formalizes this intuition and in turn informs our empirical work. The family labor supply model we develop yields a simple and rather intuitive prediction: the optimal labor supplied by the husband is a function of the relative family income with an employed husband relative to a nonemployed husband; in other words, as the “replacement rate” of nonemployment increases, the husband will supply less labor over his lifetime.<sup>1</sup> Surprisingly, there

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<sup>1</sup>We use the term husband throughout the chapter to match with the PSID definition—the male household member

is little empirical evidence on income replacement in nonemployment. The main contribution of this chapter is to understand both the level and time trend of replacement rates.

The virtue of this simple theoretical prediction is that it is possible to estimate an empirical analogue of the relevant replacement rate from data on family income available in standard datasets. We use data from the Panel Study of Income Dynamics (PSID) to infer estimates of family income replacement rates among low-skilled men in the United States over time since the 1970s. Our method exploits the panel dimension of the PSID to infer the average decline in family income associated with male nonemployment.

We begin by confirming the previous literature in finding increasing rates of joblessness for low-skilled prime-aged males over the past 30 years (Figure 4.1). The PSID additionally allows us to examine individual labor market histories. We find a marked increase since the early 1980's in spells of labor market detachment lasting five years, indicating that long-term joblessness is a growing trend among this population (see Figure 4.2). The PSID data further indicate that workers face longer spells of joblessness after transitioning out of employment in recent years compared to the early 1970's.

Using the PSID's rich set of socio-economic data, we first explore the distribution and sources of income of low-skilled males by labor force attachment. We find that government transfers and spousal income is a large share of the family income of nonemployed males. For instance, among those with at most a high school degree and a husband who worked less than one of the previous five years, 31.5% of family income came from spouses. The spousal contribution was only 20% for families in which the husband worked more than four of the previous five years.

Transfer income is a particularly large source of income support for nonemployed males. For low-skilled, married man who worked less than one of the previous five years, transfer income accounted for 38% of income. For non-married men in the same category, it was almost two-thirds of income. By comparison, for husbands who worked more than four of the previous five years, transfer only accounted for 2% of income.

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when a man or woman cohabit. Since we restrict our attention to men, this will encompass all male household heads.

We then directly estimate the family income replacement rate and its evolution over time. We estimate the empirical counterpart to the family income replacement rate in the model by estimating the fraction of income lost during spells of nonemployment. The replacement rate of those with at most a high school degree averages about 53%, showing the substantial costs of nonemployment to families.

We then ask the question: are changes in the family income replacement rate from nonemployment consistent with increasing low-skilled male nonemployment since the late 1960's? A simple explanation for the substantial secular rise in male joblessness would be that replacement rates have risen, causing individuals increasingly to choose not to work. In direct contrast, we find that family income replacement rates have, if anything, fallen over the past thirty years. The replacement rate begins in the late 1960's slightly above 60% but ends at a low of 40% in the mid-to-late 2000's.

Thus, viewed through the lens of a standard labor supply model an important puzzle emerges: simple economic theory suggests that a key determinant of long run employment rates is the replacement rate for family income. In contrast, the data do not support a strong relationship between the two. If replacement rates were steady, what has caused the rise in joblessness? Other potential explanations include increasing disability benefits, declining demand for low-skilled workers due to skill-biased technical change, and declining returns to labor market experience, among others.

The chapter proceeds as follows. Section 4.2 derives a theoretical prediction for the importance of the family income replacement rate in men's labor supply decision. Section 4.3 uses PSID data to document the evolution of nonemployment among low-skilled males over time. Section 4.4 describes the sources of income relied upon for males with different levels of labor market attachment and estimates replacement rates over time. Section 4.5 discusses the role of disability insurance. Section 4.6 discusses our findings and concludes.

## **4.2 What Determines Male Nonemployment?**

In this section, we lay out of simple model of an extensive margin labor supply choice to highlight the determinants of nonemployment. Consider a family that consists of a "husband" and a "wife"

and  $n$  children who live for  $T$  periods. The family maximizes lifetime total utility, discounting at a rate  $\rho = r$ , where utility is derived from total consumption minus the disutility from work.

The husband can either decide to participate in the labor market or remain nonemployed. If he works, he receives  $w_H$  in wages and salaries and  $b$  if he does not.  $b$  is the income from any government programs such as Unemployment Insurance or Social Security Disability Insurance. The husband's labor supply choice will be given by the indicator function,  $h$ .  $h = 1$  denotes a husband that works. The wife is assumed to choose hours freely and receives  $w_W$  per hour,  $n_W$ .<sup>2</sup> The family potentially also derives income from its stock of assets,  $a(t)$ .<sup>3</sup> The families stock of wealth evolves according to this differential equation

$$\dot{a}(t) = ra(t) + h(t)w_H + (1 - h(t))b + n_W(t)w_W - C(t). \quad (4.1)$$

Family income is defined as the sum asset, labor, and non-labor incomes. The difference of family income and consumption is saved and earns interest at the rate,  $r$ . Per period utility is given by

$$\ln(C) + (1 - h)\nu_H + \nu_W \ln(1 - n_W). \quad (4.2)$$

$\nu_H > 0$  is the level of disutility from the head working. The family's full problem can now be stated:

$$\begin{aligned} \max_{C, h, n_W} \int_0^T e^{-\rho t} [\ln(C) + (1 - h)\nu_H + \nu_W \ln(1 - n_W)] dt, \text{ s.t.} \\ h \in \{0, 1\}, n_W \in (0, 1) \\ a(0) = 0 \text{ and } a(T) = 0, \\ C > 0, \end{aligned} \quad (4.3)$$

and the equation of motion for assets. It is useful to set up the standard Hamiltonian to solve the

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<sup>2</sup>While it is not true that females have less of an extensive margin labor supply choice, it is easiest to communicate the point of the model with this set up. The dual indivisible labor problem is an important area for future research.

<sup>3</sup>Allowing for constant non-labor income does not change the results.

family's program. The Hamiltonian is given by

$$\mathcal{H} = e^{-\rho t} [\ln(C) + (1 - h)\nu_H + \nu_W \ln(1 - n_W)] + \lambda_t [ra(t) + h(t)w_H + (1 - h(t))b + n_W(t)w_W - C(t)]. \quad (4.4)$$

This problem results in a standard Euler equation relating marginal utilities across time. Since we have assumed that  $r = \rho$ , consumption will be equal to a constant in all periods,  $C \equiv \bar{C}$ . The first order condition for female labor supply is the standard condition that the marginal utility from an additional hour of work equals its attendant marginal disutility

$$\frac{\nu_W}{1 - n_W} = \frac{w_W}{\bar{C}}. \quad (4.5)$$

By virtue of the constant stream of consumption, female labor supply is also constant,  $n_W = 1 - \frac{\nu_W}{w_W} \bar{C}$ .

#### 4.2.1 Reservation Wage Policy

The husband's optimal labor supply decision is determined by a reservation policy whereby he works if the wage is above some threshold,  $w^R$ . The first order condition of the Hamiltonian with respect to  $h$  gives the threshold policy

$$\frac{w^R - b}{\bar{C}} = \nu_H \Rightarrow w^R = \nu_H \bar{C} + b. \quad (4.6)$$

In the case of linear utility in which the family simply maximizes lifetime income, the going wage  $w_H$  is either above or below the reservation wage and the husband will either work or not work his entire life. Due to the diminishing marginal utility of income, the husband's optimal policy is to work a fraction of his life.

We restrict attention, for simplicity, to a stationary economy in which  $\rho = r$ . As shown in Sargent and Ljungqvist (2011), the husband is therefore indifferent between the timing of his labor supply

path.<sup>4</sup> We follow Sargent and Ljungqvist (2008) and allow the husband to “time average” his labor supply decision. Thus, we assume that he chooses to work each period with constant probability  $\bar{h}$ , allowing us now to state the husband’s full strategy for employment

$$h = \begin{cases} 0 & \text{if } w_H < w^R(\bar{C}) \\ \bar{h} & \text{if } w_H = w^R(\bar{C}) \\ 1 & \text{if } w_H > w^R(\bar{C}). \end{cases} \quad (4.7)$$

Note now that consumption in each period is given by

$$\bar{C} = b + \bar{h}(w_H - b) + n_{\bar{W}}w_W. \quad (4.8)$$

We can solve explicitly for consumption using the wife’s labor supply condition, which results in

$$\bar{C} = \frac{b + \bar{h}(w_H - b) + w_W}{1 + \nu_W}. \quad (4.9)$$

Plugging this into the reservation policy we can derive the labor supply fraction,  $\bar{h}$ , which uniquely satisfies  $w^R = w_H$

$$w_H - b = \nu_H \bar{C} = \nu_H \frac{b + \bar{h}(w_H - b) + w_W}{1 + \nu_W}. \quad (4.10)$$

Solving for the optimal labor supply shows that the fraction employed is given by

$$\bar{h} = \frac{1 + \nu_W}{\nu_H} - \frac{b + w_W}{w_H - b}. \quad (4.11)$$

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<sup>4</sup>In the Sargent and Ljungqvist (2011) model without human capital accumulation, the husband is indifferent over the timing of his labor supply even if  $r = \rho > 0$ .



#### 4.2.2 Sufficiency of Family Income Replacement Rate

Consider expected family income in a period in which the husband does and does not work (but, importantly, remaining on the optimal plan in all other periods),<sup>5</sup>

$$\begin{aligned}\text{Family Income}(h = 0) &= F^0 = \frac{b + w_W}{1 + \nu_W}, \\ \text{Family Income}(h = 1) &= F^1 = \frac{w_H + w_W}{1 + \nu_W}.\end{aligned}\tag{4.12}$$

It follows that  $F^1 - F^0 = \frac{w_H - b}{1 + \nu_W}$ . The expected percentage increase from working relative to not working is therefore just

$$\frac{1 + \nu_W}{1 + \nu_W} \frac{F^1 - F^0}{F^0} = \frac{w_H - b}{b + w_W},\tag{4.13}$$

which is just the reciprocal of the last term in the equation for  $\bar{h}$ . We can now state the simple prediction of the sufficiency of the family income replacement rate in determining the husband's labor supply.

**Proposition 1** *Let the family income replacement rate be defined as  $RR = \frac{F^0}{F^1} \in (0, 1)$ . The fraction of time the husband spends employed,  $h$ , is decreasing the family income replacement rate. Furthermore, changes in wages,  $w_H, w_W$ , or benefits,  $b$ , do not affect the husband's labor supply decision other than through the family income replacement rate.*

To show this, first suppose that  $h = \bar{h} \in (0, 1)$ . Then equation (4.10) gives the optimal solution for the fraction worked.

$$\bar{h} = \frac{1 + \nu_W}{\nu_H} - \frac{F^0}{F^1 - F^0} = \frac{1 + \nu_W}{\nu_H} - \frac{RR}{1 - RR}\tag{4.14}$$

The derivative of  $h$  with respect to the replacement rate gives the main part of the proposition's first result.

$$\frac{dh}{dRR} = - \left[ \frac{1}{1 - RR} + \frac{RR}{(1 - RR)^2} \right] < 0\tag{4.15}$$

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<sup>5</sup>If we take the model literally and assume the husband truly randomizes,  $F^0$  and  $F^1$  are the values of income he receives in periods he does not work and does work, respectively. Alternatively, we might interpret the optimal  $h$  as a choice of a constant fraction of each year to work. In this case, the husband would receive  $F^0$  and  $F^1$  on off-equilibrium paths in which he deviated from the optimal  $h$  only in that period so that no reoptimization would occur in consumption or female labor supply.

Further examining equation (4.14) shows, conditional on an interior solution, changes in wages or benefits do not affect  $h$  other than through the family income replacement rate. To fully characterize the husband's choice, we must check the corner solutions by comparing the utilities from a life out of work, from a life of work, and from the optimal interior solution. In the case that the husband works his entire life or does not work at all, consumption streams are

$$\bar{C}(h = 1) = \frac{w_H + w_W}{1 + \nu_W}, \text{ or} \quad (4.16)$$

$$\bar{C}(h = 0) = \frac{b + w_W}{1 + \nu_W}. \quad (4.17)$$

Note that, under each choice for  $h$ , consumption is just equal to family income.<sup>6</sup> The lifetime utilities from the three possible labor supply paths are

$$\begin{aligned} h = 1 : & \quad \int_0^T e^{-\rho t} \left[ \ln(\bar{C}(h = 1)) + \nu_W \ln \left( \frac{\nu_W \bar{C}(h = 1)}{w_W} \right) \right] dt \\ \bar{h} \in (0, 1) : & \quad \int_0^T e^{-\rho t} \left[ \ln(\bar{C}(\bar{h})) + (1 - \bar{h})\nu_H + \nu_W \ln \left( \frac{\nu_W \bar{C}(\bar{h})}{w_W} \right) \right] dt \\ h = 0 : & \quad \int_0^T e^{-\rho t} \left[ \ln(\bar{C}(h = 0)) + \nu_H + \nu_W \ln \left( \frac{\nu_W \bar{C}(h = 0)}{w_W} \right) \right] dt \end{aligned} \quad (4.18)$$

Recall that consumption simply equals family income in each case, so that the comparison of lifetime utilities boils down to the following comparison of family income

$$\begin{aligned} h = 1 : & \quad \int_0^T e^{-\rho t} [(1 + \nu_W) \ln(F(h = 1))] dt \\ \bar{h} \in (0, 1) : & \quad \int_0^T e^{-\rho t} [(1 + \nu_W) \ln(F(\bar{h})) + (1 - \bar{h})\nu_H] dt \\ h = 0 : & \quad \int_0^T e^{-\rho t} [(1 + \nu_W) \ln(F(h = 0)) + \nu_H] dt \end{aligned} \quad (4.19)$$

As the replacement rate from nonemployment increases, the relative value of employment decreases and the husband will choose to supply less labor. Finally, note that wages and benefits only affect

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<sup>6</sup>Again, if we take randomization literally when  $h \in (0, 1)$ , consumption will equal family income in expectation. Otherwise, if we interpret the randomization as a choice of the fraction of each year to work, consumption will exactly equal family income.

labor supply through family income, which completes the proof of the proposition's conjecture.

Figure 4.3 gives an example of the optimal choice for  $h$  as the ratio of nonemployed income ( $F(h = 0)$ ) to employed family income ( $F(h = 1)$ ) increases. As the return to not working increases relative to working, the husband's optimal choice of employment is declining.

This simple prediction the model yields an important insight into the underlying trends of nonemployment among low-skilled males. Has the increase in their nonemployment been driven by increasing returns to nonemployment over time? We turn now to analyzing PSID data on trends in nonemployment as well as direct evidence on the change in family income replacement rates over time.

### 4.3 Labor Market Attachment, 1967-2008

We use Panel Study of Income Dynamics data to document changes in nonemployment over time, extending the work of Juhn, Murphy, and Topel (1991, 2002) to study long-term spells of joblessness. We first describe the data used for this analysis. The PSID began in 1968 as a sample of about 4,800 families and has followed those individuals and their families over time. Until 1997, PSID data were collected each year; afterwards, respondents are interviewed once every two years. The 1968 PSID sample consisted of two groups—(1) the Survey Research Center (SRC) sample was a nationally-representative cross-section of roughly 3,000 families and (2) the Census Bureau's Survey of Economic Opportunity (SEO) was a sample of about 2,000 low-income families. The PSID "core" sample combines these two groups.

We use the PSID core sample (SRC and SEO) for all years, plus the immigrant sample for years after and including 1997; we exclude the Latino sample that was added in 1990. Survey weights account for the over-sampling of low-income and immigrant families.<sup>7</sup> The PSID includes detailed variables regarding employment in the year before the interview for household heads. We focus on the question in which household heads are asked to report the number of weeks they worked in the previous calendar year.<sup>8</sup> The main variable of interest, what we call  $h$  as in the model, is the

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<sup>7</sup>Where appropriate, we use the core sample weight prior to 1993 and the newly revised longitudinal weights for all years after and including 1993.

<sup>8</sup>For survey years 1968 and 1969, weeks of work was reported only in intervals. We impute weeks worked by

proportion of the year the respondent worked, merely reported weeks divided by 52. One minus this fraction is the proportion of the year the respondent was nonemployed—either unemployed or out of the labor force.

We restrict our sample to white male household heads who are between 16 and 62. We drop observations for which those husbands report either being in school or after they first report being retired. Demographic variables we include in the sample are age, marital status, non-spouse adult cohabitants, the number of children under 18, and the total number of family members.<sup>9</sup> The presence of a wife is defined to be consistent with the PSID definition of “wife”—that is, whether a legal wife or female cohabitor was living with the male household head for a year or more. A non-wife adult cohabitant is any other non-related adult living in the family unit who is not a “wife”.

We measure consumption as the sum of food expenditures inside the home, outside the home, and food delivered (when available). We categorize individuals in one of four education groups: less than high school, high school graduates, some college, and college graduates or more. We construct a measure of actual labor market experience. Details of this variable’s construction are in Section 4.7.1.

Family income is the sum of head’s income, wife’s income and income from other family members. Head’s, wife’s, and others’ income are divided into taxable income and transfer income. All dollar values are adjusted for inflation using the CPI-U to 2008 dollars. One variable of particular interest is disability income from Social Security. The PSID does not directly ask respondents the amount and type of Social Security benefits. Because of our sample restrictions, we follow the literature and consider Social Security income to be a proxy for disability income.<sup>10</sup> To the extent that we mis-measure Social Security income, we will overstate the degree of income replacement from Disability Insurance, and therefore, overstate the degree that this might lead to labor force detachment. We return to our findings on Disability Income later in the chapter.

We utilize the wealth supplements available in five year intervals between 1984 and 1999 and applying the within-category means from 1970-1974 weeks variables.

<sup>9</sup>Non-spouse cohabitants are those who are not coded to be wives in the PSID.

<sup>10</sup>Using the available data for type of Social Security benefit, it appears that most of the reported Social Security income reported by these families is for a disabled worker. Other possible benefits are survivors (a very small reported fraction) or retirement benefits of other family members.

then in every wave since 2001. Total financial wealth is defined as the sum of wealth from stocks, bonds and insurance policies, real estate, business and farm value, cash, retirement annuities, and vehicles minus debts.<sup>11</sup> All data on wealth are averaged over the years it is available only.

The final sample consists of 5235 non-retired, out-of-school, male, household heads between the ages of 16 and 62 for whom we have data for at least five survey years. Respondents are observed at most over 36 waves, with a median spell of 21 observations.

#### 4.3.1 Nonemployment Rates Over Time

Figure 4.1 charts the nonemployment rate—the fraction of the year not working—from 1967 to 2008 for high school dropouts and high school graduates separately. Nonemployment rates for high school dropouts began at 15% in 1967 and rose to over 30% in 1992; high school graduates had uniformly lower nonemployment rates, but the trend over time was strikingly similar, going from about 10% to almost 20% over the period. During the boom of the late 1990's, nonemployment rates fell substantially for both groups, but nonemployment remains about 7 percentage points higher for both education groups in the 1990's.<sup>12</sup>

Reporting only the fraction of the year not employed masks some of the divergence in employment outcomes experienced since the 1970's. The top line in Figure 4.2 shows the fraction of high school dropouts who spent the entire year nonemployed, a particularly severe form of joblessness. Again, this figure shows the large increase in year-long detachments, going from under 4% in 1967 to almost 16% in the early 1990's. After falling during the late 1990's, it remains at 12% in the most recent data.

Using the PSID allows us to extend the results of Juhn et al. (2002) and examine the evolution of long-duration nonemployment over time among the lowest skilled. The bottom two lines show the fraction of dropouts who spent the *entire* five or ten year period out of work. The contribution of long-term nonemployment to the nonemployment rate is significant. Five year nonemployment

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<sup>11</sup>In 1984, investment retirement accounts are not reported.

<sup>12</sup>For comparison, data from the Current Population Survey show a more pronounced upward trend in nonemployment rates over time. For dropouts, for instance, nonemployment began at 7% in 1967 and was about 25% in 2006. For high school graduates, nonemployment increased from 3.6% to 14.8%. The CPS data are the same as those used in Elsby and Shapiro (2012) and are available upon request.

spells only affected 2% of dropouts in 1972 and quadrupled to 8% in the mid-1990's. Additionally, while still a relatively infrequent occurrence, 3.5% of dropouts experienced a ten year detachment during the late 1980's to mid-1990's. By contrast, this was simply not observed in the early years of the sample.

Comparing the increase in each duration of nonemployment spells indicates that long-term nonemployment accounted for a large portion of the increase in one year nonemployment spells. One year nonemployment increased by six percentage points from 1976-2008 with five and ten year spells accounting for two-thirds of that increase.

Thus, these PSID data paint a picture of substantially increasing joblessness among the low-skilled over the prior 30 years. While the boom of the 1990's alleviated some of increase, the business cycle of 2007-2009 surely returned nonemployment to peak levels. We find new evidence, however, that increased joblessness is a phenomenon driven by long detachments from employment.

#### 4.3.2 Transitions in the Labor Market

The consequences of a spell of nonemployment are not restricted to loss of income, but also include the loss of human capital and added difficulties of returning to full-time work. We capture the dynamics of transitions from detachment, defined as working less than 50% of the year, to attachment (working more than 50%). In particular, for those with a high school degree or less, we estimate the age-adjusted probability of attachment before and after a transition to detachment with Probit models of the form

$$Pr(h_{i,t-n} > 50\%) = \Phi(\alpha + x'_{it}\beta + \gamma\Psi'\Gamma(h_{i,t} < 50\%)), \text{ for } n = -6, \dots, 6. \quad (4.20)$$

$h_{i,t}$  is the fraction of the year worked and  $\Gamma(h_{i,t} < 50\%)$  is a history of attachment statuses in the past year to three years.  $x'_{it}$  is merely a quartic in age. We estimate models separately for different spells of detachment: one year, two year, and three year periods of working less than 50%. The dependent variable is the probability that the individual returns to working 50% in the years after those detachments.

The results are presented in Figure 4.4 where the y-axis gives the dependent variable in 4.20 and the x-axis is years before and after detachments. The top line (blue with diamonds) shows that if one works less than 50% in year 0, the probability of working more than 50% six years before was about 70%. After the detachment in year zero, however, there is considerable path dependence: six years after the detachment, individuals only have a 55% chance of working more than 50% in the year.

Conditional on a three year period of 50% or greater nonemployment, individuals have an even harder time returning to pre-detachment levels of employment. Four years prior to the three year detachment, there is a 53% probability of working more than 50%. Note that this probability is lower than the probability four years before an individual experienced a one year detachment (62%). Again, six years after the three-year nonemployment spell is over, an individual only has a 35% chance of a year of attachment to the labor market.

Not only has nonemployment become more common over time, returning to full-time work after 50% or greater nonemployment has become harder. To summarize these transitions, we estimate age-adjusted probabilities of working more than 50% of the year as a function of working less than 50% in the last year (or two years before). In other words, we estimate

$$Pr(h_{i,t} > 50\%) = \Phi \left( \alpha + \alpha_t + x'_{it}\beta + \sum \gamma_t \mathbb{1}(\text{Year} = t) \mathbb{1}(h_{i,t+j} < 50\%) \right), \quad (4.21)$$

where  $j = \{-2, -1\}$ .<sup>13</sup>  $h_{it}$  is again the fraction of the year worked and  $x'_{it}$  contains a quartic in age. We group years into non-overlapping intervals of three years (1967-1969, 1970-1972, etc) to obtain more precise estimates of the predicted probabilities.  $\alpha_t$  is a time period fixed effect and  $\gamma_t$  are the coefficients on the interaction between  $h$  and year. Due to the biennial sampling after 1997, we estimate the model with only one year lag ( $j = 1$ ) prior to 1997 and with a two year lag ( $j = 2$ ) for all years. Figure 4.5 shows the age-adjusted predicted probabilities in each of time period.

A decrease in the predicted probabilities indicates that transitioning from out of the labor market in one year to attached in the next (or subsequent year) has decreased over time; it is therefore more

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<sup>13</sup>The linear probability fixed effects specifications for both equations 4.20 and 4.21 yields similar results.

likely for workers to detach one year and struggle to regain attachment to the labor force. In 1967-1969, the probability of returning to full-time employment was 50% after the previous year was spent mostly nonemployed; it was 64% if the year before last was spent mostly nonemployed. These probabilities fell steadily over time so that the probability of returning to more than 50% employment in year  $t$  after nonemployment in  $t - 2$  was only 32% in 2006-2008.

After establishing the increasing rate and length of nonemployment spells, we turn to examining the family income replacement rate.

## 4.4 Sources of Income and the Replacement Rate

In the preceding section, we documented the substantial increase in nonemployment among less-skilled, prime-aged men. In this section, we first focus on the level and composition of income for men with differing levels of attachment to the labor market. Following the prediction of the family labor supply model of section 4.2, we then turn to an empirical estimate of the replacement rate over time.

### 4.4.1 Sources of Income

We categorize individuals in our sample by the employment fraction of the previous five years and break the sample in to five groups based on the fraction of those years worked (0%-20%, 20%-40%, and so on).<sup>14</sup> Separate tables are displayed for high school graduates or less and those with some college education, but we concentrate mainly on the low-skilled group in the text. Tables 4.1 and 4.2 begin by looking at socioeconomic characteristics of families by employment rates. The first row gives the fraction of the previous five years worked within each category—for both skill levels, if the individual was in the lowest bin, he worked less than 5% on average of the five year window. Alternatively, those within the highest bin worked almost full time at 93% for both groups. Five year nonemployment spells are still relatively unlikely with only 3.4% of the high school graduates or less in the lowest bin and only 1% of the college educated.

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<sup>14</sup>Results using a one year window are quantitatively similar, although substantially noisier.



Both education groups are very likely to be living with a wife or non-related adult, ranging from 70-90%. The less-employed are less likely to be married or cohabiting. The average age of the nonemployed, despite being non-retired, is high—among the less-skilled in the lowest bin, the average age is 52 whereas it is 42 in the highest employment bin, indicating an important life-cycle dimension to the nonemployment decision. Additionally, the nonemployed are much more likely to report a work-limiting disability—85.2% for those who worked less than one of the previous five years and only 8.7% for those who worked more than four of those years (among the low-skilled group, Table 4.1).

Tables 4.3 through 4.10 explore the composition and level of family income by employment fraction, again separated by education group. First, Tables 4.3 and 4.4 show the distribution of family income within each employment bin (read from top of the column to bottom). These tables show the relatively serious income difference between those at the bottom of the distribution of the employment and those at the top. Among the low-skilled, low-employment group (Table 4.3, column 2), the median family income is \$33,410; it is more than double that for the median family with a steadily employed head (row 4, column 6). In fact, the 10th percentile of family income for men who are fully-employed is higher than the median family income for men who are nonemployed.

Turning to Tables 4.5 and 4.6, we break the low-educated group into those who are living with a wife or are cohabiting and those who are not; these tables show a clear picture that spousal income is an important source of income for nonemployed husbands. Average family income for those who worked less than one year and where a wife is present is about \$44,000 as opposed to only \$14,000 where the wife is not present. Further, the wife's income comprises about 32% of family income where the husband is nonemployed; that fraction falls by 10 percentage points as the husband's employment fraction rises, even though the absolute level of wife's income is relatively constant.<sup>15</sup> For both families with and without wives, transfer income is particularly important; it comprises almost 65% of family income for the nonemployed without wives and almost 40% for those with wives. These proportions fall to only 2% and 1.7% in families with fully-employed heads.

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<sup>15</sup>This lends some credence to the separability of labor supply assumed in the model above.

Thus, the average percentage loss of income from nonemployment relative to employment from 1967-2008 is about 40% for those with wives (\$44,000 vs. \$75,000) and about almost 70% for those without wives, among the less-educated. Among the more educated (Tables 4.7 and 4.8), the losses are 30% and 70%.

While the individuals in these data report not being retired, the pension income of the head remains a very large source of family income among the nonemployed. For instance, Table 4.5 shows that heads in the lowest employment bin take home almost \$7,000 from private pensions, which accounts for more than a third of other taxable income of the head and wife. In addition, in Table 4.7, the level of wealth of families actually decreases in the employment fraction of the head—those in the lowest bin have almost \$400,000 in non-housing wealth (this is the only table in which that trend occurs). These households are likely older and their husbands truly retired. These two facts do call in to question the meaning of self-reported retirement for older heads who have been out of work for a substantial period of time. When estimating the replacement rate in the next section, it will be important to control for age and other family characteristics.

It is worth noting, in addition, that the food consumption gradient is less steep than that of family income, suggesting some ability for families to smooth consumption. For instance, Table 4.4 shows that total food consumption is about \$7,800 for families with a nonemployed husband. For the attached husbands, their families spend about \$9,800 on food, a loss of only 20% (versus the loss of 40% of income).

Families with less employed heads receive substantial income from government and other transfers. Tables 4.9 and 4.10 focus on several major sources of transfer income that comprise this income. For each type of transfer, the first row gives the fraction who received any income from that program over the five year window, and the second and third are conditional on that positive receipt. Total transfer income of the family (including from other family members), is listed at the bottom of the table to compare each source of transfers to the total receipt.

The programs that are crucial to family income for the least-employed heads are Social Security (\$12,000 on average for those who receive it), Workers Compensation (\$6,000), and Supplemental

Security Income (\$5,000). Social Security income, as these household heads are below the Social Security retirement age, is taken to be disability insurance.<sup>16</sup> For the nonemployed, low-skilled heads, almost 70% received some Social Security. Those who received it, did so for more than three of the previous five years. Families do not appear to receive very much income support from relatives, as only around 15-20% receive an average of \$400-\$600 in transfers. In addition, many families receive substantial support from Food Stamps (average of \$1,800 for recipients) and non-cash housing subsidies of either rent support or public housing (about 35%).

In sum, we find that household heads who are nonemployed receive a large fraction of family income from spousal earnings and government transfers. But what has happened those sources of income over time? Figures 4.6 and 4.7 give the composition of family income of those with at most a high school degree by income type (head and wife labor income, other taxable income, transfer income, and income from other family members), again averaging over five year periods. The top panel of both figures are data for heads who worked less than 50% of the previous five years and the bottom is for heads who worked more than 50%.<sup>17</sup>

One trend is striking: transfer income as a share of family income drops steadily over time from 52% to 21%. The top panel of Figure 4.7 gives the same data in levels—the average family income hovered around \$40,000 with transfer income dropping from \$17,000 to \$8,600. For those who worked more than 50% of the time, family income rose substantially in the 90's from about \$60,000 to \$80,000, largely due to increased wife's income (from \$8,700 to \$19,000). These data indicate less availability of substantial transfer income for nonemployed heads over the period of time that nonemployment has increased.

#### **4.4.2 Estimating the Replacement Rate Over Time**

We have found that family income of nonemployed heads is composed of substantial spousal and and transfer income. The analysis of the previous section, however, did not control for family characteristics or other issues of selection into nonemployment. In this section, we estimate an

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<sup>16</sup>The available data on type of Social Security income indicates that this is true.

<sup>17</sup>We categorize heads this way to smooth some of the noise in the yearly data.

empirical analogue of the replacement rate from the model of Section 4.2 which took the form

$$RR = \frac{F(h = 0)}{F(h = 1)}.$$

A natural estimator for the replacement rate is obtained as follows. First, we estimate the log of family income using the following fixed effects specification

$$\ln(F_{it}) = \alpha + \alpha_i + \alpha_t + x'_{it}\gamma + \delta h_{i,t} + \sum \beta_t \mathbb{1}(Year = t) h_{i,t} + \epsilon_{it}, \quad (4.22)$$

where  $\ln(F_{it})$  is the log of total family income,  $h_{i,t}$  is the fraction of the year worked,  $x'_{it}$  is a vector of controls, and  $\alpha_t$  and  $\alpha_i$  are year and individual fixed effects.

Recall that the parameter of interest is the expected drop in family income from a year not working relative to working. That replacement rate is given by a simple manipulation of the parameter estimates of the above equation:

$$\zeta_t \equiv \beta_t + \delta = \mathbb{E} \left[ \ln \left( \frac{F(h = 1|x, t)}{F(h = 0|x, t)} \right) \right]. \quad (4.23)$$

This can be converted to the same replacement rate as in the model by the transformation

$$RR_t = \exp(-\zeta_t) = \mathbb{E} \left[ \frac{F(h = 0|x, t)}{F(h = 1|x, t)} \right]. \quad (4.24)$$

The standard error of the replacement rate is given by  $\text{se}(RR_t) = \exp(-\zeta_t)\text{se}(\zeta_t)$  from the delta method.<sup>18</sup> In order to precisely estimate coefficients over time, we group years into non-overlapping intervals of three years (1967-1969, 1970-1972, etc) and we estimate the model only for those household heads who have at most a high school degree. The covariates included are a quartic in age, a quartic in actual experience, whether the head is cohabiting with a non-related adult, whether the individual is married, whether the family receives Social Security income, whether the wife has income, and the number of family members. We weight all regressions by the sampling weight and

<sup>18</sup>Controlling for potential heteroskedasticity that might affect the average replacement rate does not change the trends that we find.

cluster the standard errors on individual.<sup>19</sup>

Figure 4.8 is a scatterplot of the residuals of log family income versus the fraction of the year worked where each variable has been cleansed of the regressors in equation 4.22. The solid red line is the OLS regression line through the residuals; converting this slope coefficient into a replacement rate, we find that the average replacement rate over the whole sample is 52.6%. We find strong evidence, beginning in Figure 4.9, that the replacement rate has, if anything, fallen over time.

In 1967-1979, the replacement rate began at about 55%, rising to 62% in the early 1970's. Since then, the replacement rate has steadily decreased, with the exception of the boom of the mid-to-late 1990's. During the 1990's, the replacement rate recovered from below 50% to 56% in 1996, but has since then decreased. During the last years of the PSID, the replacement rate fell to sample low of 40% (statistically different from the beginning of the sample as seen from the dotted blue 95% confidence interval lines), implying a loss of 60% of family income due to the husband's spell of nonemployment. The rise and fall of the replacement rate, further, is opposite the trend for nonemployment—nonemployment rose in the 80's and fell in the 90's.

In Figures 4.10-4.12, we estimate the replacement rate separately for different types of families to explore whether some families had substantially rising replacement rates. Figure 4.10 shows the replacement rate by two age categories, younger workers, aged 16-45, and older worker, age 46-62. Younger workers experienced a larger decrease in their replacement rate, going from about 50% in 1967-1969 and falling to a low of 40% in the late 1980's. Both age groups, however, experienced constant or falling replacement rates.

In Figure 4.11, we estimate the replacement rate for those families that had positive Social Security income (our measure of disability income). The replacement rate for those who received Social Security did not fall over time, and in fact increased in the mid-to-late 1990's, increasing to almost 70% from around 50% in the mid-1970's. For those who did not receive Social Security, on the other hand, the replacement rate fell substantially from about 50% in the mid-1970's as well to just over 30% in the most recent years. These data suggest rising disability benefits during the

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<sup>19</sup>Technically, we use the mean of the weight across the sample for the fixed effects specification. There is very little within variation in the sampling weight, so this is not quantitatively important.

1990's as one cause of nonemployment, as in Autor and Duggan (2003) and others. We address this further below in Section 4.5

Figure 4.12 confirms what the analysis of the previous section also showed: income from wives composes a substantial portion of family income for less employed men. The two estimates began at 55% but diverged from then—the replacement rate for families with wives rose to about 70% in the boom of the 90's, but has fallen back to about 55%. For those without wives, however, the replacement rate fell almost constantly to around 27% in the most recent years.

Finally, Figure 4.13 estimates the replacement rate of total food expenditures using the baseline specification above. Consistent with the tables and the discussion above, those who are out of work are able to smooth consumption, so the level of the replacement rate is higher on average. Importantly, the replacement rate is falling in the late 1970's through the mid-to-late 1980's only to recover after the mid-1990's. Thus, the decrease in the replacement rate of food consumption coincided with the large increase in nonemployment.

The merit of estimating the replacement rate with this method deserves further discussion. First, the linear specification in 4.22 is not as restrictive as it first seems. Figure 4.8 demonstrates the data do not suggest an important nonlinear relationship. As a robustness check, we ran these models using several nonparametric specifications for fraction of the year worked, including a dummy for nonemployed, either defined as working less than 50% or 75% of the year or dummies for quantiles of fraction of the year worked. We also ran the model without individual fixed effect as well as used the level of family income as opposed to its log. We found similar results using these specifications.<sup>20</sup>

While we are able to control for some observable family characteristics correlated with family income and employment in our estimates, we cannot control here for all types of selection into nonemployment. The availability of the PSID's panel data allows us to use within household head variation in  $h$ , the fraction of the year worked. Therefore, the fixed effects specification controls for permanent differences in the types of household heads with different average levels of employment.

The selection, however, of those household heads who change their nonemployment over time

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<sup>20</sup>Further, allowing the fraction worked to enter in higher order terms yielded similar results with a quadratic in fraction worked, but the standard errors on higher terms were too large to generate useful replacement rates.

cannot be controlled for in the present model. We are, in fact, particularly interested in the types of workers who choose to work less in a given year. If, even among those who choose nonemployment, the replacement rate is falling, it casts serious doubt on its role in driving up nonemployment rates. But, to the extent that heads in those families with high replacement rates choose to reduce weeks worked, the replacement rates estimated in 4.22 will be biased upwards. Whether this bias should understate the rise in the replacement rate over time is unclear. Estimates that instrument for changes in  $h$  with plausibly exogenous changes in employment status, such as mass layoff events, is an important avenue for future research.

#### 4.5 The Role of Disability Income

We found that families receiving Social Security disability income experienced increasing replacement rates in the 1990's. In this section, we analyze the PSID data to (1) ensure the PSID is not undercounting disabilities and disability income and (2) to understand if disability income could be driving rising nonemployment.

There is mixed evidence on the roll of more generous Disability Insurance (SSDI) benefits on decreased male labor force participation. In an influential study, Autor and Duggan (2003), find that the combination of more generous DI benefits along with less stringent qualification tests decreased male labor force participation significantly. SSDI benefit rates increased in the 1980's and 1990's, especially for lower waged workers, due to the formula for indexing benefits to real wage growth (some benefits increased by more than 20 percentage points). Over the same period, rates of DI receipt also increased. For instance, among 25-39 year old male, high school dropouts, DI receipt increased from 2.1% in 1984 to 5.3% in 1999. Put together, Autor and Duggan find that increasing DI benefit eligibility and generosity increased the unemployment rate by half a percentage point.

Von Wachter et al. (2010) use data on DI applicants and find that younger workers whose DI applications were rejected worked 60% more of the subsequent five years, suggesting a large disincentive effect of DI. Chen and van der Klaauw (2007) use discontinuities in eligibility determination, however, and find that DI receipt only accounted for a reduction of 20 hours of work per month.

Bound and Waidmann (2002) also find that increasing benefit receipt in the 1990's accounts for the entire decline in labor force participation among men and women with disabilities. However, some of the same authors in Bound, Lindner, and Waidmann (2010) point out that nonemployment among disabled men continued to increase while the DI growth rate fell in the late 1990's.

Our results, at first glance, do not suggest a large increase in Disability Insurance in family income. In particular, Figure 4.11 showed that, even conditional on receiving Social Security income (our proxy for disability income), the family income replacement rate from nonemployment is not rising substantially over time. In this section, we examine whether we undercount disability income, and therefore, understate the increase in the replacement rate in the 1980's and 1990's. First, from Autor and Duggan (2003), we can get a sense for the increase in family income from rising disability that we should expect to see. SSDI benefit rates for males 30-39 increased between 5 and 8 percentage points of lost income. Disability rolls increased from 2.3 to 5.3 percentage points in the 25-39 age range. This suggests a fairly limited role for disability in family income, given the relatively small disability rolls and that men's earnings as a fraction of family income attenuate the increase in replacement rates by the fraction of income from the disabled worker.

Figure 4.14 shows that the PSID does reflect a sizeable increase in nonemployment among those with a work-limiting disability. The dashed, red line (left axis) shows that the rate of work-limiting disability is between 11-18%.<sup>21</sup> The fraction of disabled workers who spent an entire year out of employment (solid line on right axis) increased from around 11% in the late 1960's to 32% in the mid-1980's. Nonemployment rates among the disabled took off after 1990, rising to 41% by 1994. Therefore, consistent with the literature, we find an increase in the rate of nonemployment among disabled workers in the 1990's. The overall rate of full-year nonemployment for this education group increased by 9.6 percentage points over the same period, with 4.6 percentage point attributable to the increased nonemployment of disabled workers. It is unclear, however, whether disability benefits and claims are a cause or symptom of nonemployment.

One reason to doubt that it is a cause are the data in Figures 4.15 and 4.16. Figure 4.15 plots

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<sup>21</sup>These estimates are in line with those from in Bound, Lindner, and Waidmann using the CPS.



the fraction of disabled heads who received Social Security and the percentage of family income that Social Security comprised. We do find that, among the disabled, the percentage of family income from Social Security increased from the early 1980's to the 1990's. The percent receiving Social Security rises over time, especially the 1980's and 1990's as well. Therefore, the PSID data capture the well-known increase in DI benefits. Because of the relatively low rates of disability, however, it is unsurprising that replacement rates across the whole population would be relatively unaffected by disability income.

In Figure 4.16, we re-estimate replacement rates as above only for the household heads with a disability. The blue line is the replacement rate of family income without Social Security while the red line is the replacement rate of family income including Social Security. While the line with Social Security is much higher due to the large fraction of income from Social Security, the lines move roughly in tandem. Therefore, disability income does not seem to play an important role in the time series movement of the replacement rate, even for families with disabled heads.

In all, our data are consistent with the finding of increased nonemployment among the disabled as well as increasing disability income through late 1980's to early 1990's. While there may be a strong disincentive effect on disabled heads, it does not appear that disability income is a large enough component of overall family income to affect our finding that replacement rates are constant or falling over time.

## 4.6 Discussion and Conclusion

In this chapter, we have reexamined the driving forces behind the decline in male employment prospects in the United States over the previous thirty years. Informed by the work by Juhn, Murphy, and Topel (1991, 2002), we study the evolution of the rates of nonemployment—the fraction of the year either unemployed or out of the labor force—in the Panel Study of Income Dynamics. We find that rates of nonemployment have increased substantially over time, except during the boom of the late 1990's. Among high school dropouts, the nonemployment rate went from 15% to a high of 30% in the mid-1990's and is hovering around 22% in recent years. A substantial portion of the

rise in nonemployment has been due to low-skilled men spending entire five and ten year period out of work—at its peak, almost 10% of white, male, high school dropouts experience a five year nonemployment spell.

The main contribution of this chapter is to understand the driving forces behind nonemployment. Following the literature on indivisible labor supply, such as Hansen (1985), Rogerson (1988), and more recently Sargent and Ljungqvist (2008, 2011), we develop a model of family labor supply in which the husband makes an extensive margin labor supply decision. We derive a simple prediction from this model: the extent to which the husband chooses to work will be declining in the replacement rate of family income from nonemployment.

The first question we address is what types of income do the nonemployed live on. Consistent with Dynarski and Gruber (1997), we find that family income for families with nonemployed heads is comprised largely of government transfers and spousal income. Government transfers among the non-married, low-skilled account for 65% of family income for nonemployed and only 4% for the fully-employed. Spousal income among the low-skilled accounted for 31.5% of income among the nonemployed.

We estimate an empirical analogue of the family income replacement rate over time. If anything, the replacement rate fell while the nonemployment rate increased substantially. In the late 1960's, the replacement rate was around 60%; it is now at 40%. We uncover that family income replacement rates and nonemployment rates are seemingly unlinked over the past thirty years.

If not an increasing replacement rate, then what is driving the increase in nonemployment? Several authors have suggested that increasing disability benefits are a large cause. We find evidence that this is likely true, although the effects do not seem large enough to explain the entire nonemployment picture. Juhn (1992) and Juhn et al. (2002) attribute rising nonemployment to declining wages due to skill-biased technical change. Elsby and Shapiro (2012) find that declining returns to experience of low-skilled males can account for the increase in nonemployment since the 1970's. Intuitively, as the benefit of working an additional year falls, the value of staying attached the labor market falls and marginal workers decide to remain nonemployed. For each of these explanations to

be true, however, it should not be the case that the replacement rate fell over time.

The puzzle we have outlined here has important policy implications, especially in the aftermath of the Great Recession. In future work, additional data from matched Current Population Survey data will be used to more precisely estimate replacement rates over time. Using data from the CPS on plausibly-exogenous displacements will also permit estimation of the replacement rate that is uncontaminated by potential selection issues.

## 4.7 Appendix

### 4.7.1 Experience Imputation

To construct potential experience, we simply need to construct a years of schooling variable.<sup>22</sup> Constructing actual experience is more complicated however, since most household heads in the PSID are not observed in the first year that they work, therefore we must impute the experience prior to the respondents first wave as household head.<sup>23</sup> For individuals in the PSID who are first observed as heads after they finish schooling, we use the variable number of years worked since age 18 as the starting level of actual experience. For each year after the first year they are observed as a head out of school, and prior to retirement, we maintain a running sum of the fraction of all years worked. Therefore, for new household heads, we can observe not only their employment history as heads in the PSID, but also their employment history from at least age 18.

In order to account for the fraction of years worked before we first observe the individual, we use the following imputation procedure. We first use the individual's retrospective report of the number of years worked prior to entering the PSID survey (years worked since age 18). This provides an indicator of accumulated past labor market experience, but there remains a question of the fraction of the reported years that the respondent actually worked in the past. Our identifying assumption is that, when a respondent reports that he worked in the past, he worked the same fraction of the year that he did in subsequent surveys later in the sample. Based on this, we impute past experience as the retrospective number of years worked since age 18, multiplied by the observed average fraction of subsequent years in the PSID sample in which the respondent reports having worked.

Before 1974, the number of years worked since age 18 variable is not available. For this, we backcast the number of years worked, subtracting off a year if they reported having worked.<sup>24</sup> If the actual experience variable is higher than potential experience, we cap actual experience at potential experience. Because of the biennial surveys in 1999 and beyond, we undercount actual experience

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<sup>22</sup>For those without valid observations for years of schooling, we assign the number of years of schooling from the head's bracketed education variable. For years after 1974, the years of schooling variable alone is used.

<sup>23</sup>In other words, these household heads' experience levels are left-censored.

<sup>24</sup>In addition, this variable is not re-asked of heads in 1994-1997, 1999, and 2001, so we use the same procedure to bring forward the information for the old heads.

since we do not have off survey year (t-2) data on employment. So, we instead reduce potential experience for one year for each calendar year we do not have information (i.e., reduce potential experience by four for the 2005 survey because we are missing 1998, 2000, 2002, and 2004).<sup>25</sup>

One concern is that the imputation strategy will yield a biased sample when examining other aspects of their career, including nonemployment rates. A check of this sub-samples nonemployment rates gives us an indication that this group is not very different from the entire sample.<sup>26</sup> Since our measure of actual experience is merely the sum of employment rates over the PSID sample, this indicates that our imputed sample does not differ vastly in their labor market experience profiles.<sup>27</sup>

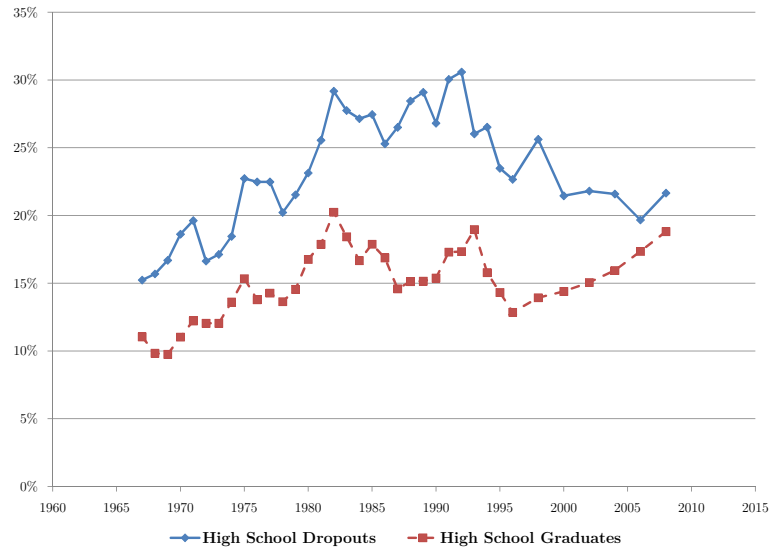
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<sup>25</sup>We are implicitly acting as though the missing years do not affect the cross-sectional distribution of experience in population. Of course, each additional year will widen the gap between persistently attached workers and the marginally attached. Thus, the data analyzed here would tend to underestimate on the differences in accumulated experience.

<sup>26</sup>Data available upon request from authors.

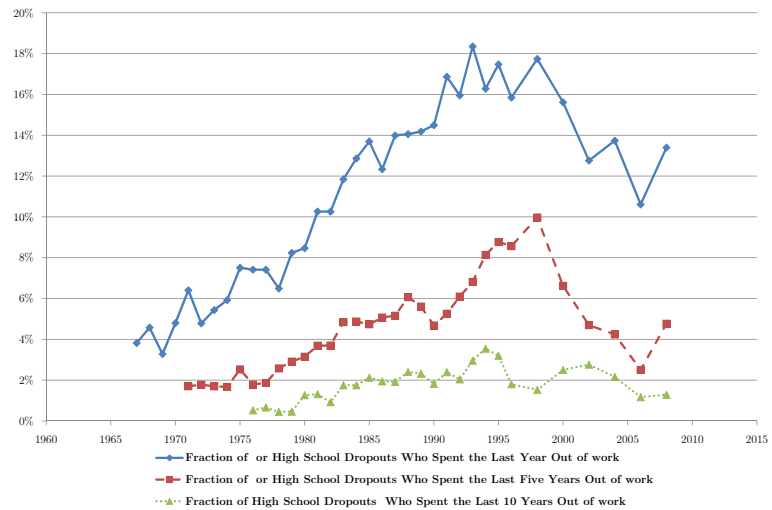
<sup>27</sup>This holds for the five-year nonemployment rates and the proportion who did not work in the previous year over the entire sample, as well.

**Figure 4.1: Nonemployment Rates by Education**



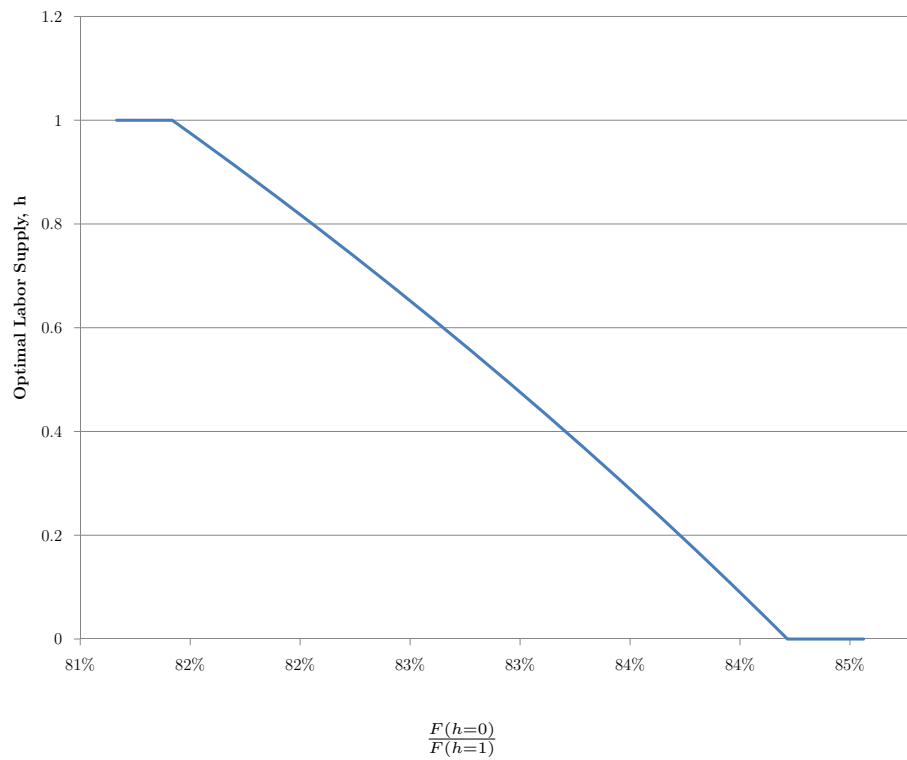
Note: PSID data from 1967-2008: 16-62 year old male, household heads who do not report being retired or in school and are observed for five or more waves. Nonemployment is the fraction of the year, in weeks, not employed. Data are weighted by sample weights.

**Figure 4.2: Long Duration Nonemployment  
High School Dropouts Only**



Note: PSID data from 1967-2008: 16-62 year old male, household heads who do not report being retired or in school and are observed for five or more waves. Nonemployment is the fraction of the year, in weeks, not employed. Data are weighted by sample weights.

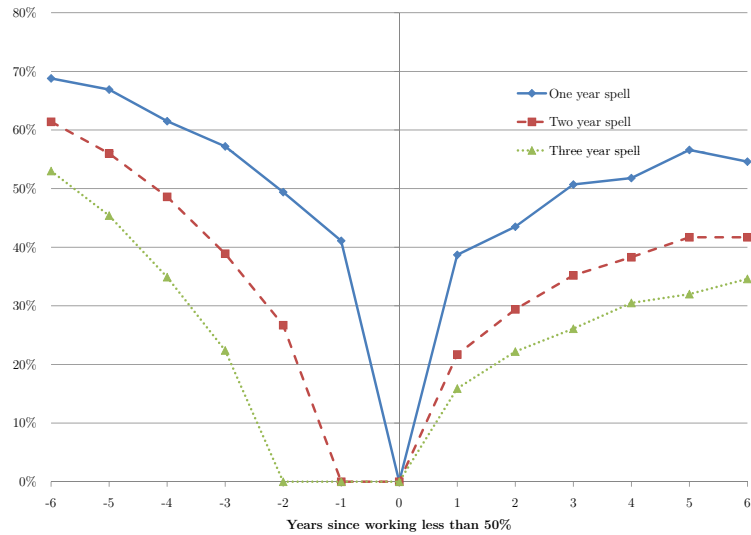
**Figure 4.3:** Optimal  $h$  as a Function of the Family Income Replacement Rate



Ratio of Family Income from Nonemployment to Family Income From Employment.

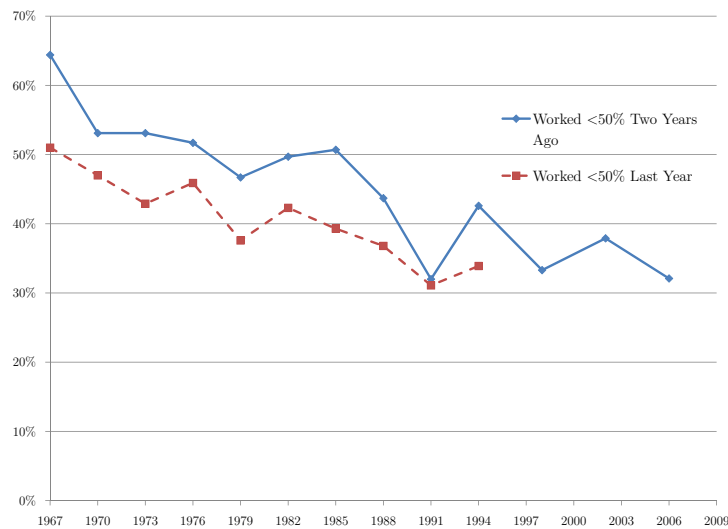
Note: Solution to model of Section 4.2 with parameters:  $\nu_H = 1$ ,  $\nu_W = 4.5$ .

**Figure 4.4:** Transition to Working More than 50% of Year, Conditional on Spells of at Least 50% Nonemployment  
High School or Less



Note: Estimates from weighted, age-adjusted Probit. PSID data from 1967-2008: 16-62 year old male, household heads who do not report being retired or in school and are observed for five or more waves. Nonemployment is the fraction of the year, in weeks, not employed.

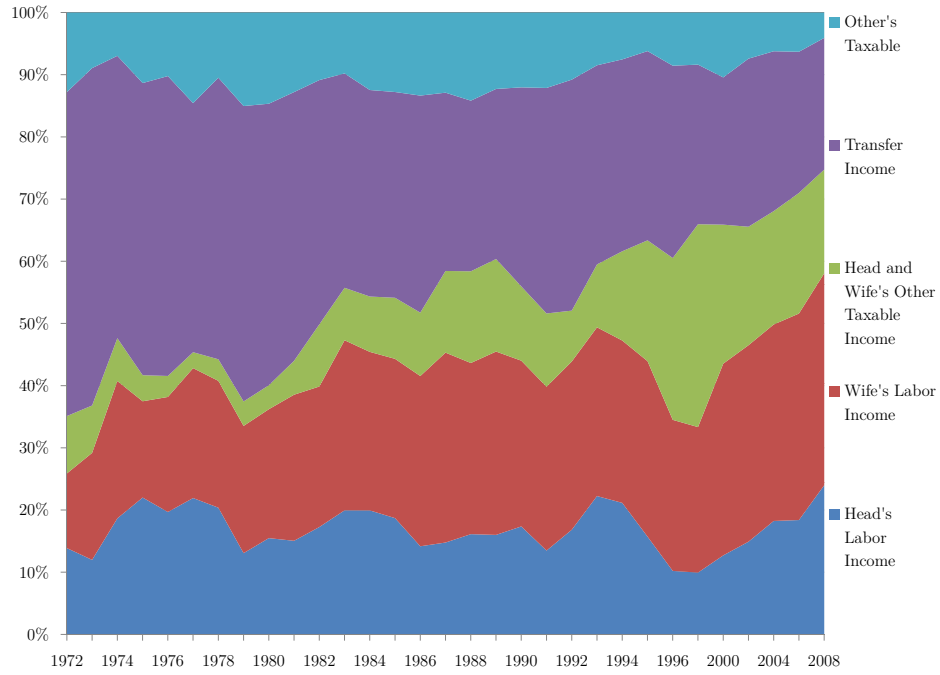
**Figure 4.5:** Transition to Working more than 50% of Year After Year of at Least 50% Nonemployment, by Year  
High School or Less



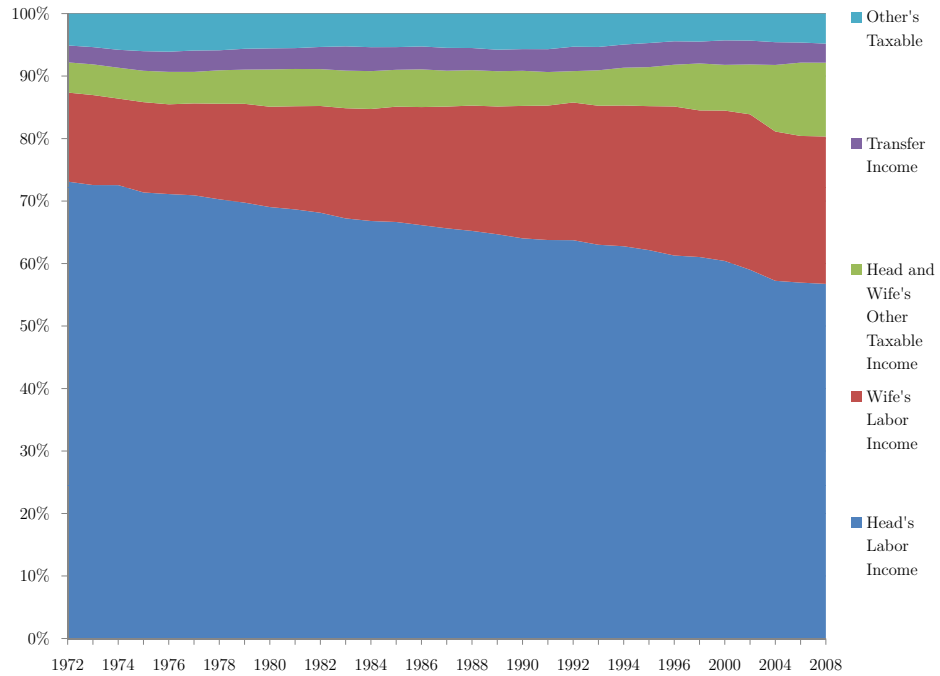
Note: Estimates from weighted, age-adjusted Probit. PSID data from 1967-2008: 16-62 year old male, household heads who do not report being retired or in school and are observed for five or more waves. Nonemployment is the fraction of the year, in weeks, not employed. Years are grouped non-overlapping intervals of three calendar years.



**Figure 4.6:** Composition of Family Income, High School or Less.  
Worked Less than 50% of Last Five Years

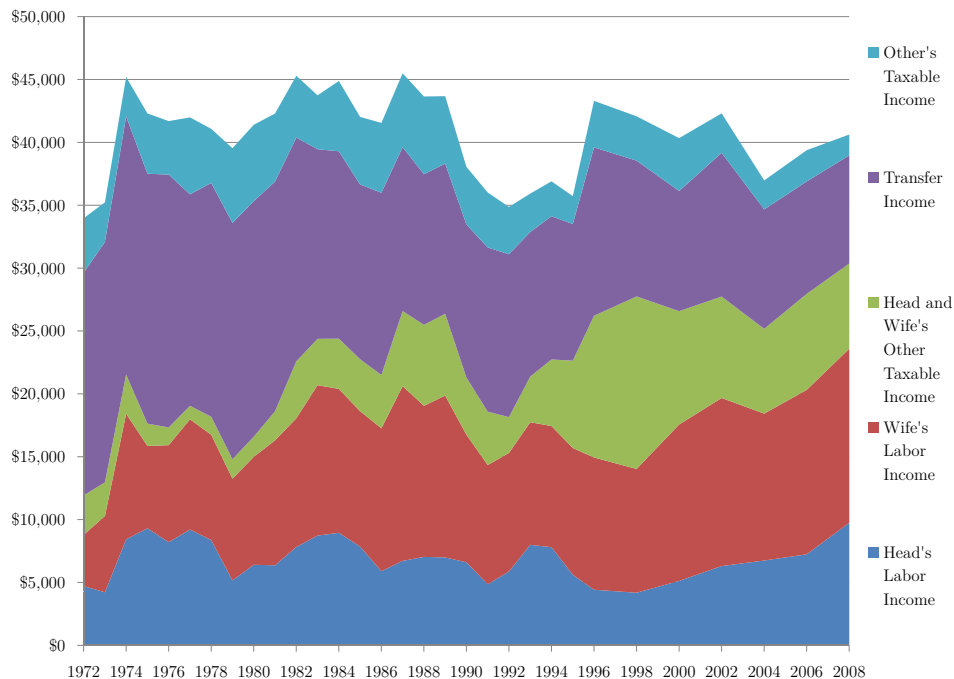


Worked More than 50% of Last Five Years

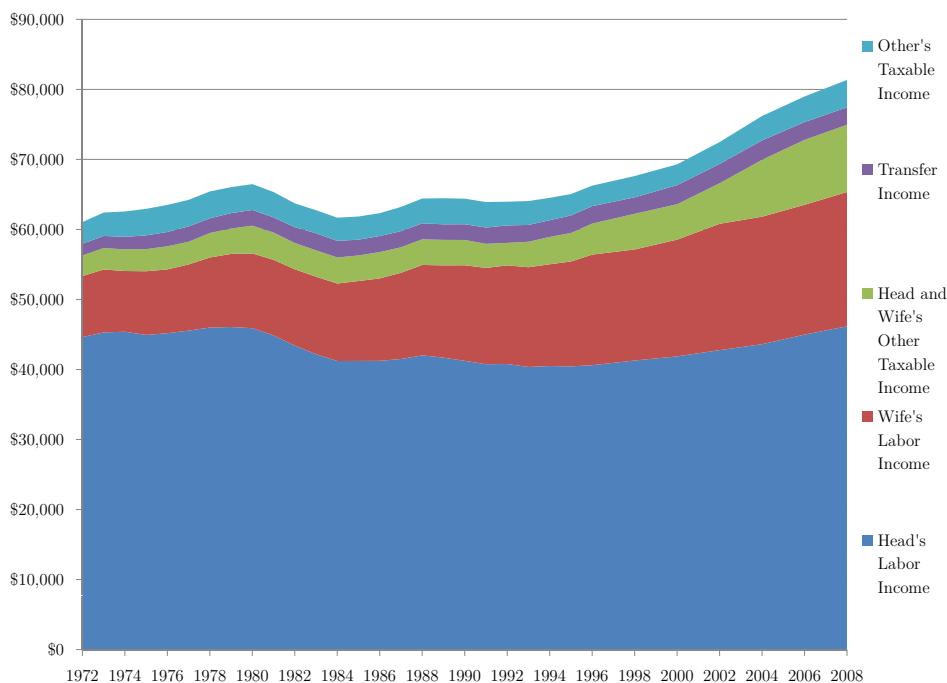


Note: PSID data from 1967-2008: 16-62 year old male, household heads who do not report being retired or in school and are observed for five or more waves. All variables are averaged over rolling five year periods. Series begins in 1972 after first five year window. All dollar values adjusted to 2008 dollars by the CPI-U. Data are weighted by sample weights.

**Figure 4.7: Family Income by Type, High School or Less.**  
 Worked Less than 50% of Last Five Years

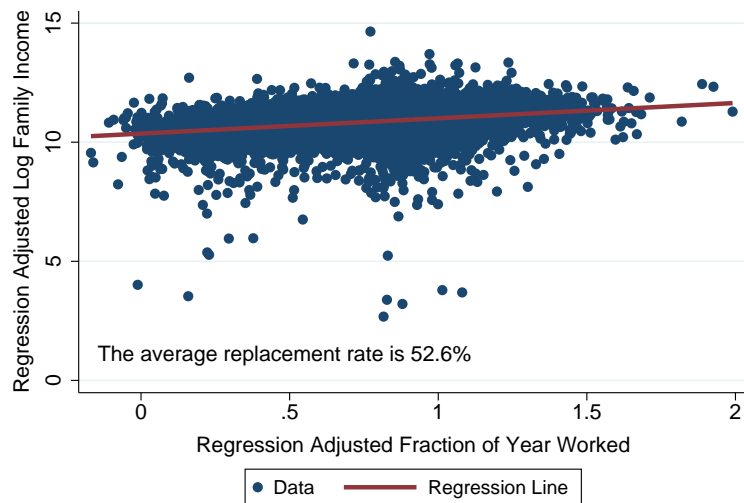


Worked More than 50% of Last Five Years



Note: PSID data from 1967-2008: 16-62 year old male, household heads who do not report being retired or in school and are observed for five or more waves. All variables are averaged over rolling five year periods. Series begins in 1972 after first five year window. All dollar values adjusted to 2008 dollars by the CPI-U. Data are weighted by sample weights.

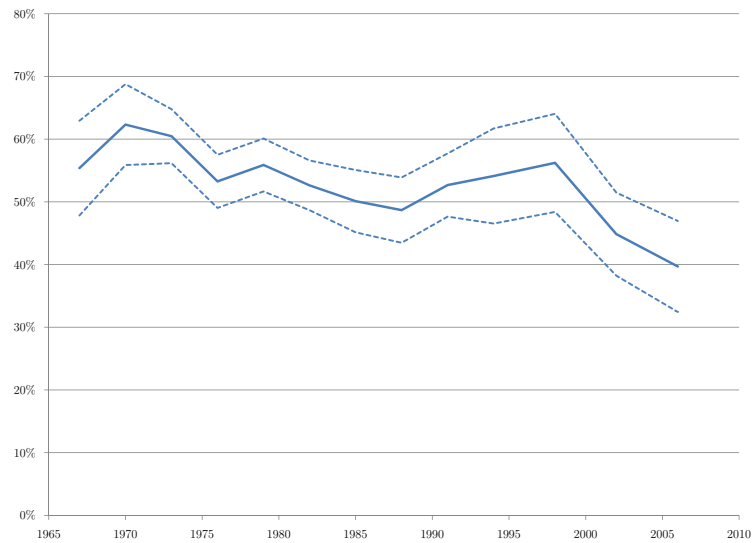
**Figure 4.8:** Family Income versus Fraction of Year Worked  
High School or Less



Note: Scatter plot of residuals of Log Family Income and Fraction of Year Worked each on quartic in age, quartic in actual experience, whether the head is cohabiting with a non-related adult, whether the individual is married, whether the family receives Social Security income, whether the wife has income, and the number of family members. Solid red line is the OLS regression line.

PSID data from 1967-2008: 16-62 year old male, household heads who do not report being retired or in school and are observed for five or more waves. All dollar values adjusted to 2008 dollars by the CPI-U. Data are weighted by sample weights.

**Figure 4.9: Family Income Replacement Rate**  
High School or Less

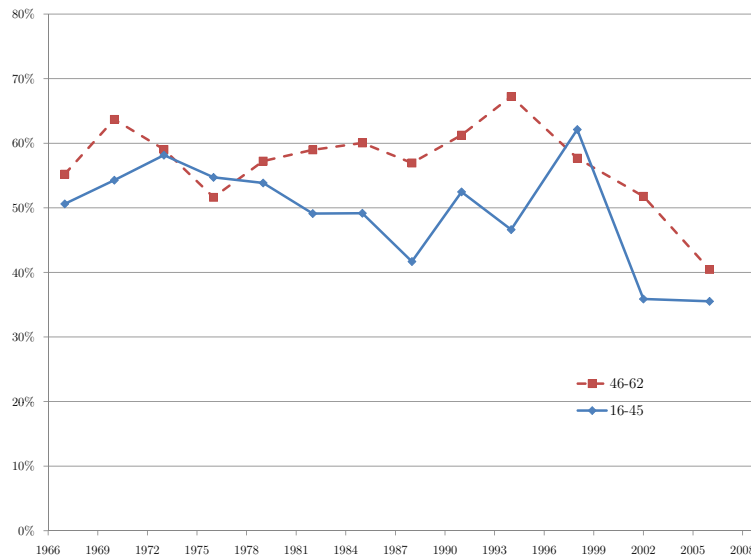


Note: Estimates from fixed effects regression of Log Family Income on Fraction of Year Worked interacted with year dummies. Solid line is point estimate, dotted lines are 95% confidence bands.

Covariates include individual and year fixed effects, quartic in age, quartic in actual experience, whether the head is cohabiting with a non-related adult, whether the individual is married, whether the family receives Social Security income, whether the wife has income, and the number of family members. Years are grouped non-overlapping intervals of three calendar years.

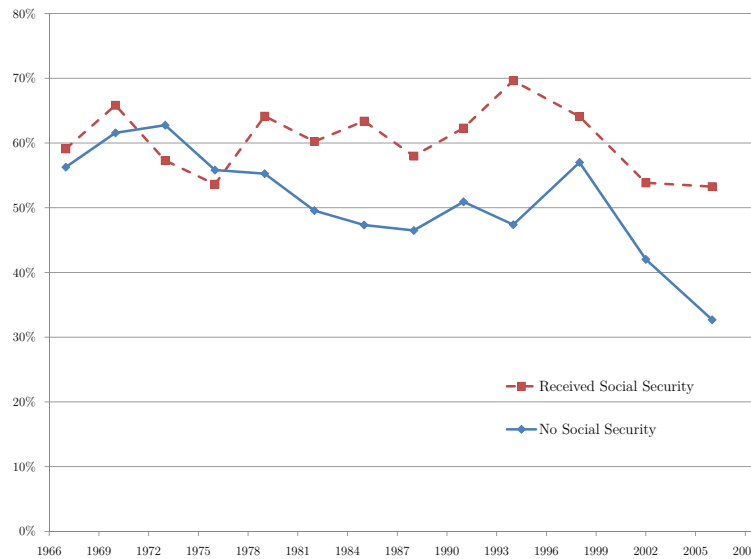
PSID data from 1967-2008: 16-62 year old male, household heads who do not report being retired or in school and are observed for five or more waves. All dollar values adjusted to 2008 dollars by the CPI-U. Data are weighted by sample weights.

**Figure 4.10: Family Income Replacement Rate, by Age Group**  
High School or Less



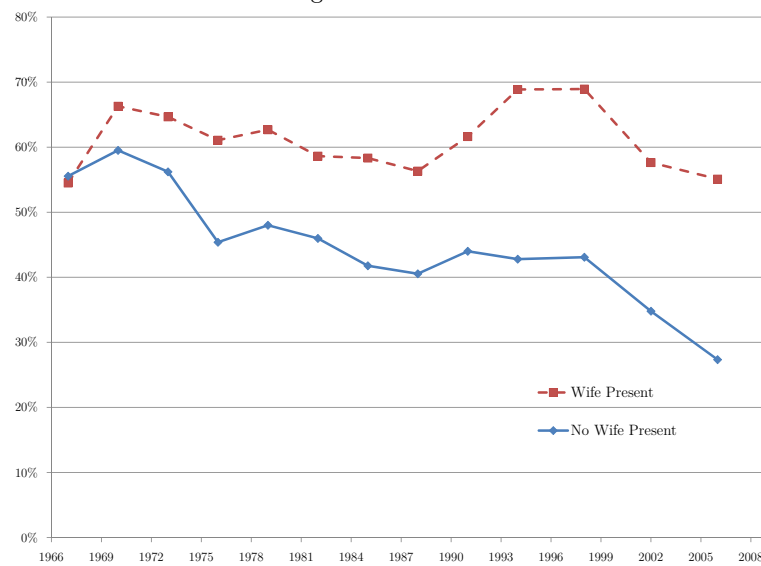
Note: Estimates of fixed effects regression of Log Family Income on Fraction of Year Worked interacted with year dummies and age group. See Figure 4.9 for details.

**Figure 4.11: Family Income Replacement Rate, by Social Security Receipt**  
High School or Less



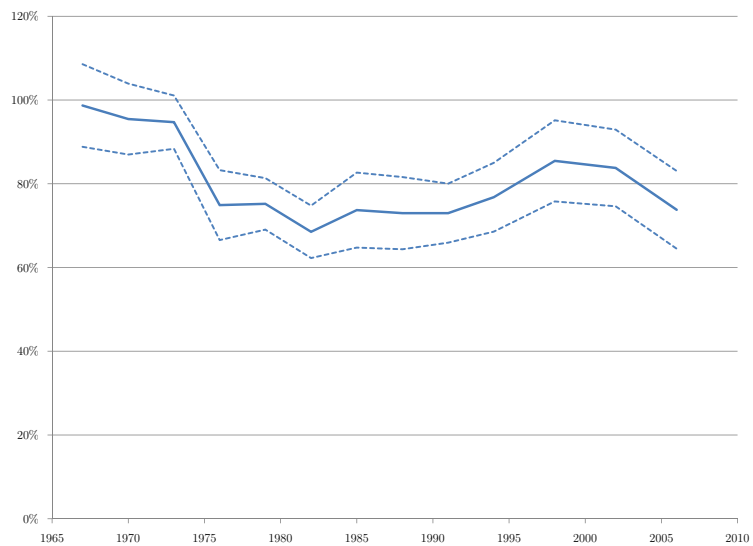
Note: Estimates of fixed effects regression of Log Family Income on Fraction of Year Worked interacted with year dummies and Social Security Income receipt status. See Figure 4.9 for details.

**Figure 4.12:** Family Income Replacement Rate, by Presence of Wife  
High School or Less



Note: Estimates of fixed effects regression of Log Family Income on Fraction of Year Worked interacted with year dummies and marital status. See Figure 4.9 for details.

**Figure 4.13: Food Consumption Replacement Rate**  
High School or Less

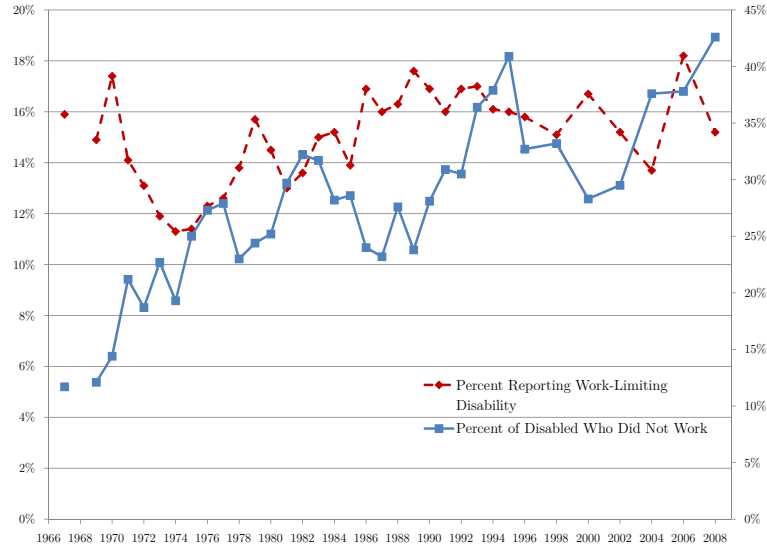


Note: Estimates from fixed effects regression of Log Total Food Consumption on Fraction of Year Worked interacted with year dummies. Solid line is point estimate, dotted lines are 95% confidence bands.

Covariates include individual and year fixed effects, quartic in age, quartic in actual experience, whether the head is cohabiting with a non-related adult, whether the individual is married, whether the family receives Social Security income, whether the wife has income, and the number of family members. Total Food Consumption is food expenditures in and outside the house and delivery. Years are grouped non-overlapping intervals of three calendar years.

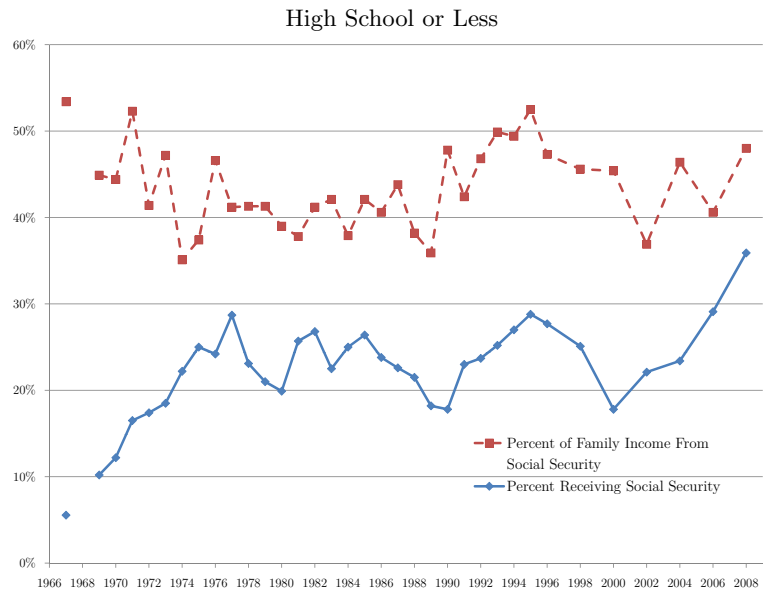
PSID data from 1967-2008: 16-62 year old male, household heads who do not report being retired or in school and are observed for five or more waves. All dollar values adjusted to 2008 dollars by the CPI-U. Data are weighted by sample weights.

**Figure 4.14:** Fraction of Disabled Heads Who Did Not Work Entire Year  
High School or Less



Note: Left axis is fraction of heads reporting that they suffer from a work-limiting disability. Right axis is the fraction of those respondents who did not work at all. Disability data is unavailable in survey year 1969. PSID data on white, male household heads, ages 16-62 who have a high school degree of less. Data are weighted by sample weights.

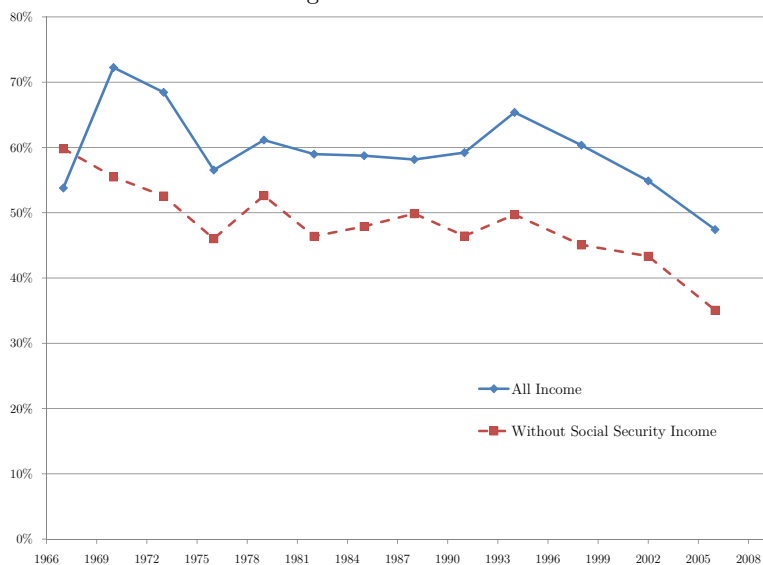
**Figure 4.15:** Fraction of Disabled Heads Receiving Social Security and its Percent of Family Income  
High School or Less



Note: Solid line is fraction of those reporting a disability who received Social Security. Dashed line is fraction of income that Social Security accounts for of family's with disabled heads. Disability data is unavailable in survey year 1969. PSID data on white, male household heads, ages 16-62 who have a high school degree of less. Data are weighted by sample weights.



**Figure 4.16:** Disabled Heads' Family Income Replacement Rate, With and Without Social Security Income  
High School or Less



Note: Estimates of fixed effects regression of Log Family Income on Fraction of Year Worked interacted with year dummies for disabled heads only. Solid line is all Family Income and dashed line excludes Social Security Income. See Figure 4.9 for details on estimation. Disability data is unavailable in survey year 1969.

PSID data on white, male household heads, ages 16-62 who have a high school degree of less. Data are weighted by sample weights.

**Table 4.1:** Characteristics of Household Heads by Fraction of Five Years Employed, High School or Less. 1967-2008

	0-20%	20%-40%	40%-60%	60%-80%	80%-100%
Proportion Employed	3.3%	29.7%	50.7%	71.5%	96.7%
Spouse or Cohabiting Adult	78.4%	82.9%	83.3%	84.3%	90.8%
Number of Family Members	2.9	3.1	3.1	3.3	3.4
Number of Children	0.7	1.0	1.0	1.2	1.2
Disability*	85.0%	60.5%	41.6%	26.5%	9.2%
Age	52.0	48.7	45.4	42.4	41.7
Below Poverty Line?	23.8%	29.9%	21.7%	12.6%	2.6%
Years spent below	1.9	2.2	1.9	1.4	0.4
N	1026	560	959	2461	28312
Fraction of Sample	3.1%	1.7%	2.9%	7.4%	85.0%

Note: PSID data from 1967-2008: 16-62 year old male, household heads who do not report being retired or in school and are observed for five or more waves. Fraction of previous five years employed is calculated over rolling five year windows. Variables only averaged over years they are available in PSID. A disability is a self-reported disability that limits work. Data are weighted by sample weights.

**Table 4.2:** Characteristics of Household Heads by Fraction of Five Years Employed, Some College or More. 1967-2008

	0-20%	20%-40%	40%-60%	60%-80%	80%-100%
Proportion Employed	3.1%	29.8%	51.6%	73.1%	97.3%
Spouse or Cohabiting Adult	69.4%	81.6%	77.6%	77.6%	88.6%
Number of Family Members	2.3	2.6	2.5	2.7	3.3
Number of Children	0.4	0.6	0.5	0.7	1.2
Disability*	73.1%	48.1%	31.2%	13.6%	6.9%
Age	54.5	52.1	45.5	42.6	42.5
Below Poverty Line?	16.6%	12.5%	9.5%	3.9%	0.8%
Years spent below	1.5	1.4	1.0	0.6	0.2
N	258	177	377	1636	27872
Fraction of Sample	0.9%	0.6%	1.2%	5.4%	91.9%

Note: PSID data from 1967-2008: 16-62 year old male, household heads who do not report being retired or in school and are observed for five or more waves. Fraction of previous five years employed is calculated over rolling five year windows. Variables only averaged over years they are available in PSID. A disability is a self-reported disability that limits work. Data are weighted by sample weights.

**Table 4.3:** Distribution of Family Income by Fraction of Five Years Employed, High School or Less. 1967-2008

	0-20%	20%-40%	40%-60%	60%-80%	80%-100%
<b>Quantiles of Family Income</b>					
5th Percentile	7,134	7,311	11,145	19,052	28,577
10th Percentile	10,281	11,253	15,167	24,060	35,744
25th Percentile	16,890	18,529	26,887	34,016	48,840
50th Percentile	33,410	35,561	41,789	50,653	67,085
75th Percentile	52,073	58,515	63,693	70,781	89,132
90th Percentile	74,905	89,677	89,890	98,245	116,286
95th Percentile	88,751	108,979	110,002	119,463	136,662

Note: PSID data from 1967-2008: 16-62 year old male, household heads who do not report being retired or in school and are observed for five or more waves. Fraction of previous five years employed is calculated over rolling five year windows. Variables only averaged over years they are available in PSID. All dollar values adjusted to 2008 dollars by the CPI-U. Data are weighted by sample weights.

**Table 4.4:** Distribution of Family Income by Fraction of Five Years Employed, Some College or More. 1967-2008

	0-20%	20%-40%	40%-60%	60%-80%	80%-100%
<b>Quantiles of Family Income</b>					
5th Percentile	7,787	14,431	18,049	26,659	42,084
10th Percentile	10,886	18,291	25,297	33,899	52,213
25th Percentile	25,924	33,605	40,489	51,135	70,209
50th Percentile	46,394	64,286	69,291	74,480	96,854
75th Percentile	76,686	94,797	100,386	110,139	133,216
90th Percentile	145,885	138,626	138,006	149,855	186,404
95th Percentile	191,978	197,614	171,244	186,862	239,300

Note: PSID data from 1967-2008: 16-62 year old male, household heads who do not report being retired or in school and are observed for five or more waves. Fraction of previous five years employed is calculated over rolling five year windows. Variables only averaged over years they are available in PSID. All dollar values adjusted to 2008 dollars by the CPI-U. Data are weighted by sample weights.

**Table 4.5:** Income, Wealth, and Expenditures by Fraction of Five Years Employed, High School or Less, Wife Present. 1967-2008

	0-20%	20%-40%	40%-60%	60%-80%	80%-100%
<b>INCOME</b>					
Total Family Income	43,759	46,302	50,528	58,775	74,999
Head's Labor Income	1,546	13,103	23,210	34,499	48,924
Share	3.5%	28.3%	45.9%	58.7%	65.2%
Wife's Labor Income	13,768	11,757	11,573	11,849	14,712
Share	31.5%	25.4%	22.9%	20.2%	19.6%
Head and Wife's Other Taxable Inc.	19,401	16,934	15,497	15,445	20,075
Share	44.3%	36.6%	30.7%	26.3%	26.8%
Head and Wife's Transfer	16,707	11,397	7,639	4,449	1,603
Share	38.2%	24.6%	15.1%	7.6%	2.1%
Other Family Members	6,105	4,868	4,181	4,383	4,397
Share	14.0%	10.5%	8.3%	7.5%	5.9%
Head's Pension Income	6,768	5,210	2,598	907	390
<b>WEALTH</b>					
Mean Non-housing Wealth	40,935	76,834	102,203	85,594	104,445
Median Non-housing Wealth	9,074	12,063	16,861	16,167	34,615
<b>EXPENDITURES</b>					
Total Food	7,799	7,971	8,401	9,393	9,793
Rent	6,422	6,252	6,501	6,914	7,755
Own Home?	70.4%	63.4%	62.6%	61.9%	77.1%
House value	101,032	94,562	99,039	101,886	118,534
Own Car?	90.3%	91.2%	90.7%	95.3%	98.3%

Note: PSID data from 1967-2008: 16-62 year old male, household heads who do not report being retired or in school and are observed for five or more waves. Fraction of previous five years employed is calculated over rolling five year windows. Variables only averaged over years they are available in PSID. All dollar values adjusted to 2008 dollars by the CPI-U. Data are weighted by sample weights.

**Table 4.6:** Income, Wealth, and Expenditures by Fraction of Five Years Employed, High School or Less, No Wife. 1967-2008

	0-20%	20%-40%	40%-60%	60%-80%	80%-100%
<b>INCOME</b>					
Total Family Income	14,356	19,162	26,274	34,943	43,358
Head's Labor Income	421	8,496	17,708	28,525	38,099
Share	2.9%	44.3%	67.4%	81.6%	87.9%
Wife's Labor Income	0	0	0	0	0
Share	--	--	--	--	--
Head and Wife's Other Taxable Inc.	2,403	1,597	1,975	1,537	1,818
Share	16.7%	8.3%	7.5%	4.4%	4.2%
Head and Wife's Transfer	9,236	6,846	4,036	2,669	721
Share	64.3%	35.7%	15.4%	7.6%	1.7%
Other Family Members	2,296	2,224	2,556	2,213	2,721
Share	16.0%	11.6%	9.7%	6.3%	6.3%
Head's Pension Income	1,898	2,795	944	440	102
<b>WEALTH</b>					
Mean Non-housing Wealth	4,392	5,433	46,552	31,066	51,817
Median Non-housing Wealth	920	2,014	5,215	12,244	16,213
<b>EXPENDITURES</b>					
Total Food	4,334	5,245	5,511	5,809	5,726
Rent	4,002	5,636	5,280	5,137	5,825
Own Home?	15.4%	25.6%	27.0%	27.6%	32.4%
House value	59,706	104,592	63,371	58,761	79,513
Own Car?	46.2%	73.4%	67.8%	79.1%	89.3%

Note: PSID data from 1967-2008: 16-62 year old male, household heads who do not report being retired or in school and are observed for five or more waves. Fraction of previous five years employed is calculated over rolling five year windows. Variables only averaged over years they are available in PSID. All dollar values adjusted to 2008 dollars by the CPI-U. Data are weighted by sample weights.

**Table 4.7:** Income, Wealth, and Expenditures by Fraction of Five Years Employed, Some College or More, Wife Present. 1967-2008

	0-20%	20%-40%	40%-60%	60%-80%	80%-100%
<b>INCOME</b>					
Total Family Income	82,445	87,536	83,953	94,580	119,903
Head's Labor Income	3,622	22,047	33,259	53,540	79,696
Share	4.4%	25.2%	39.6%	56.6%	66.5%
Wife's Labor Income	27,177	29,614	25,736	25,164	22,668
Share	33.0%	33.8%	30.7%	26.6%	18.9%
Head and Wife's Other Taxable Inc.	46,753	41,922	35,891	33,505	34,573
Share	56.7%	47.9%	42.8%	35.4%	28.8%
Head and Wife's Transfer	27,668	20,411	10,941	4,303	2,169
Share	33.6%	23.3%	13.0%	4.5%	1.8%
Other Family Members	4,403	3,156	3,862	3,233	3,465
Share	5.3%	3.6%	4.6%	3.4%	2.9%
Head's Pension Income	15,323	13,699	6,170	1,820	643
<b>WEALTH</b>					
Mean Non-housing Wealth	374,999	321,822	255,123	232,323	213,006
Median Non-housing Wealth	192,197	154,202	98,306	101,599	106,079
<b>EXPENDITURES</b>					
Total Food	9,422	9,512	9,560	10,087	11,155
Rent	16,455	13,129	11,758	11,889	14,044
Own Home?	83.9%	77.3%	68.7%	73.4%	83.0%
House value	281,098	209,209	180,932	185,886	221,336
Own Car?	96.7%	95.9%	97.4%	97.9%	98.5%

Note: PSID data from 1967-2008: 16-62 year old male, household heads who do not report being retired or in school and are observed for five or more waves. Fraction of previous five years employed is calculated over rolling five year windows. Variables only averaged over years they are available in PSID. All dollar values adjusted to 2008 dollars by the CPI-U. Data are weighted by sample weights.

**Table 4.8:** Income, Wealth, and Expenditures by Fraction of Five Years Employed, Some College or More, No Wife. 1967-2008

	0-20%	20%-40%	40%-60%	60%-80%	80%-100%
<b>INCOME</b>					
Total Family Income	20,469	28,119	52,259	48,777	68,703
Head's Labor Income	1,196	13,968	29,715	39,255	57,110
Share	5.8%	49.7%	56.9%	80.5%	83.1%
Wife's Labor Income	0	0	0	0	0
Share	--	--	--	--	--
Head and Wife's Other Taxable Inc.	6,143	3,441	9,602	3,190	6,283
Share	30.0%	12.2%	18.4%	6.5%	9.1%
Head and Wife's Transfer	11,701	6,352	6,137	4,320	1,827
Share	57.2%	22.6%	11.7%	8.9%	2.7%
Other Family Members	1,428	4,359	6,805	2,013	3,483
Share	7.0%	15.5%	13.0%	4.1%	5.1%
Head's Pension Income	7,072	3,649	2,721	2,215	686
<b>WEALTH</b>					
Mean Non-housing Wealth	25,993	27,740	331,891	133,913	107,545
Median Non-housing Wealth	6,608	3,943	48,998	27,398	32,175
<b>EXPENDITURES</b>					
Total Food	3,781	5,093	6,087	6,063	6,681
Rent	5,562	6,117	9,656	7,928	9,828
Own Home?	31.1%	23.6%	39.7%	26.6%	42.0%
House value	86,247	107,851	182,126	113,776	153,759
Own Car?	69.3%	57.9%	72.6%	83.0%	91.9%

Note: PSID data from 1967-2008: 16-62 year old male, household heads who do not report being retired or in school and are observed for five or more waves. Fraction of previous five years employed is calculated over rolling five year windows. Variables only averaged over years they are available in PSID. All dollar values adjusted to 2008 dollars by the CPI-U. Data are weighted by sample weights.

**Table 4.9:** Transfer Programs by Fraction of Five Years Employed, High School or Less.  
1967-2008

	0-20%	20%-40%	40%-60%	60%-80%	80%-100%
<b>TRANSFERS</b>					
Received Welfare?	12.5%	19.6%	14.8%	7.9%	1.2%
Average Number of Years	0.7	0.8	0.5	0.4	0.1
Average Benefit	2,705	3,518	3,169	2,303	1,478
Received Food Stamps?	32.8%	44.2%	39.0%	30.6%	7.4%
Average Number of Years	1.7	1.9	1.7	1.4	0.4
Average Benefit	1,749	1,970	1,386	1,032	677
Received SSI?	23.4%	14.4%	6.1%	3.8%	1.1%
Average Number of Years	0.9	0.5	0.2	0.1	0.0
Average Benefit	5,090	2,514	2,629	2,576	2,148
Received UI?	17.4%	37.3%	50.7%	60.0%	24.4%
Average Number of Years	1.2	1.9	2.4	2.6	1.3
Average Benefit	1,761	2,437	2,878	2,446	924
Received Workers Comp?	15.5%	19.2%	21.5%	21.9%	9.8%
Average Number of Years	0.9	1.0	1.0	1.0	0.5
Average Benefit	6,065	5,686	4,332	2,286	905
Received Transfer from Rel?	14.9%	23.1%	24.0%	19.1%	9.2%
Average Number of Years	0.8	1.0	1.0	1.0	0.5
Average Benefit	603	434	524	476	417
Received Social Security?	69.4%	42.7%	27.0%	13.9%	7.0%
Average Number of Years	3.1	1.4	0.8	0.5	0.3
Average Benefit	12,122	6,672	5,226	4,566	4,685
Received Housing Subsidy?	34.8%	28.8%	22.2%	17.1%	11.0%
Average Number of Years	1.9	1.4	1.2	0.9	0.7
Received any Transfer Income?	99.8%	97.3%	94.5%	91.2%	59.7%
Average Number of Years	4.9	4.6	4.4	4.2	3.0
Average Transfers	18,743	12,846	8,660	5,287	3,180

Note: PSID data from 1967-2008: 16-62 year old male, household heads who do not report being retired or in school and are observed for five or more waves. Fraction of previous five years employed is calculated over rolling five year windows. Variables only averaged over years they are available in PSID. All dollar values adjusted to 2008 dollars by the CPI-U. Data are weighted by sample weights.



**Table 4.10:** Transfer Programs by Fraction of Five Years Employed, Some College or More.  
1967-2008

	0-20%	20%-40%	40%-60%	60%-80%	80%-100%
<b>TRANSFERS</b>					
Received Welfare?	1.4%	2.8%	2.9%	0.8%	0.3%
Average Number of Years	0.1	0.2	0.1	0.0	0.0
Average Benefit	884	760	1,862	1,685	953
Received Food Stamps?	17.2%	14.5%	15.4%	7.7%	1.6%
Average Number of Years	0.9	0.7	0.6	0.3	0.1
Average Benefit	728	640	762	543	403
Received SSI?	17.4%	6.5%	5.2%	1.1%	0.6%
Average Number of Years	0.8	0.2	0.2	0.0	0.0
Average Benefit	4,154	3,934	4,264	2,646	1,991
Received UI?	16.8%	26.4%	33.6%	30.2%	13.8%
Average Number of Years	1.0	1.4	1.5	1.4	0.7
Average Benefit	1,501	1,904	2,585	2,117	958
Received Workers Comp?	5.0%	9.9%	11.5%	8.5%	3.9%
Average Number of Years	0.3	0.5	0.5	0.4	0.2
Average Benefit	4,498	4,534	4,692	2,910	1,131
Received Transfer from Rel?	15.8%	19.2%	29.6%	22.6%	12.6%
Average Number of Years	0.7	0.8	1.2	1.1	0.7
Average Benefit	1,207	746	1,039	781	662
Received Social Security?	60.4%	38.8%	21.9%	7.8%	4.5%
Average Number of Years	2.6	1.3	0.7	0.3	0.2
Average Benefit	12,325	8,188	5,770	4,142	4,982
Received Housing Subsidy?	29.5%	13.3%	10.3%	8.9%	5.2%
Average Number of Years	1.5	0.9	0.8	0.4	0.3
Received any Transfer Income?	94.3%	91.6%	92.9%	73.9%	54.5%
Average Number of Years	4.6	4.1	4.3	3.5	2.7
Average Transfers	29,245	21,719	12,193	6,259	4,531

Note: PSID data from 1967-2008: 16-62 year old male, household heads who do not report being retired or in school and are observed for five or more waves. Fraction of previous five years employed is calculated over rolling five year windows. Variables only averaged over years they are available in PSID. All dollar values adjusted to 2008 dollars by the CPI-U. Data are weighted by sample weights.

## CHAPTER V

### Conclusion

This dissertation has contributed to the empirical and theoretical understanding of the determinants of long-term trends in unemployment as well as the response of the labor market to recessions. The first and third chapters study policies that affect the dynamics of the labor market over the business cycle and different policies that might contribute to detachment from the labor market, respectively. The third chapter shows that real economic frictions to adjusting capital can generate prolonged recessions.

In the first chapter, the tax system used to finance UI benefits is shown to have effects on the steady state unemployment rate as well as the dynamics of the labor market over the business cycle. Empirically, when firms are charged higher tax rates after a layoff, they are less likely to both hire and fire. In a DSGE model of unemployment, this policy-induced layoff cost is shown to be capable of reducing unemployment as well as reducing the amplitude of labor market slumps. Experience rating can, however, prolong the rise in unemployment during a recession.

The second chapter shows that real frictions at the firm level to adjusting its capital stock in response to an aggregate shocks has important dynamics effects on the labor market. Whether they face costs to adjusting the level of capital or the level of investment, capital adjustment costs can fully explain the empirical sluggishness in labor market tightness over the business cycle.

Finally, the third chapter studies the underlying causes of rising male nonemployment since the 1970's. Theoretically, if the generosity of government transfers raised the replacement rate of income of those nonemployed, the rates of joblessness should rise as employment is relatively less attractive.

Direct empirical evidence on the replacement rate suggests the opposite: if anything replacement rates from nonemployment have fallen over time while nonemployment has increased.

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