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A dissertation submitted in partial satisfaction
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by

Kyle Frederic Herkenhoff

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Abstract of the Dissertation

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Kyle Frederic Herkenhoff

Doctor of Philosophy in Economics

University of California, Los Angeles, 2014

Professor Lee E. Ohanian, Chair

This dissertation studies the interaction between private consumption smoothing mechanisms and labor markets. Chapter 1 studies the growth in credit card access among the unemployed over the last 40 years and how this credit growth has impacted labor markets. I begin by developing a general equilibrium business cycle model with search in both the labor market and in the credit market. Calibrating to the observed path of credit between 1974 and 2012, I find that growth in credit card access can lead to deeper and longer recessions as well as moderately slower recoveries. Chapter 2, which is co-authored with Lee E. Ohanian, looks at the impact of foreclosure protection on unemployment during the 2007-2009 financial crisis. Through a purely positive lens, we study and document the growing trend of mortgagors who skip mortgage payments as an extra source of "informal" unemployment insurance during the 2007 recession and the subsequent recovery. In a dynamic model, we capture this behavior by treating both delinquency and foreclosure not as one period events, but rather as protracted and potentially reversible episodes that influence job search behavior and wage acceptance decisions. After calibrating, we find that the observed foreclosure delays increase the unemployment rate by an additional $\frac{1}{3}$%-$\frac{3}{4}$%. And finally, Chapter 3, which is co-authored with Lee E. Ohanian, Kris Gerardi, and Paul Willen, looks at the empirical determinants of default and provides a new suggestive measure of strategic default. In sharp contrast to prior studies that proxy for individual unemployment status using regional unemployment rates, we find that individual unemployment is the strongest predictor of default. We also find that only 13.9% of defaulters have both negative equity and enough liquid or illiquid assets to make 1 month's mortgage payment. This suggests that "ruthless," or "strategic" default during the 2007-2009 recession is relatively rare, and suggests that policies designed to promote employment, such as payroll tax cuts, are most likely to stem defaults in the long run rather than policies that temporarily modify mortgages.

The dissertation of Kyle Frederic Herkenhoff is approved.

Pierre-Olivier Weill

Gary D. Hansen

Stuart A. Gabriel

Lee E. Ohanian, Committee Chair

University of California, Los Angeles

2014

There were many key ingredients that went into this dissertation. I began the process with, and have always felt throughout, the strong encouragement of my parents, Linda & Fred Herkenhoff, my brothers, Eric & Brett Herkenhoff, and my grandma, Betty Nelson. I met the love of my life, Ana Luisa Pessoa Araujo, along the way, and her unconditional and sometimes unconventional support always kept me balanced along the right path. I started out with two close friends, Joseph Severino and Lance Sarabia, who stuck with me through the entire process and who were always there for a good 445am surf session or a good laugh. I made so many strong friendships along the way including Pedro Aratanha and Paulo Coutinho and had so many fun trips during the PhD that it would be impossible to list them all. Everything was essential, and it all came together in the end.

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CHAPTER 1

The Impact of Consumer Credit Access on Unemployment

1.1 Introduction

Over the last 30 years, the fraction of unemployed households with access to unsecured revolving credit (e.g. credit cards) nearly quadrupled from 12% in 1977 to 45% in 2010. Such access to credit is quantitatively important for the unemployed. Unemployed households replace 11-18% of lost income through unsecured borrowing (Sullivan (2008)) while nearly 40% of households self-report defaulting on non-mortgage payments in response to job loss (Hurd and Rohwedder (2010)). Although a large literature including Ljungqvist and Sargent (1998) examines the impact of unemployment benefit duration and replacement rates on employment incentives and economic recoveries, the macroeconomic effects of credit access on households' job finding behavior remains an open question. In this paper, I theoretically and quantitatively examine how the growth in households' access to credit markets over the last 3 decades has affected the way employment evolves over the business cycle.

Through addressing this question, the paper makes three contributions. Theoretically, it develops a general equilibrium search and matching model with defaultable debt. Quantitatively, it measures the mechanisms through which credit access impacts unemployment over the business cycle, detailing in a series of experiments the crucial role of credit access *growth* and its impact on employment recoveries from 1974 to 2012. And empirically, it presents aggregate time series for unemployed households' access to credit and use of credit from 1970 onwards.

After calibrating to the observed path of credit use between 1974 and 2012, I find that growth in credit coming out of the 1990, 2001, and 2007 recessions delays the trough of employment by about 1 quarter and generates up to an additional .8 percentage point decline in employment three years after the initial downturn relative to an economy in which credit access is fixed at 1970s levels.[1] The mechanism generating this employment slowdown is that growth in credit access coming out of a recession acts as a safety net allowing households to search for better-paying but harder-to-find jobs. The side effects are lower job finding rates and higher unemployment. Nevertheless, because credit access reduces consumption volatility and improves job-match quality, households would be willing to sacrifice .12% of lifetime consumption in order to be born in an economy with 2010 levels of credit access as opposed to an economy with 1970s levels of credit access.[2]

Underlying these results is a general equilibrium business cycle model in which households search for both jobs and borrowing opportunities. Business cycles are driven by aggregate labor productivity and households choose which jobs to search for, knowing that higher paying jobs take longer to find, especially when labor productivity is depressed (Menzio and Shi (2010, 2011)). If a household successfully meets a lender in the credit market, it has access to defaultable debt contracts which are priced similar to Eaton and Gersovitz (1981). On the other side of the market, lenders direct credit offers to households to maximize profits, and so the arrival rate of borrowing opportunities is an equilibrium object that depends on the household's employment status and fluctuates with the aggregate state.[3] This market structure delivers heterogeneous and endogenously fluctuating access to three insurance channels of unsecured revolving credit: agents can borrow more, roll over prior

[1] E.g., employment is depressed by 2.8% with credit growth rather than 2% with fixed 1970s levels of credit three years after the onset of the recession, and the employment trough is reached 5 quarters after the peak rather than 4 quarters after the peak.

[2] While not the focus, this paper has implications for the jobless recovery literature, suggesting that some portion of these slow recoveries may actually be optimal. Concurrent work by Mitman and Rabinovich (2012) finds a large impact of unemployment benefits on recoveries and is the closest study to the present paper (see also Schreft and Singh (2003), Bachmann (2009), Shimer (2010), Jaimovich and Siu (2012), and Berger (2012) among many others).

[3] By using directed search in the consumer credit market, this paper relates to the market microstructure of consumer credit markets. Related work by Drozd and Nosal (2008) and Drozd and Serrano-Padial (2012) study a consumer credit market with similar features to Burdett and Judd (1983). Work by Wasmer and Weil (2000), Petrosky-Nadeau (2009), and Petrosky-Nadeau and Wasmer (2013) find important interactions between random search in the labor market and random search in the credit market for firms.

debts, or default if neither of the prior options are optimal.

To generate the *persistent and continual* credit expansions observed over the last 3 decades, the model incorporates stochastic, exogenous technological progress in the aggregate efficiency of matching lenders to households. The empirical counterpart of such credit matching efficiency growth is credit scoring, the digitization of the banking sector, and the availability of online loans, among other numerous innovations.[4] In addition to this exogenous growth in credit, as unemployment durations and default risks endogenously change over the business cycle, lenders expand and restrict the number of credit offers they send, altering household job finding behavior. The general mechanism is that when borrowing opportunities are easy to find, households optimally search for higher-paying but scarcer jobs knowing that if the job search fails they can obtain credit to smooth consumption.

Because the model features directed search in both the labor market and asset market, and since debt contracts are individually priced, I am able to prove that a Recursive Competitive Equilibrium exists with aggregate risk in which the distribution of agents across states does not enter policy functions or prices. In other words, the economy admits a Block Recursive Equilibrium (Menzio and Shi (2010, 2011)).

In the first set of stochastic steady-state experiments, I shut down the exogenous credit matching efficiency growth, and I show that business cycle dynamics across economies with constant but differing levels of credit access are nearly identical. This is because greater credit access produces two offsetting effects. The first of which is a pure *self-insurance effect*. In the short run, holding the wealth distribution constant, greater credit access allows households to be more selective with the jobs they take. The second effect is an offsetting *wealth distribution effect*. In the long run with greater credit access, households save less and borrow more. As they deplete their savings, the ability of households to self-insure actually returns to its pre-credit expansion levels. But, it is precisely this ability to self-insure which determines how employment evolves during a recession. As a result, business cycles which occur close to credit expansions, before the offsetting wealth adjustment occurs, are fundamentally different

[4]See Mester (1997) for more on credit scoring and the decline in time to process loans, and see Berger et al. (1995) for more on the digitization of banking.

from business cycles which occur during periods of constant credit.

The main experiment is then to feed actual labor productivity residuals into two identical economies from 1974-2012, except one economy receives increases in the credit matching efficiency calibrated to observed credit use among the unemployed while the other economy has credit matching efficiency remain at 1970s levels, and to then compare employment recoveries *along the transition path*. Following the 1990, 2001, and 2007 recessions, *growth* in access to unsecured revolving credit generates up to an additional .8 percentage point decline in employment 12 quarters after the initial onset of these recessions compared to an economy that has 1970s levels of credit access.[5] These estimates of employment effects from credit growth straddle those of the 2008 unemployment benefit extensions (Rothstein (2011) and Hagedorn et al. (2013)). Compared to the economy with 1970s levels of credit access, allowing for credit growth brings employment deviations 24%, 48%, and 15% closer to the data three years after the initial onset of the 1990, 2001, and 2007 recessions, respectively.

There are several testable implications of the theory. The model is consistent with the precipitous reduction in liquid asset holdings by households over the 1974-2012 time period, the trend rise in defaults per capita over that same time period, and the long run decline in consumption volatility relative to income volatility. The model's self-insurance mechanism also produces a long run rise in unemployment durations that is broadly consistent with the aggregate data (Abraham and Shimer (2001) and Mukoyama and Şahin (2009)). Using the new 2007-2009 Survey of Consumer Finances (SCF) panel, I also provide suggestive evidence that the model's self-insurance mechanism is consistent with micro data by showing that credit access is significantly and positively correlated with individual unemployment durations. Among credit applicants, those who were denied credit had unemployment durations that were 6 weeks shorter, on average. However the inherent endogeneity, time aggregation bias, and lack of business cycle variation in the data require the use of a structural model to properly answer the question posed in this paper.

While much is known both theoretically and empirically about the way unemployment

[5] Jappelli and Pagano (1994) find that loose consumer credit limits may harm economic growth, and Calvo et al. (2006) finds that there can be strong recoveries without private credit expansions.

insurance and saving decisions impact employment incentives (*inter alia* Mortensen (1976), Katz and Meyer (1990), Hansen and İmrohoroğlu (1992), Hopenhayn and Nicolini (1997), Ljungqvist and Sargent (1998), and Acemoglu and Shimer (1998)), only recently has the profession considered the way labor markets are affected by other private consumption smoothing mechanisms such as home equity loans (Hurst and Stafford (2004)), default arrangements (Athreya and Simpson (2006), Han and Li (2007), Gordon (2011), Herkenhoff and Ohanian (2012a), Herkenhoff (2012a), Chen (2012) and Dobbie and Song (2013)), and mortgage modifications (Mulligan (2008, 2012) and Herkenhoff and Ohanian (2011)). The present paper contributes to this research agenda by explicitly modeling and measuring the interaction between access to credit markets and household job search behavior over the business cycle.

Several other studies including Crossley and Low (2005), Athreya and Simpson (2006), Rendon (2006), and Guerrieri and Lorenzoni (2011) have looked at the role borrowing constraints play in models with partial equilibrium labor markets and found significant interactions between borrowing constraints and labor supply, while general equilibrium work by Krusell et al. (2010) and Nakajima (2012) find moderate effects of saving on labor markets.[6] Concurrent work by Bethune et al. (2013) provides a steady state general equilibrium analysis of the way consumer credit affects labor markets through firm productivity. The present paper departs from theirs as their model shuts off the insurance channel of unsecured credit by assuming households cannot carry debts between periods, households do not make job search decisions in their model, and their analysis is not concerned with business cycles.

The paper proceeds as follows. Section 1.2 presents evidence of unsecured credit use by the unemployed, Section 1.3 outlines the model, Section 1.4 describes the steady state calibration, Section 1.5 provides steady state results, Section 1.6 analyzes the non-linear impulse responses of the model near steady state, Section 1.7 explains the transition path calibration, Section 3.4 includes the transition path results, and Section 1.9 concludes.

[6]In one extension Nakajima (2012) modifies his model to allow for borrowing. He finds that allowing for borrowing has little impact on aggregates largely because the calibration produces near-zero borrowing in equilibrium and by assumption households do not make job search decisions.

1.2 Credit and Unemployment in the Data

Section 1.2.1 presents time series of access to credit by the unemployed, showing that access more than doubled between 1983 and 1992 and more than tripled between 1977 and 1992. Section 1.2.2 describes existing evidence of credit use among the unemployed. Section 1.2.3 analyzes the correlation between credit access and time spent unemployed, framing the inherent endogeneity and data limitations associated with any reduced form answer to the main question.

1.2.1 Unemployed Access to Credit 1970-2012

In this section I present new time series for credit access and credit use based on the Survey of Consumer Finances from 1983 to 2010 and its predecessor, the Survey of Consumer Credit, from 1970 to 1977. Figure 1.1 depicts the unsecured revolving credit access rates among all households as well as among the unemployed. Unsecured revolving credit is taken to be the fraction of households with bankcards that have a revolving feature (when I refer to credit cards, I am referring to bankcards). Between 1983 and 1992, unsecured revolving credit access rates among the unemployed doubled. Among all households including those without credit access, Figure 1.2 shows that the fraction of unemployed households carrying positive balances also doubled between 1983 and 1992. Figure 1.3 plots the ratio of revolving credit balance to monthly income (measured as an average over the prior year) for the sample of borrowers with positive balances. These borrowers carried revolving balances of roughly 100% of their prior monthly wages in 1991 and 200% of their prior monthly wages by 2001. Figure 1.4 shows the average nominal balance for those with positive balances, the numerator of Figure 1.3. The main takeaway from these pictures is that revolving credit access and use grew enormously during the 1980s, not just for the employed but also for the unemployed.

1.2.2 Existing Evidence of Credit Use Among the Unemployed

Evidence that the unemployed borrow to replace income is provided by Sullivan (2008) and Hurd and Rohwedder (2010). Using an indirect approach, Sullivan (2008) finds that unemployed households with low assets increase unsecured debt by 11-18 cents per dollar of

Figure 1.1: Fraction of Population with Access to Credit

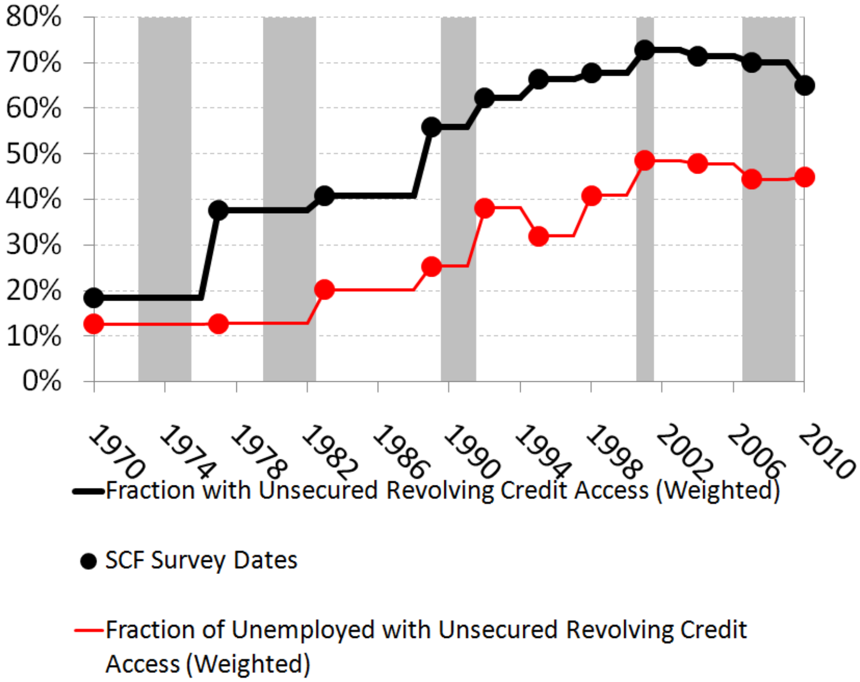
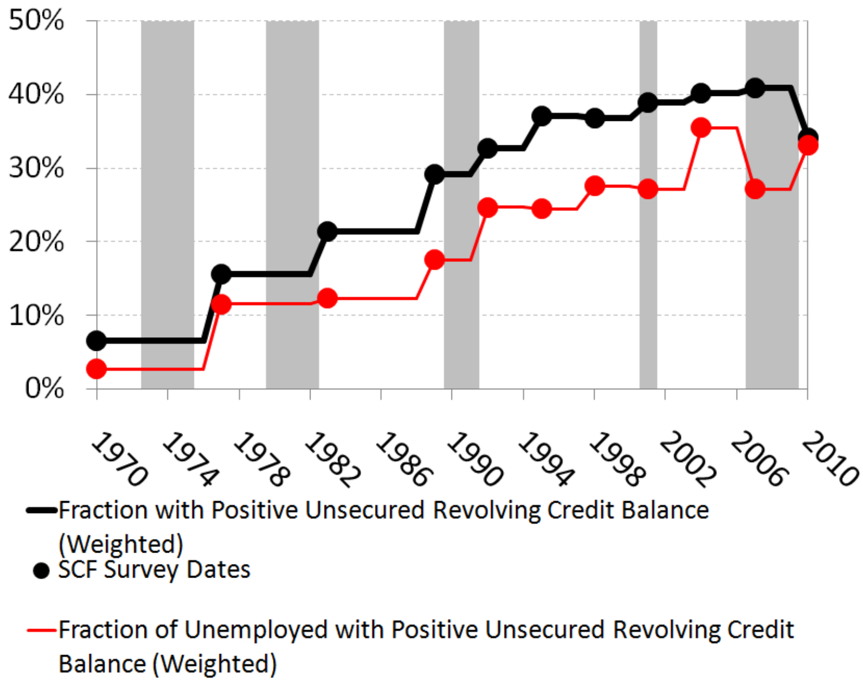


Figure 1.2: Fraction of Population Carrying Positive Balances



lost income (this effect holds in both the Panel Study of Income Dynamics and Survey of Income and Program Participation). Using a more direct approach, Hurd and Rohwedder (2010) find that 18% of unemployed households self-report using unsecured credit to replace

Figure 1.3: Revolving Credit to Monthly Income Ratios, Conditional on Holding a Positive Balance

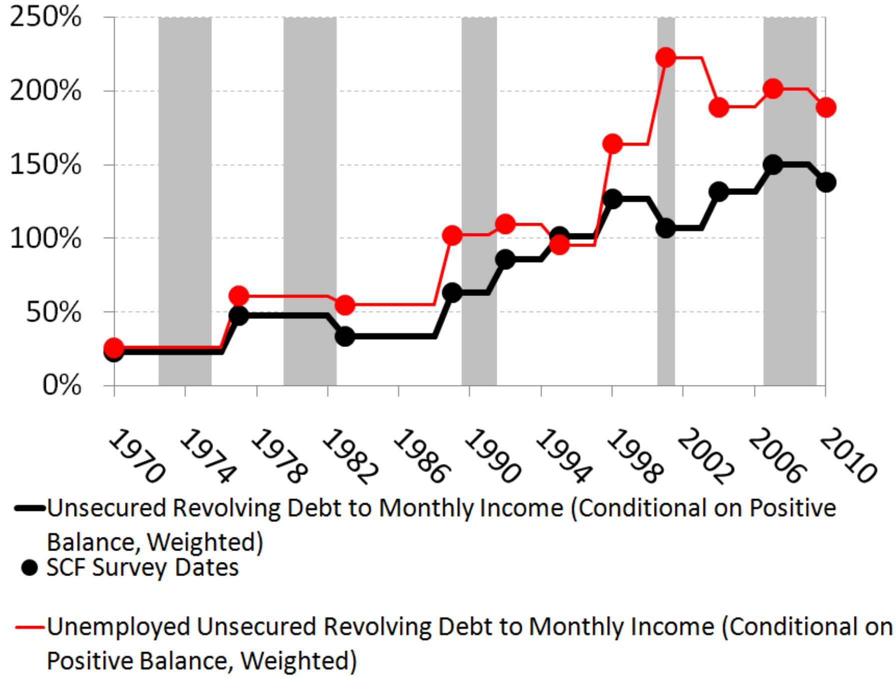
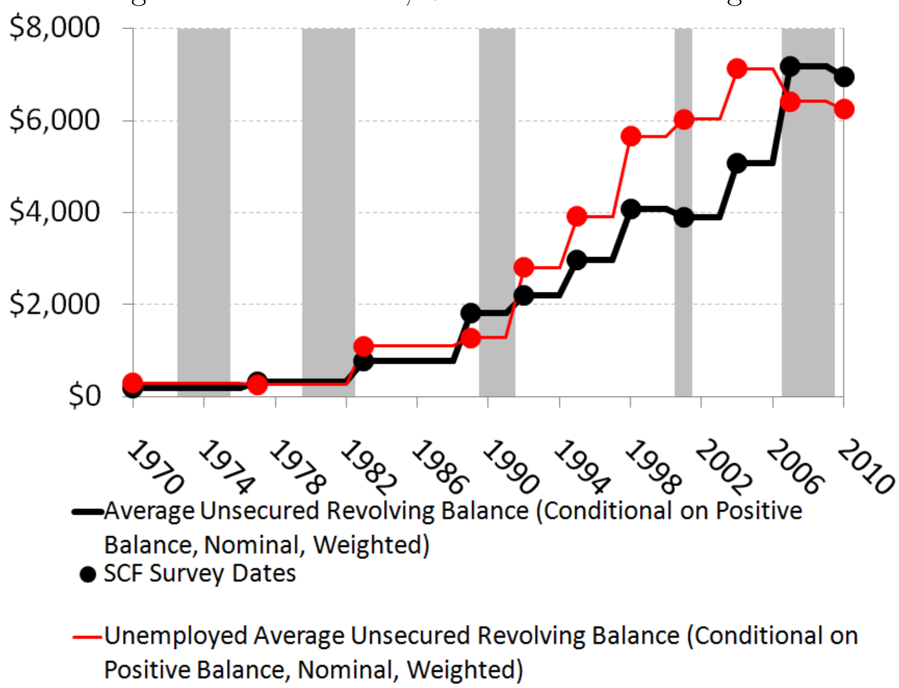


Figure 1.4: Average Nominal Balance, Conditional on Holding a Positive Balance



lost income. Hurd and Rohwedder (2010) also find that at least 36% of households self-report at least some degree of non-mortgage default in response to job loss. Their study is based on the 2009 RAND American Life Panel.

1.2.3 Credit Supply and Time Spent Unemployed

While recent work by Chetty (2008) has shown that access to liquid assets in the form of severance payments increases unemployment durations significantly, there is limited evidence regarding credit access and time spent unemployed. In this section, I show that being denied credit is associated with a 38.4% reduction in the reported time spent unemployed for the subsample of 2007-2009 SCF panel heads, detailed below. While this is suggestive evidence of the mechanism being studied, the inherent endogeneity of the credit denial regressor motivates the structural model of Section 1.3.

Table 1.1: Weeks Spent Unemployed and Credit Denial Status, Basic Tabulations (2009, SCF)

	Mean (Wtd.)	**Mean**	**Std.**	**Min**	**Max**	**Obs.**
Weeks Unemployed During ’08-’09 if Denied During ’07-’09	17.0	17.3	14.4	1	52	40
Weeks Unemployed During ’08-’09 if Not Denied During ’07-’09	23.3	23.4	16.6	2	52	55
Weeks Unemployed During ’06-’07 if Denied During ’02-’07	16.2	16	13.8	1	52	38
Weeks Unemployed During ’06-’07 if Not Denied During ’02-’07	18.8	19.7	18.1	1	52	42

Notes. 2007 and 2009 SCF non-mortgagor working-age heads who are labor force participants, reported a positive number of weeks spent unemployed over the prior 12 months, and sent at least one loan application over the relevant time interval (see above) as of the respective survey date.

Table 1.2: Weeks Spent Unemployed and Credit Denial Status, Summary Statistics (2009, SCF)

Variable	**Mean**	**Std.**	**Variable**	**Mean**	**Std.**
Log Weeks Unemployed over Prior Year	2.67	0.96	Credit Utilization Rate 2009	0.25	0.43
Strict Credit Denial 2009 (d)	0.42	0.50	College Degree (d)	0.20	0.40
Total Income in 2006 ($ ten thousands)	5.32	13.89	Male (d)	0.74	0.44
Liquid Assets to Income Ratio 2009	0.26	1.15	Married (d)	0.45	0.50
Illiquid Assets to Income Ratio 2009	1.20	5.90	Age	39.58	11.07
Unsecured Debt to Income Ratio 2009	0.10	0.41	Race (d)	0.27	0.45
Observations	95				

Notes. 2009 SCF non-mortgagor working-age heads who are labor force participants, reported a positive number of weeks spent unemployed over the prior 12 months, and sent at least one loan application between the 2007 and 2009 survey dates.

Before the more formal analysis that follows, Table 1.1 illustrates the unemployment

Table 1.3: Weeks Spent Unemployed Between 2008-2009 and Credit Denial Between 2007-2009. Dependent Variable is Log of Weeks Spent Unemployed Between 2008-2009, (2007-2009 SCF)

	(1)	(2)	(3)	(4)
Credit Denial 2009 (d)	-0.415**	-0.412*	-0.394*	-0.384*
	(0.202)	(0.210)	(0.212)	(0.215)
Total Income in 2006 ($ ten thousands)		0.00209	0.00388	0.00351
		(0.00325)	(0.00295)	(0.00300)
Liquid Assets to Income Ratio 2009			0.137***	0.131***
			(0.0348)	(0.0358)
Illiquid Assets to Income Ratio 2009			0.0204***	0.0200***
			(0.00696)	(0.00691)
Unsecured Debt to Income Ratio 2009			0.00637	0.0588
			(0.148)	(0.164)
Credit Utilization Rate 2009				-0.175
				(0.232)
Demographic Controls	No	No	Yes	Yes
Observations	95	95	95	95
R-squared	0.046	0.077	0.123	0.129

Notes. Robust Standard Errors in parentheses. Asterisk legend: *** p<0.01, ** p<0.05, * p<0.1. 2009 SCF non-mortgagor working-age heads who are labor force participants, reported a positive number of weeks spent unemployed over the prior 12 months, and sent at least one loan application between the 2007 and 2009 survey dates. Demographic controls include, age, race, sex, marital status, and education. OLS coefficients reported in columns (1) - (4). Dependent variable is the log of weeks spent out of work over the prior 12 months to the 2009 survey date. Observations are unweighted.

durations of working age heads who are labor force participants, reported a positive unemployment duration over the prior year, and applied for at least 1 loan during the 2007-2009 time period.[7] These restrictions yield a sample of 95 individuals (see Table 1.2 for summary statistics). The average time spent out of work between 2008 and 2009 was 17 weeks for those who were denied credit between 2007 and 2009, versus 23.3 weeks for those who obtained credit, i.e. those who were denied credit had a 6.3-week shorter average time unemployed.[8] This correlation persists in the more formal analysis below once I control for

[7] I use the 2007-2009 SCF Panel since it has the least aggregation bias regarding credit denial. The survey asks respondents about credit denial between 2007 and 2009 (other SCF surveys use 5 year windows) and total time spent out of work during the 12 months prior to the 2009 survey date. There is still time aggregation bias since the date of loan application and date of unemployment spell (as well as the length of any single unemployment spell) are unknown, and so the statistics reported are interpreted as correlations.

[8] It is also important to note that 49.1% of those who reported a positive unemployment duration during 2008-2009 applied for credit whereas 53.6% of the employed applied for credit. Thus, the correlation is not simply driven by the fact that employed persons apply more often and are thus denied more often.

observables. The same correlation pattern also holds true among mortgagors (in fact the correlation is even stronger) and also in previous time periods which are subject to much more time aggregation bias.

Wages, education, and other demographics may play an important role in understanding this negative correlation between weeks spent unemployed and credit denial. Low wage workers are more likely to be denied credit, and, as we know from Autor and Dorn (2009) and Jaimovich and Siu (2012) among others, the labor market has polarized and low wage workers have more job opportunities than before (thus lower durations). I correct for this observed heterogeneity by including controls for prior income during 2006, as well as basic demographic and balance sheet controls.[9]

Table 1.3 reports OLS coefficients from a regression of the log number of weeks spent unemployed between 2008 and 2009 on the credit denial status measured between 2007 and 2009. Column (1), which has no controls, shows that being denied credit between 2007 and 2009 is associated with a 41.5% reduction in the reported time spent unemployed between 2008 and 2009. The correlation is essentially unchanged in column (2) after including total 2006 income, in levels, as a proxy for prior wages. Including controls for age, marital status, sex, and education as well as balance sheet controls for liquid assets and illiquid assets does not significantly alter the result as shown in Column (3).[10] Finally, as Column (4) demonstrates, credit utilization rates are not driving the correlation. Column (4) shows that being denied credit between 2007 and 2009 is associated with a 38.4% reduction in the reported time spent unemployed between 2008 and 2009. While this is suggestive of the static mechanism, the inherent endogeneity, time aggregation bias, and lack of business cycle variation make such estimates difficult to interpret. Therefore, I will turn to a structural model.

[9]There is also an important role for unobserved heterogeneity as there may be 'bad types' who are denied credit and have trouble finding jobs. This would bias the coefficient on credit denial toward zero.

[10]While not reported here, including unemployment benefits, another extremely endogenous covariate, does not alter the reported relationship.

1.3 Model

The model features labor productivity-driven business cycles with directed search and matching in both the labor market and defaultable debt market. Households direct their search among wage submarkets, and once matched with a firm, wages are fixed until there is an exogenous separation (Appendix 1.10.3 allows for on-the-job-search). Firms operate a constant returns to scale technology which converts one indivisible unit of labor into final consumption goods, where the amount of final consumption goods produced depends solely on aggregate labor productivity.

Households also search for lenders. Once matched with a lender, households can borrow using one-period, non-contingent, and non-enforceable loans. Taking into account default risk, these loans are priced individually along the intensive margin as in Eaton and Gersovitz (1981) and Chatterjee et al. (2007). On the other side of the credit market, lenders observe the state space of households and then direct credit offers toward households to maximize expected profits. Consequently, the household's employment status and prior financial position endogenously determine access to credit.

To generate the large and persistent increases in credit access observed from 1970 to 2012, I allow for technological progress in the efficiency of matching households to lenders. As I will explain in detail below, *growth* in credit access is crucial for understanding business cycles over the 1970-2012 time period. When credit expands coming out of a recession, households optimally choose to look for scarcer jobs in high-wage submarkets, understanding that if their job search fails they can easily obtain credit to smooth consumption.

To obtain analytical results and clarify the economic mechanism at play, I start with a model in which all lending relationships last one period. In the calibrated model, however, I consider multi period lending relationships to establish better contact with the data. In a separate extension in Appendix 1.10.3, I also consider the role of on-the-job-search.

1.3.1 Household Problem

Time is discrete and runs forever. As in Menzio et al. (2012), there are $T \geq 2$ overlapping generations of risk averse households that face both idiosyncratic and aggregate risk. Each household lives T periods deterministically and discounts the future at a constant rate $\beta \in (0,1)$. Every period households first participate in an asset market where they search for borrowing opportunities and make asset accumulation and default decisions. After the asset market closes, households enter the labor market where they make job search decisions.

Similar to Dubey et al. (1990, 2005) and Zame (1993), consumers maximize the present discounted value of preferences over non-durable consumption (c) and leisure (η) net of any utility penalties of default, $x(D)$, where D is the fraction of debt defaulted upon.[11] I assume that labor is indivisible so that employed households consume their entire time endowment of leisure, and preferences are separable between consumption and leisure. The utility function of the employed is $u(c) - x(D)$ and the utility function of the unemployed is $u(c) + \eta - x(D)$ so that the interpretation of η is as a flow utility of leisure. Let t be age and t_0 index birth cohort, and let h_{t,t_0+t} equal one if the agent is employed. Then c_{t,t_0+t}, $\eta \cdot (1 - h_{t,t_0+t})$, and D_{t,t_0+t} respectively denote the consumption, leisure, and default outcomes of an age t agent at date $t_0 + t$. The goal of a newly born in cohort t_0 is to maximize

$$E_{t_0}\left[\sum_{t=1}^{T} \beta^t \Big(u(c_{t,t_0+t}) + \eta \cdot (1 - h_{t,t_0+t}) - x(D_{t,t_0+t}) \Big)\right].$$

Anticipating the recursive nature of the problem below, I will drop the age and time subscripts from variables and only retain the age subscript t for the value function.

A household's state vector consists of their current employment status $e \in \{W, U\}$ where $e = W$ if employed and $e = U$ if unemployed, their credit access status $a \in \{C, N\}$ where a=C indicates the individual has credit access and is synonymous with being matched to

[11] Unlike bankruptcy which is acyclical, Herkenhoff (2012a) uses Equifax data to show that default (defined to be 90+ days late) is approximately a continuous choice (i.e. consumers default on 2 or 3 out of 6 credit lines), is highly procyclical, and occurs 6x more frequently than bankruptcy. Herkenhoff (2012a) also shows that nearly 30% of delinquent credit lines end up in collection, indefinitely, and Furletti (2003) documents that banks sell defaulting non-bankrupt accounts to collection agencies for 5 cents per 1 dollar.

a lender and a=N indicates no credit access, their current wage $w \in \mathcal{W} \equiv [\underline{w}, \overline{w}] \subseteq \mathbb{R}_+$ if employed or unemployment benefits $z \in \mathcal{Z} \equiv [\gamma\underline{w}, \gamma\overline{w}] \subseteq \mathbb{R}_+$ where $\gamma \in (0,1)$ is the replacement rate if unemployed, their net assets $b \in \mathcal{B} \equiv [\underline{b}, \bar{b}] \subseteq \mathbb{R}$, their age $t \in \mathbb{N}_T \equiv \{1, \ldots, T\}$, and the aggregate state Ω.[12]

The aggregate state Ω includes three components. The first component is aggregate productivity $y \in \mathcal{Y}$, the second component is the aggregate credit matching efficiency $A \in \mathcal{A}$, and the third component is an infinite dimensional object μ which summarizes the distribution of households across all state variables, i.e. $\mu : \{W, U\} \times \{C, N\} \times \mathcal{W} \cup \mathcal{Z} \times \mathcal{B} \times \mathbb{N}_T \to [0,1]$. Let $\mu' = \Phi(\Omega, A', y')$ be the law of motion for the distribution.

At the start of every period, households wait passively to match with lenders. I will refer to this as search in the classic Mortensen and Pissarides (1994) sense. Similar to Mortensen and Pissarides (1994) in which firms post vacancies to attract employees, in the present model, lenders send credit offers to attract borrowers. Similar to the way a job vacancy is filled by a household in Mortensen and Pissarides (1994), in the present paper, if a credit offer successfully reaches a household, a match is struck between the lender and household – I call this obtaining credit access. The terms of the loan are then determined by bargaining.

As is standard in the literature b' is net assets. If $b' > 0$ the agent is saving and if $b' < 0$ the agent is borrowing. If the agent is matched with a lender and opts to borrow, then $b' < 0$ indicates the face value of the loan, q is the discount on the face value (which I will also call the bond price), and thus households receive $-q \times b'$ units of the numeraire (the final consumption good) in exchange for their non-enforceable promise to repay $-b'$ units of the final consumption good tomorrow. The discount on the bonds q, in equilibrium, is a function of the state space of the household; for example, if today's aggregate state is Ω, the resulting bond price for an age t unemployed household (U) with unemployment benefits z who is requesting a loan of size b' is $q_{U,t}(z, b'; \Omega)$. In general, the discount on the face value of the loan is greater than the riskless discount $q_{U,t}(z, b'; \Omega) \leq \frac{1}{1+r_f}$ and will vary individually depending on the household's individual default risk (Section 1.3.2 provides more details

[12] The set of operating wage submarkets is an equilibrium object. The bounds $[\underline{w}, \overline{w}]$ are non-binding but used in the existence proofs.

about lenders). If the household saves $b' > 0$ then the household must pay $\frac{1}{1+r_f} \times b'$ units of the final consumption good today in order to receive b' units of the final consumption good tomorrow. To unify notation, $q_{U,t}(z, b'; \Omega) = \frac{1}{1+r_f}$ if $b' > 0$ and the household saves.

Because I assume that lenders can direct their search toward households, the probability a household receives a credit offer is a function of the state space of the household. I define $A\psi(\theta^C_{U,t}(z, b; \Omega))$ to be the probability that an age t unemployed (U) household with net assets b and unemployment benefit income z in aggregate state Ω meets a lender. I define $\theta^C_{U,t}(z, b; \Omega)$ to be the corresponding credit submarket tightness (lender to household ratio) among all such households looking for credit; Section 1.3.2 will explain the credit market in more detail. Let $U^C_t(z, b; \Omega)$ be the value function of an unemployed household matched with a lender and $U^N_t(z, b; \Omega)$ be the value function of an unemployed household without credit access. Using this notation, the Bellman equation for an unemployed agent looking for a lender, $U_t(z, b; \Omega)$, is

$$U_t(z, b; \Omega) = \underbrace{A\psi(\theta^C_{U,t}(z, b; \Omega))}_{\text{Find Lender}} U^C_t(z, b; \Omega) + \big(1 - A\psi(\theta^C_{U,t}(z, b; \Omega))\big) U^N_t(z, b; \Omega)$$
$$\forall t \leq T$$

$$U_{T+1}(z, b; \Omega) = 0.$$

In the current section, matches between households and lenders are destroyed at the end of every period. Households then re-match at the beginning of the period with a new lender. Later on, I allow for long term relationships with lenders.

After the asset market closes, the aggregate state is realized, and then unemployed agents enter the labor market where they look for jobs paying $\tilde{w} \in \mathcal{W}$. Each submarket is indexed by a wage and age pair $(\tilde{w}, t)$ and $p\big(\theta^L_t(\tilde{w}; \Omega')\big)$ is the probability of successfully matching to an employer paying $\tilde{w}$. In this section the wage is fixed over the duration of the employment relationship, but this is relaxed in Appendix 1.10.3 when on-the-job-search is allowed. The function $\theta^L_t(\tilde{w}; \Omega')$ is the submarket tightness (job vacancy to unemployment ratio) for an age t agent looking for jobs paying $\tilde{w}$ given the aggregate state Ω'. If an agent successfully matches with an employer paying $\tilde{w}$ their continuation value is given by $W_{t+1}(\tilde{w}, b'; \Omega')$. Section 1.3.3 will explain the labor market in more detail.

The unemployed receive a separable flow utility η from leisure by assumption. For those with access to credit, their choice set for assets includes loans, i.e. their asset choice is unrestricted $b' \in \mathcal{B}$. Thus, the problem solved by an age t unemployed agent (U) with credit access (C), unemployment benefits z, net assets b in aggregate state Ω is

$$\begin{aligned} U_t^C(z, b; \Omega) = \max_{b' \in \mathcal{B}, D \in [0,1]} u(c) - x(D) + \eta + \beta \mathbb{E}\Big[\max_{\tilde{w} \in \mathcal{W}} \; p(\theta_{t+1}^L(\tilde{w}; \Omega')) W_{t+1}(\tilde{w}, b'; \Omega') \\ + \Big(1 - p\big(\theta_{t+1}^L(\tilde{w}; \Omega')\big)\Big) U_{t+1}(z, b'; \Omega') \Big] \quad \forall t \leq T \end{aligned}$$

$$U_{T+1}^C(z, b; \Omega) = 0$$

subject to the budget constraint,

$$c + q_{U,t}(z, b'; \Omega) b' \leq z + (1 - D) b,$$

and taking as given the law of motion for the aggregate state,

$$\begin{aligned} \Omega' &= (\mu', A', y') \\ \mu' &= \Phi(\Omega, A', y') \\ y' &\sim F(y' \mid y) \\ A' &\sim G(A' \mid A). \end{aligned} \tag{1.1}$$

For those who are unemployed (U) without access to credit (N), the problem is similar except the household's asset choice b' is restricted to be positive, $b' \geq 0$,

$$\begin{aligned} U_t^N(z, b; \Omega) = \max_{b' \geq 0, D \in [0,1]} u(c) - x(D) + \eta + \beta \mathbb{E}\Big[\max_{\tilde{w} \in \mathcal{W}} \; p(\theta_{t+1}^L(\tilde{w}; \Omega')) W_{t+1}(\tilde{w}, b'; \Omega') \\ + \Big(1 - p\big(\theta_{t+1}^L(\tilde{w}; \Omega')\big)\Big) U_{t+1}(z, b'; \Omega') \Big] \quad \forall t \leq T \end{aligned}$$

$$U_{T+1}^N(z, b; \Omega) = 0$$

subject to the budget constraint

$$c + \frac{1}{1 + r_f} b' \leq z + (1 - D)b$$

and taking as given the aggregate law of motion (1.1).

Employed agents in this economy face a similar credit constraint to unemployed agents. At the start of the period, employed agents are able to obtain access to credit markets with probability $A\psi(\theta^C_{W,t}(w, b; \Omega))$ which depends on the vector of household attributes. Let $W^C_t(w, b; \Omega)$ be the value function for an employed agent that successfully matches with a lender, and $W^N_t(w, b; \Omega)$ be the value function for an employed agent that is unable to match with a lender. Using this notation, the Bellman equation for an employed household looking for credit, $W_t(w, b; \Omega)$, is

$$\begin{aligned} W_t(w, b; \Omega) = {} & A\psi(\theta^C_{W,t}(w, b; \Omega)) W^C_t(w, b; \Omega) + \big(1 - A\psi(\theta^C_{W,t}(w, b; \Omega))\big) W^N_t(w, b; \Omega) \\ & \forall t \leq T \end{aligned}$$

$$W_{T+1}(w, b; \Omega) = 0.$$

Let $\delta_{t+1}(w; y)$ be the state contingent job separation rate.[13] Also let $q_{W,t}(w, b'; \Omega)$ be the bond price for an employed household. Since the model will be calibrated at a quarterly frequency, it is important to allow workers to immediately search for a job following a separation. Therefore, the problem solved by an age t employed agent (W) with credit access (C), wage w, and net assets b in aggregate state Ω is given by

$$\begin{aligned} W^C_t(w, b; \Omega) = \max_{b' \in \mathcal{B}, D \in [0,1]} & u(c) - x(D) + \beta \mathbb{E}\Big[(1 - \delta_{t+1}(w; y')) W_{t+1}(w, b'; \Omega') \\ & + \delta_{t+1}(w; y') \max_{\tilde{w} \in \mathcal{W}} \Big\{ p(\theta^L_{t+1}(\tilde{w}; \Omega')) W_{t+1}(\tilde{w}, b'; \Omega') \\ & + \Big(1 - p\big(\theta^L_{t+1}(\tilde{w}; \Omega')\big)\Big) U_{t+1}(\gamma w, b'; \Omega') \Big\} \Big] \end{aligned}$$

[13] The state contingency of the separation rate is used in the existence proof to bound the firm continuation value away from zero, but will be set to a constant for computations.

subject to the budget constraint,

$$c + q_{W,t}(w, b'; \Omega)b' \leq w + (1 - D)b.$$

and taking as given the aggregate law of motion (1.1).

For those who are employed (W) and without access to credit (N), they face the same problem except their asset choice is restricted to be positive, $b' \geq 0$,

$$\begin{aligned} W_t^N(w, b; \Omega) = \max_{b' \geq 0, D \in [0,1]} u(c) - x(D) + \beta \mathbb{E} \Big[& (1 - \delta_{t+1}(w; y'))W_{t+1}(w, b'; \Omega') \\ & + \delta_{t+1}(w; y') \max_{\tilde{w} \in \mathcal{W}} \ \{ p(\theta^L_{t+1}(\tilde{w}; \Omega'))W_{t+1}(\tilde{w}, b'; \Omega') \\ & + \Big(1 - p\big(\theta^L_{t+1}(\tilde{w}; \Omega')\big)\Big) U_{t+1}(\gamma w, b'; \Omega') \} \Big] \end{aligned}$$

subject to the budget constraint

$$c + \frac{1}{1 + r_f} b' \leq w + (1 - D)b$$

and taking as given the aggregate law of motion (1.1).

1.3.2 Saving Institutions and Lending Institutions

There is a loanable funds market with a unit measure of risk neutral saving institutions and a unit measure of risk neutral lending institutions. Saving institutions are competitive and face a frictionless market where they accept deposits each period. These institutions have access to a risk-free technology that yields r_f on deposits. With free entry, the yield on savings offered to consumers is this risk free rate r_f. Lending institutions on the other hand must look for agents who want to borrow. Lenders send out one-period credit offers to potential borrowers based on the borrower's characteristics. Each set of characteristics is a different submarket. The cost of sending a credit offer is κ_C.

It is important to note that a credit offer is an invitation to bargain. If a lender successfully meets a households who wants to borrow, the lender and household Nash bargain over the bond price schedule $q_{e,t}(w, b'; \Omega)$ which is a function of loan size b', employment status e, wage w if employed or unemployment benefits z if unemployed, and the aggregate state Ω. I assume households have a bargaining weight of unity, i.e. households make take-it-or-leave-it bond price proposals. As is, this assumption leaves lenders with no incentives to enter the lending market. To generate incentives for lenders to send credit offers, I assume that lenders are guaranteed a proportional minimum servicing fee τ which is based on the loan size. Consumers then bargain over the bond schedule taking as given the proportional minimum servicing fee τ.[14] Let $b'^{*}_{e,t}(w, b; \Omega)$ be the present bond policy of the household and $D^{a'}_{e',t+1}(w', \hat{b}; \Omega')$ be the future default decision of the household which depends on tomorrow's employment e', access to credit a', age $t+1$, wage w' (which takes into account the risk the household loses its job), loan size $\hat{b}$, and the aggregate state Ω'. With this notation, the expected profits accruing to a matched lender, $Q_t(e, w, b; \Omega)$, are given by,

$$Q_t(e, w, b; \Omega) = q_{e,t}(w, \hat{b}; \Omega)\hat{b} - \frac{1}{1+r_f}\mathbb{E}\Big[(1 - D^{a'}_{e',t+1}(w', \hat{b}; \Omega')) \cdot \hat{b}\Big]$$
$$\forall e \in \big\{W, U\big\},\ b \in \mathcal{B}, \hat{b} = b'^{*}_{e,t}(w, b; \Omega)$$

To ensure an expected minimum servicing fee of τ on the resources lent, the expected yield on the loan must be $(1 + r_f + \tau)$:

$$(1 + r_f + \tau) \leq \frac{\mathbb{E}\Big[(1 - D^{a'}_{e',t+1}(w', \hat{b}; \Omega')) \cdot \hat{b}\Big]}{q_{e,t}(w, \hat{b}; \Omega)\hat{b}} \forall e \in \big\{W, U\big\},\ \hat{b} \in \mathcal{B}_{-}$$

Thus the general menu of prices across loans as well as savings contracts is given below (note,

[14] This could be endogenized as a choice by the household but at the expense of tractability. In the model, τ covers the credit offer cost and yields an incentive for lending institutions to look for potential borrowers. In the literature, imposing this wedge τ is common; see Livshits et al. (2007) for an example. From a theoretical perspective, the ex-post bargaining over the bond price makes lender's profit expectations independent of the distribution of households across states. If a lender simply posted a spread, they would have to forecast the statespace of households who would arrive at their door to form profit expectations.

the price is indexed by employment status $e \in \{W, U\}$):

$$q_{e,t}(w, \hat{b}; \Omega) = \begin{cases} \frac{\mathbb{E}\left[(1 - D^{a'}_{e',t+1}(w', \hat{b}; \Omega'))\right]}{(1 + r_f + \tau)}, & \hat{b} \in \mathcal{B}_- \\ \frac{1}{(1 + r_f)}, & \hat{b} \in \mathcal{B}_+ \end{cases} \tag{1.2}$$

Define $A \cdot M_C(u_c(\mathbf{x}), v_c(\mathbf{x}))$ to be the constant returns to scale matching function in credit submarket $\mathbf{x}$, where $u_c(\mathbf{x})$ is the number of households searching for credit with state vector $\mathbf{x}$, $v_c(\mathbf{x})$ is the number of credit offers sent to such households, and A is the aggregate credit matching efficiency. Then, the credit-filling rate, which is the probability a lender matches with a household, is given by,

$$A \cdot \phi(\theta^C_{e,t}(w, b; \Omega)) = \frac{A \cdot M_C(u_{c,t}(e, w, b; \Omega), v_{c,t}(e, w, b; \Omega))}{v_{c,t}(e, w, b; \Omega)}$$

And the credit-finding rate, which is the probability a household meets a lender, is given by,

$$A \cdot \psi(\theta^C_{e,t}(w, b; \Omega)) = \frac{A \cdot M_C(u_{c,t}(e, w, b; \Omega), v_{c,t}(e, w, b; \Omega))}{u_{c,t}(e, w, b; \Omega)}$$

The free entry condition for lenders will bind for every submarket of consumers that takes loans:

$$\kappa_C = A \cdot \phi(\theta^C_{e,t}(w, b; \Omega))Q_t(e, w, b; \Omega) \tag{1.3}$$

The free entry condition can be inverted to obtain the equilibrium tightness in the credit market, $\theta^C_{e,t}(w, b; \Omega)$, which can then be used to recover the credit-finding rate of the household.

1.3.3 Firms

As in Moen (1997), Menzio and Shi (2009, 2010), Karahan and Rhee (2011), and Menzio et al. (2012), I assume that firms post fixed wage contracts and there is free entry of firms.

In particular, firms post vacancies in certain submarkets that are indexed by wage $w \in \mathcal{W} \subset \mathbb{R}_{++}$ and age t (this setup is most similar to Menzio et al. (2012)). The posted wage w is fixed once an employee is found.[15] The submarket tightness is given by $\theta_t^L(w;\Omega) = \frac{v_t(w;\Omega)}{u_t(w;\Omega)}$ where $v_t(w;\Omega)$ is the number of vacancies posted in the (w,t) submarket and $u_t(w;\Omega)$ is the number of unemployed households in that submarket.[16] The constant returns to scale of the matching function $M(u,v)$ will guarantee that the ratio of unemployed persons to vacancies is all that matters for determining job finding rates. Let the vacancy filling rate be given by $f(\theta_t^L(w;\Omega)) = \frac{M(u_t(w;\Omega),v_t(w;\Omega))}{v_t(w;\Omega)}$ and let the job finding rate be given by $p(\theta_t^L(w;\Omega)) = \frac{M(u_t(w;\Omega),v_t(w;\Omega))}{u_t(w;\Omega)}$. The value to a firm of posting a vacancy in submarket (w,t) is given below:

$$V_t(w;\Omega) = -\kappa_L + f(\theta_t^L(w;\Omega))J_t(w;\Omega)$$

With free entry it must be the case that profits are competed away. Substituting, the free entry condition is given below:

$$\kappa_L = f(\theta_t^L(w;\Omega))J_t(w;\Omega) \quad \text{if } \theta(w;\Omega) > 0 \tag{1.4}$$

The equilibrium market tightness in the labor market, $\theta_t^L(w;\Omega)$, can be obtained by inverting the free entry condition and then be used to recover the job finding rate of households.

To characterize $J_t(w;\Omega)$, I assume that firms operate a linear technology and are subject to an exogenous job destruction rate $\delta_{t+1}(w;y')$ that is state dependent. The firm value of an ongoing match to a worker of age t being paid wage w in aggregate state Ω is given below:[17]

$$J_t(w;\Omega) = y - w + \beta \mathbb{E}_{\Omega'}\Big[(1-\delta_{t+1}(w;y'))J_{t+1}(w;\Omega')\Big] \quad \forall t \leq T$$

$$J_{T+1}(w;\Omega) = 0$$

[15] Appendix 1.10.3 allows for on the job search.

[16] Off equilibrium path markets will have a tightness of 0 which can be justified as the limit of a sequential game in which workers tremble as in Menzio and Shi (2011).

[17] Notice that the expectation $\mathbb{E}_{\Omega'}$ is over the aggregate state vector which includes the distribution of people across states (I will omit the subscript from now on)

where the aggregate law of motion for Ω' given by (1.1) is taken as given.

1.3.4 Timing

The timing of the model is outlined below:

(1) Asset Market Opens: (i) Search and Matching in Asset Market, (ii) Default Decision and Asset Accumulation Decision;

(2) Aggregate Risk Resolved, Age Advances;

(3) Labor Market Opens: (i) Job Destruction, then (ii) Search and Matching in Labor Market.

1.3.5 Equilibrium

Definition of a Recursive Competitive Equilibrium: A recursive competitive equilibrium for this economy is a list of household policy functions for assets,

$$\left\{b'^{*}_{e,a,t}(w,b;\Omega)\right\}_{e=W,U\ \ a=C,N\ \ t\in\mathbb{N}_T}$$

wage search decisions,

$$\left\{\tilde{w}^{*}_{a,t}(w,b;\Omega)\right\}_{a=C,N\ \ t\in\mathbb{N}_T}$$

and the fraction of debt to default upon,

$$\left\{D^{*,a}_{e,t}(w,b;\Omega)\right\}_{e=W,U\ \ a=C,N\ \ t\in\mathbb{N}_T}$$

a bond price,

$$\left\{q_{e,t}(w,b;\Omega)\right\}_{e=W,U\ \ t\in\mathbb{N}_T}$$

a labor market tightness function,

$$\left\{\theta^{L}_{t}(w;\Omega)\right\}_{t\in\mathbb{N}_T}$$

a credit market tightness function,

$$\left\{\theta^C_{e,t}(w,b;\Omega)\right\}_{e=W,U\ \ t\in\mathbb{N}_T}$$

distributions for the aggregate shocks (F and G), and an aggregate law of motion

$$\Omega' = (\Phi(\Omega, A', y'), A', y')$$

such that:

i. Given the prices, shock processes, and the aggregate law of motion, the household's policy functions solve their respective dynamic programming problems.

ii. The labor market tightness is consistent with free entry equation (1.4).

iii. The credit market tightness is consistent with free entry equation (1.3) .

iv. Debt is priced consistent with households making take-it-or-leave-it proposals according to equation (1.2).

v. The law of motion of the aggregate state is consistent with household policy functions.

In order to solve the problem numerically, I will focus on a subset of competitive equilibria called *Block Recursive Equilibria* (see Menzio and Shi (2009), Menzio and Shi (2010), and Menzio et al. (2012) for more). A block recursive competitive equilibrium is a recursive competitive equilibrium in which the resulting decision rules and prices do not depend on the aggregate distribution of agents across states (i.e μ is not a state variable for the household, lending institutions, saving institutions, or firms). Under relatively innocuous assumptions, a Block Recursive equilibrium exists.

1.3.6 Theoretical Characterization

I will first start with characterizing the optimal default rule and bond price, two ingredients that are essential to understand the model's insurance mechanisms.

Lemma 1.3.1 *Under Inada conditions outlined in assumption A.ii (see Appendix 1.10.1.1), for initial debt levels such that* $b \in \mathcal{B}$ *and* $b < 0$, *(1) the optimal choice of* D *is continuously differentiable over the set* $[\underline{b}, \epsilon]$ *for arbitrarily small* $\epsilon < 0$, *(2) the fraction of debt defaulted upon is monotone increasing in the initial debt position* $\mid b \mid$, $b < 0$ *and (3) the fraction of debt defaulted upon is monotone decreasing in subsequent resources borrowed* $\mid q_{e,t}(w, b'; \Omega)b' \mid$, $b' < 0$ *across all ages.*

The well-behaved intratemporal utility penalty of default is the key ingredient to obtain differentiability of the bond price. Why is the first claim of Lemma 2.5.1 important? If τ were set to zero, the bond price would be differentiable everywhere, and the model could be linearized and then potentially estimated. The second claim of Lemma 2.5.1 says that if $b < 0$ and households begin the period with greater indebtedness (i.e. b is slightly more negative) they will default on a larger fraction of that debt position. The third claim says that the fraction of debt defaulted upon is weakly increasing in the *subsequent* amount of resources borrowed. Thus, if the household has access to more credit *in the present period*, then the household will repay more of its prior debts that are due in the present period. Each of these results are intuitive and will be crucial to understanding the way bond prices reflect credit conditions as explained below.

As described in Corollary 1.3.2, since the bond price is an affine function of the household's default policy function, it inherits many properties.

Corollary 1.3.2 *Under the Inada conditions outlined in assumption A.ii (see Appendix 1.10.1.1), for initial debt levels such that* $b \in \mathcal{B}$ *and* $b < 0$, *(1) the equilibrium bond price is continuously differentiable over the interval* $[\underline{b}, \epsilon]$, $\epsilon < 0$, *(2) the equilibrium bond price is monotone decreasing in resources lent and (3) the equilibrium bond price is monotone increasing in subsequent resources borrowed across all ages.*

Corollary 1.3.2 is important for understanding the model's intertemporal mechanics. The cost of funds today is impacted by access to funds tomorrow. Namely, if aggregate credit conditions are expected to be tight tomorrow, resources today will be lent at a higher premium, further limiting the availability of self-insurance. The opposite holds true in a credit boom where expected easy credit tomorrow results in cheap self-insurance today. This cheap self-insurance is what ultimately changes job search decisions as shown in Corollary 1.3.6.

I follow a similar strategy of Menzio et al. (2012) to prove the existence of a Block Recursive Equilibrium for the T-span economy. The basic strategy is to show that age T terminal prices and value functions are independent of the distribution and then use backward induction to show that the remaining value functions are independent of the distribution. I deviate in some regards to Menzio et al. (2012) since, in my model, the welfare theorems break down and it does not suffice to simply solve the social planner's problem.

Proposition 1.3.3 *Under the boundedness conditions and Inada conditions outlined in assumptions A.i-A.ii (see Appendix 1.10.1.1), a Block Recursive Equilibrium exists for the T-span economy.*

This is a computationally useful proposition since it states that solutions exist in which agents do not need to forecast the law of motion for the aggregate state. Is this without loss of generality? Lemma 1.3.4 shows that for certain functional forms, only one Recursive Competitive Equilibrium exists and it is Block Recursive.

Lemma 1.3.4 *Suppose that $x(0) = 0$ and $x(D) \rightarrow \infty$ $\forall D > 0$, $M(u, v) = \min\{u, v\}$ and $M_C(u_C, v_C) = v_C^{\alpha_C} u_C^{1-\alpha_C}$ with $\alpha_C \rightarrow 0$ (i.e. constant arrival rate of credit offers). Under assumptions A.i-A.ii there exists a unique Competitive Equilibrium that is also Block Recursive.*

To motivate an alternative existence proof for Block Recursivity which does not rely on Schauder's fixed point theorem, I ask the question, does a Block Recursive Equilibrium exist for a version of my economy with infinitely lived agents? Under mild assumptions, the answer is yes. I adapt the 'limit of finite horizon economies' proof strategy popularized by Balasko and Shell (1980), Aiyagari (1988), and Levine (1989) among others to a setting in which I extend the lifespan in a finitely lived economy to infinity.

Proposition 1.3.5 *Under assumptions A.i-A.ii (see Appendix 1.10.1.1) and B.i-B.iii (see Appendix 1.10.1.3), there exists an equilibrium sequence of prices for an infinitely lived agent* *economy where the equilibrium sequence of prices is independent of the distribution across states.*

Proposition 1.3.5 is useful if one wants to drop the dimensionality of the problem and drop $t \in \mathbb{N}_T$ as a state variable. The only potential drawback is that the limiting set may potentially include non-stationary equilibria. In practice however, it is simple to check numerically that the limiting set contains at least one recursive equilibrium.

Ultimately, the assumptions of Lemma 1.3.4 allow one to characterize the mechanism at the heart of the model – when credit access increases agents optimally search for better-paying but scarcer jobs. [18]

Corollary 1.3.6 *Under the assumptions of Lemma 1.3.4, the wage policy function of the household is increasing in credit access.*

The intuition behind Corollary 1.3.6 is that credit access acts as a safety net allowing the unemployed to search for better-paying but harder-to-find jobs, knowing that if the job search fails they can obtain credit to smooth consumption. This lowers the aggregate job finding rate, *ceteris paribus*. In the long run, however, households ultimately save less which tends to raise the aggregate job finding rate. The experiments designed below measure these competing effects over the business cycle (see Section 1.6.2).

1.3.7 Computational Extension: Long Lived Credit Relationships with Semi-Endogenous Default Punishments

In this section, I allow households to match with lenders for more than one period in order to make better contact with data. While the problem of the firm remains unchanged, both the household and lender problems undergo several modifications.

With long term lending relationships, lenders are forward looking and therefore understand that households who will not necessarily borrow today may borrow in the future.

[18] Computationally, Corollary 1.3.6 holds for every set of functional forms and parameters tested by the author.

Therefore *all* households receive credit offers and enter into matches which will persist even though the household does not immediately borrow.

It also becomes possible to punish households not only using a direct utility penalty function but also by excluding the household from borrowing in the period of default and destroying their existing match. The time it takes for the household to then regain credit access is an endogenous outcome.

1.3.7.1 Long Lived Credit Relationships: Households

Matches with lenders occur exactly as before, except once a household matches with a lender, the household remains matched to the lender until the household defaults or the match is destroyed exogenously (the exogenous breakup rate is given by $\bar{s}$). Let $s(D)$ describe the credit relationship breakup probability which is assumed to be contingent on the default choice D:

$$s(D) = \begin{cases} 1 & \text{if } D > \underline{D} \\ \bar{s} & \text{if } D = \underline{D} \end{cases}$$

In this scenario, credit access $a \in \{C, N\}$ is a persistent state. The problem now solved by an unemployed agent (U) with credit access (C) is given by,

$$\begin{aligned} U_t^C(z, b; \Omega) = \max_{b' \in \mathcal{B}, D \in [0,1]} & \; u(c) - x(D) + \eta \\ & + (1 - s(D)) \cdot \beta \mathbb{E}\Big[\max_{\tilde{w} \in \mathcal{W}} \; p(\theta_{t+1}^L(\tilde{w}; \Omega')) W_{t+1}^C(\tilde{w}, b'; \Omega') \\ & + \Big(1 - p\big(\theta_{t+1}^L(\tilde{w}; \Omega')\big)\Big) U_{t+1}^C(z, b'; \Omega') \Big] \\ & \underbrace{+ \qquad s(D)}_{Lose\ Credit} \cdot \beta \mathbb{E}\Big[\max_{\tilde{w} \in \mathcal{W}} \; p(\theta_{t+1}^L(\tilde{w}; \Omega')) W_{t+1}(\tilde{w}, b'; \Omega') \\ & + \Big(1 - p\big(\theta_{t+1}^L(\tilde{w}; \Omega')\big)\Big) U_{t+1}(z, b'; \Omega') \Big] \quad \forall t \leq T \end{aligned}$$

$$U_{T+1}^C(z, b; \Omega) = 0$$

such that the law of motion for aggregates (1.1) is taken as given and the budget constraint is satisfied,

$$c + q_{U,t}(z, b', D; \Omega)b' \leq z + (1 - D)b.$$

Notice that the bond price $q_{U,t}(z, b', D; \Omega)$ now depends on the default decision. I assume that if the household defaults, no loanable funds will be made available to the household. This type of 'universal default rule' is discussed in more in Appendix 1.10.2.

Universal Default Assumption: Default results in the immediate severance of all lending relationships.

In the case of a default, the household is excluded for an endogenous number of periods. The household's state vector pins down the subsequent credit-finding rate and ultimately determines when access is regranted; when lenders determine whether to lend to households, they take into account future default risk. This endogenous reaccess time is what I call a 'semi-endogenous' default punishment.

The only other household value function that changes is for an employed (W) household with credit access (C):

$$\begin{aligned}
W_t^C(w, b; \Omega) &= \max_{b' \in \mathcal{B}, D \in [0,1]} u(c) - x(D) \\
&+ (1 - s(D)) \cdot \beta \mathbb{E}\Big[(1 - \delta_{t+1}(w; y'))W_{t+1}^C(w, b'; \Omega') \\
&+ \delta_{t+1}(w; y')\Big\{ \max_{\tilde{w} \in \mathcal{W}} p(\theta_{t+1}^L(\tilde{w}; \Omega'))W_{t+1}^C(\tilde{w}, b'; \Omega') \\
&+ \Big(1 - p\big(\theta_{t+1}^L(\tilde{w}; \Omega')\big)\Big)U_{t+1}^C(\gamma w, b'; \Omega')\Big\}\Big] \\
&\underbrace{+ \quad s(D)}_{\text{Lose Credit}} \cdot \beta \mathbb{E}\Big[(1 - \delta_{t+1}(w; y'))W_{t+1}(w, b'; \Omega') \\
&+ \delta_{t+1}(w; y')\Big\{ \max_{\tilde{w} \in \mathcal{W}} p(\theta_{t+1}^L(\tilde{w}; \Omega'))W_{t+1}(\tilde{w}, b'; \Omega') \\
&+ \Big(1 - p\big(\theta_{t+1}^L(\tilde{w}; \Omega')\big)\Big)U_{t+1}(\gamma w, b'; \Omega')\Big\}\Big]
\end{aligned}$$

such that the law of motion for aggregates (1.1) is taken as given and the budget constraint is satisfied,

$$c + q_{W,t}(w, b', D; \Omega)b' \leq w + (1 - D)b.$$

1.3.7.2 Long Lived Credit Relationships: Lending Institutions

When there are long lived credit relationships, the lender's problem is no longer static and must be solved via dynamic programming. The resulting bond price and lender profit function are included in Appendix 1.10.2.

1.4 2010 Stochastic Steady State Calibration

I will first consider a stochastic steady state to illustrate the model's mechanism. Then I argue that in order to understand the 1974-2012 time period, one must consider an environment in which credit is *continually and persistently* expanding as opposed to a steady state experiment.

Stochastic steady state means that aggregate labor productivity still fluctuates but that aggregate credit matching efficiency is constant forever. The period is set to one quarter. I calibrate the aggregate labor productivity process to match the Bureau of Labor Statistic's output per worker in the non-farm business sector. The series is logged and band pass filtered to obtain deviations from trend with periods between 6 and 32 quarters. Aggregate productivity deviations are assumed to fluctuate over time according to an AR(1) process:

$$\ln(y') = \rho \ln(y) + \epsilon_1 \quad \text{s.t.} \quad \epsilon_1 \sim N(0, \sigma_e^2)$$

Estimation yields $\rho = 0.8961$ and $\sigma_e = 0.0055$, and the process is discretized using Rouwenhurst's method.

The benefit replacement rate is set to 50% ($\gamma = .5$) which is in line with OECD estimates of the replacement rate for the United States. For this numeric exercise, I set the job destruction rate to a constant 10% per quarter as in Shimer (2005a), and so $\delta_{t+1}(w; y') = .1$

across all states. The labor vacancy posting cost κ_L is chosen to target a mean unemployment rate of 5.6% which is the average postwar BLS unemployment rate. For the labor market matching function, I follow Haan et al. (1997) and use a constant returns to scale matching function that yields well-defined job finding probabilities:

$$M(u,v) = \frac{u \cdot v}{(u^{\zeta} + v^{\zeta})^{1/\zeta}} \in \left[0,1\right)$$

The matching elasticity parameter is chosen to be $\zeta = 1.6$ as in Schaal (2012).

The aggregate credit matching efficiency A_{2010} is chosen to match the fraction of unemployed households with positive balances in the 2010 SCF. The household discount factor is set to $\beta = .98$, and the risk free rate is set to 4% as in Livshits et al. (2007). The model closely replicates the left tail of the liquid wealth distribution for the employed and unemployed (see Table 1.6). I use aggregate data on credit card offers in combination with Survey of Consumer Finance application rates and denial rates to estimate a credit matching elasticity parameter of $\zeta_C = .37$ assuming the matching function is also the same as Haan et al. (1997):[19]

$$M_C(u_c,v_c) = \frac{u_c \cdot v_c}{(u_c^{\zeta_C} + v_c^{\zeta_C})^{1/\zeta_C}} \in \left[0,1\right)$$

The proportional minimum servicing fee is set to τ =8% based on the spread between the risk free rate in the model and the average real credit card interest rate from 1974-2011 which was 12.02%.[20]

Using Equifax data, the exogenous credit separation rate $\bar{s}$ is chosen in order to match the probability of obtaining a new credit line among credit inquirers. The model equivalent of credit inquirers are those agents with non-zero credit-finding rates. This yields $\bar{s} = .25$ which yields an average credit relationship duration of roughly 1 year. Following an analogous strategy to Shimer (2005a), I normalize the credit entry costs $\kappa_C = 1.75e^{-6}$ such that the implied average credit market tightness lies in the interval [127.1, 206.1].[21]

[19]See Appendix 1.10.6 for more details. I use non-linear least squares to estimate the elasticity parameter.

[20]This is an upper bound on the over-head costs since this includes a default risk component. The results are unchanged for lower values of τ. Interest rate data come from the Board of Govenors and inflation data come from the BLS.

[21]The credit market tightness measure is available from 1995 to 2007 and is constructed as the ratio of

Preferences are given below (let h=1 for employed persons and h=0 otherwise):

$$u(c) + \eta(1-h) - x(D) \equiv \frac{c^{1-\sigma} - 1}{1-\sigma} + \eta(1-h) - \kappa_D \cdot \frac{D}{1 - D + \epsilon}$$

I set the risk aversion parameter to a standard value, $\sigma = 2$. The functional form of $x(D)$ is one of many that satisfies the necessary inada conditions (assumption A.ii).[22] I set κ_D to match the average fraction of balances involved in a default episode (see Table 1.5 below).[23] To guarantee boundedness of returns, I take ϵ to be an arbitrarily small finite number. In terms of the flow utility of leisure, I follow most of the quantitative search and matching literature by setting η to target a labor market moment. I choose η to match the autocorrelation of unemployment since the flow utility of leisure determines unemployed households' willingness to remain out of work. The life span is set to $T = 120$ quarters (30 years), and newly born agents are born unemployed, with zero assets, and the highest possible unemployment benefits.

Table 1.4 summarizes the model's calibrated parameters. Table 1.5 summarizes the model's fit relative to the targeted moments. And Table 1.6 summarizes the liquid wealth distribution in both the model and the data.

1.5 Stochastic Steady State Comparison, 1977 vs. 2010

I begin the analysis by considering the stochastic steady state of two economies with different levels of credit access. Holding all other parameters fixed, I calibrate the 1977 steady state by setting A_{1977} to match the fraction of unemployed households with positive balances in 1977.

Table 2.1 illustrates the stochastic steady state results. The model predicts that the unemployment rate is .34 percentage points higher in the economy with credit access. The mechanism driving this difference is that credit acts as a safety net allowing households to

credit card mail volume (Synovate) to credit card applicants (SCF).

[22] I have found that the functional form is unimportant for the main quantitative results.

[23] In the past, utility penalties have been calibrated to levels of asset exemption across states as in Araujo and Funchal (2006).

Table 1.4: Summary of Parameters, 2010 Stochastic Steady State Calibration

Parameter	Value	Description
Pre-Calibrated:		
β	0.98	Quarterly Discount Factor (Implied Annual Rate 8%)
r_f	0.04	Annualized Risk Free Rate
τ	0.08	Annualized Proportional Servicing Fee
δ	0.1	Quarterly Job Destruction Rate
ρ	0.8961	Auto Correlation of Labor Productivity
σ_ϵ	0.0055	Standard Deviation of Labor Productivity
γ	0.5	Benefit Replacement Rate
ζ	1.6	Labor Match Elasticity
ζ_C	0.37	Credit Match Elasticity
κ_C	$1.75e^{-6}$	Credit Vacancy Cost
σ	2	Risk Aversion
T	120	Lifespan in Quarters
Calibrated:		
κ_L	0.02	Labor Vacancy Posting Cost
η	0.58	Flow Utility of Leisure
A_{2010}	0.374	Credit Matching Efficiency
$\bar{s}$	0.25	Exogenous Separation Rate
κ_D	2.3	Disutility of Default

Table 1.5: Simulated Moments, 2010 Stochastic Steady State Calibration

Parameter	Target	Model	Data	Source
κ_L	Unemployment Rate	5.59%	5.60%	BLS (1948-2007)
η	Autocorrelation of Unemployment	0.953	0.94	Shimer (2005)
A_{2010}	Fraction of Unemployed Borrowing	0.332	0.331	SCF (2010)
$\bar{s}$	Approval Rate	23%	25%	Equifax (1999-2011)
κ_D	Default Fraction	24%	27%	Equifax (1999-2011)

Table 1.6: 2010 Stochastic Steady State Wealth Distribution

Ratio of Liquid Wealth to Annual Income				
	All Households		**Unemployed Households**	
	Model	Data	Model	Data
p10	0.01	-0.06	-0.10	-0.08
p25	0.04	0.00	-0.05	0.00
p50	0.06	0.03	0.00	0.00
p75	0.10	0.21	0.10	0.04
p90	0.18	1.41	0.20	0.29
Mean	0.08	0.51	0.03	0.23

search for better-paying and harder-to-find jobs. The increased availability of credit lowers the job finding rate by 1 percentage point and doubles the fraction of households with liquid assets to annual gross income less than 1%. In the data, the fraction of households with liquid assets to annual gross income less than 1% went from 18% in 1977 to 38% in 2010. To check the mechanism is providing a degree of insurance consistent with the data, I report the quarterly debt to income ratios of unemployed borrowers along with the mean unemployment duration. On average households who do not immediately find a new job upon being laid-off are out of a job for roughly 1.3 quarters. Combining this with the fact that the average debt to income ratio of the unemployed is 36%, it is possible to calculate that unemployed borrowers in the model replace approximately 18% of their lost income in the 2010 steady state ($DTI * \gamma = .36 * .5 = 18\%$) which is in line with what Sullivan (2008) finds.

The annual default rate in the model increases enormously from .004% to .015% between 1977 and 2010. The model's concept of default is quite different from bankruptcy, but the bankruptcy series is the only proxy for consumer default spanning the relevant time period. The bankruptcy rate increased from .1% of the working age population per annum in 1977 to .7% of the working age population per annum in 2010. While the trend is correct, the model's *level* of defaults is quite low compared to the data. The approval rate is also much higher in the 2010 stochastic steady state, but there is no data counterpart available in 1977.

The observed income process is also affected by credit access. Table 1.8 shows the model's annual log income processes, estimated as an AR(1), versus the data. The model's income process in both steady states is more persistent than the data due to the fixed wage contracts, but there are occasionally large income swings when agents lose their jobs. The volatility of the income process is actually greater in the economy with increased credit access since agents take larger risks in the labor market (looking for harder-to-find, better-paying jobs) and the income distribution fans out. But, as I will discuss in Section 1.8.3, consumption volatility is lower in the economy with greater credit access.

To calculate the welfare gains in the model, I follow Lucas (1987) and consider the fraction of ex-ante lifetime consumption a newly born agent living in an economy with 1977 levels of credit access would give up in order to be a newly born in the economy with 2010 levels of credit access. The results show that it is welfare improving to have more credit even though the unemployment rate increases. Table 2.3 shows that a newly born agent in the 1977 steady state would sacrifice .12% of expected lifetime consumption in order to be a newly born agent in the 2010 steady state.

Table 1.7: Stochastic Steady State Comparison

	2010	**1977**	**Ratio (2010/1977)**
Fraction of Unemployed Borrowing (Target)	0.33	0.12	2.78
Unemployment Rate	5.59%	5.25%	1.07
LQTI< 1%	8.92%	4.78%	1.87
Job Finding Rate	0.65	0.66	0.98
Average Credit Approval Rate	0.23	0.05	4.45
Annualized Default Rate (Post)	0.015%	0.004%	3.88
DTI Unemployed Borrowers	0.36	0.32	1.12
Mean Unemployment Duration in Years	0.388	0.379	1.024

Table 1.8: Income Process, Log Annual Income

Income Process		
	Data	
	Auto Corr.	Std. Dev
Storesletten et al. (2004)	0.95	0.12
	Model	
	Auto Corr.	Std. Dev
2010 Stochastic Steady State	0.997	0.106
1977 Stochastic Steady State	0.997	0.102

Table 1.9: Stochastic Steady State Welfare Analysis

	2010	**1977**	**Ratio (2010/1970)**
Ex-Ante Expected Utility of Newly Born	-0.40	-0.45	0.90
Fraction of Lifetime Consumption Willing to Forego to Move from 1977 to 2010 SS	0.12%		

1.6 Understanding How Credit Access Changes Business Cycles: Impulse Response Experiments

To answer the question of how credit access has changed the way employment responds to downturns, the simplest experiment is to compare business cycle recoveries across the 2010 stochastic steady state and 1977 stochastic steady state. Such a steady state experiment yields inconclusive differences in the business cycle behavior of employment. I first explain why that is the case in a series of experiments, and then I argue that in order to understand the 1974-2012 time period, one must consider an environment in which credit is *continually and persistently* expanding as opposed to a steady state experiment.

In general, greater credit access has two effects. The first of which is a pure *self-insurance effect*. Holding the wealth distribution constant, greater credit access allows households to be more selective with the jobs they take. The second effect is a *wealth distribution effect*. In the long run with greater credit access, households save less and borrow more. Such a leftward shift in the wealth distribution increases the job finding rate; a household with a previous debt position or little savings will find a job much faster than a similar household with a larger savings buffer. The experiments I run in this section are designed to illustrate these two forces and how they operate over the business cycle. The experiments have the following setup:

i. Consider 2 economies in good times with productivity 1.5% above trend.

ii. Both economies endure the same temporary productivity drop (productivity is 1.5% below trend for 3 quarters).

iii. One economy has a credit expansion while the other does not. I model a credit expansion as a change in the credit matching efficiency from A_{1977} to $\widehat{A}$ where I will consider several different values of $\widehat{A}$ (a more disciplined data exercise will follow in Section 1.7).

iv. I assess two timing assumptions:

   A. The credit expansion occurs immediately *after* the recession

B. The credit expansion occurs 5 years *before* the recession (and so the economies are approximately in their respective steady states when the recession occurs)

I assume that all agents have the same beliefs about transitions over $[A_{1977}, \hat{A}]$ given by

$$P_A = \begin{bmatrix} 0.975 & 0.025 \\ 0 & 1 \end{bmatrix}$$

1.6.1 Credit Expands After Recession: Self-Insurance Effect

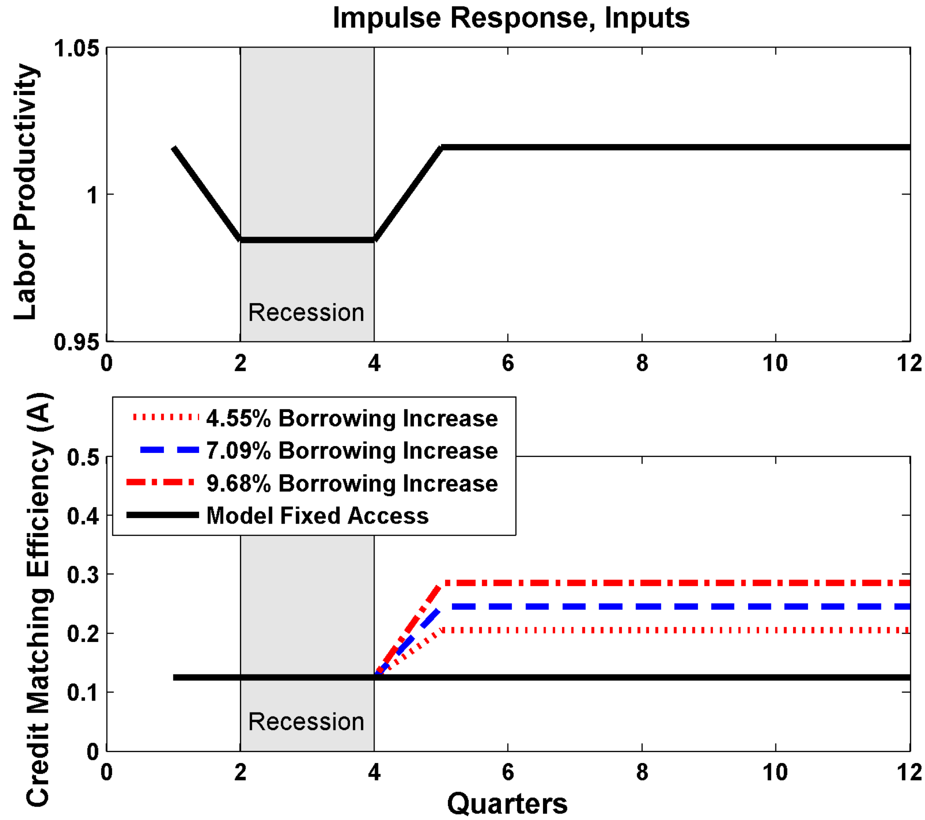
To isolate the *self-insurance effect*, consider first the case in which credit expands immediately following a recession.[24] Figure 1.5 illustrates the productivity decline and the various values of $\widehat{A}$ fed into the model (to give these credit expansions context, I have enclosed in parentheses the increase in the fraction of unemployed households borrowing before the recession compared to 2 years after the recession). The blue heavy-dashed middle line corresponding to a 7.09% increase in borrowing is closest to the data in terms of actual observed credit expansions (a more disciplined data exercise will follow in Section 1.7). Figure 1.6 shows that the unemployment rate is greater in the economy with the credit expansion and takes significantly longer to reach pre-recession levels compared to the world in which credit access is fixed at A_{1977}. Figure 1.7 shows that the job finding rate falls significantly during the recession and takes longer to recover to pre-recession levels in the economy with increased credit access; the slowdown in job finding is driven by a rise in reservation wages as illustrated in Figure 1.8.[25] While this experiment shuts down immediate shifts in the wealth distribution, in the long run *all* households eventually lower their liquid asset positions as shown in Figure 1.9.

In Figure 1.10, the blue heavy-dashed line plots the difference in unemployment rates between the economy with a credit expansion (the 7.09% increase in borrowing) versus the economy with fixed credit over a longer period of time. Figure 1.10 shows that the peak difference in unemployment rates between the economies reaches nearly $\frac{1}{2}\%$ three quarters

[24] This experiment is particularly relevant for the transition results in Section 1.7.

[25] The reservation wage is defined in this context as the wage-submarket in which the households searches

Figure 1.5: Credit Expansion After Recession: Inputs

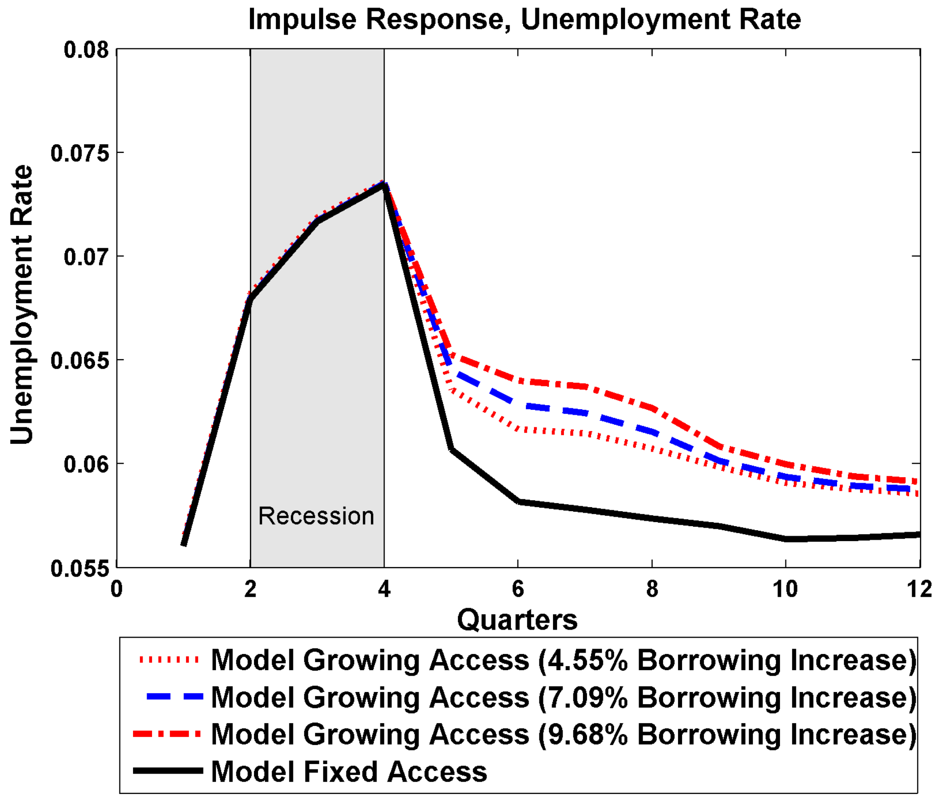


after the expansion. In the long run the difference in the unemployment rates actually becomes negative indicating a higher unemployment rate in the economy with fixed access–ultimately households save less and the *wealth distribution effect* wins when the economy suffers no further productivity shocks.

1.6.1.1 The Interaction Between Labor Productivity and Credit Matching Efficiency

To understand how the productivity shock interacts with the increase in credit matching efficiency, the line with circular markers in Figure 1.10 corresponds to the difference in unemployment rates between the economy with growing credit access and the economy with fixed access when the only shock allowed is the credit matching efficiency increase (i.e. productivity is set to 1.5% above trend forever and the size of the credit shock $\widehat{A}$ is the same

Figure 1.6: Credit Expansion After Recession: Unemployment Rate



as that of the heavy-dashed blue line with a 7.09% borrowing increase). The large mass of unemployed households at the end of the recession uses the new credit to look for higher paying jobs; in a world with no credit expansion, there are simply fewer households that use credit. This interaction between the productivity shock and credit matching efficiency shock results in an additional increase in the unemployment rate of .2%.

Figure 1.7: Credit Expansion After Recession: Job Finding Rate

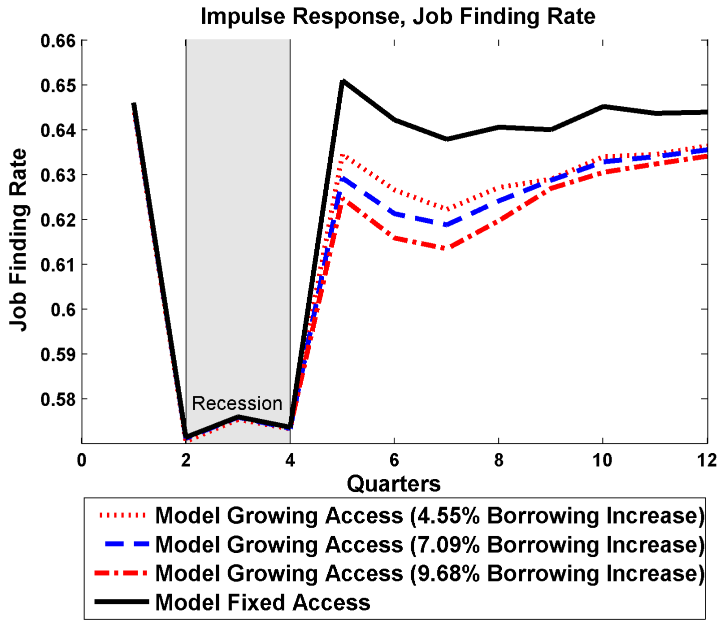


Figure 1.8: Credit Expansion After Recession: Reservation Wages

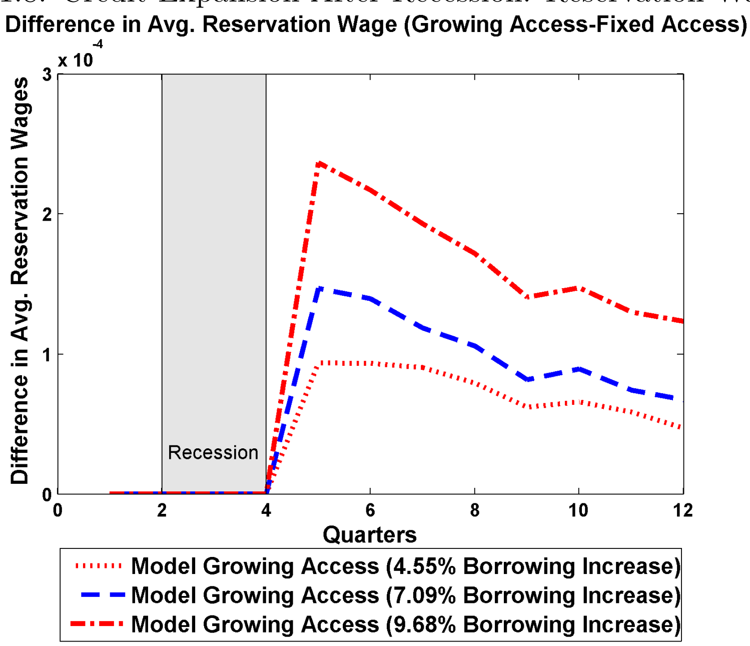


Figure 1.9: Credit Expansion After Recession: Fraction of the Population with a Liquid Asset to Annual Gross Income Ratio < 1% (LQTI < 1%)

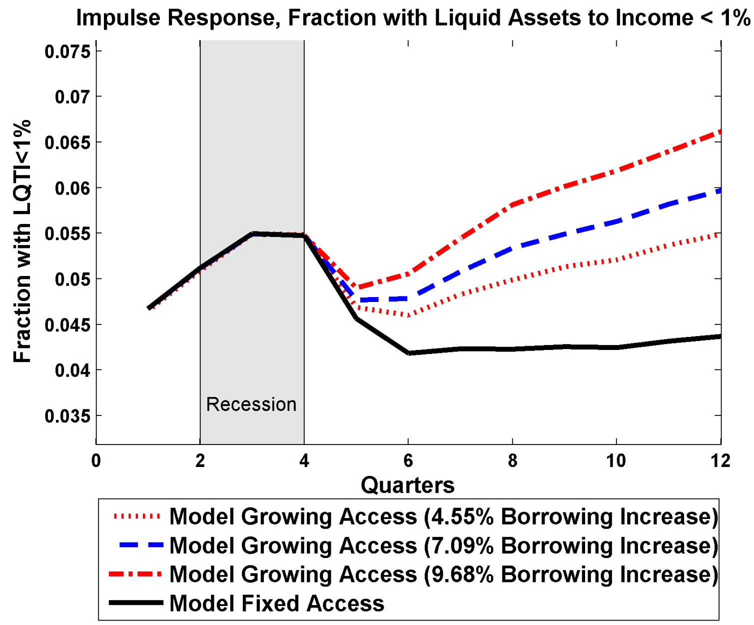
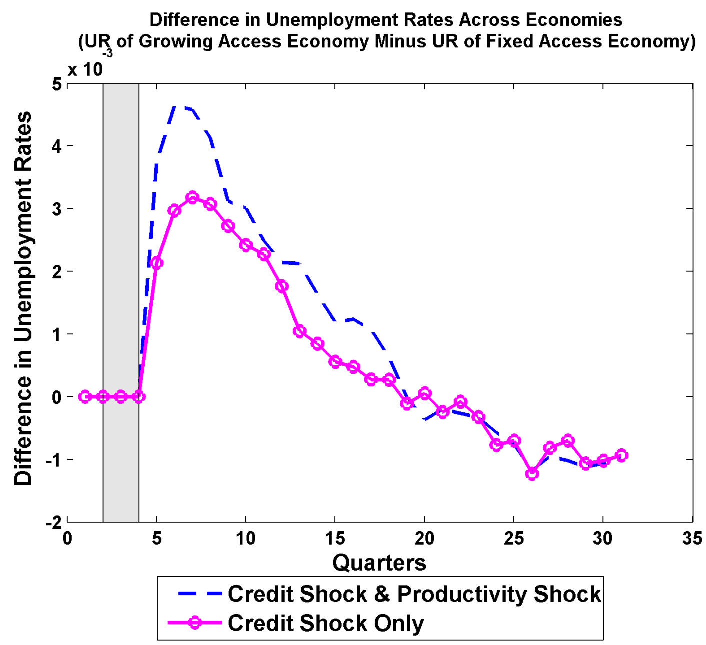


Figure 1.10: Difference in Unemployment Rates (UR with Expansion Minus UR with Fixed Access)



1.6.2 Credit Expands Before Recession: Wealth Distribution Effect

Figure 1.11 shows the inputs for the experiment in which credit expands 5 years before the recession (all of the shocks are the same size as in Section 1.6.1, and the borrowing increase is still measured 2 years after the *initial* shock). The two economies are close to their respective steady states when the business cycle occurs. Figure 1.12 shows that it is difficult to determine which economy has a stronger recovery since the percentage change in employment is quite similar across these economies (this is also reflected in the job finding rates of Figure 1.13). Employment in the economy in which credit expands remains everywhere below employment in the economy with fixed credit access; however, in first-differences the change in employment as productivity recovers is larger in the economy with the credit expansion.

What matters most for understanding why these two economies respond to business cycles so similarly is that the wealth distribution shifts prior to the business cycle (see Figure 1.14). By the time of the recession, households have reduced their liquid asset holdings in the economy for which credit access expands (this is the *wealth-distribution effect*). Thus, even though there is greater credit access, total liquid resources available for self-insurance (unused credit plus liquid assets) actually returns to pre-credit expansion levels. More formally, to measure total liquid resources available for self-insurance, the dashed line with circular markers in Figure 1.15 plots aggregate liquid assets plus aggregate unused credit per capita for the economy with an 8.47% borrowing increase (this image is zoomed-out to show the entire sample period).[26] This figure shows that by the time of the recession, the economy with the credit expansion actually has slightly *less* total liquid resources available to households. This reversal is due to the fact that some households were actually constrained prior to the credit expansion. It is precisely because these two economies enter the recession with similar degrees of total liquid resources available for self-insurance that the employment dynamics across these two economies closely track each other.

[26] Let $b_{-,avg}$ be the average amount of debt among borrowers. Unused credit among non-borrowers with state space $\mathbf{x}$ is calculated as $\psi(\theta_c(\mathbf{x}))\cdot \mid b_{-,avg} \mid$. Unused credit among borrowers is calculated as $\mid \min\{b_{-,avg} - b, 0\} \mid$.

Prima facie, the two business cycles are quite similar. However, two additional forces operate during the recession, the strength of which depends on the composition of borrowers and savers in an economy: (i) credit approval rates fall for households who enter the credit market with moderately negative net worth (whose default risks increase), and (ii) credit approval rates *increase* for relatively high net worth households (who are now more likely to be out of a job for multiple periods and thus start borrowing). This asymmetric change in the safety net is shown through the credit approval rates across asset positions in Table 1.10. The subgroups with initial negative net worth are forced to find jobs quickly since its less likely they can roll over their debts, while the subgroups with positive net worth are able to obtain more borrowing opportunities and thus take longer to find jobs. To show the aggregate impact of these approval rate fluctuations, Figure 1.16 plots the difference in liquid assets plus unused credit across the two economies (i.e. the difference between the circularly marked dashed curve and solid hash marked curve in Figure 1.15). Figure 1.16 shows that total available resources for self-insurance expands relatively more in the economy with the credit expansion during the initial phase of the recession but contracts as households begin to repay the interest on their loans. This temporary expansion, in combination with a differing composition of households across assets, is the main reason why there is any divergence in employment dynamics across the two economies. To better understand why these business cycles are so similar, the following section methodically isolates changes in the composition of borrowers and savers over the business cycle.

1.6.2.1 Isolating the Wealth Effect

This section isolates the wealth distribution effect and its impact on the business cycle. Figure 1.17, which is just the blue heavy-dashed line corresponding to the 8.47% borrowing increase in Figure 1.13, plots the job finding rate when both the wealth distribution and self-insurance effects are allowed to adjust prior to the business cycle as well as during the business cycle. While the two job finding rates start at the same pre-recession level, the job finding rates diverge briefly in the recession only to return to nearly identical levels in the recovery.

To isolate the wealth distribution effect, I freeze the pre-credit expansion wealth distribution and look at only the movements in the job finding rate attributable to the self-insurance effect. I simulate an economy in which credit expands (using the 8.47% borrowing increase) to obtain a vector of job finding rates for households by assets $\{jf_1^A(t), jf_2^A(t), \ldots\}_t$ and a vector describing the fraction of households in each asset interval $\{f_1^A(t), f_2^A(t), \ldots\}_t$ for each date of the simulation t. I repeat the same exercise in the economy with fixed credit access to obtain vectors $\{jf_1^N(t), jf_2^N(t), \ldots\}_t$ and $\{f_1^N(t), f_2^N(t), \ldots\}_t$ such that the superscripted N indicates fixed credit access. The job finding rates in Figure 1.18 are calculated as

$$\overline{jf}(t)^A = \sum_i f_i^A(t) \times jf_i^A(t)$$

in the case when credit expands and

$$\overline{jf}(t)^N = \sum_i f_i^N(t) \times jf_i^N(t)$$

in the case when credit is fixed.

To isolate the wealth distribution effect, I calculate counterfactual job finding rates $\overline{jf}(t)^A_{No\ Wealth}$ and $\overline{jf}(t)^N_{No\ Wealth}$ by holding the wealth distribution constant but letting the asset-specific job finding rates vary over time:

$$\overline{jf}(t)^A_{No\ Wealth} = \sum_i f_i^A(\mathbf{1}) \times jf_i^A(t)$$

$$\overline{jf}(t)^N_{No\ Wealth} = \sum_i f_i^N(\mathbf{1}) \times jf_i^N(t)$$

Figure 1.18 plots $\overline{jf}(t)^A_{No\ Wealth}$ and $\overline{jf}(t)^N_{No\ Wealth}$. There is a difference in job finding rates prior to the recession since the wealth distribution is methodically blocked from adjusting in the preceding 5 years. Without the wealth distribution effect, the self-insurance effect is the only effect present. During a recession the self-insurance effect becomes disproportionately more important for households since unemployment durations increase. Given any initial asset position, the likelihood increases of remaining unemployed long enough that borrowing becomes optimal. As result, the job finding rate of the economy with the credit expansion drops by more in a recession as compared to the economy with fixed access. If the wealth distribution were able to freely move, households in the economy with greater credit access would borrow and then have to repay those loans during the recovery. However, since this mitigating channel is shutdown by fixing the wealth distribution, there is actually a large and persistent difference in job finding rates between the two economies during the recovery. Consequently, without the wealth distribution effect, more credit access would result in unambiguously deeper recessions and slower recoveries.

Table 1.10: Credit Expansion Before Recession: Credit Approval Rates Among Unemployed

Credit Approval Rates Among Unemployed by Assets Carried Into Credit Market Search							
	$b \leq -.2$	$-0.2 < b \leq -0.05$	$-0.05 < b \leq .1$	$.1 < b \leq .25$	$.25 < b \leq .4$	$.4 < b \leq .55$	$.55 < b$
Quarter Prior Recession	19.61%	16.79%	13.59%	13.79%	14.24%	14.87%	16.63%
Average During Recession	19.85%	16.15%	13.84%	14.32%	15.17%	17.43%	17.27%
Quarter After Recession	19.79%	15.59%	13.71%	13.53%	14.12%	14.73%	16.09%

Figure 1.11: Credit Expansion Before Recession: Inputs

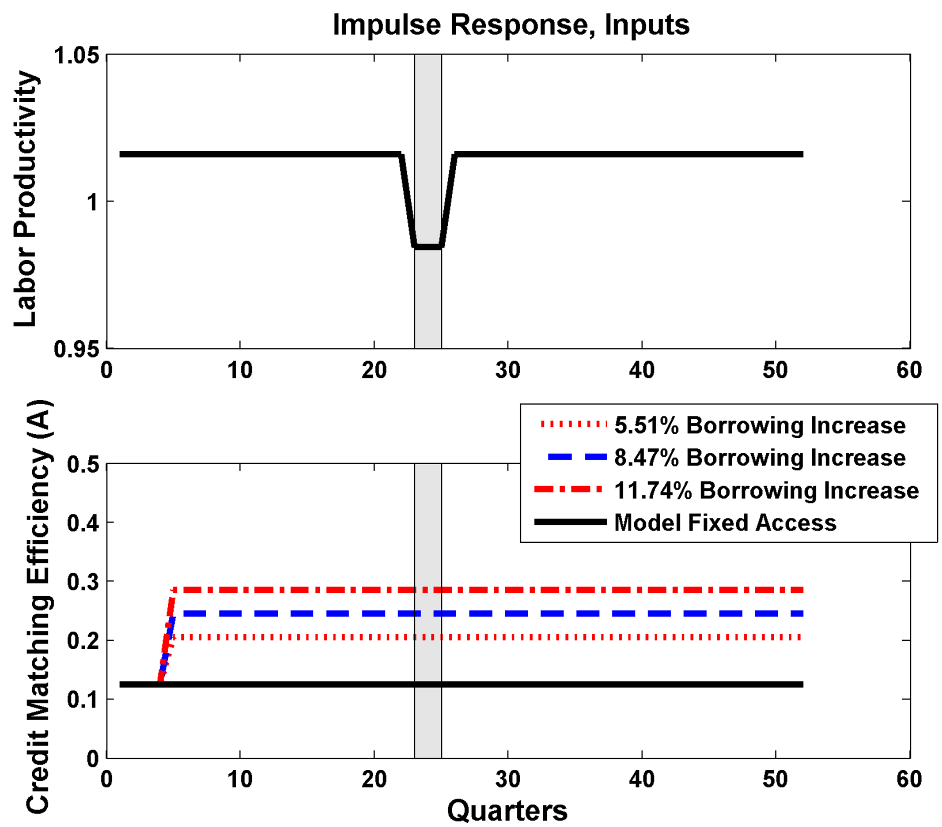


Figure 1.12: Credit Expansion Before Recession: Percentage Change in employment

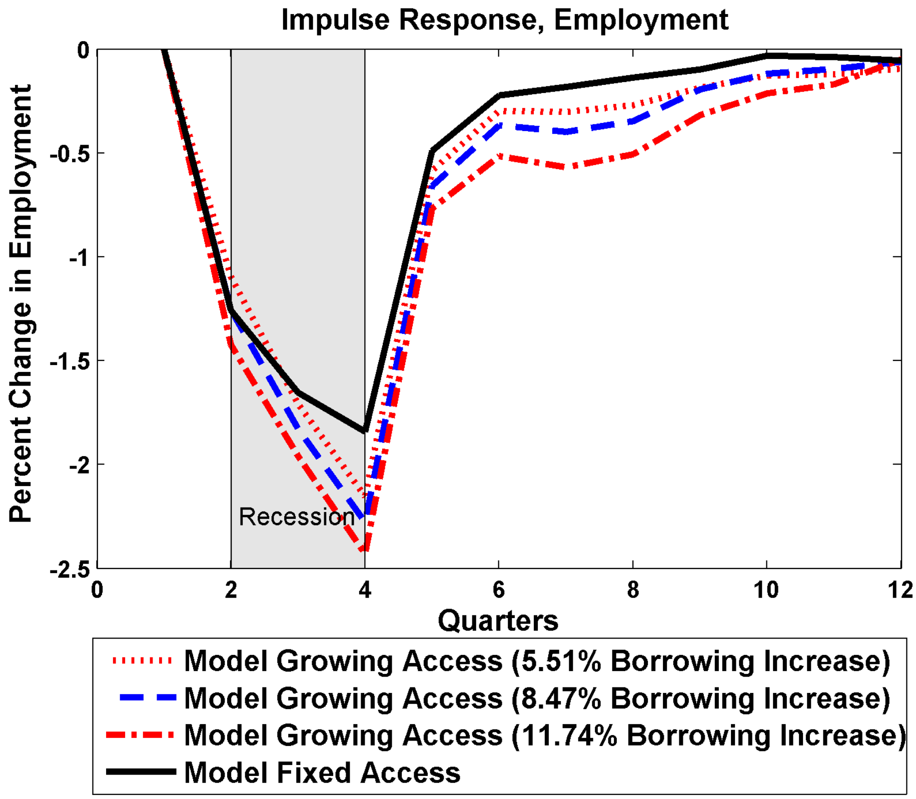


Figure 1.13: Credit Expansion Before Recession: Job Finding Rate

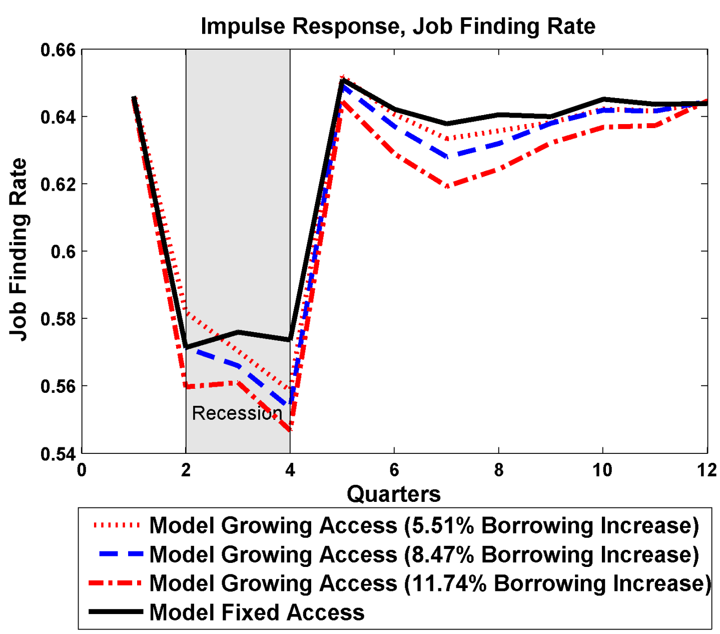


Figure 1.14: Credit Expansion Before Recession: Fraction of Unemployed Households Borrowing

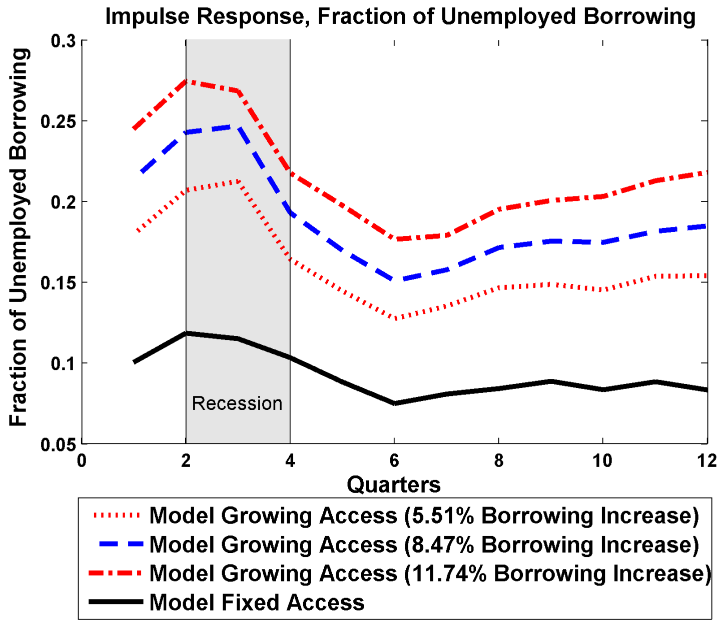


Figure 1.15: Credit Expansion Before Recession: Aggregate Liquid Assets and Unused Credit Per Capita

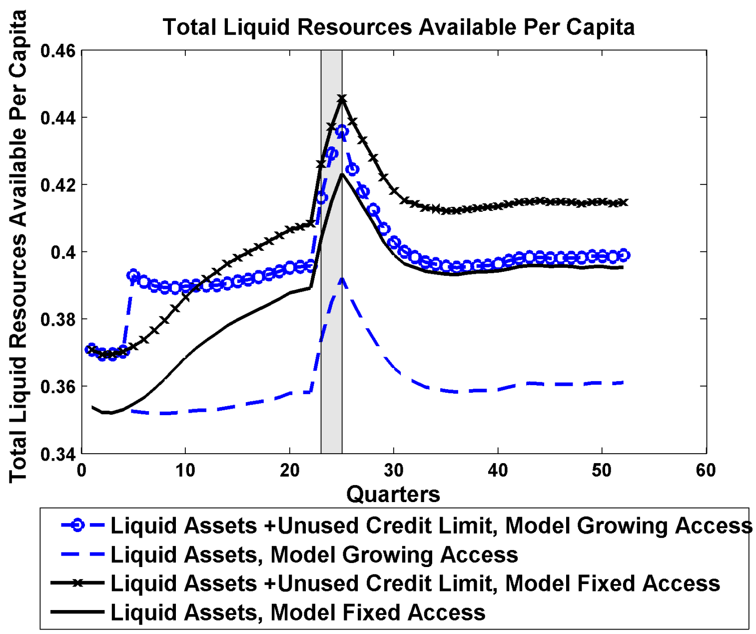


Figure 1.16: Credit Expansion Before Recession: Aggregate Liquid Assets and Unused Credit Per Capita in Fixed Access Economy Minus Growing Access Economy

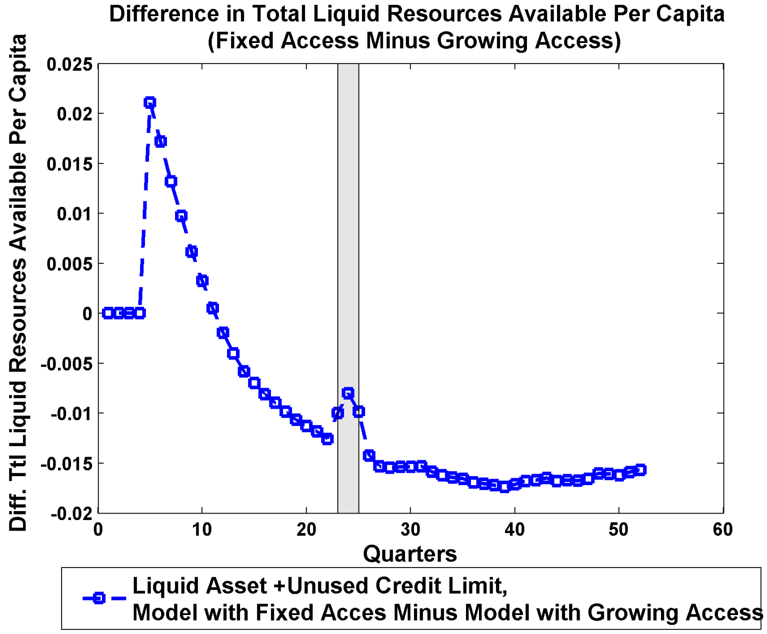


Figure 1.17: Credit Expansion Before Recession: Comparing Job Finding Rates *Allowing Wealth Distribution to Adjust*

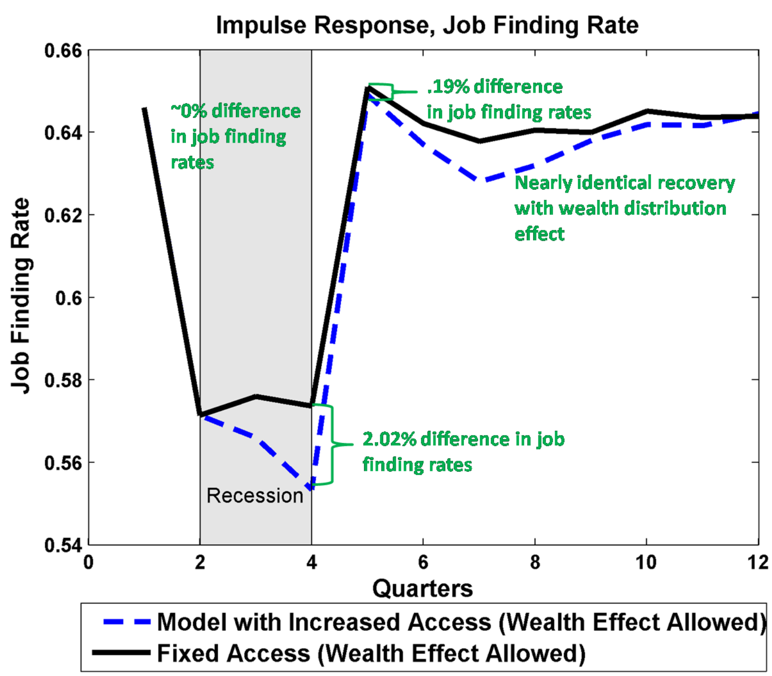
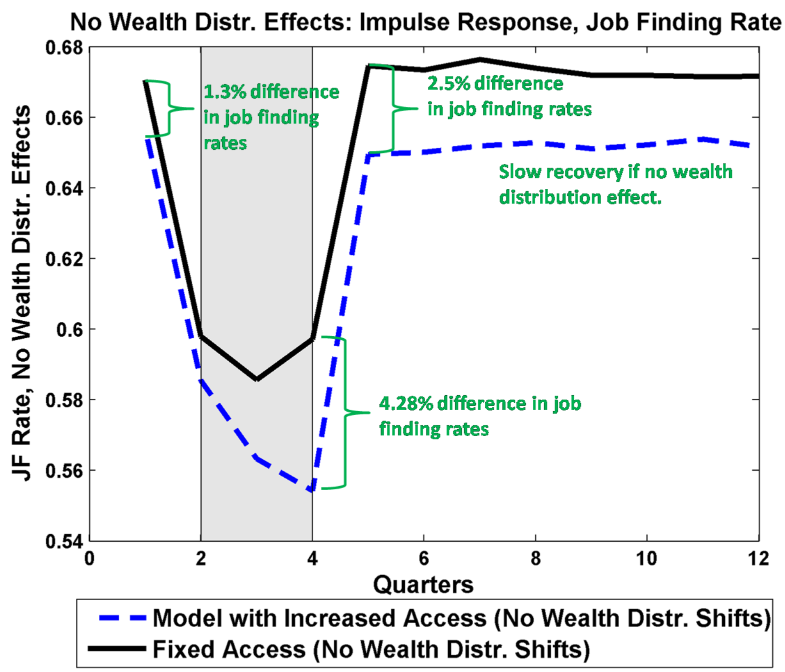


Figure 1.18: Credit Expansion Before Recession: Job Finding Rates Holding Wealth Distribution Fixed



1.7 Transition Experiment

While stochastic steady state analysis is useful to understand the basic mechanisms at work, it is not an accurate portrayal of the 1974-2012 time period which exhibited continual and persistent increases in credit. To better understand the business cycles during this time period, I compare labor market recoveries across two economies, one in which credit *grows* to 2010 levels and the other in which credit remains fixed at 1977 levels. The details are explained below:

i. Two identical economies are simulated for a large number of periods with productivity set to its non-stochastic mean and with aggregate credit matching efficiency set to A_{1977}.

ii. Both economies then receive actual labor productivity residuals from 1974-I to 2012-IV.

iii. **Economy With Growing Access:** Credit matching efficiency grows according to actual SCF data over the sample period, 1974-I to 2012-IV.

iv. **Economy With Fixed Access:** Credit matching efficiency remains fixed at A_{1977} over the sample period, 1974-I to 2012-IV.

1.7.1 Transition Experiment Calibration

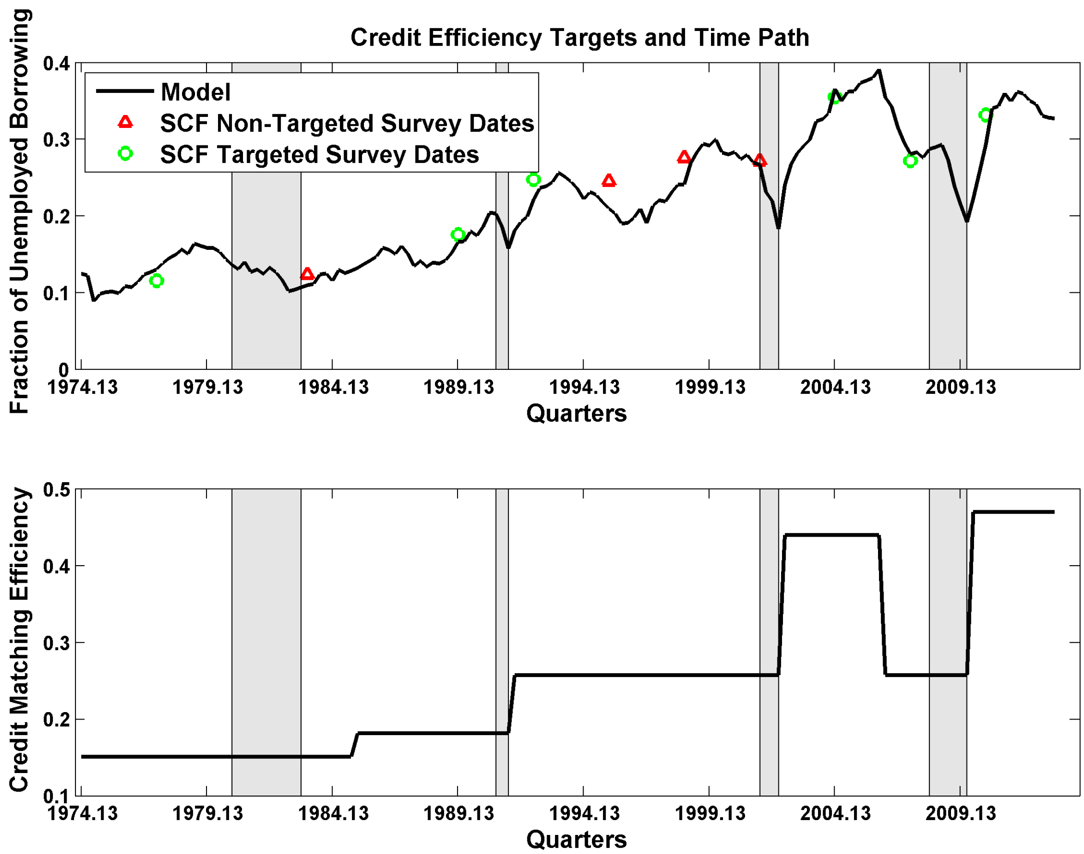
In order to match the SCF data on the fraction of unemployed households borrowing, I assume the aggregate credit matching efficiency process follows a 6-state markov chain taking the possible values A_{1977}, A_{1985}, A_{1991}, A_{2002}, A_{2006}, and A_{2009}.[27] I calibrate each aggregate credit matching efficiency A_j to match the fraction of the unemployed borrowing in the SCF survey date closest to year j. For example, A_{1991} is set to target the fraction of the unemployed who are borrowing in the 1992 SCF survey (the closest available date). The top panel of Figure 1.19 illustrates that the calibrated process matches the data quite well, correctly replicating the fraction of unemployed households borrowing in each targeted SCF year as well as coming close to the non-targeted SCF years.[28] The fraction of unemployed

[27]See the text and Appendix 2.5 for more on timing.

[28]The numeric naming convention is such that 1974.13 corresponds to 1974-Q1

households borrowing in each targeted SCF year as well as the model's corresponding average over the target year are reported in Table 1.11.

Figure 1.19: Transition Experiment: Calibration Targets and Credit Matching Efficiency Time Path



Optimizing behavior endogenously generates a sharp reduction in borrowing during the 1990, 2001, and 2007 recessions as illustrated in the top panel of Figure 1.19. In order to match the observed levels of borrowing by the time of the 1992, 2004, and 2010 SCFs the model requires large credit expansions coming out of each recession as illustrated in the bottom panel of Figure 1.19. In the data, since credit moves pro-cyclically (see Table 1.12), I assume that these expansions occur following each of the 1990, 2001, and 2007 recession. For example, since the model implies a large borrowing contraction during the 1990 recession, at some point between 1991 and 1992 credit matching efficiency must grow in order for the model to replicate the observed fraction of households with access to credit in the 1992 SCF. I assume the expansion occurs immediately after the 1990 recession, and in Appendix 2.5 I explore alternate timing assumptions. The SCF data implies a credit contraction between 2004 and 2007, and so I allow for a contraction in 2006 which is the first year that mortgage originations began to decline.

The transition matrix governing the matching efficiencies, which is known by agents, is rational. For example, the transition probability governing the switch from A_{1991} to A_{2002} is set such that the expected time to transit from A_{1991} to A_{2002} is 11 years. This implies the transition matrix for aggregate credit matching efficiency P_A below:

$$P_A = \begin{bmatrix} 0.9773 & 0.0227 & 0 & 0 & 0 & 0 \\ 0 & 0.9583 & 0.0417 & 0 & 0 & 0 \\ 0 & 0 & 0.9773 & 0.0227 & 0 & 0 \\ 0 & 0 & 0 & 0.9375 & 0.0625 & 0 \\ 0 & 0 & 0 & 0 & 0.9167 & 0.0833 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Table 1.11: Transition Experiment: Fraction of Unemployed Borrowing, Calibration Targets

Fraction of Unemployed Borrowing (Annual Avg.)						
	1977	1989	1992	2001	2007	2010
Model	0.115	0.181	0.244	0.347	0.276	0.334
Data	0.115	0.175	0.247	0.355	0.272	0.331
Credit Matching Efficiency (A)	0.151	0.182	0.258	0.439	0.258	0.470

1.8 Results of the Transition Experiment

After solving for the transition path of the two economies I find that (i) growth in credit access coming out of the 1990, 2001, and 2007 recessions results in moderately slower recoveries as compared to a world with fixed credit access, and the model predicts (ii) a large trend increase

Table 1.12: Cyclical and Trend Correlation of Credit and Productivity

Correlation Between Quarterly Credit Approval Rate and Labor Productivity			
	Productivity(t-1)	Productivity(t)	Productivity(t+1)
Approval Rate Deviation (t)	0.54	0.40	0.18
Approval Rate Trend (t)	0.44	0.31	0.11

Notes: Band Pass Filtered (6,32). Sample period in model and data is 1999-II to 2012-I. Productivity is BLS Output Per Worker. Approval rate is fraction of credit inquirers with new credit line in Equifax.

in defaults from 1974-2012 as well as (iii) a large trend decline in liquid asset holdings. The model also exhibits a decline in the relative standard deviation of consumption to income as well as a trend increase in unemployment durations, both of which are also seen in the data (Mukoyama and Şahin (2009) and Krueger and Perri (2006)).

1.8.1 Cyclical Response of Employment Along Transition Path

While the full transition path is solved from 1974 to 2012, I will focus on several specific episodes along the transition path in the current section.

2001 Recession: Consider zooming in on the transition path to a window around the 2001 recession. Figure 1.20 illustrates what labor productivity and aggregate credit matching efficiency look like around the 2001 recession. As described in Section 1.7, band passed output per worker residuals are fed into the model as measured from the data, and credit matching efficiency growth is fed into the model to generate the same fraction of unemployed households borrowing as observed in the data (see Section 1.7.1 for more details).

Figure 1.21 plots the percentage change in employment across these two economies. The peak difference in employment deviations between the two economies is .63 percentage points and that occurs 7 quarters after the onset of the recession. Figure 1.21 shows that 16 quarters after the onset of the recession, the economy with fixed credit predicts a full recovery to prior peak employment levels; for the economy in which credit expands, employment is still .4 percentage points below the prior peak employment levels after 16 quarters. Figure 1.22 plots the job finding rate for the two economies. The lower job finding rate in the economy with growing credit access is a direct result of increased self-insurance afforded by the credit expansion (see Figure 1.23 which plots the fraction of unemployed agents who borrow). Those with the ability to borrow optimally take longer to find a job which was shown theoretically in Corollary 1.3.6. For those denied access to credit and carrying a large amount of debt into the present period, default provides the same type of safety net (see Section 1.8.5 for more on the insurance role of default).

1990 Recession: Now, consider zooming in on the transition path to a window around the 1990 recession. Figure 1.24 illustrates what labor productivity and aggregate credit matching efficiency look like around the 1990 experiment. Figure 1.25 reveals an interesting feature of the 1990 recession which is that the implied credit expansion is large enough that it shifts the trough of employment by one quarter later. Figure 1.25 also shows that the difference in employment deviations between the two economies peaks at .44 percentage points seven quarters after the onset of the recession.

2007 Recession: Again, consider zooming in on the transition path to a window around the 2007 recession. Figure 1.26 illustrates what labor productivity and aggregate credit matching efficiency look like around the 2007 recession. Similar to the 1990 recession, the implied credit expansion coming out of the 2007 recession shifts the trough of employment by 1 quarter. The difference in employment deviations peaks at 1.03 percentage points ten quarters after the onset of the recession. Moreover, this difference in employment deviations is still .82 percentage points sixteen quarters after the start of the recession.

In the model, the large endogenous decline in borrowing during the 2007 recession implies a large credit expansion to match the fraction of unemployed households borrowing in the 2010 SCF (see Figure 1.19). In the real world, where is this credit coming from? There has been a large subprime credit card expansion coming out of the 2009 recession, and, although only a limited fraction of student loans have a revolving feature, the United States' student loan programs have subsidized households to be non-labor force participants for extended periods of time and subsequently be choosier about wages upon reentry to the labor force. This is one the largest expansions of credit among the non-employed in US history.

Table 1.13 summarizes the percentage change in employment per capita 12 quarters after its prior peak for the 1990, 2001, and 2007 recessions. In each of these recessions, credit access results in moderately slower employment recoveries, with employment remaining depressed by .2 percentage points to .8 percentage points three years after the initial onset.

Table 1.13: Transition Experiment: Percentage Change in Employment 12 Quarters Since the Peak

Percentage Change in Employment 12Q Since Peak			
	Model with Fixed Access	Model with Access	Data
1990	1.09	0.86	0.12
2001	-1.02	-1.42	-1.85
2007	-0.13	-0.94	-5.59

Notes. Data is Nonfarm Business Sector Employment. Percentage change formula: 100*(E(t)/E(0)-1) where E(0) is employment in period prior to NBER dated recession.

Table 1.14: Transition Experiment: Reduction in Employment Discrepancy Between Model and Data by Including Credit Matching Efficiency Expansions

Reduction in Employment Discrepancy Between Model and Data by Including Credit Matching Efficiency Expansions				
	1990	2001	2007	Average
8 Quarters from Peak	-21%	-189%	-5%	-71%
12 Quarters from Peak	-24%	-48%	-15%	-29%

Notes. Formula: (E(Fixed Access)-E(Access))/(E(Fixed Access)-E(Data)) where E(·) is employment.

The timing of the revolving credit boom and its effect on employment make it a potentially important component of the jobless recovery phenomenon. Take for instance the 2007 recession simulation. While productivity grows enormously from its trough during the 2007 recession, employment remains much lower in the economy with credit access. Table 1.14 shows that allowing for credit expansions can rationalize 29% of the gap between the model with fixed access and the data three years after the 1990, 2001, and 2007 recoveries, on average. Since productivity and output move one for one in the model, the model, to a certain degree, disconnects employment movements from output movements. Table 1.15 shows that the correlation between productivity and unemployment from 1974-2012 is -.77 in the model with credit growth and -.84 in the model with fixed credit. In the data there is considerable discrepancy over the size of the drop in the correlation between unemployment and productivity (see Hagedorn and Manovskii (2010) for more).

Table 1.15: Transition Experiment: Summary of Labor Market Moments

Access							
x	u_1	v	θ	y	$\tilde{w}$	UE Rate	Default Rate
SD(x)/SD(y)	12.59	3.39	5.41	1.00	0.58	5.23	0.002
Autocorr(x)	0.93	0.60	0.87	0.85	0.85	0.89	0.081
Corr(·,x)							
u_1	1.00	-0.37	-0.94	-0.77	-0.76	-0.98	0.09
No Access							
x	u_1	v	θ	y	$\tilde{w}$	UE Rate	Default Rate
SD(x)/SD(y)	12.19	3.17	4.92	1.00	0.57	5.04	0.001
Autocorr(x)	0.93	0.61	0.87	0.85	0.85	0.89	-0.001
Corr(·,x)							
u_1	1.00	-0.30	-0.94	-0.84	-0.83	-0.98	0.13
Data							
x	u_1	v	θ	y	$\tilde{w}$	UE Rate	Default Rate*
SD(x)/SD(y)	9.50	10.10	19.10	1.00	-	5.90	6.07
Autocorrelation	0.94	0.94	0.94	0.88	-	0.91	0.92
Corr(·,x)							
u_1	1.00	-0.89	-0.97	-0.41	-	-0.95	0.55

Notes: HP filtered with smoothing parameter 10^5 to be consistent with Shimer (2005a). Data are from Shimer (2005a), except (*) the default rate which is taken from Equifax (1999-2012). As in the data, u_1 is calculated as the fraction of unemployed households at the end of a quarter. $\theta = \frac{v}{u_1+u_2}$ includes the measure of households that immediately found jobs (u_2), hence the low volatility as that mass is quite large and very stable.

Figure 1.20: Transition Experiment: Labor Productivity & Credit Match Efficiency Inputs, 2001 Recession

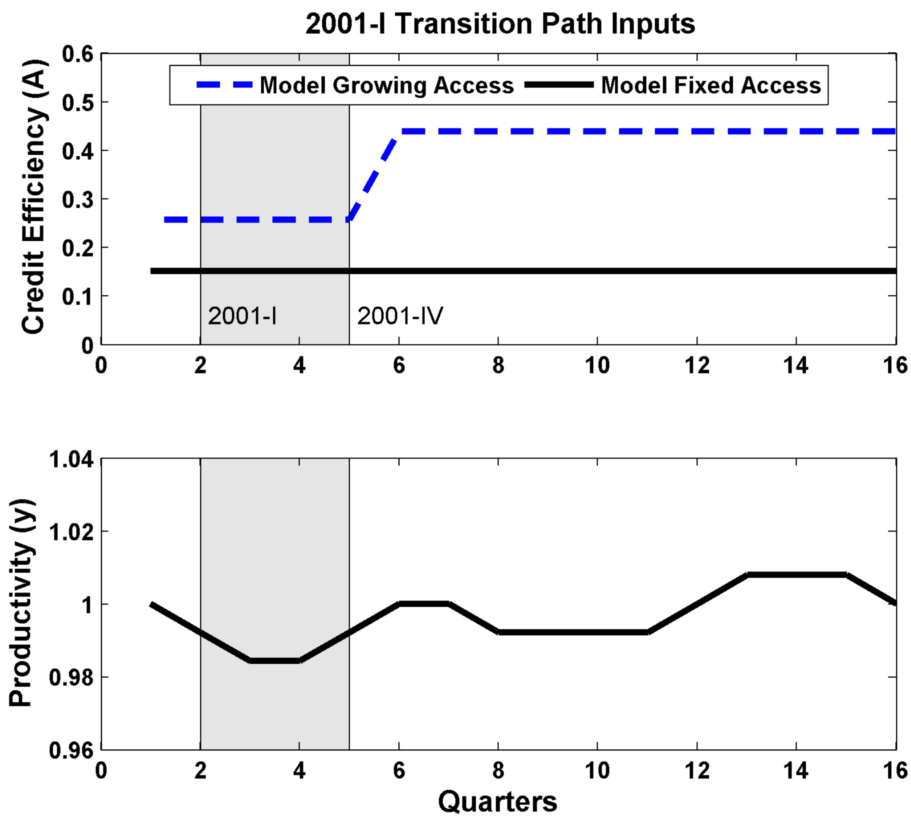


Figure 1.21: Percentage Change in employment, 2001 Recession

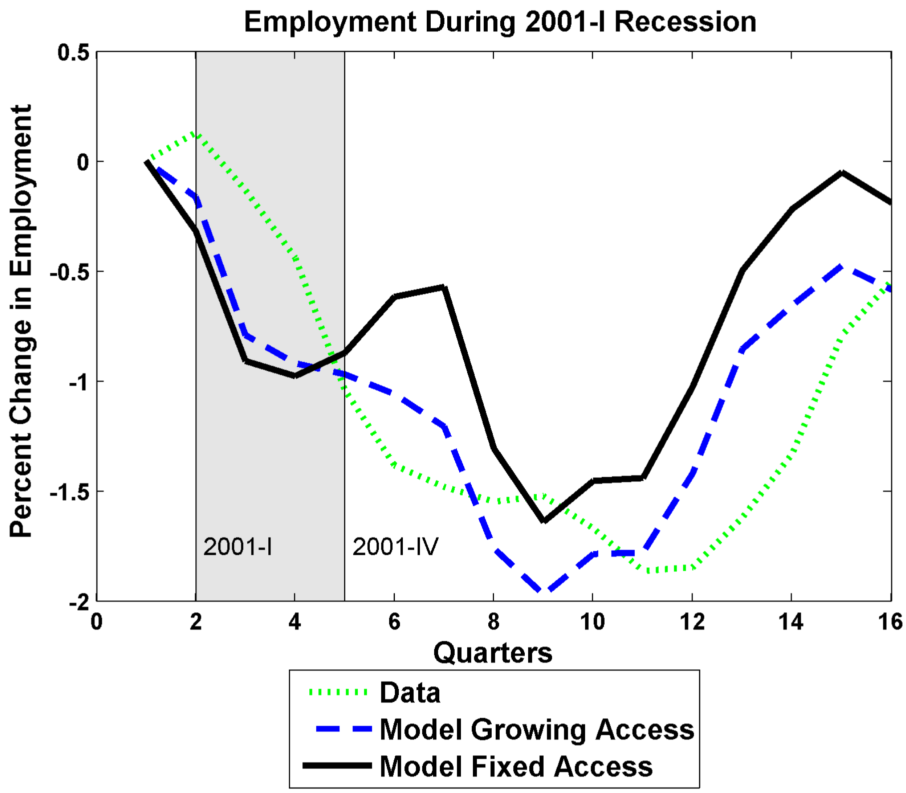


Figure 1.22: Transition Experiment: Job Finding Rate, 2001 Recession

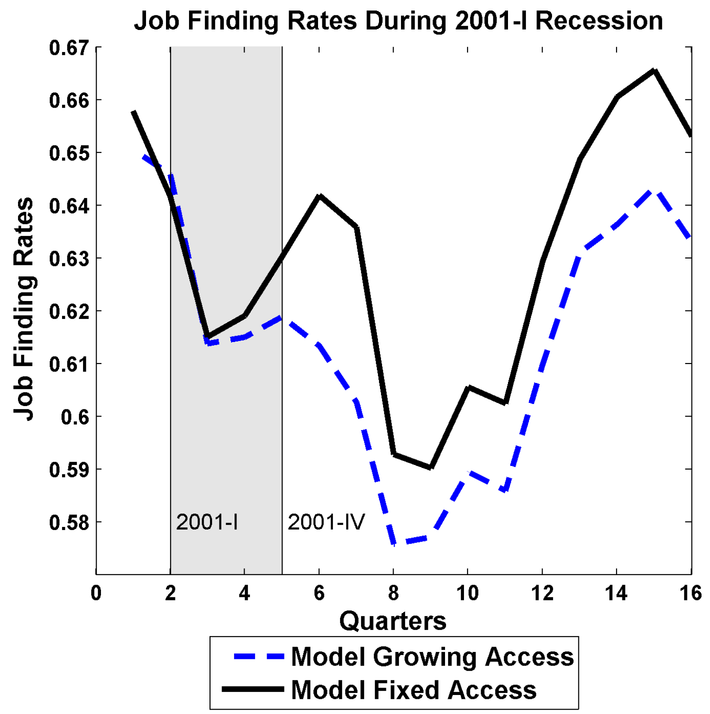


Figure 1.23: Fraction of Unemployed Borrowing, 2001 Recession

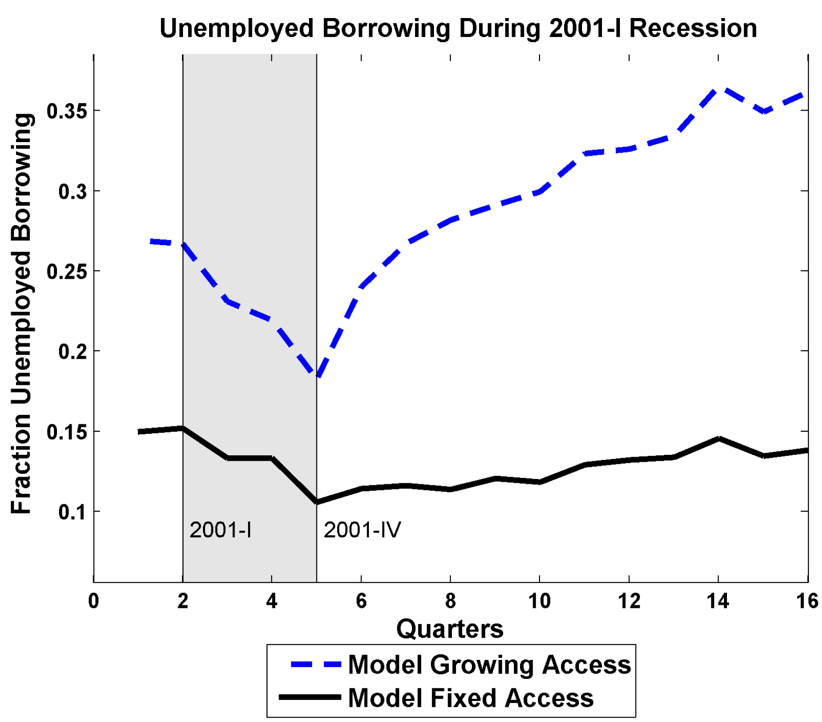


Figure 1.24: Transition Experiment: Labor Productivity and Credit Match Efficiency Inputs, 1990 Recession

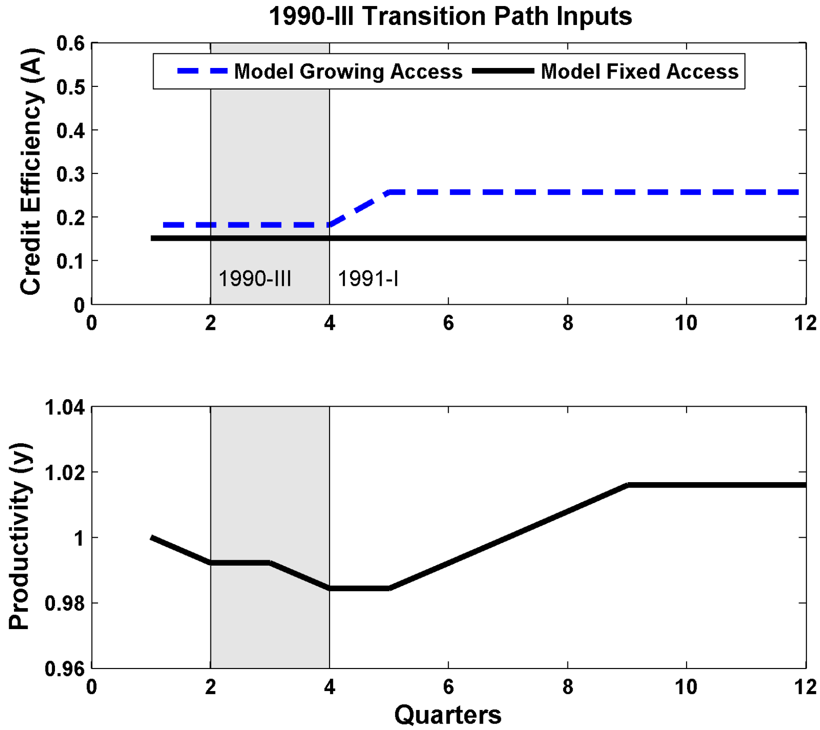


Figure 1.25: Transition Experiment: Percentage Change in employment, 1990 Recession

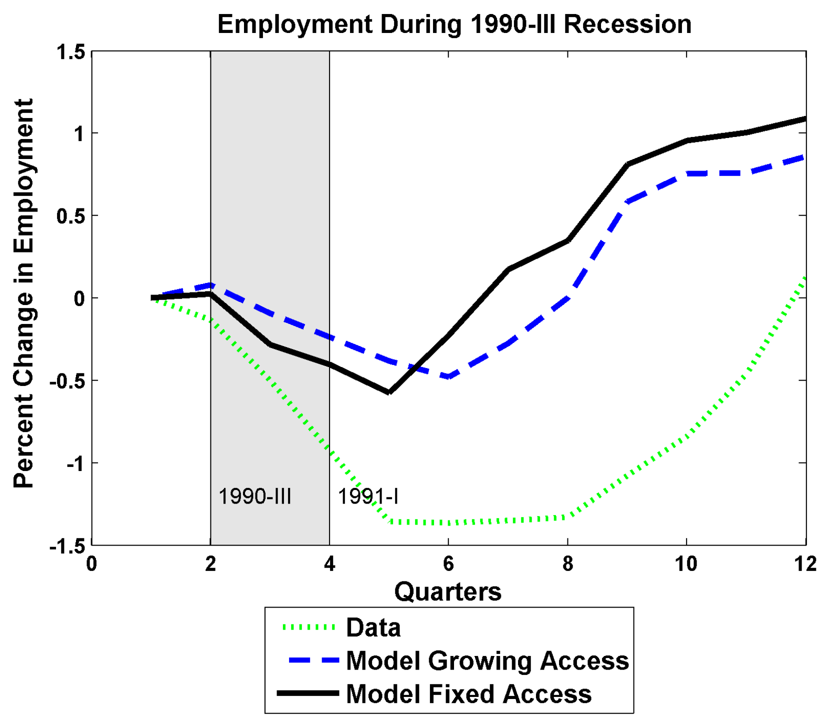


Figure 1.26: Transition Experiment: Labor Productivity and Credit Match Efficiency Inputs, 2007 Recession

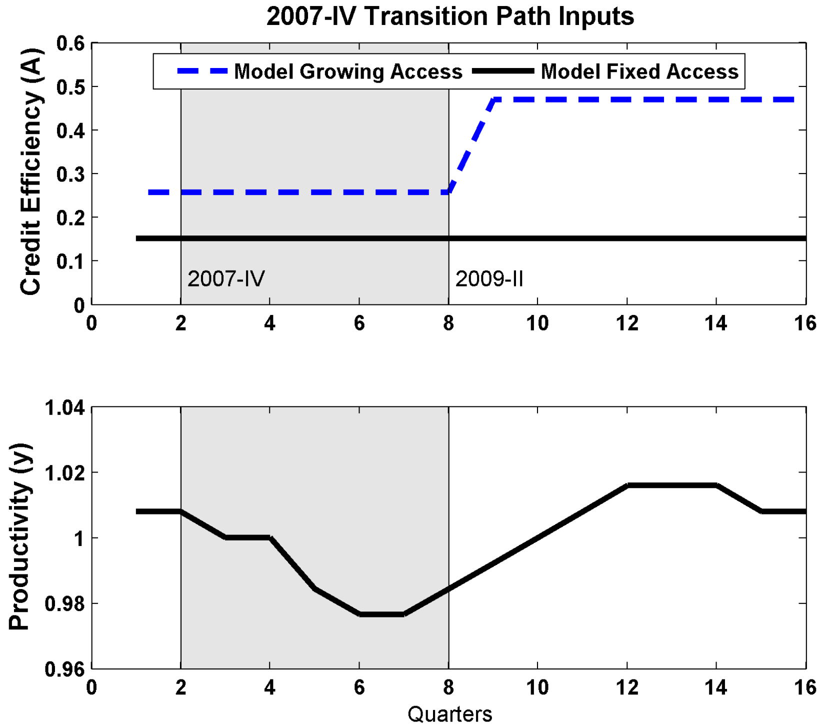
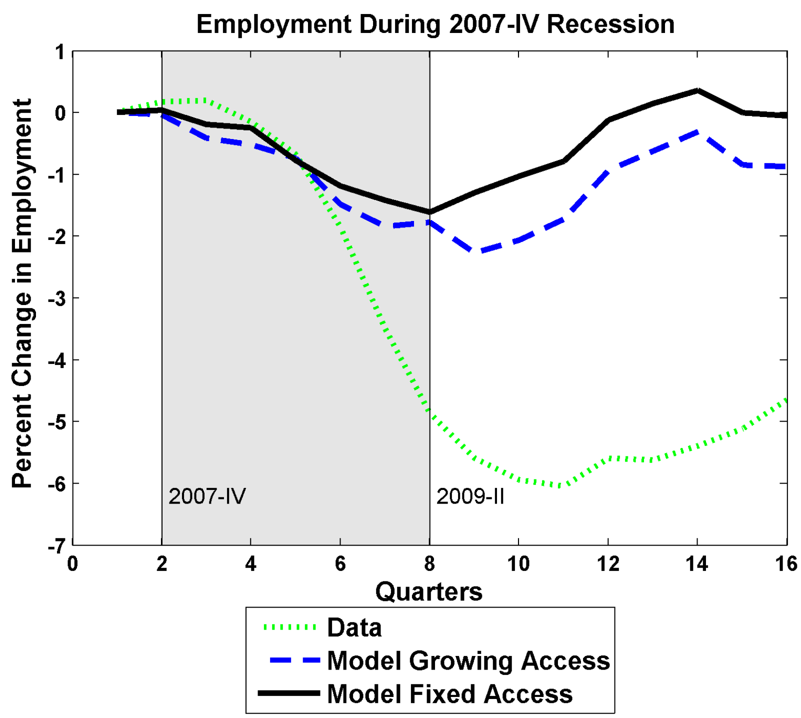


Figure 1.27: Transition Experiment: Percentage Change in employment, 2007 Recession



1.8.2 Trends in Saving and Default

The model does quite well at capturing the precipitous decline in the liquid asset holdings of households. Figure 1.28 plots the fraction of households with liquid assets to gross annual income less than 1% (LQTI<1%) from 1974-I to 2012-IV on the right hand axis (the solid line) versus the data on the left hand axis (the dashed line).[29] In the model there is a secular decline in liquid savings such that the fraction of households with LQTI<1% more than doubles, similar to the data (see Carroll et al. (2012) for more).

Figure 1.29 plots the model's annual trend in defaults per agent against the annual trend in bankruptcy per working age individual in the United States (the only default proxy available over the sample period).[30] There is enormous growth in bankruptcies following the financial liberalization of the 1980s, and a pronounced increase in bankruptcies after bankruptcy reform (dashed red line). Similarly, the model predicts a large increase in defaults caused by the growth in credit access (solid black line). The model's default rate should, in theory, be 6 times larger than the bankruptcy rate (see Herkenhoff (2012a) and Athreya et al. (2012)) but in the present calibration the model's default rate is an order of magnitude smaller than the data. Nonetheless, the model broadly captures the trend in default rates over the last 40 years.

[29] The data is taken from the SCF (and it predecessor survey), and computed as the sum of cash, checking, money market funds, CDS, corporate bonds, government saving bonds, stocks, and mutual funds less credit card debt.

[30] The bankruptcy data is from the Historical Statistics of the United States Millennial Edition for the years 1948 to 1998 and the American Bankruptcy Institute for the years 1998 to 2012.

Figure 1.28: Transition Experiment: Savings Rate

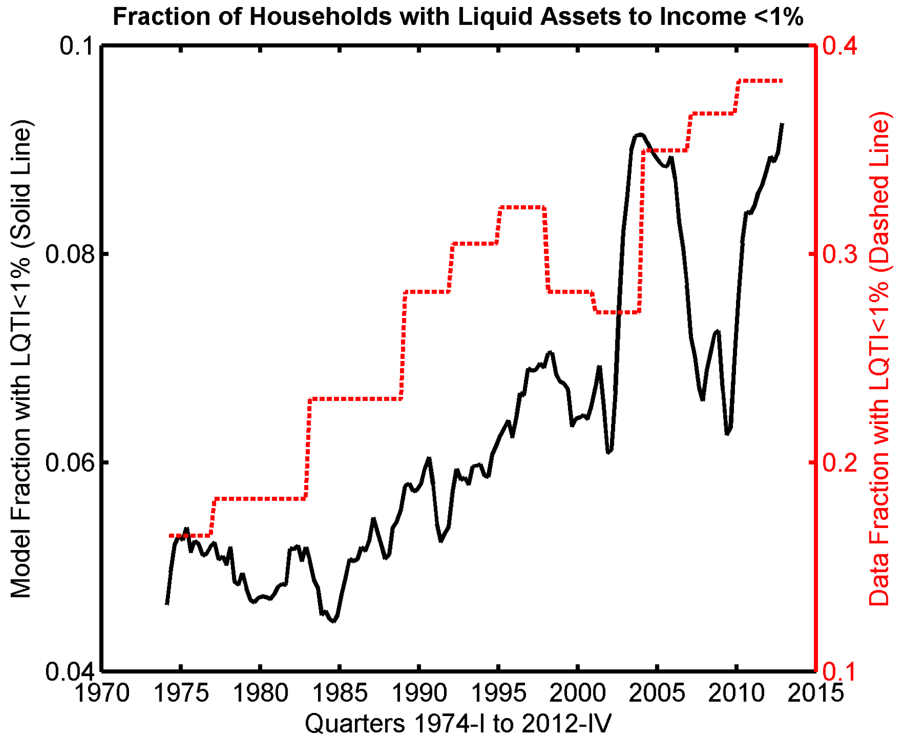
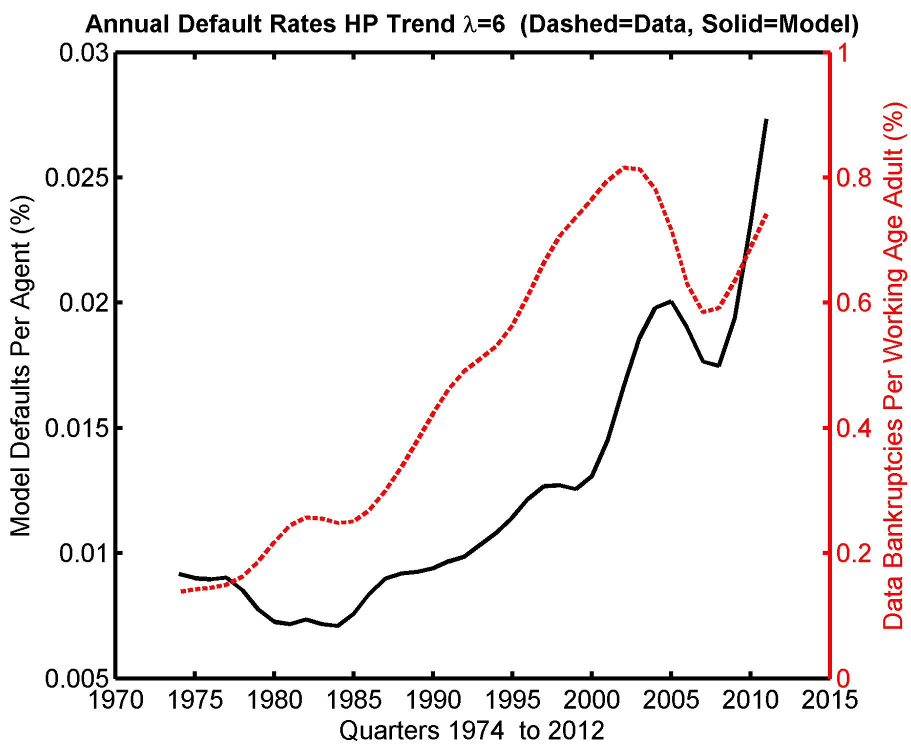


Figure 1.29: Transition Experiment: Default/Bankruptcy Rate



1.8.3 Trends in Income and Consumption Dispersion

Figure 1.30 shows that income dispersion rises in the economy from 1974-2012 while consumption dispersion, depicted in Figure 1.31, actually falls. Credit access leads to more risky wage posting behavior by households which tends to fan out the income distribution. However, the ability to insure that risky behavior allows households to reduce consumption volatility. While the relative change in standard deviations is consistent with the data, the decline in consumption volatility is counterfactual.

When credit expands in 1985 and the wealth distribution is roughly constant in the short run, average consumption increases as shown in Figure 1.33. However, over time, households save less and ultimately consume less. The mechanism is that credit access allows households to borrow while unemployed, but the loans must be repaid. On average, agents are willing to trade high consumption dispersion and higher average consumption for lower consumption dispersion with lower average consumption.

Income per capita depicted in Figure 1.32 behaves somewhat differently (here income is defined as the sum of wages and benefits over the number of agents in the model). When credit expands in the short term, households are out of jobs for longer which immediately lowers income per capita. If productivity remains above trend for a prolonged period of time, then income per capita in the economy with credit access expansions surpasses the economy with fixed credit due to the higher wages sought by better-insured households.

Table 1.16 compares the aggregate correlations between the model and data. After averaging across agents, the times series for aggregate consumption is slightly more volatile with credit access. From an agents perspective in the model, the benefit of credit is that the correlation between employment and consumption drops from .77 to .69, whereas in the data, the correlation between employment and consumption is .68.

1.8.4 Cyclical Properties of the Credit Market

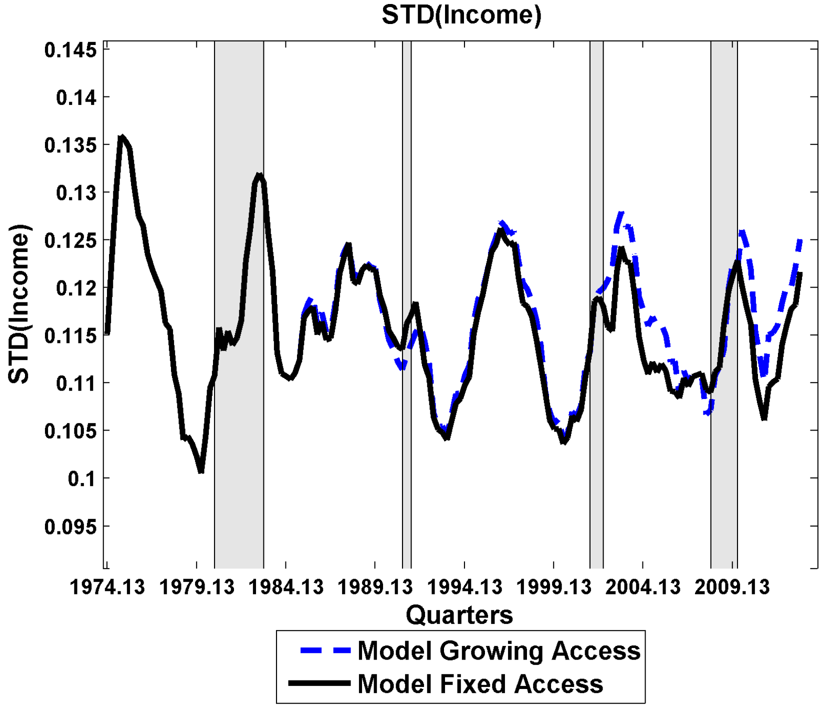
As shown in Table 1.10, during a recession the model predicts increased credit access among relatively wealthy households and decreased credit access among households with moderate

Table 1.16: Transition Experiment: Summary of Aggregate Moments

Growing Access							
x	Employment	Consumption	Approval Rate	Productivity (y)	Wages	Labor Share	Output
SD(x)/SD(y)	0.72	0.69	15.34	1.00	0.18	0.93	1.64
Autocorr(x)	0.90	0.82	0.77	0.83	0.94	0.82	0.86
Corr(·,x)							
Employment	1.00	0.69	-0.21	0.81	0.68	-0.73	0.93
Fixed Access							
x	Employment	Consumption	Approval Rate	Productivity (y)	Wages	Labor Share	Output
SD(x)/SD(y)	0.70	0.67	1.27	1.00	0.18	0.94	1.64
Autocorr(x)	0.90	0.83	0.81	0.83	0.94	0.82	0.86
Corr(·,x)							
Employment	1.00	0.77	-0.86	0.86	0.67	-0.79	0.95
Data							
x	Employment	Consumption	Approval Rate*	Productivity (y)	Wages	Labor Share	Output
SD(x)/SD(y)	1.24	1.05	11.91	1.00	0.88	0.95	1.32
Autocorr(x)	0.95	0.89	0.41	0.77	0.68	0.61	0.88
Corr(·,x)							
Employment	1.00	0.68	0.58	-0.02	-0.09	0.25	0.84

Notes: Logged and HP-Filtered with smoothing parameter 1600. (*) Credit approval data is only available from 1999-II to 2012-I. Nonfarm Business Sector Employment, Chained Personal Consumption Expenditures, BLS Output Per Worker, BLS Nonfarm Business Sector Real Compensation Per hour, BLS Nonfarm Business Sector Labor Share all from 1974-I to 2012-IV. The different time period and different smoothing parameter are why the correlations differ from Shimer (2005a).

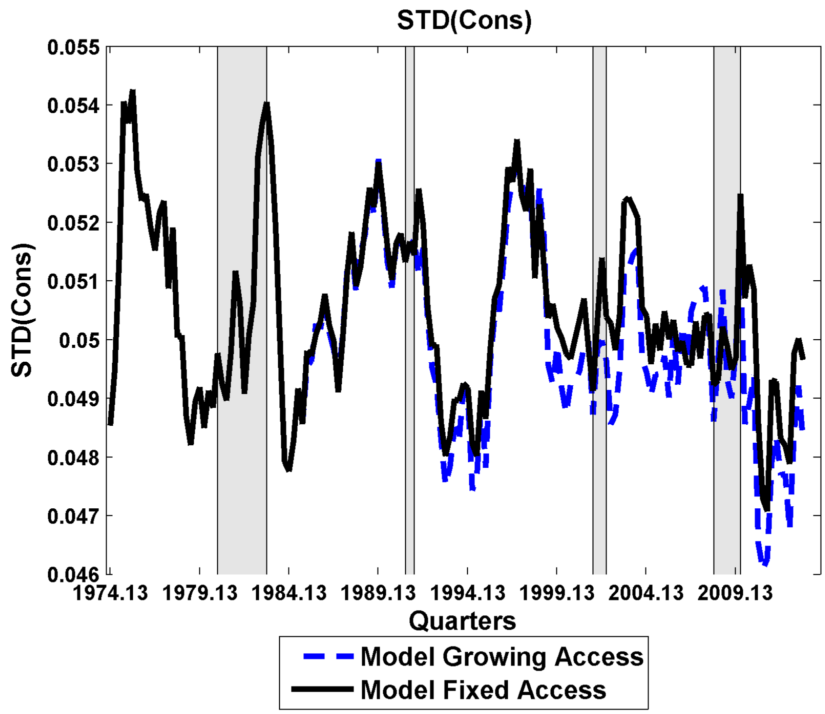
Figure 1.30: Transition Experiment: Income Dispersion



negative net worth. Table 1.17 shows what this micro-behavior implies for business cycle correlations between credit and other variables. In the model with access, because the exogenous credit access expansions occur during recoveries, the correlation between productivity and credit approval rates is .13, and in the model with fixed credit access this number is -.93. In the data the correlation between productivity and credit approval rates (measured over 1999-2012) is .34, and so the credit expansions bring the model closer to the data. Table 1.16 also shows that the economy in which credit expands has a significantly higher volatility of credit access due to the exogenous movements in the credit matching efficiency, which also helps reconcile the model with the data.

The model, however, does produce several counterfactual business cycle moments including a highly positive correlation between wages and employment. What would help remedy this problem is an idiosyncratic component of productivity (see Menzio and Shi (2011)), but such a modification is beyond the scope of this paper.

Figure 1.31: Transition Experiment: Consumption Dispersion



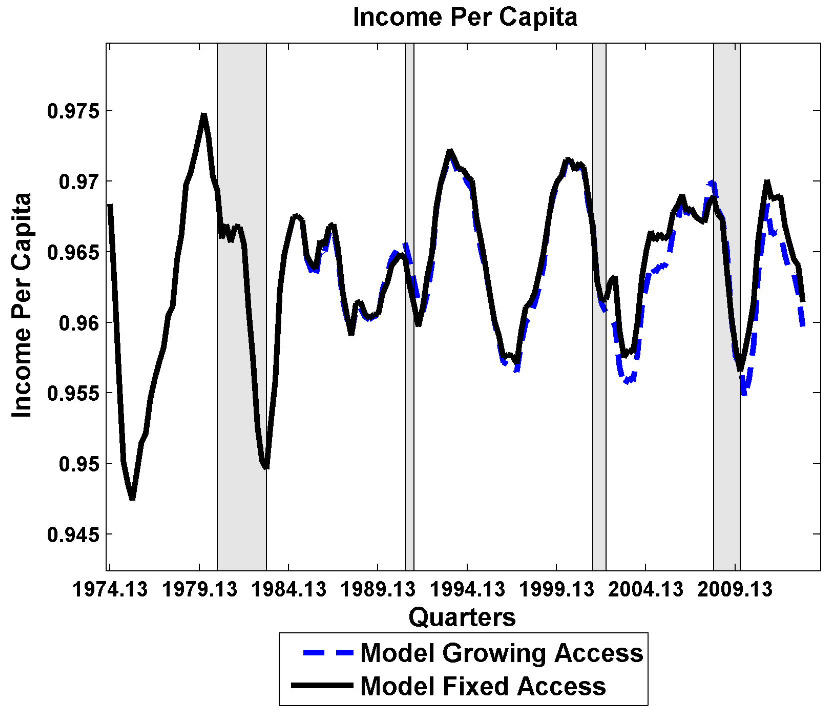
1.8.5 Default as Unemployment Insurance

In terms of default, Figure 1.34 illustrates what income, debt, employment, and repayment ($r = 1 - D$) look like 4 quarters before and after the average default episode (t=0 is the default event).[31] In the period before default, almost every agent is unemployed (some may have borrowed 2 or 3 periods ago from a prior job loss) and levers up. After unsuccessfully finding a job, the agents default– nearly every agent is unemployed in the period of default (there are some employed agents who find jobs and default when credit access is irrelevant to them). This group of unemployed agents is using default as a pure insurance mechanism.

The model's semi-endogenous exclusion response to default shown in Figure 1.35 can also be compared with reaccess rates from the data. After default, the slow reintegration into credit markets is endogenous and determined by the creditors' willingness to lend to

[31] Default is defined to be 90+ days late in Equifax. Default is defined to be any partial repayment in the model. The figures were generated by simulating the economy, marking default episodes as date 0, and looking at behavior 4 quarters before the default and 4 quarters after the default. I then took averages across people to build the measures (to be consistent, I did the same for the Equifax data).

Figure 1.32: Transition Experiment: Income Per Capita



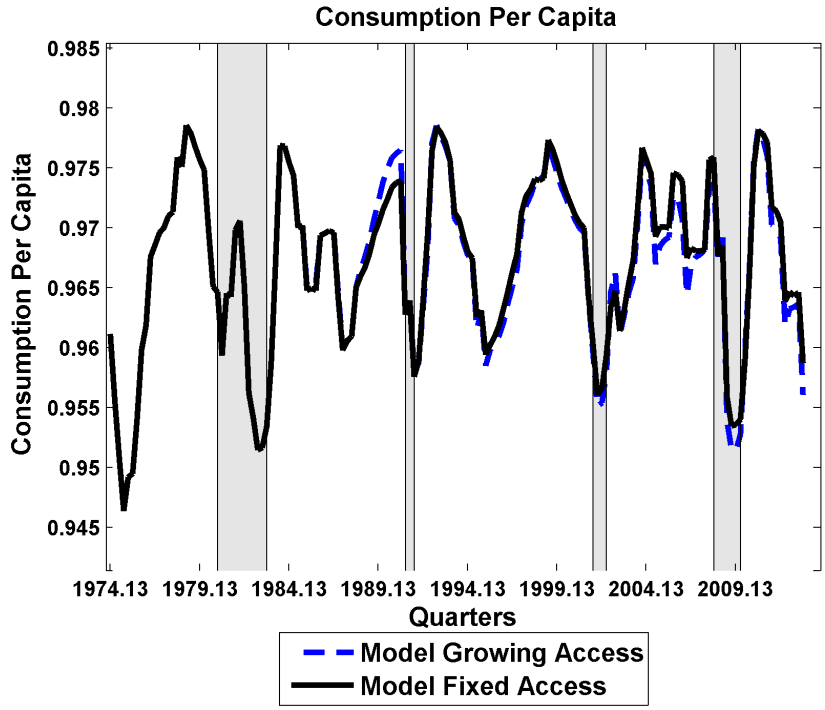
the household. Compared to Equifax credit approval rate data, the model produces approximately similar dynamics, with access remaining relatively low for the 4 quarters following default.

1.9 Conclusions

Unemployed households' access to unsecured revolving credit has grown remarkably over the last 3 decades, and existing studies have shown that such access is an empirically meaningful consumption smoothing mechanism for job losers. The objective of this paper has been to understand how this increased access to unsecured revolving credit affected business cycles.

The paper makes three contributions. Empirically, it presents time series for unemployed households' credit access and credit use from 1970 to 2010. Theoretically, it develops a general equilibrium search and matching model with defaultable debt. And quantitatively, it measures the mechanisms through which credit access impacts unemployment over the

Figure 1.33: Transition Experiment: Consumption Per Capita



business cycle, detailing in a series of experiments the crucial role of credit access *growth* and its impact on employment recoveries from 1974 to 2012.

After calibrating to the times series on unsecured revolving credit use, the model's transition path shows that growth in households' access to credit markets coming out of the 1990, 2001, and 2007 recessions results in an additional .2 to .8 percentage point decline in employment 12 quarters after the initial downturn. In both the 1990 and 2007 recessions, the increased credit access delays the trough of employment by 1 quarter. The mechanism that generates this employment slowdown is that credit access growth coming out of a recession acts as a safety net allowing households to search for better-paying but harder-to-find jobs. Even though this mechanism protracts recessions and slows recoveries, households would be willing to sacrifice .12% of lifetime consumption in order to be born in an economy with 2010 levels of credit access as opposed to an economy with 1970s levels of credit access.

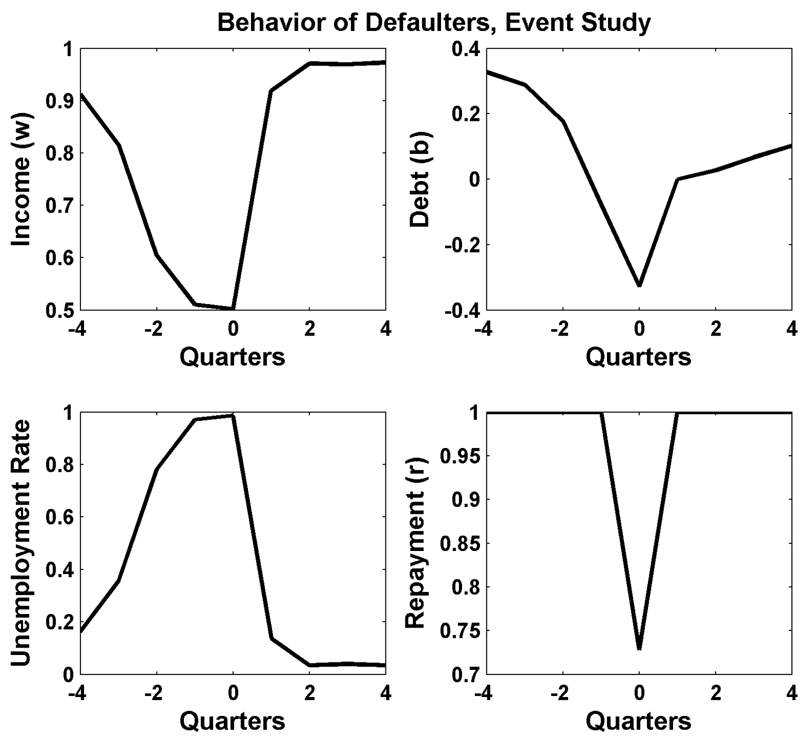
This exercise produces many testable implications. The theory is shown to be consistent with several low frequency trends including the increase in defaults per capita from 1974 to

Table 1.17: Transition Experiment: Business Cycle Correlations of Model's Credit Approval Rate vs. Data (1999-II to 2012-I)

Growing Access						
x	Productivity	Consumption	Output	Employment	Wage Bill	Labor Share
Corr(Credit Approval Rate,x)	0.13	0.17	-0.02	-0.21	-0.14	-0.16
Fixed Access						
x	Productivity	Consumption	Output	Employment	Wage Bill	Labor Share
Corr(Credit Approval Rate,x)	-0.93	-0.81	-0.93	-0.86	-0.58	0.88
Data						
x	Productivity	Consumption	Output	Employment	Wage Bill	Labor Share
Corr(Credit Approval Rate,x)	0.34	0.73	0.73	0.58	0.07	0.07

Notes: Logged and HP-Filtered with smoothing parameter 1600. Sample period in model and data is 1999-II to 2012-I. Nonfarm Business Sector Employment, Chained Personal Consumption Expenditures, BLS Output Per Worker, BLS Nonfarm Business Sector Real Compensation Per hour, BLS Nonfarm Business Sector Labor Share all from 1974-I to 2012-IV.

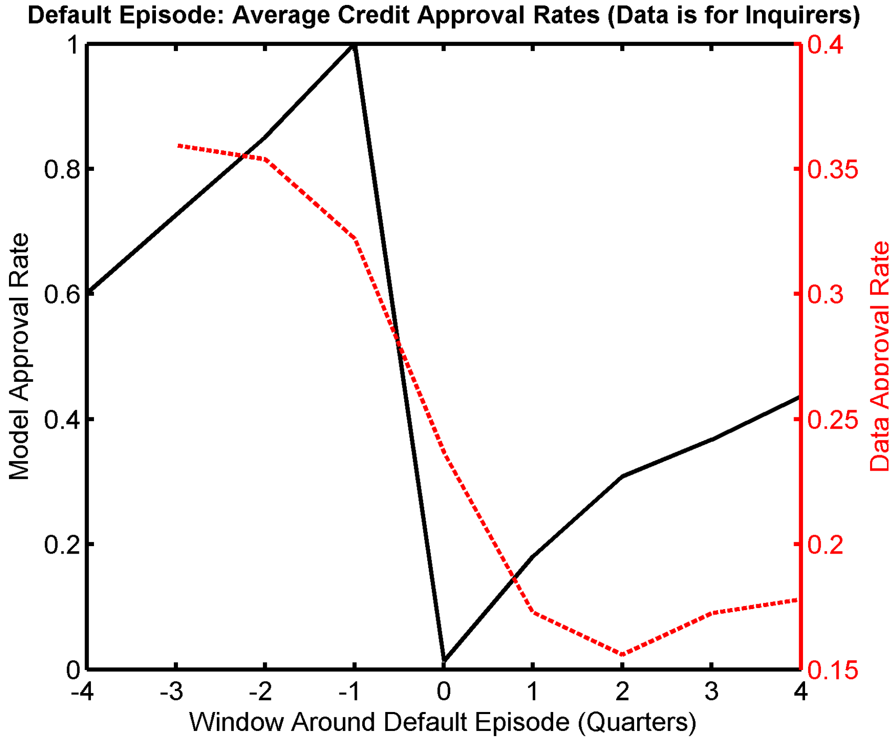
Figure 1.34: Average Default Episode, Employment, Income, Repayment



2012, the long run decline in liquid asset holdings, the rise in unemployment durations, and the decline in consumption dispersion relative to income dispersion.

In light of these findings, there remain several unanswered questions that I plan to pursue

Figure 1.35: Average Default Episode, Credit Access



in future work. How has default protection changed over this time frame? Has that influenced self-insurance opportunities? Does credit access interact with unemployment benefits? And if so, should the government use loan programs in place of unemployment insurance or is there an optimal mix?

1.10 Appendix

1.10.1 Proofs for Theoretic Characterization

1.10.1.1 Finite Life Span Economy

To characterize the model analytically, I must make several basic Assumptions:

A.i **Boundedness:**

(a) $w \in \mathcal{W} \equiv [\underline{w}, \overline{w}] \subseteq \mathbb{R}_+$

(b) $z \in \mathcal{Z} \equiv [\gamma \underline{w}, \gamma \overline{w}] \subseteq \mathbb{R}_+$ where $\gamma \in (0,1)$

(c) $b \in \mathcal{B} \equiv [\underline{b}, \bar{b}] \subseteq \mathbb{R}$

(d) $y \in \mathcal{Y} \in [\underline{y}, \overline{y}] \subseteq \mathbb{R}_+$

(e) $A \in \mathcal{A} \in [\underline{A}, \overline{A}] \subseteq \mathbb{R}_+$

(f) $\mu : \{W, U\} \times \{C, N\} \times \mathcal{W} \times \mathcal{B} \times \mathbb{N}_T \to [0,1]$ (the distribution now includes a distribution over ages $t \in \mathbb{N}_T$)

A.ii **Inada Conditions:**

(a) The utility function is twice continuously differentiable, $u'' < 0$, $u' > 0$, $\lim_{c \to 0} u'(c) = +\infty$, and $\lim_{c \to +\infty} u'(c) = 0$.

(b) The penalty function is also twice continuously differentiable $x'' > 0$, $x' > 0$, $\lim_{D \to \overline{D}} x'(D) = \infty$, $\lim_{D \to 0} x'(D) = 0$.

Restatement of Lemma 2.5.1: *Under the Inada conditions outlined in assumption A.ii (see Appendix 1.10.1.1), for initial debt levels such that $b \in \mathcal{B}$ and $b < 0$, (1) the optimal choice of D is continuously differentiable over the set $[\underline{b}, \epsilon]$ for arbitrarily small $\epsilon < 0$ (2) the fraction of debt defaulted upon is monotone increasing in the initial debt position $\mid b \mid$, $b < 0$ and (3) the fraction of debt defaulted upon is monotone decreasing in resources borrowed $\mid q_{e,t}(w, b'; \Omega) b' \mid$, $b' < 0$ across all ages.*

Proof.

Claim (1): Under the hypothesis, first order conditions suffice to characterize D when $b \in \mathcal{B}$ and $b < 0$:

$$-u'\big(w + (1 - D)b - q_{e,t}(w, b'; \Omega)b'\big)b = x'(D)$$

Definition: Define the continuously differentiable function $\nu : [0,1] \times \mathcal{B} \to \mathbb{R}$ as follows:

$$\nu(D, b) = -u'\big(w + (1 - D)b - q_{e,t}(w, b'; \Omega)b'\big)b - x'(D)$$

Jacobian: The Jacobian of the function $\nu(D,b)$ is shown below for any coordinates such that $\nu(D_0,b_0)=0$ and $(D_0,b_0)\in[0,1]\times\mathcal{B}_{--}$ where $\mathcal{B}_{--}$ are all the elements $b\in\mathcal{B}$, $b<0$,

$$\begin{aligned}
(D\nu)(D_0,b_0) &= \left[\frac{\partial\nu}{\partial D}(D_0,b_0)\middle|\frac{\partial\nu}{\partial b}(D_0,b_0)\right] \\
&= \Bigg[u''\big(w+(1-D)b-q_{e,t}(w,b';\Omega)b'\big)b^2-x''(D)\Bigg| \\
&\quad -u''\big(w+(1-D)b-q_{e,t}(w,b';\Omega)b'\big)(1-D)b \\
&\quad -u'\big(w+(1-D)b-q_{e,t}(w,b';\Omega)b'\big)\Bigg]
\end{aligned}$$

Since $u''<0$ and $x''>0$, the first element of the Jacobian is non-zero so long as the initial state is such that $b\in\mathcal{B}$ and $b<0$. Thus there exists an open set containing D_0, $D_\epsilon=N_\epsilon(D_0)$, an open set containing b_0, $B_\epsilon=N_\epsilon(b_0)$, and a unique continuously differentiable function $D^*:B_\epsilon\to D_\epsilon$.

Claim (2): Applying the envelope theorem, the expression for the optimal default fraction is given below:

$$\frac{dD}{db}=\frac{u''\big(w+(1-D)b-q_{e,t}(w,\hat{b};\Omega)\hat{b}\big)b(1-D)+u'\big(w+(1-D)b-q_{e,t}(w,\hat{b};\Omega)\hat{b}\big)}{u''\big(w+(1-D)b-q_{e,t}(w,\hat{b};\Omega)\hat{b}\big)b^2-x''(D)}\Bigg|_{\hat{b}=b'^*_{e,t}(w,b;\Omega)}<0 \quad \forall b\in\mathcal{B},b<0$$

If $b<0$ (the only case in which a household would default) then since $u''<0$, $u'>0$, and $x''>0$, then $\frac{\partial D}{\partial b}<0$. This means that if households begin the period with a small positive perturbation of debt (i.e. b is slightly more negative) they will default on a larger fraction of that debt position.

Claim (3): Let $R=q_{e,t}(w,b';\Omega)b'<0$ denote total resources borrowed (saved) in the present period.

$$\frac{\partial D}{\partial R} = \frac{-u''\big(w + (1-D)b - q_{e,t}(w,b';\Omega)b'\big)b}{u''\big(w + (1-D)b - q_{e,t}(w,b';\Omega)b'\big)b^2 - x''(D)} > 0 \quad \forall b \in \mathcal{B}, b < 0$$

This expression says that the fraction of debt defaulted upon is weakly increasing in the amount of resources borrowed. Thus, if R is perturbed to be slightly more negative (i.e. the household has access to more resources), then the household will repay more of the present debt.

■

Restatement of Corollary 1.3.2: *Under the Inada conditions outlined in assumption A.ii (see Appendix 1.10.1.1), for initial debt levels such that $b \in \mathcal{B}$ and $b < 0$, (1) the equilibrium bond price is continuously differentiable over the interval $[\underline{b}, \epsilon]$, $\epsilon < 0$, (2) the equilibrium bond price is monotone decreasing in resources lent and (3) the equilibrium bond price is monotone increasing in subsequent resources borrowed across all ages.*

Proof. This is a direct implication of Lemma 2.5.1 in combination with the equilibrium pricing equation 1.2. ■

Restatement of Proposition 1.3.3: *Under the boundedness conditions and Inada conditions outlined in assumptions A.i and A.ii, a Block Recursive Equilibrium exists for the T-span economy.*

Proof. Solution Method for T-span Economy: For any given lifespan, it is possible to construct an equilibrium following Menzio et al. (2012).

i. In the last period of life, $q_{e,T}(w,b;A,y) = 0 \quad \forall b \in \mathcal{B}_{-}$ (anyone that borrows in their last period of life will not repay anything next period because they will be dead). Thus, $\theta^C_{e,T}(w,b;A,y) = 0$ and no one gets credit in the last period. Neither object depends on the distribution.

ii. Obtain the default rule $D^{*,a}_{e,T}(z,b;A,y)$ and the degenerate asset accumulation rule

$b'^{*,a}_{e,T}(z, b; A, y)$ from the household problem at date T:

$$W^C_T(w, b) = \max_{D\in[0,1],b'\geq 0} u(w + (1 - D)b) - x(D)$$

$$U^C_T(z, b) = \max_{D\in[0,1],b'\geq 0} u(z + (1 - D)b) - x(D) + \eta$$

iii. Obtain the labor market tightness $\theta^L_T(w; y)$ from the free entry condition and using the fact that $J_T(w; \Omega) = J_T(w; y) = y - w$.[32]

$$\theta^L_T(w; y) = q^{-1}\left(\frac{\kappa_L}{J_T(w; y)}\right)$$

iv. Given the household default rule $D^{*,a}_{e,T}(z, b; A, y)$ and the fact that it never makes sense to lend to someone in their last period of life ($\theta^C_{e,T}(w, b; A, y) = 0$), the household makes new take-it-or-leave-it bond proposals $q_{e,T-1}(w, b; y, A)$ based on the date T default policies.

v. Solve HH problem at date $T - 1$:[33]

$$\begin{aligned} W^C_{T-1}(w, b; A, y) = &\max_{b'\in\mathcal{B},D\in[0,1]} u(c) - x(D) \\ &+ \beta\mathbb{E}\Big[(1 - \delta(w; y'))W_T(w, b'; A', y') + \delta(w; y')U_T(\gamma w, b'; A', y')\Big] \end{aligned}$$

Such that:

$$c + q_{W,T-1}(w, b'; A, y)b' \leq w + (1 - D)b$$

$$y' \sim F(y' \mid y)$$

$$A' \sim G(A' \mid A)$$

[32]This object is only well defined if $J_T > 0$ which is discussed below. In general $J_T > 0$ since $\delta(y, w) = 1$ if $y \leq w$, and $J_T \geq \min_{i,j\ s.t.\ y(i)>w(j)} \{y(i) - w(j)\}$. Notice that the tightness does not depend on credit conditions but the weighted average tightness of visited submarkets will fluctuate with credit access.

[33]For the purposes of reducing clutter, I assume laid off workers must wait one period for search. The same proof works without this assumption.

$$
\begin{aligned}
U^C_{T-1}(z,b;A,y) = \max_{b'\in\mathcal{B},D\in[0,1]} & u(c) - x(D) + \eta \\
& + \beta\mathbb{E}\Bigg[\max_{\tilde{w}\in\mathcal{W}} p(\theta^L_T(\tilde{w};A',y'))W_T(\tilde{w},b';A',y') \\
& + \Big(1 - p\big(\theta^L_T(\tilde{w};A',y')\big)\Big)\widehat{U}_T(z,b';A',y')\Bigg]
\end{aligned}
$$

Such that:

$$c + q_{U,T-1}(z,b';\Omega)b' \leq z + (1-D)b$$

$$y' \sim F(y' \mid y)$$

$$A' \sim G(A' \mid A)$$

and

$$\widehat{U}_T(z,b';A',y') = p_z U_T(\underline{z},b';A',y') + (1-p_z)U_T(z,b';A',y')$$

These problems imply optimal rules for default $D^{*,a}_{e,T-1}(z,b;A,y)$,

assets $b'^{*,a}_{e,T-1}(z,b;A,y)$, and, in the case of the unemployed, the optimal wage posting rule $\tilde{w}^*_{T-1}(w,b;A,y)$. In general, under assumptions A.ii, $D^{*,a}_{e,T-1}(z,b;A,y)$ is unique; however, $b'^{*,a}_{e,T-1}(z,b;A,y)$ may not be unique. The objective function is continuous and the choice set $\mathcal{B}$ is by assumption compact, thus the objective is bounded and the maximum and minimum are obtained over $\mathcal{B}$ (i.e. the Weierstrass extreme value theorem attains). While this guarantees *a* solution, the objective function might attain the maximum at two or more different points in the state space. This is irrelevant for the proof that follows, but in section 1.10.1.2, I prove that for a certain class of matching functions and penalty functions, the asset policy function is unique.

vi. Now move back to $T-1$ for the firm to obtain $J_{T-1}(w;y)$:

$$J_{T-1}(w;y) = y - w + \beta E\Big[(1-\delta_{T-1}(w,y'))J_T(w;y')\Big]$$

Such that

$$\delta_t(w, y') = \begin{cases} 1 & \text{if } t > T \text{ or } y < w \\ \bar{\delta} & \text{otherwise} \end{cases}$$

and the shock follows the process

$$y' \sim F(y' \mid y)$$

vii. Obtain the labor market tightness $\theta^L_{T-1}(w; y)$ from the free entry condition:

$$\theta^L_{T-1}(w; y) = q^{-1}\left(\frac{\kappa_L}{J_{T-1}(w; y)}\right)$$

viii. Given $q_{T-1}(w, b; A, y)$, use $D^{*,a}_{e,T-1}(z, b; A, y)$, $b'^{*,a}_{e,T-1}(z, b; A, y)$ to solve for $Q_{T-1}(e, w, b; A, y)$. The free entry condition can then be inverted to obtain the credit market tightness:

$$\theta^C_{e,T-1}(w, b; A, y) = \phi^{-1}\left(\frac{\kappa_C}{A \cdot Q_{T-1}(e, w, b; A, y)}\right)$$

ix. Repeat this process for t=$T-2, \cdots, 1$ to obtain a sequence of equilibrium prices that does not depend on the distribution.

This process results in a vector of equilibrium prices for agents aged 1 through T. ■

1.10.1.2 Uniqueness of Finite Life Span Equilibrium

For certain functional forms, the equilibrium is shown to exist and be unique.

Restatement of Lemma 1.3.4: *Suppose that* $x(0) = 0$ *and* $x(D) \to \infty\ \forall D > 0$, $M(u, v) = \min\{u, v\}$ *and* $M_C(u_C, v_C) = v_C^{\alpha_C} u_C^{1-\alpha_C}$ *with* $\alpha_C \to 0$ *(i.e. constant arrival rate of credit offers). Under assumptions A.i-A.ii there exists a unique Competitive Equilibrium that is also Block Recursive.*

Proof. (1) Asset Policy Uniqueness: By hypothesis, the bond price is given by $q = \frac{1}{1+r_f}$ for $b \geq 0$ and $q = \frac{1}{1+r_f+\tau}$ for $b < 0$ and the arrival rate of credit is given by a constant $p(\theta^C) = A$.

Let $\mathcal{B}_- = \{b \mid b \in \mathcal{B} \cap b \leq 0\}$ be the lending contract space and $\mathcal{B}_+ = \{b \mid b \in \mathcal{B} \cap b > 0\}$ be the saving contract space. Define the strictly concave functions (inherited from u by hypothesis) $u_j : \mathcal{B} \to \mathbb{R}$ for $j \in \{+, -\}$ such that:

i. $u_-(b') = u(w + b + \frac{b'}{1+r_f+\tau})$ which corresponds to the actual utility function $\forall b' \in \mathcal{B}_-$.

ii. $u_+(b') = u(w + b + \frac{b'}{1+r_f})$ which corresponds to the actual utility function $\forall b' \in \mathcal{B}_+$.

Define $u^*(b') = \min_j \{u_j(b')\}$. By construction, this is the objective function of the household's dynamic programming problem. The minimum of continuous functions is continuous and the minimum of strictly concave functions is strictly concave (see Boyd and Vandenberghe (2004)), but may not be differentiable. However, since the theorem of the maximum does not require differentiability, there exists a unique policy function b'^* and the resulting objective function is strictly concave in b. Iterating backwards from $t = T, T-1, \dots, 1$, the objective function is strictly concave in net assets and there exists a unique net asset policy function for each age.

(2) Wage Policy Uniqueness: Iterating backwards from $t = T, T-1, \dots, 1$, the objective function is strictly concave and differentiable with respect to the wage. In the last period of life, trivially $W_T^j(w, b'; \Omega)$ for $j \in \{C, N\}$ is strictly concave and differentiable in the wage.

For ease of exposition, consider the case where y is non-stochastic and job destruction is constant $\bar{\delta}$.[34] Under these assumptions, the value of a firm is given by:

$$J_t(w; y) = \frac{y - w}{1 - \beta(1 - \bar{\delta})} - \beta^{T-t}(1 - \bar{\delta})^{T-t} \frac{y - w}{1 - \beta(1 - \bar{\delta})}$$

[34] All of the following results are attainable with a Markovian assumption for y and no restrictions on the job destruction rate. An N-state Markov process allows one to solve for $J_t(w; y_N)$ analytically, similar to what is done here.

Using the matching function and the free entry condition, it is possible to solve for the job finding rate of households:

$$p(\theta_t^L(w;y)) = \theta_t^L(w;y) = \frac{\kappa_L}{AJ_t(w;y)} \propto c_0(t)w + c_1(t)y$$

with $c_0(t) < 0$ and $c_1(t) > 0$ for all $t \in \{1, \ldots, T\}$. It is straightforward to show that for any strictly concave function $f(x)$, the function $(ax+b) \cdot f(x) + (1-(ax+b)) \cdot \bar{u}$ is strictly concave and differentiable for any constant $\bar{u}$ so long as $a < 0$ and $ax + b > 0$. Therefore, the objective function of households in the labor market is strictly concave and differentiable with respect to wages:

$$\max_{\tilde{w}} p(\theta_t^L(\tilde{w};y))W_t^j(\tilde{w}, b'; \Omega) + (1 - p(\theta_t^L(\tilde{w};y)))U_t^j(z, b'; \Omega)$$

Thus starting from T and working backward and repeatedly applying the theorem of the maximum, a unique $\tilde{w}^*$ exists and the resulting objective function is strictly concave in w.

■

Restatement of Corollary 1.3.6: *Under the assumptions of Lemma 1.3.4, the wage policy function of the household is increasing in credit access.*

Proof.

Suppressing states to conserve space, the optimal wage is chosen such that:

$$\frac{\partial p_t}{\partial \theta_t}\frac{\partial \theta_t}{\partial \tilde{w}}(W_t - U_t) \leq -p_t \frac{\partial W_t}{\partial \tilde{w}} \quad \text{(with equality if } w \in (\underline{w}, \overline{w}))$$

Use the functional form assumption for $M(u,v)$ and the fact that $p_t = \theta_t > 0$ to obtain the following criteria for an interior wage choice:

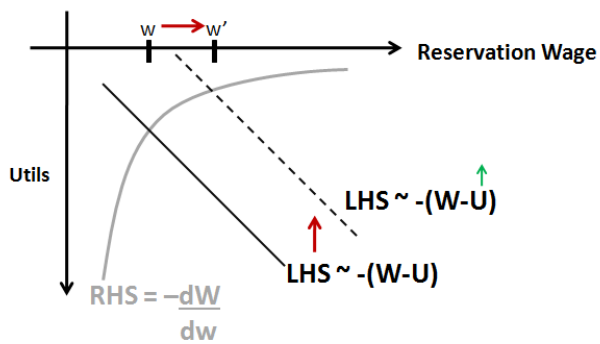
$$\frac{c_0(t)}{p_t}(W_t - U_t) = -\frac{\partial W_t}{\partial \tilde{w}} \tag{1.5}$$

$$LHS = \underbrace{\frac{c_0(t)}{p_t}}_{\text{(-), grows more neg as w incr.}} \times \underbrace{(W_t - U_t)}_{\text{(+), grows more pos as w incr.}}$$

$$RHS = \underbrace{-\frac{\partial W_t}{\partial \tilde{w}}}_{\text{(-), grows \textbf{less} neg as w incr.}}$$

An increase in credit access increases the value of unemployment U_t relative to working W_t. Thus, the increase in credit access tends to make the LHS of Equation 1.5 (the incremental value of waiting) less negative at every point in the wage choice set. Equality is restored by increasing the reservation wage to make the RHS of Equation 1.5 (the incremental value of taking a job) less negative. Following such a credit access perturbation, the resulting reservation wage is *strictly* greater than the initial reservation wage if the agent begins with an interior initial wage. Figure 1.36 illustrates this graphically.

Figure 1.36: Comparative Statics: Increase Access to Unsecured Credit, Increase the Reservation wage from w to w'



■

1.10.1.3 Infinite Life Span Existence

I will use arguments similar to Balasko and Shell (1980) and Levine (1989) in order to establish existence. The basic premise of the proof is as follows.

i. Solve for the finite T-lifespan set of equilibrium prices using backward induction as in

Proposition 1.3.3. The solution should be independent of the distribution of households across states.

ii. This price vector is compact and non-empty.[35]

iii. Now increase the lifespan by 1 year. Repeat the above steps. The new price vector is compact and non-empty, but more importantly, it is nested in the previous price vector.

iv. As the life span tends to infinity, the limiting price vector is the intersection of these nested compact non-empty sets, and is therefore non-empty.

Fix the lifespan at T years and apply the backward induction steps of Section 1.10.1.1. This process results in a vector of equilibrium prices for agents aged 1 through T. I will call these prices the *determinate prices*. For technical reasons, I must define *indeterminate prices* for ages $-1, -2, \ldots$. Even though these prices are irrelevant for the t-span economy, I must define these prices in a way such that they take values in compact intervals that are consistent with t+n-span economies, $n \in \mathbb{N}_+$ arbitrary. For these reasons, I must make several additional assumptions:

Assumptions to Ensure Equilibrium Prices Contained in Compact Set:

B.i **Labor Tightness:** I will assume that zero profit matches are destroyed with probability 1:

$$\delta_t(w; y) = \begin{cases} 1 & \text{if } t > T \text{ or } y < w \\ \bar{\delta} & \text{if } y > w \end{cases}$$

Define $J_{max} = 1/(1-\beta)$ $J_{min} = \min_{i,j \ s.t. \ y(i) > w(j)} \left\{ y(i) - w(j) \right\}$ Then labor market tightness lies in a closed and bounded interval.

$$\theta_t^L(w; y) \in \Theta^L \equiv [\underline{\theta}, \overline{\theta}] = \left[q^{-1}\left(\frac{\kappa_L}{J_{min}}\right), q^{-1}\left(\frac{\kappa_L}{J_{max}}\right) \right] \quad \forall t$$

[35] Conditions to ensure all potential t-span prices lie in a compact space are given below. Technically, as will be explained below, the price vector is also defined to include the irrelevant ages from -1,-2,-3, and onward.

B.ii **Credit Tightness:** Assume there is a minimum loan size $\mathcal{B} = [\underline{b}, -\epsilon_b] \cup [0, \overline{b}]$ and further assume that repayment is strictly positive $D \leq \epsilon_D < 1$, but small enough that even the worst-off unemployed agents with expired benefits can obtain positive consumption $(-1)(1-\epsilon_D)\underline{b} < \underline{z}$. Define $Q_{max} = \frac{\tau}{1+r_f}\overline{b}$ and $Q_{min} = \frac{\tau}{1+r_f}\epsilon_b \cdot (1-\epsilon_D)$ Then the credit market tightness lies in a closed and bounded interval, $A \in [\underline{A}, \overline{A}]$.

$$\theta_t^C(w; y, A) \in \Theta^C \equiv [\underline{\theta}, \overline{\theta}] = \left[\phi^{-1}\left(\frac{\kappa_C}{\underline{A}Q_{min}}\right), \phi^{-1}\left(\frac{\kappa_C}{\overline{A}Q_{max}}\right)\right] \quad \forall t$$

B.iii **Bond Price:** Since $D \in [0, \epsilon_D]$ and $\epsilon_D > 0$ it must be the case that $q \in [\frac{1-\epsilon_D}{1+r_f}, \frac{1}{1+r_f}] \equiv \mathcal{Q}$.

Consider equilibrium prices vectors that extend from $-\infty$ to T, where bond prices lie in their respective compact intervals outlined above $q_{0,e}(w,b;A,y)$, $q_{-1,e}(w,b;A,y)$,$\ldots \in \mathcal{Q}$, labor market tightnesses lie in their respective compact intervals outlined above $\theta_0(w,b;A,y)$, $\theta_{-1,e}^L(w,b;A,y)$,$\ldots \in \Theta^L$, and credit market tightnesses lie in their respective compact intervals outlined above $\theta_{0,e}^C(w,b;A,y)$, $\theta_{-1,e}^C(w,b;A,y)$, $\ldots \in \Theta^C$. The price vector is thus given below:[36]

$$p_{T,e}(w,b;A,y) = \left[\begin{array}{cc|ccc} \cdots & q_{0,e}(w,b;A,y) & q_{1,e}(w,b;A,y) & \cdots & q_{T,e}(w,b;A,y) \\ \cdots & \theta_0^L(w,b;A,y) & \theta_1^L(w,b;A,y) & \cdots & \theta_T^L(w,b;A,y) \\ \cdots & \theta_{0,e}^C(w,b;A,y) & \theta_{1,e}^C(w,b;A,y) & \cdots & \theta_{T,e}^C(w,b;A,y) \end{array}\right]$$

Define p_T^+ as the sub matrix of equilibrium prices for ages 1 through T. This vector is unique and pinned down using the solution method outlined above.

$$p_{T,e}^+(w,b;\Omega) = \begin{bmatrix} q_{1,e}(w,b;A,y) & \cdots & q_{T,e}(w,b;A,y) \\ \theta_1^L(w,b;A,y) & \cdots & \theta_T^L(w,b;A,y) \\ \theta_{1,e}^C(w,b;A,y) & \cdots & \theta_{T,e}^C(w,b;A,y) \end{bmatrix}$$

[36] I have partitioned the matrix in a particular way to isolate the determinate portion from the indeterminate portion.

Define p_T^- as the sub matrix of ages less than or equal to zero. In a T-period economy, the vector of prices for ages less than 1 are arbitrary so long as they live in the compact intervals implied by assumption A.i-A.iii:

$$p_{T,e}^-(w,b;\Omega) = \begin{bmatrix} \cdots & q_{-1,e}(w,b;A,y) & q_{0,e}(w,b;A,y) \\ \cdots & \theta_{-1,e}^L(w,b;A,y) & \theta_0^L(w,b;A,y) \\ \cdots & \theta_{-1,e}^C(w,b;A,y) & \theta_{0,e}^C(w,b;A,y) \end{bmatrix}$$

Suppose instead consumers live until age $T+1$. The price vector for the T+1 economy is given below:

$$p_{T+1,e}(w,b;A,y) = \left[\begin{array}{cc|ccc} \cdots & q_{0,e}(w,b;A,y) & \cdots & q_{T,e}(w,b;A,y) & q_{T+1,e}(w,b;A,y) \\ \cdots & \theta_1^L(w,b;A,y) & \cdots & \theta_T^L(w,b;A,y) & \theta_{T+1}^L(w,b;A,y) \\ \cdots & \theta_{1,e}^C(w,b;A,y) & \cdots & \theta_{T,e}^C(w,b;A,y) & \theta_{T+1,e}^C(w,b;A,y) \end{array}\right]$$

Relabel the elements such that $\tilde{T} = T+1$ (it is always possible to relabel the elements such that $\tilde{T} = T+N$ as $N \to \infty$). Define $p_{\tilde{T}}^+$ as the sub matrix for agents whose transformed age is between 1 and $\tilde{T}$.

Based on the equilibrium construction method, $p_{\tilde{T}}^+ = p_T^+$. In other words, the prices implied by solving the model in the last period of life are the same across different life spans. It does not matter if the life span is 10 years or 20 years, in the last period of life the problem is always the same.

Now notice that when $\tilde{T} < 1$, the implied prices

$$(q_{\tilde{T},e}(w,b;A,y), \theta_{\tilde{T}}^L(w,b;A,y), \theta_{\tilde{T},e}^C(w,b;A,y))) \in \mathcal{Q} \times \Theta^L \times \theta^C$$

must lie in the compact intervals outlined in assumptions A.i-A.iii. Thus, the equilibrium price vectors are nested since the elements of p_T^- can assume any value in the set $\mathcal{Q} \times \Theta^L \times \theta^C$.

Definition: Let $\mathcal{P}(t)$ be the equilibrium vector of prices for an economy in which agents live t periods:

$$\mathcal{P}(t) = \left\{ p_t \mid p_t^+ \text{ solves eq. conditions age 1 to age t \& all elements} p_t^- \in \mathcal{Q} \times \Theta^L \times \theta^C \right\}$$

As outlined above, $p_t = (q, \theta^L, \theta^C)'$ summarizes the age specific equilibrium prices and p_t^+ a determinate vector of the sub-coordinates of p_t for attainable ages.

Lemma 1.10.1 *Under assumptions A.i-A.ii and B.i-B.iii, $\mathcal{P}(t)$ is non-empty and compact.*

Proof.

Non-emptiness: The above solution method yields a unique vector for p_t^+. Let p_t^- have arbitrary elements selected from the set $\mathcal{Q} \times \Theta^L \times \theta^C$. Then $p = [p_t^-, p_t^+] \in \mathcal{P}(t)$ is an equilibrium price vector.

Compactness: Under assumptions B.i-B.iii, all possible t-span equilibrium price vectors have elements that reside in the compact set $\mathcal{Q} \times \Theta^L \times \theta^C$.

p_t^+ is uniquely defined thus, those coordinates are compact. The arbitrary price vector p_t^- is forced to live in a closed and bounded interval. Thus $\mathcal{P}(t)$ is compact for every $t = 0, 1, 2, \cdots$.

■

Lemma 1.10.2 *The equilibrium price vectors are nested such that $\mathcal{P}(t+1) \subset \mathcal{P}(t) \quad \forall i > 1$*

Proof. Implied by construction. ■

Restatement of Proposition 1.3.5: *Under assumptions A.i-A.ii and B.i-B.iii, there exists an equilibrium sequence of prices for an infinitely lived agent economy where the equilibrium sequence of prices is independent of the distribution across states.*

Proof. Following Balasko and Shell (1980) it is sufficient to show that $\mathcal{P}(\infty)$ is non-empty to establish existence. Note that $\mathcal{P}(\infty) = \cap_{t=1}^{\infty} \mathcal{P}(t)$ by construction. Since $\mathcal{P}(\infty)$ is the intersection of nested, non-empty, compact intervals, $\mathcal{P}(\infty)$ is non-empty. ■

1.10.2 Long Lived Credit Relationships: Lending Institutions

When there are long lived credit relationships, the lender's problem is no longer static and must be solved via dynamic programming. I assume that the relationship is broken up endogenously in the case of a default and for exogenous reasons with probability $\bar{s}$. To operationalize endogenous separation, lenders use a universal default rule.

Universal Default Assumption: Default results in the immediate severance of all lending relationships (summarized by $\Xi(D)$).

In the period of default, no credit is made available to the household within the period, and the credit relationship is destroyed with probability one. Let $\Xi(D)$ summarize this universal default rule, where $\Xi(D) = 0$ if there is a default.

$$\Xi(D) = \begin{cases} 0 & \text{if } D > \underline{D} \\ 1 & \text{if } D = \underline{D} \end{cases}$$

As before, households make take it or leave it bond price proposals to lenders taking into account the proportional minimum servicing fee. This assumption guarantees lenders the proportional minimum servicing fee τ on a *per-period* basis and allows me to express the bond pricing function in a familiar form. Let $D^{a'}_{e',t+1}(w', \hat{b}; \Omega')$ be the policy function implied by the household's problem, then the bond price can be written as,

$$q_{e,t}(w, \hat{b}, \hat{D}; \Omega) = \begin{cases} \frac{\bar{s} \cdot \mathbb{E}\left[(1 - D^{a'}_{e',t+1}(w', \hat{b}; \Omega'))\right] + (1-\bar{s})\mathbb{E}\left[\cdot(1 - D^{C}_{e',t+1}(w', \hat{b}; \Omega'))\right]}{(1+r_f+\tau)}, & \hat{b} \in \mathcal{B}_-, \quad \hat{D} = \underline{D} \\ 0, & \hat{b} \in \mathcal{B}_-, \quad \hat{D} > \underline{D} \\ \frac{1}{(1+r_f)}, & \hat{b} \in \mathcal{B}_+ \end{cases}$$

The net present value of profits accruing to the lender must now reflect the future service revenue flows which depend on household policy functions. As such, the lender must forecast future household decisions which is summarized by the recursive equation below:

$$Q_t(e,w,b;\Omega) = (1-\Xi(\hat{D}))\Big\{ q_{e,t}(w,\hat{b},\hat{D};\Omega)\hat{b} \\ - \bar{s}\cdot\frac{1}{1+r_f}\mathbb{E}\big[(1-D^{a'}_{e',t+1}(w',\hat{b};\Omega'))\cdot\hat{b}\big] \\ - (1-\bar{s})\cdot\frac{1}{1+r_f}\mathbb{E}\big[(1-D^{\mathbf{C}}_{e',t+1}(w',\hat{b};\Omega'))\cdot\hat{b}\big] \\ + (1-\bar{s})\frac{1}{1+r_f}\mathbb{E}\big[Q_{t+1}(e',w',\hat{b};\Omega')\big]\Big\} \\ \Big|_{\hat{b}=b'^{*}_{e,t}(w,b;\Omega),\quad \hat{D}=D^{C}_{e,t}(w,b;\Omega),\quad e\in\{W,U\},\quad b\in\mathcal{B}}$$

1.10.3 On The Job Search Extension

Let λ be the probability of a worker conducting on-the-job-search. Firms must know the entire state vector of the household in order to forecast future job changes and form expectations. In this extension, firms are allowed to condition job offers on the proposed wage $w\in\mathcal{W}$, the assets of the applicant $b\in\mathcal{B}$, the current credit access of the applicant $a\in\{C,N\}$ (in the case of long lived credit relationships, this is a relevant state), the age of the applicant t, and the aggregate state $\Omega=(\mu,y,A)$.

The submarket tightness is therefore given by $\theta^L_t(a,w,b;\Omega)=\frac{v_t(a,w,b;\Omega)}{u_t(a,w,b;\Omega)}$ where

$$v_t(a,w,b;\Omega)$$

is the number of vacancies posted in the $(a,w,b,t;\Omega)$ submarket and $u_t(a,w,b;\Omega)$ is the number of unemployed people in that submarket. The corresponding vacancy-filling rate in that submarket is $f(\theta^L_t(a,w,b;\Omega))$. Let $J^a_t(w,b;\Omega)$ be the continuation value of a firm matched with a household state vector $(a,w,b,t;\Omega)$. With this notation, the value of posting a vacancy in submarket $(a,w,b;\Omega)$ is given by,

$$V_t(a,w,b;\Omega) = -\kappa_L + f(\theta^L_t(a,w,b;\Omega))J^a_t(w,b;\Omega)$$

With free entry it must be the case that profits are competed away. Thus, the market tightness is given by,

$$\theta_t^L(a,w,b;\Omega) = f^{-1}\left(\frac{\kappa_L}{J_t^a(w,b;\Omega)}\right) \text{ if } \theta_t^L(a,w,b;\Omega) > 0$$

The firm takes as given (i) $\tilde{w}_C^* = \tilde{w}_{W,t+1}^C(w,b;\Omega)$ which is the optimal 'on-the-job-search' policy function for households with credit, (ii) $\tilde{w}_N^* = \tilde{w}_{W,t+1}^N(w,b;\Omega)$ which is the optimal on-the-job-search policy for households without credit, (iii) $D^* = D_{W,t}^{C*}(w,b;\Omega)$ which is the optimal default policy function for employed households with credit, and (iv) $b^{'*} = b_{W,t}^{'*,C}(w,b;\Omega)$ which is the optimal asset accumulation policy function for households with credit. Taking the household policy functions as given, the value of an ongoing match to a firm with an age t worker with credit access (C), wage w, and assets b is given below:

$$\begin{aligned}
&J_t^C(w,b;\Omega) = y - w + \\
&(1-s(D^*))\beta\mathbb{E}_{\Omega'}\Big[(1-\lambda p(\theta_{t+1}^L(C,\tilde{w}_C^*,b^{'*};\Omega'))) \cdot (1-\delta_{t+1}(w;y')) \cdot J_{t+1}^C(w,b^{'*};\Omega')\Big] \\
&+ s(D^*)\beta\mathbb{E}_{\Omega'}\Big[(1-\lambda p(\theta_{t+1}^L(N,\tilde{w}_N^*,b^{'*};\Omega'))) \cdot (1-\delta_{t+1}(w;y')) \cdot J_{t+1}(w,b^{'*};\Omega')\Big]
\end{aligned}$$

such that firms take the aggregate law of motion as given (the equations are given by (1.1)) and the evolution of the credit status of the employee is taken into account,

$$J_t(w,b;\Omega) = A\psi(\theta_{W,t}^C(w,b;\Omega))J_t^C(w,b;\Omega) + \big(1 - A\psi(\theta_{W,t}^C(w,b;\Omega))\big)J_t^N(w,b;\Omega)$$

A similar set of equations hold for a firm matched with a household that does not have credit access.

1.10.3.1 On the Job Search: Household Problem

With on-the-job-search and long term credit relationships, the household problem must reflect the probability that a credit relationship is destroyed ($s(D)$) along with the opportunity to engage in on-the-job-search.[37] For an employed agent (W) with credit access (C), their

[37] For the purposes of reducing clutter, I assume laid off workers must wait one period to search. The simulations shown below add back this feature.

dynamic programming problem is given by,

$$
\begin{aligned}
&W_t^C(w,b;\Omega) = \max_{b'\in\mathcal{B}, D\in[0,1]} u(c) - x(D) \\
&+ s(D)\cdot\beta\mathbb{E}\Bigg[(1-\delta_{t+1}(w;y'))\Bigg\{\max_{\tilde{w}\in\mathcal{W}} \lambda p(\theta^L_{t+1}(N,\tilde{w},b';\Omega'))W_{t+1}(\tilde{w},b';\Omega') \\
&+ \Big(1-\lambda p\big(\theta^L_{t+1}(N,\tilde{w},b';\Omega')\big)\Big)W_{t+1}(w,b';\Omega')\Bigg\} + \delta_{t+1}(w;y')U_{t+1}(\gamma w,b';\Omega')\Bigg] \\
&+ (1-s(D))\cdot\beta\mathbb{E}\Bigg[(1-\delta_{t+1}(w;y'))\Bigg\{\max_{\tilde{w}\in\mathcal{W}} \lambda p(\theta^L_{t+1}(C,\tilde{w},b';\Omega'))W^C_{t+1}(\tilde{w},b';\Omega') \\
&+ \Big(1-\lambda p\big(\theta^L_{t+1}(C,\tilde{w},b';\Omega')\big)\Big)W^C_{t+1}(w,b';\Omega')\Bigg\} + \delta_{t+1}(w;y')U^C_{t+1}(\gamma w,b';\Omega')\Bigg]
\end{aligned}
$$

Such that the law of motion for aggregates holds (the equations are given by (1.1)) and the budget constraint is satisfied:

$$c + q_{W,t}(w,b',D;\Omega)b' \leq w + (1-D)b$$

1.10.3.2 On the Job Search: Lending Institutions

The profit function is the same as before, the only difference is the expectation over w' now takes into account that there is on-the-job-search. The recursive statement of the profit function is given below:

$$
\begin{aligned}
&Q_t(e,w,b;\Omega) = (1-\Xi(\hat{D}))\Bigg\{q_{e,t}(w,\hat{b},\hat{D};\Omega)\hat{b} - \bar{d}\cdot\frac{1}{1+r_f}\mathbb{E}\big[(1-D^{a'}_{e',t+1}(w',\hat{b};\Omega'))\cdot\hat{b}\big] \\
&-(1-\bar{d})\cdot\frac{1}{1+r_f}\mathbb{E}\big[(1-D^{\mathbf{C}}_{e',t+1}(w',\hat{b};\Omega'))\cdot\hat{b}\big] \\
&+(1-\bar{d})\frac{1}{1+r_f}\mathbb{E}\big[Q_{t+1}(e',w',\hat{b};\Omega')\big]\Bigg\} \\
&\Bigg|_{\hat{b}=b'^*_{e,t}(w,b;\Omega),\ \ \hat{D}=D^C_{e,t}(w,b;\Omega),\ \ e\in\{W,U\},\ \ b\in\mathcal{B}}
\end{aligned}
$$

such that the universal default rule is given by,

$$
\Xi(\hat{D}) = \begin{cases} 1 & \text{if } \hat{D} > \underline{D} \\ 0 & \text{if } \hat{D} = \underline{D} \end{cases}
$$

and the bond price is given by,

$$q_{e,t}(w, \hat{b}, \hat{D}; \Omega) = \begin{cases} \frac{\bar{d} \cdot \mathbb{E}\left[(1-D^{a'}_{e',t+1}(w',\hat{b};\Omega'))\right] + (1-\bar{d})\mathbb{E}\left[\cdot(1-D^{C}_{e',t+1}(w',\hat{b};\Omega'))\right]}{(1+r_f+\tau)}, & \hat{b} \in \mathcal{B}_-, \quad \hat{D} = \underline{D} \\ 0, & \hat{b} \in \mathcal{B}_-, \quad \hat{D} > \underline{D} \\ \frac{1}{(1+r_f)}, & \hat{b} \in \mathcal{B}_+ \end{cases}$$

1.10.4 Transition Experiment: On the Job Search

Figure 1.37 illustrates the same 2007 recession experiment along the transition path with on-the-job-search (OJS). All parameters were kept fixed, except there is now a positive probability of conducting OJS given by $\lambda = .1$. Menzio and Shi (2011) use a much larger value of $\lambda = .73$ in order to entirely correct for the counterfactual Beveridge curve generated by models with directed search and *no* on-the-job-search.[38] However, such a high probability of on-the-job-search induces counterfactual wage ladders.[39] On-the-job-search alters wage search and acceptance decisions, prompting workers to take the first available job and then transit to higher paying jobs later. The gap then between the economy with access and the economy without is smaller with on-the-job-search since the insurance mechanisms are weaker. In some sense, there is an OJS insurance plan which is to take a poorly paying job and then work up the wage ladder. Overall, however, the introduction of on the job search does not change the general quantitative message.

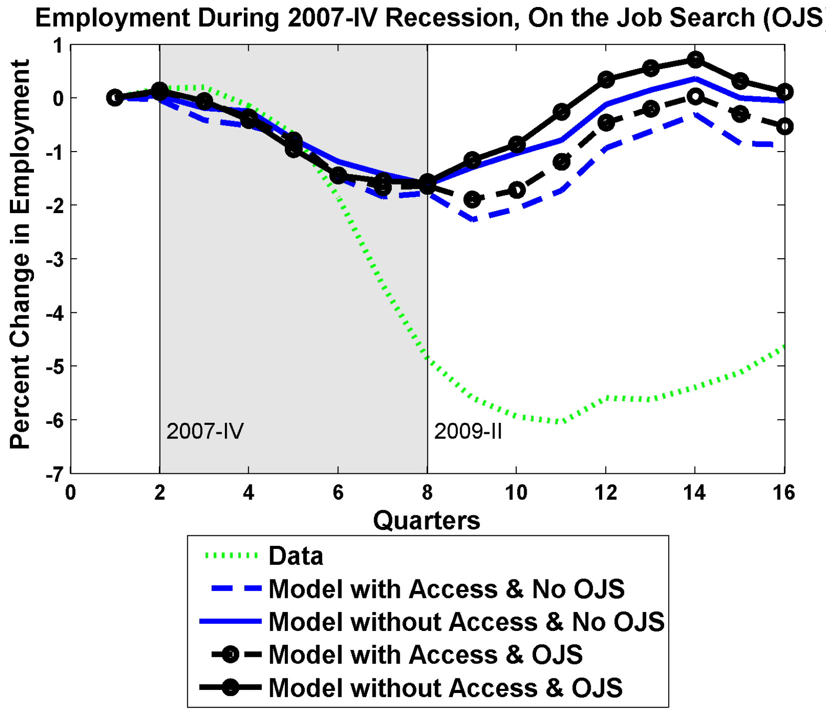
1.10.5 Robustness Checks: Timing

As a robustness check to the timing of the credit expansions used in the transition path, I consider several different timing assumptions. Holding all other parameters constant, I recalibrate the credit matching efficiency expansions to occur 2 quarters after the trough of the recession and 4 quarters after the trough of the recession. For the 2001 recession, Figure 1.38 shows the new credit matching efficiency inputs, and Figure 1.39 demonstrates that the

[38] In down times, firms post lots of vacancies since they will "lock-in" the low wages workers are willing to work for. With on-the-job-search, there is no "lock-in."

[39] See Jacobson et al. (1993) for more on earnings losses after job displacement during recessions.

Figure 1.37: On the Job Search, 2007 Recession



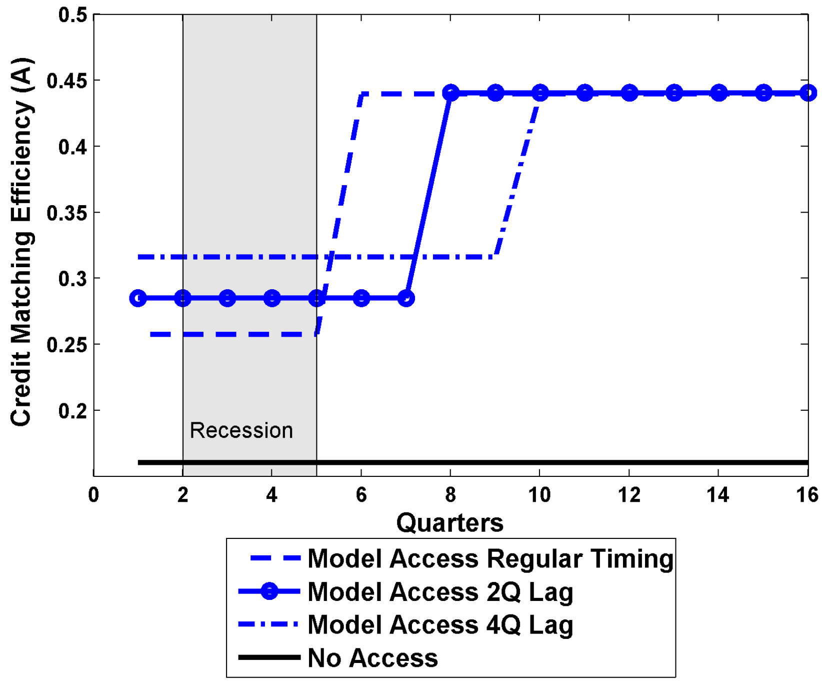
employment deviations 3 years after the 2001 recession remains virtually unchanged. The same holds true for the 1990 and 2007 recessions.

1.10.6 Estimation of Credit Matching Function

Annual data from Synovate on the number of direct mail credit card offers from 1990-2007 ($v_{c,t}$) were combined with the fraction of SCF respondents in 1995, 1998, 2001, 2004, and 2007 that applied to credit, weighted to reflect the population ($f_{c,t}$).[40] I also collected data on the CPS civilian working age population (pop_t). From this data, it is possible to estimate the number of households that applied for credit ($u_{ct} = pop_t \cdot f_{c,t}$). I also used the SCF

[40]Direct mail credit card orders have been in decline for several years as internet offers have risen, but Synovate estimates that 60% of the offers direct respondents online to apply. The SCF credit application question is worded as follows: "Have you and your (husband/wife/partner) applied for any type of credit or loan in the last five years? Include Pre-Approved Credit that Respondent Accepted." I aggregate all time series to reflect the 5 year interval in the estimation that follows.

Figure 1.38: Alternate Credit Expansion Timing: Credit Match Efficiency Inputs, 2001 Recession



question regarding credit denial to obtain the probability a household received credit $p_{c,t}$.[41] Define $\theta_{c,t} = \frac{v_{c,t}}{u_{c,t}}$ Using the assumed functional form, I estimated γ using non-linear least squares:

$$A_c M(u_c, v_c) = A_c \frac{u_c \cdot v_c}{(u_c^\gamma + v_c^\gamma)^{1/\gamma}} \in \big[0, 1)$$

$$\underbrace{A_c p(\theta)}_{Observed\ Match\ Probability\ p_{c,t}} = A_c \theta \cdot (1 + \theta^\gamma)^{\frac{-1}{\gamma}}$$

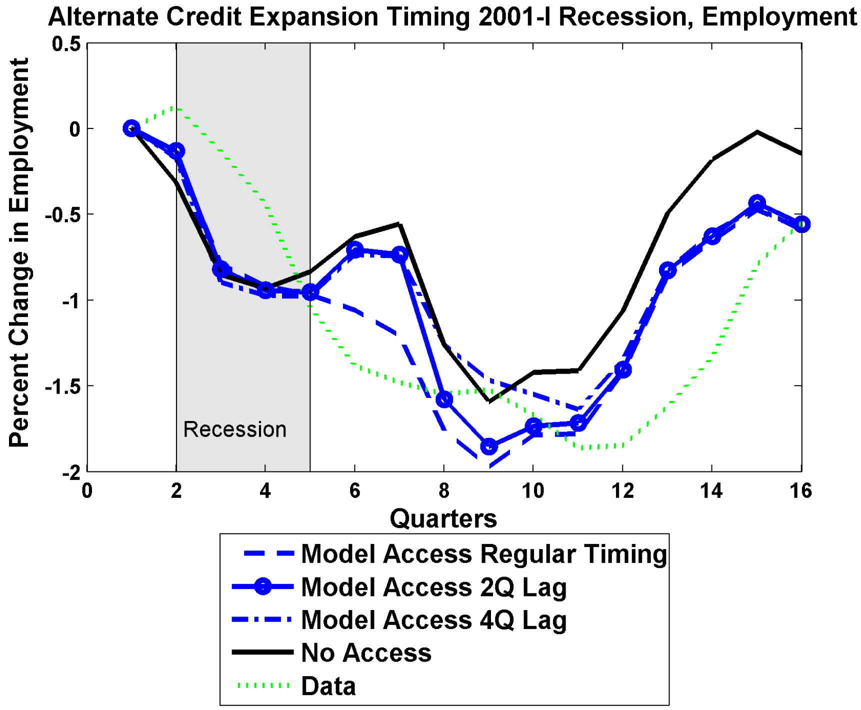
The equation that I estimate is given below:

$$p_{c,t} = A_c \theta_{c,t} (1 + \theta_{c,t}^\gamma)^{\frac{-1}{\gamma}} + \epsilon_t$$

Estimation yields $A_c = .974$ (significant at 1%), $\gamma = .383$ (significant at 1%), with a goodness of fit of .99. The relatively few observations (N=5) provided by the SCF limit my ability

[41] The credit denial question is given below: In the past five years, has a particular lender or creditor turned down any request you or your (husband/wife/partner) made for credit, or not given you as much credit as you applied for?

Figure 1.39: Alternate Credit Expansion Timing: Percentage Change in employment, 2001 Recession



to estimate A_c dynamically, let alone as a static parameter. Estimating the match elasticity after imposing $A_c = 1$ implies $\gamma = .372$ (significant at 1%) with a goodness of fit of .99.

1.10.7 Unemployment Duration

The model predicts an increase in unemployment durations of approximately $\frac{1}{2}$ week relative to an economy with fixed access (see Figure 1.40). In the data, there is an increase in trend unemployment durations of nearly 3.9 weeks. Thus the model is broadly consistent with the rise in unemployment durations shown in Figures 1.41 and 1.42. Table 1.18 shows that unemployment durations went up significantly since the 1980s at a low frequency whether or not the 2007-2009 recession is included in the sample.

Figure 1.40: Mean Unemployment Duration, Model 1974-2012

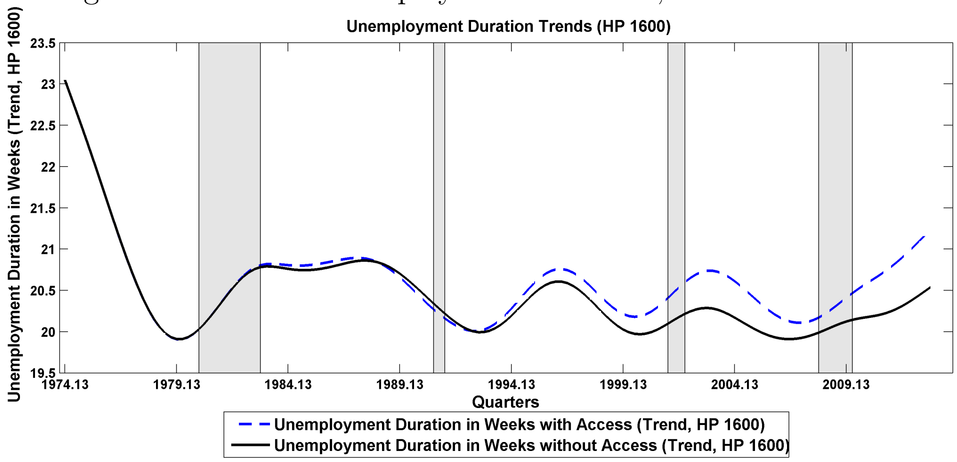


Figure 1.41: Mean Unemployment Duration, 1948-2012 (Source: CPS)

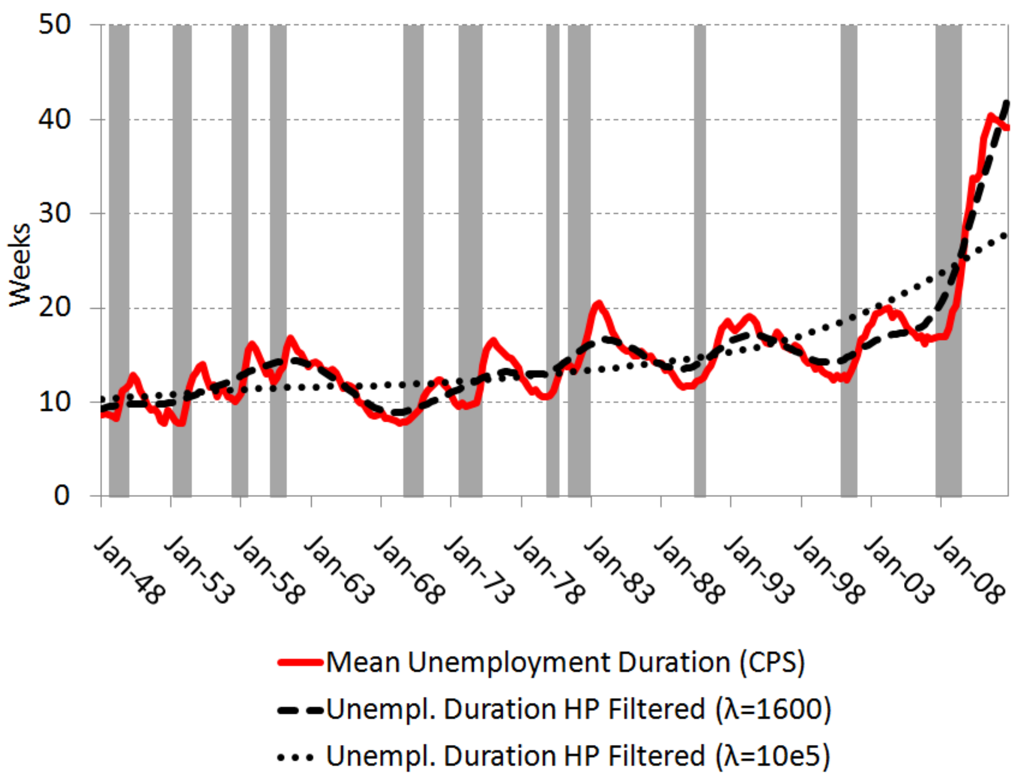


Figure 1.42: Mean Unemployment Duration, 1948-2007 (Source: CPS)

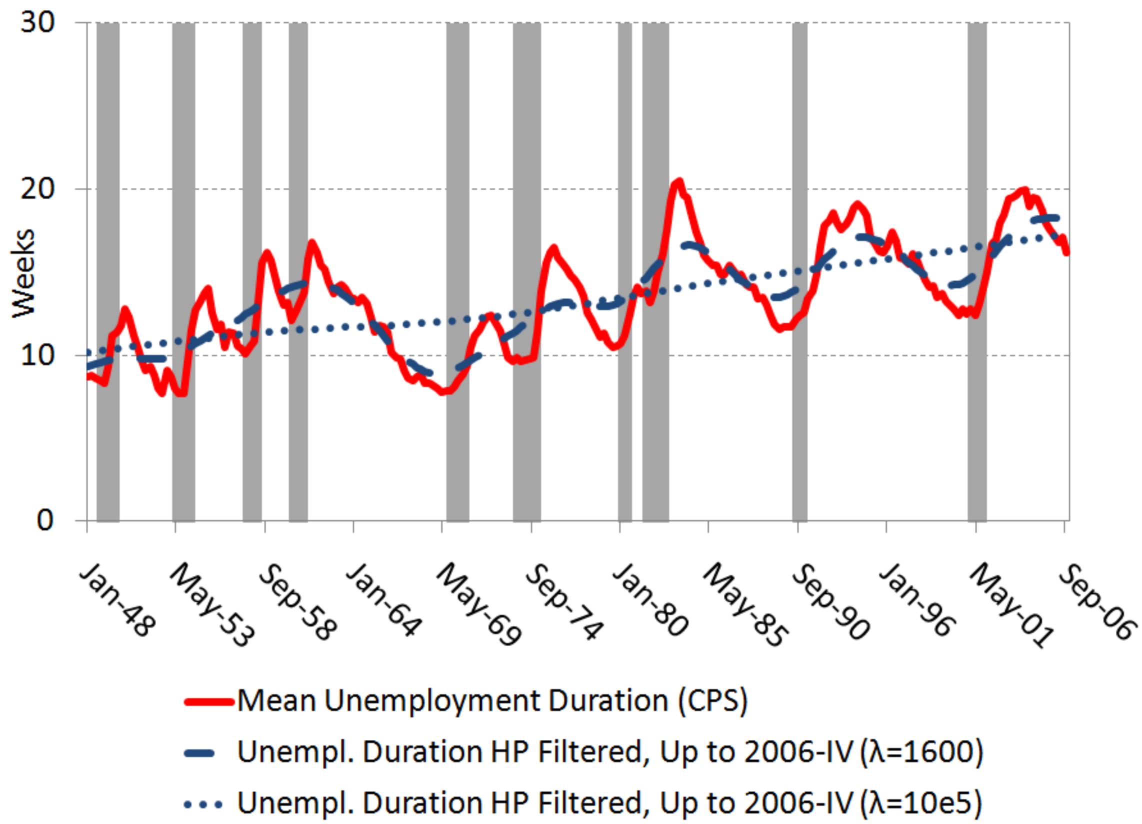


Table 1.18: Unemployment Durations

Recession Trough	Average Unemployment Duration	Unempl. Duration HP Filtered (λ=1600)	Unempl. Duration HP Filtered, Up to 2006-IV (λ=1600)	Unempl. Duration HP Filtered (λ=10e5)	Unempl. Duration HP Filtered, Up to 2006-IV (λ=10e5)
1975-I	11.4	12.5	12.5	12.3	12.7
1982-IV	17.5	16.0	16.0	13.4	13.9
1991-I	12.6	14.4	14.4	14.8	15.1
2001-IV	14.0	15.2	15.4	19.1	16.6
2009-II	22.6	25.2	NA	24.8	NA

CHAPTER 2

Foreclosure Delay and US Unemployment

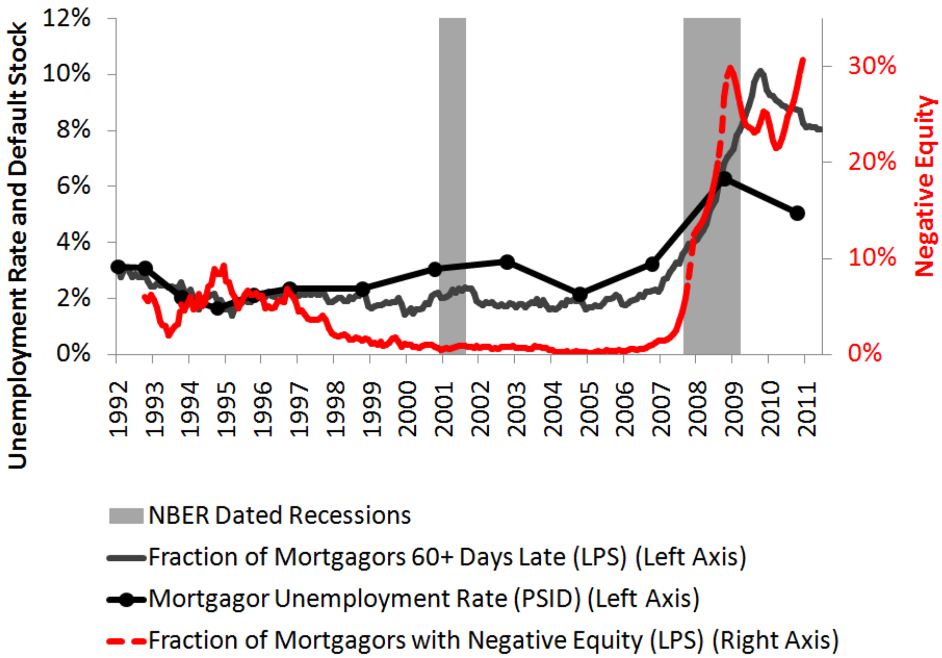
2.1 Introduction

A number of economists have suggested that chronically high unemployment may be related to the large drop in housing prices; Ohanian and Raffo (2011) document a strong relationship between labor market slumps and housing busts across OECD countries, with the highest unemployment and largest labor market wedges in countries with the largest declines in home prices (the U.S., Spain, and Ireland; see also Burnside et al. (2010)). As shown in Figure 2.1, the 2007-2009 recession in the United States is marked by a record number of unemployed mortgagors, a record number of delinquent mortgagors, and a record number of mortgagors with negative equity. Taken together, these facts suggest a need to better understand the employment-housing link.[1] In a series of papers that explores this relationship, Mulligan (2008, 2010, 2011) suggests that various government housing policies, including mortgage modifications, have increased unemployment by distorting incentives to find and accept jobs. In the present study, we explore the role that the housing bust played in the slow recovery by analyzing the job taking behavior of delinquent mortgagors.

We find strong evidence that suggests mortgagors, often times in response to job loss, use their ability to skip payments for long periods of time and then subsequently resume payments without being foreclosed upon as an implicit line of credit from the servicing bank. We show empirically, as well in a dynamic decision theoretic model, that the extra self-insurance provided by this line of credit significantly changes job finding and acceptance

[1] The image includes several data sources including the Panel Study of Income Dynamics (PSID) up to the most recent publicly available survey in 2009, Lender Processing Services Data (LPS) through 2011, CoreLogic House Price Data through 2011, and the National Bureau of Economic Research (NBER) business cycle dates.

Figure 2.1: Aggregate Time Series for the Mortgagor Unemployment Rate (PSID, Right Axis), Stock of Delinquent Mortgages (LPS, Right Axis), and Stock of Underwater Mortgages (LPS, Left Axis)



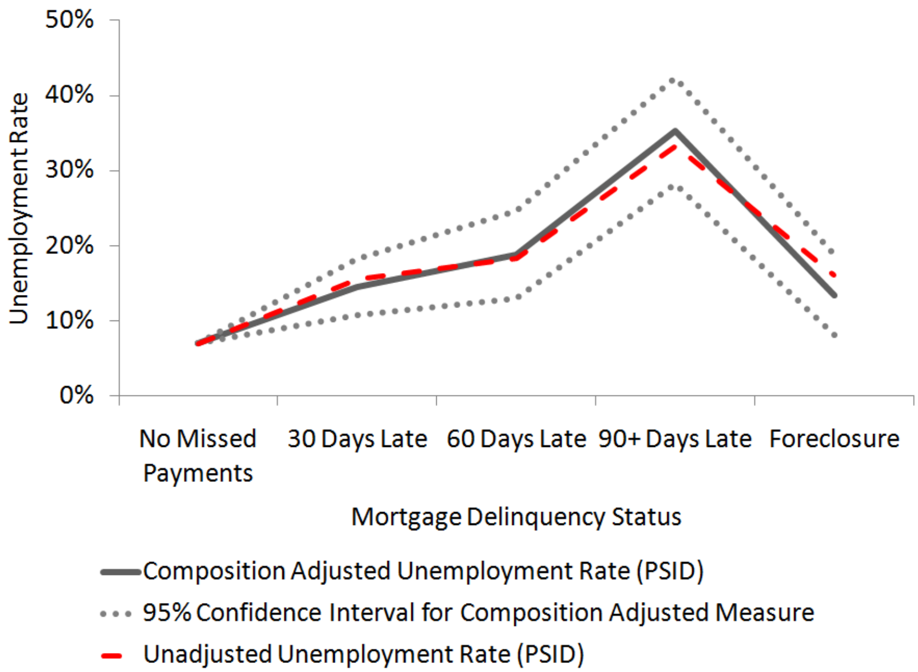
behavior. For example, Figure 2.2, which is derived from the 2009 Panel Study of Income Dynamics (PSID) Mortgage Distress Supplement, plots the cross-sectional unemployment rate of mortgagors by delinquency status.[2] As any standard model of self-insurance would predict, the figure shows that mortgagors who have missed 3 or more months worth of payments (90+ Days Late) have an unemployment rate 5 times greater than mortgagors who have not missed any payments (No Missed Payments).[3] However, the surprising aspect of the graph, and the main mechanism studied in this paper, is that the unemployment rate declines for those involved in foreclosure.

What is essential to understanding the incentive mechanism behind the non-monotonicity in Figure 2.2 is that the implicit credit line has a limited duration and this duration crucially

[2]The composition adjusted curve controls for differences in state laws, home equity, income, assets, and demographics; we are grateful to Peter Diamond for suggesting this correction. See Appendix 2.7.1.2 for more.

[3]For direct evidence that job loss causes default see Herkenhoff (2012b) and Herkenhoff (2012a).

Figure 2.2: Unemployment Rate Among Mortgagors by Delinquency Status, (Source: 2009 PSID Mortgage Distress Supplement)

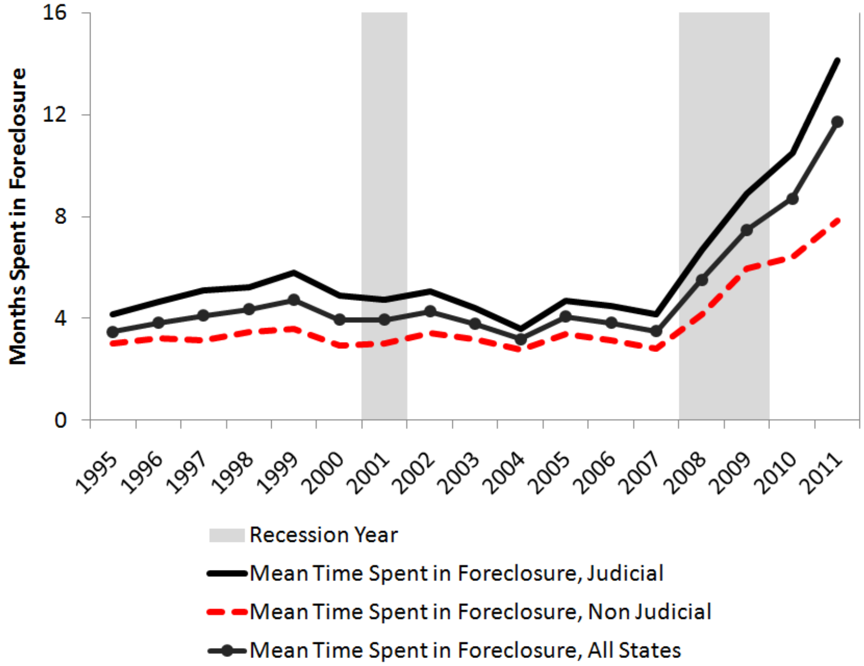


depends on the foreclosure timeline: the credit line opens with a default and is extinguished with a foreclosure. As a result, similar to the expiration of unemployment benefits, when foreclosure is imminent and the line of credit is about to run out, the mortgagor has incentives to find a job immediately.[4] The key difference is that unlike unemployment benefits, the delinquent mortgage payments must be repaid or recast over the life of the mortgage. Additionally, the incentives to find a job near foreclosure are considerably stronger than the incentives to find a job upon unemployment benefit expiration because of the potential forgone return to home tenure, the implications for credit access, the option value of owning a home, the potential deficiency judgement, etc. Figure 2.5, generated using the same methodology as Figure 2.2, shows that those involved in foreclosure are more likely to be employed than those who are severely delinquent.

There are several unique conditions that are peculiar to the 2007-2009 recession and its recovery that make default a viable implicit line of credit. Firstly, the record 3-fold increase

[4]For more on unemployment benefits and incentives effects see Chetty (2008) and Rothstein (2011).

Figure 2.3: Time spent in foreclosure (Source: LPS)

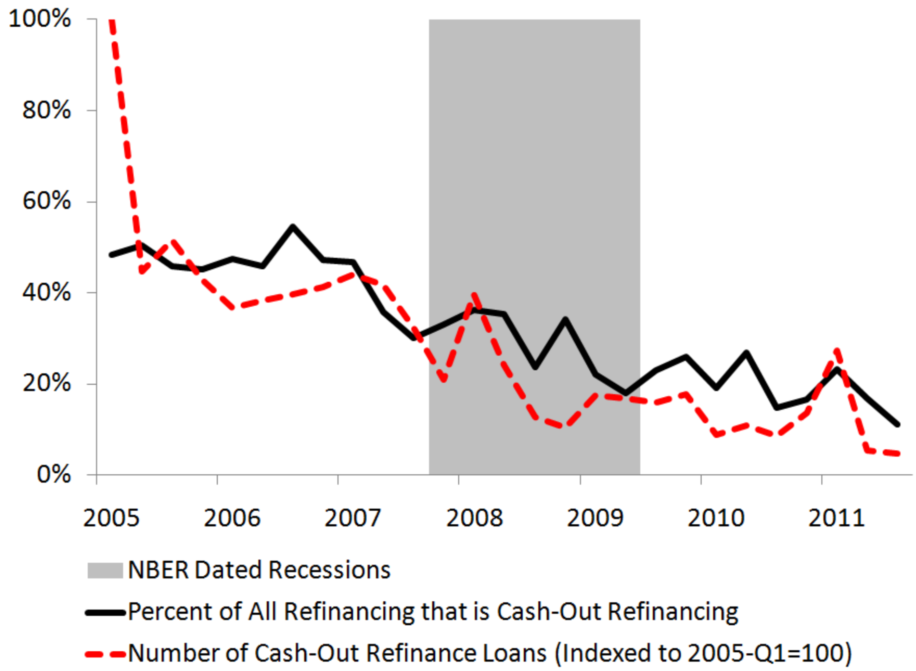


in foreclosure delays across all states ensures that mortgagors can skip payments for long periods of time and then subsequently resume payments without fear of losing their home. For example, Figure 2.3, which is based on Lender Processing Services (LPS) data, reveals that median time spent in foreclosure has jumped from 4 months in the early 2000s to 12 months during the 2007-2009 recession and ensuing recovery.[5] We argue that exogenous policies, such as the various state foreclosure moratoria, the robo-signing lawsuit, and the mortgage servicer settlement induced much of these delays. Secondly, the inability to access equity (if there is any equity) using traditional methods has made default a useful option. In the past, as analyzed by Hurst and Stafford (2004), unemployed mortgagors would use cash-out refinancing to extract equity from their homes to smooth consumption.[6] However, the 2005 housing crisis, through a combination of price declines and regulatory changes,

[5]This statistic is calculated for first residential loans in the LPS database at each date by isolating all loans in foreclosure and counting consecutive prior months in foreclosure. Later in the paper, we present several other measures that correct for state laws (judicial states require court action to foreclosure, non-judicial or "power-of-sale" states do not), censoring, and the competing risk of cures.

[6]When a house is worth more than its existing mortgage, it is possible to obtain a larger mortgage, pay off the original mortgage, and then consume/save the difference. This is called cash-out refinancing.

Figure 2.4: Cash Out Refinancing Activity (Source: LPS)



brought an end to the cash-out mortgage market. Figure 2.4 shows that according to Lender Processing Services (LPS) data, which is a nationally representative dataset that covers close to 1/3 of the residential mortgage market, almost 50% of all refinancing was cash-out refinancing in late 2005-I; by 2011-III this statistic was just above 15%.[7] Without this market, homeowners have no choice but to default or sell in order to smooth consumption. By skipping payments that are effectively added to the remaining principal balance, mortgagors are implicitly borrowing against the (limited) equity in their house.

To isolate the mechanism of interest and properly identify how this new self-insurance mechanism has impacted aggregates such as the unemployment rate and output, we build a dynamic decision theoretic model with realistic mortgage default decisions and endogenous search effort and reservation wage profiles. We then use this model as lab to study the impact of the various state foreclosure moratoria, the robo-signing lawsuit, and the mortgage servicer settlement on the model's endogenously generated aggregates following a period of depressed times. We find that in a recovery with policy induced foreclosure delays, due to distortions

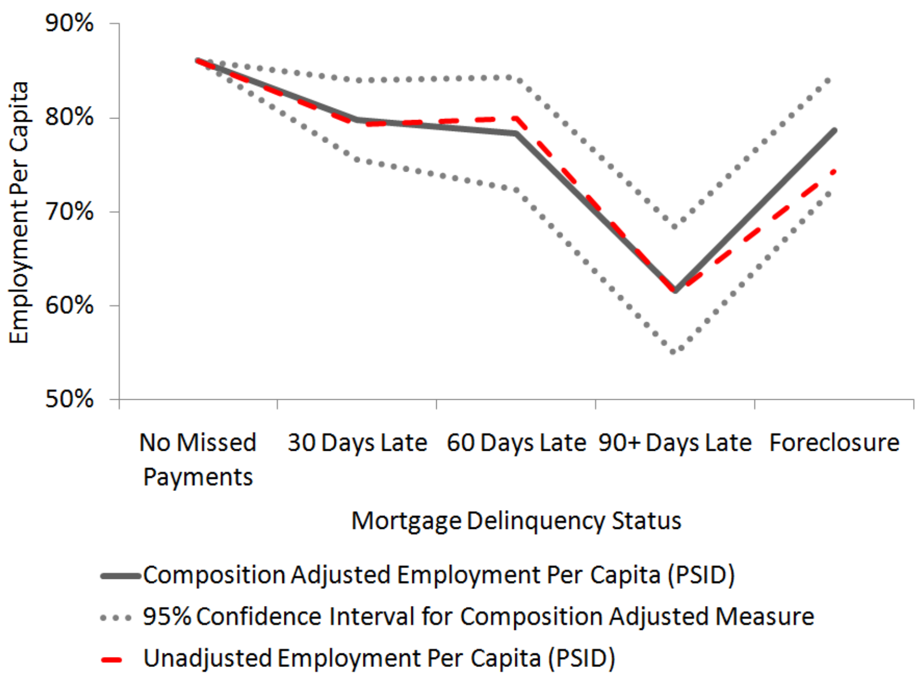
[7]See He et al. (2013) for more implications related to the boom and bust of home equity markets.

in job search and wage acceptance decisions, the unemployment rate is between $\frac{1}{3}$ and $\frac{3}{4}$% greater than it otherwise would be. However, the benefit of the delays and additional self-insurance is better wage outcomes, resulting in an additional $\frac{1}{10}$% greater long-run output.

The rest of the paper is organized as follows: Section 2.2 includes the data, Section 2.3 describes the model, Section 2.4 describes the calibration and steady state results, Section 2.5 includes the main turbulence experiment, and Section 2.6 concludes.

Appendix 2.7.1 includes the data description and small sample analysis, Appendix 2.7.2 has some details on the parametrization, Appendix 2.7.3 includes empirical work designed to quantify the incentive effects of the delays and sort out the role of congestion versus policy induced delays, Appendix 2.7.4 includes the literature review, Appendix 2.7.5 includes more discussion of the model.

Figure 2.5: Employment Per Capita Among Mortgagors by Delinquency Status, (Source: 2009 PSID Supplement)



2.2 Data

2.2.1 Employment and Foreclosure

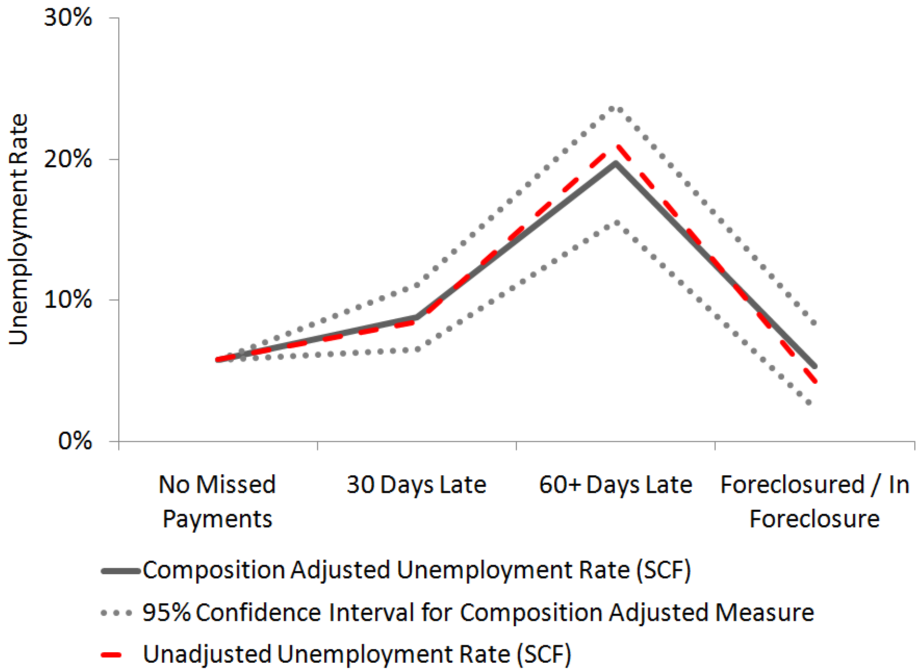
As mentioned in the introduction, Figures 2.2 and 2.5, which show the unemployment rate by delinquency status and employment per capita by delinquency status among 2009 PSID mortgagors respectively, exhibit a striking employment uptake among those involved in foreclosure. To construct the image, we use the 2009 PSID Core/Immigrant sample including all non-disabled working age heads with mortgages and those who, as of the last survey date in 2007, had a mortgage but subsequently lost it in foreclosure. The mortgage-specific delinquency question is posed as of the survey date: "How many months [on your mortgage] are you behind?" The foreclosure question refers to foreclosure completed or initiated between the two survey dates, 2007 and 2009: "Has your bank or lender started the process of foreclosing on your home?" All respondents that had foreclosures between the years 2007 and 2009 and had a mortgage in either 2007 or 2009 were counted as Foreclosed/In Foreclosure. The employment status question is posed as of the survey date and income is measured over the entirety of the prior year. We bin mortgagors by reported delinquency status (No missed payment, 30 Days Late, 60 Days Late, 90+ Days Late, and Foreclosed/In Foreclosure) and then report the relevant statistic by cell- this is what is reported as the "unadjusted" statistic. We then estimate the average marginal treatment effects from a logit of an employment indicator on indicators for each of the reported delinquency statuses, controls for Negative Equity, Liquid Assets, Illiquid Assets, Unsecured Debt, Prior Income, Age, Sex, Race, Education, and other demographic characteristics, State Judicial Controls, and State Recourse Controls. For the employment per capita composition correction the estimation is on the entire working age population, and for the unemployment rate composition correction the sample is further restricted to labor force participants. The average marginal treatment effects for the delinquency dummies estimated in the logit, which are measured relative to the omitted group of homeowners who are current, are then used to compute the composition adjusted curves. The 95% confidence interval is constructed using the associated standard errors.

We conduct an identical exercise using the 2007-2009 SCF panel, separating mortgagors into three delinquency statuses (30 Days Late, 60+ Days Late, and Foreclosed/In Foreclosure). The study includes all non-disabled working age heads with mortgages and those who, as of the last survey date in 2007, had a mortgage but subsequently lost it in foreclosure. The SCF words their default questions less precisely: "Now thinking of all the various loan or mortgage payments you made during the last year, were all the payments made the way they were scheduled, or were payments on any of the loans sometimes made later or missed?" For those who answered yes to the above question, they were asked: "Were you ever behind in your payments by two months or more?" This question does not necessarily refer to mortgage payments, and so we must assume that those who report missing payments and have a mortgage were in default on their mortgage. Those who reported being late over the last year, but never missing two or more months worth of payments, were counted as 30 days late. Those who missed two or more months worth of payments were subsequently counted as 60+ days late. The SCF asks a similar foreclosure question to the PSID "Have you ever had a foreclosure proceeding brought against a property you have owned?" Those who responded that a foreclosure occurred between 2007-2009, and had a mortgage in either 2007 or 2009, were counted as "Foreclosed/In Foreclosure." Employment status is recorded as of the survey date and income is reported for the prior year. Thus, the composition correction is *exactly* the same as the PSID composition correction less the controls for judicial/recourse states (this is because the SCF does not report state residency).

The employment measures by delinquency which are based on the Survey of Consumer Finances (SCF), Figures 2.6 and 2.7, corroborate the patterns of Figures 2.2 and 2.5 by also exhibiting a decline in unemployment for those in involved in foreclosure and a corresponding increase in employment. Moreover, for SCF respondents in foreclosure, even after correcting to potential strategic default (i.e. controlling for negative equity in the composition correction calculation), have an unemployment rate close to other mortgagors who are making payments.

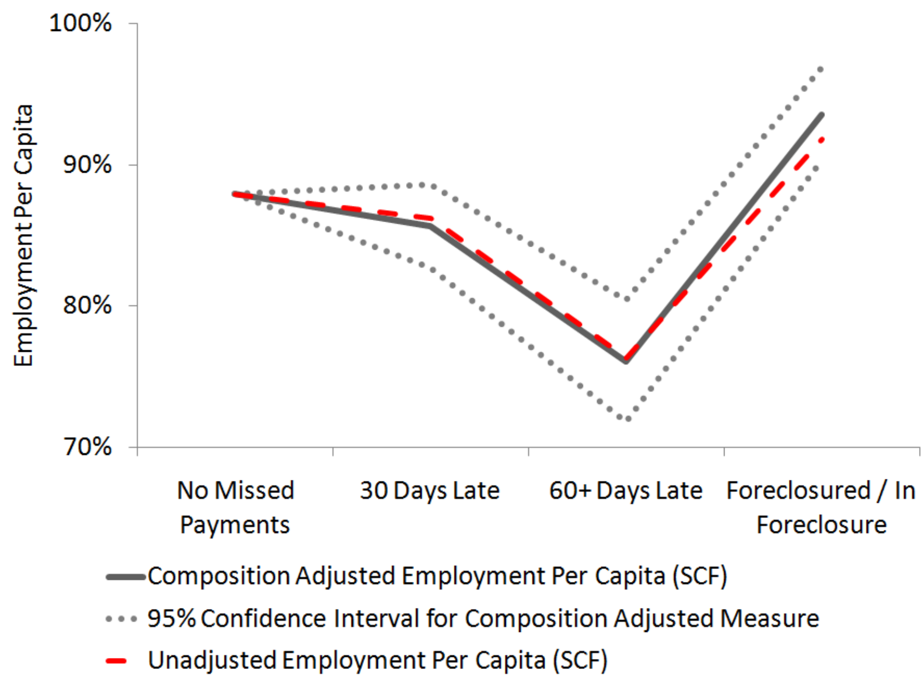
We conduct a flow analysis by limiting the sample further and employing an experimental methodology: the control group is comprised of those mortgagors who were delinquent over

Figure 2.6: Unemployment Rate Among Mortgagor Heads of Household by Delinquency Status, (Source: 2009 SCF)



the last 12 months in the SCF, reported a positive unemployment duration over the last 12 months, and did *not* receive a foreclosure notice; the treatment group is comprised of those who were delinquent over the last 12 months in the SCF, reported a positive unemployment duration over the last 12 months, and did receive a foreclosure notice. We find that those who were given the treatment were 40% more likely to be employed as of the survey date (see Appendix 2.7.1.3 for more details).

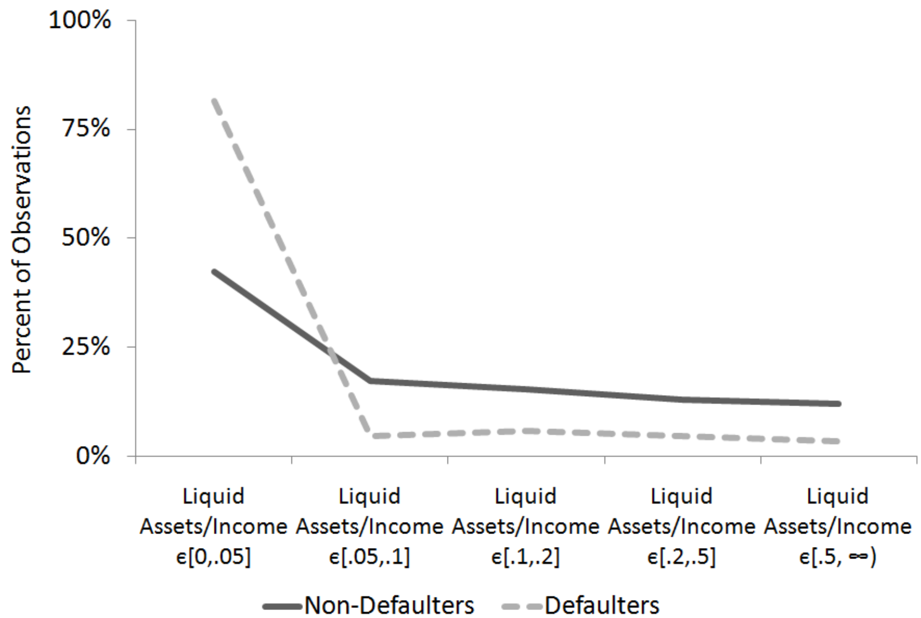
Figure 2.7: Employment Per Capita Among Mortgagors by Delinquency Status, (Source: 2009 SCF)



2.2.2 Liquid Assets

When is default a viable line of credit? Given the transaction costs associated with selling a home (including time to sale), the option value of owning a home, and the return to home tenure, negative equity is not a necessary condition for default (it is of course a necessary condition for completed foreclosure). Mortgagors can default out of pure liquidity needs. In a sample of all non-disabled working age heads with mortgages in the 2009 PSID Core/Immigrant sample, most mortgagors that default have close to zero liquid assets, where liquid assets includes regular checking and savings accounts, money market funds, CDs, government saving bonds, treasury bills, etc. Figure 2.8 illustrates that almost 80% of defaulters were constrained (for more on strategic default, see the follow up paper [cite our strategic default paper]).

Figure 2.8: Histogram of Liquid Assets to Income (Source: 2009 PSID)



2.2.3 Institutional Details of Delinquency

In order to interpret the next portion of data, this section provides background information on the way mortgage default and foreclosure typically work. It is important to note that there is considerable variability across servicers and states as to how they handle foreclosure.

2.2.3.1 Interest on Missed Payments

Mortgage payments are usually due on the first of the month, and a late fee is assessed if the payment is not received within the first two weeks of the month. The late fee is a fraction of the payment amount. If the scheduled payment is $1000 and the late fee is 3%, then the mortgagor must pay $1030 in the following month. Most late fee interest rates fall in the range of 3% to 6% (see Goodman (2009)).

2.2.3.2 Foreclosure Process

The order of events in a foreclosure has potential to distort buyers' incentives to pay since foreclosure is a slow and relatively predictable process. The usual order of events is given below:

1. Miss payments (30+ days late, Enter Delinquency)
2. Notice of Default (Enter Foreclosure)
3. Notice of Sale (1 month prior to foreclosure sale)
4. Foreclosure Auction (Sheriff Sale)
5. Eviction
6. *Potential* Deficiency Judgment if Sale Price < Remaining Mortgage Balance
7. Ineligible for government backed loans for 7 years (see Lowrey (2010)).

Legally, if a mortgagor breaks the terms of the mortgage, the bank can ask for the entire debt to be paid immediately. If the mortgagor cannot pay this entire amount, the bank can foreclosure. There are two main types of foreclosures in the United States (i) judicial, and (ii) non-judicial (see Ghent and Kudlyak (2011) for state classifications). To complete a judicial foreclosure, the bank that owns the mortgage must sue the person living in the home in a state court. A judge is required to rule on the case before a foreclosure sale can occur. A foreclosure sale is called a 'sheriff sale.' A non-judicial foreclosure, also known as a foreclosure by power of sale, allows the bank to sell the house without the court's approval. A notice of default explains that the bank intends to sell the property and that if the debt is not cured, there will be a public auction for the house. A notice of sale is issued 1 month prior to the foreclosure auction date. If the bank is unable to sell the home in a public auction, which means 'no acceptable bids are made,' or the bank bids for the house itself, then the house becomes owned by the bank. The term for this is 'real estate owned' (REO).

It is possible to temporarily postpone the foreclosure process by bankruptcy (however the courts cannot modify loans) or challenging the banks' right to the property they are trying to foreclose upon.[8] The recent robo-signing scandal has to do with the banks' inability to prove that they had the right of interest in the property, i.e. they do not have the correct paperwork showing that they have a mortgage on the property.

Regardless of the foreclosure procedure, each state has laws about recourse and non-recourse loans. In a state with recourse, selling a home for less than the amount due may result in a deficiency judgment. Deficiency judgments mandate that the borrower pay the difference between the sale price and the amount owed on the mortgage. Many mortgages however are non-recourse loans, meaning that the bank cannot go after the assets of the person who held the mortgage. As a result, in most cases, borrowers are exempt from deficiency judgments. In California, for instance, the first purchase-money mortgage for a residential property is a non-recourse loan. However, the state laws are not entirely uniform across all mortgages, e.g. all refinanced loans in California are recourse.

There is also a chance for homeowners to 'redeem' their homes after foreclosure if they are able to raise enough money. These redemption periods can last up to a year and vary

[8]For more on bankruptcy and foreclosure, see Li and White (2009), Luzzetti and Neumuller (2012), and Mitman (2011)

by state.

2.2.4 Default $\neq$ Foreclosure

In most standard models with limited commitment and housing, default is synonymous with leaving the home (see Garriga and Schlagenhauf (2009), Corbae and Quintin (2009), and Chatterjee and Eyigungor (2011)). This assumption makes it difficult to match the actual default rates observed in the real world.[9] Our earlier work found that delays played an important role in labor market outcomes through the *relocation channel*. As Herkenhoff and Ohanian (2011) find in a search economy and Chatterjee and Eyigungor (2009) find in an endowment economy, a small delay with free rent can dramatically change incentives to skip payments. On the empirical side, it is well established that default episodes are protracted and often times do not result in foreclosure (see Pennington-Cross (2010) for subprime mortgages and Capozza and Thomson (2006)). To our knowledge, we are the first to model the "ins" and subsequent "outs" of mortgage delinquency in a dynamic model optimization model with mortgages and labor markets.

Table 2.9 is a transition matrix for all possible mortgagor delinquency states. The rows are the beginning states, and the columns are the ending states. The period is 1-month, and the table includes two sets of entries: the black entries refer to the transition matrix calculated from 2009-2011 data, and the red underlined entries are for the 2001-2003 data. Table 2.9 succinctly establishes several stylized facts:[10]

i. Default/Delinquency is often temporary, with frequent transitions to current (current means up-to-date on payments) or closer to being current (i.e. the lower triangular entries for the states "30 Days Late", "60 Days Late", and "90+ Days Late" are non-sparse)

[9] Several authors use 2-4 year periods to make the discount rate small enough to generate default

[10] This is a transition matrix, so in order to read this table, the rows are the starting state at the beginning of the month and the columns are the possible states next month. For instance, in a given month the probability of moving from being current to 30 days late is 1.7% during the 2009-2011 period. See Appendix 2.7.2 for the strategy used to identify the modifications.

ii. Foreclosure is often temporary, with frequent transitions to current or closer to being current (foreclosure is the time between the notice of default being delivered and eviction)

iii. Entry into foreclosure is a slow process, loans remain in the 90+ days late category for a protracted period of time (in the absence of other outcomes, during the 2001-2003 period, loans were in this category for 1/(1-.68)=3.2 months on average and during the 2009-2011 period, loans were in this category for 1/(1-.83)=5.9 months on average)

iv. Conditional on reaching foreclosure, households spent significant portions of time in foreclosure (in the absence of other outcomes, during the 2001-2003 period, loans were in this category for 1/(1-.752)=4.0 months on average and during the 2009-2011 period, loans were in this category for 1/(1-.883)=8.3 months on average)

v. The unconditional monthly hazard of receiving a foreclosure notice dropped by 1/3 (from 14.6% in 2001-2003 to 9.8% in 2009-2011)

vi. The unconditional monthly hazard completing foreclosure by REO or Liquidation dropped by 1/3 (from 8.7% in 2001-2003 to 5.6% in 2009-2011)

vii. The self-cure probabilities (the lower triangular entries) decreased in every single category between 2001-2003 and 2009-2011.

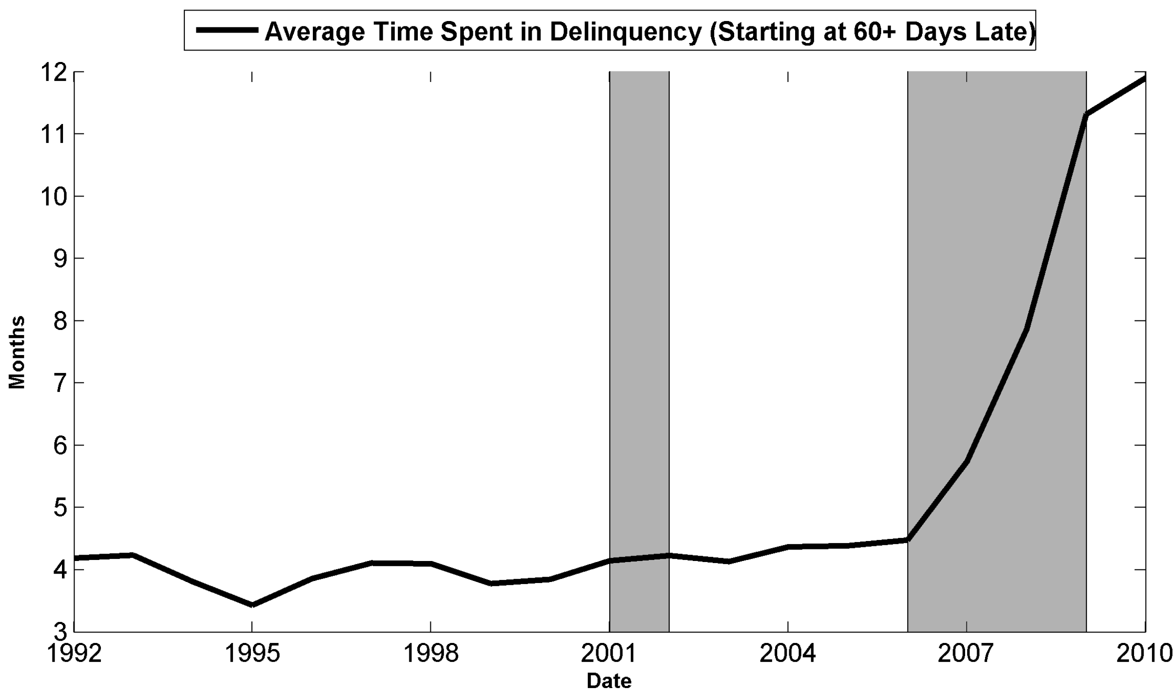
Figure 2.9: Homeowner Transitions 2009-2011 (Black) Homeowner Transitions 2001-2003 (Red and Underlined) (Source: LPS)

	Current	30 Days Late	60 Days Late	90+ Days Late	In Foreclosure	REO	Paid Off	Liquidated	Modified
Current	96.0 / 97.0	1.5 / 1.7	0.0 / 0.0	0.0 / 0.0	0.0 / 0.0	0.0 / 0.0	2.5 / 1.3	0.0 / 0.0	0.0 / 0.0
30 Days Late	41.2 / 24.4	38.7 / 47.8	15.9 / 26.7	0.4 / 0.1	0.0 / 0.0	0.0 / 0.0	3.8 / 0.6	0.0 / 0.0	0.0 / 0.3
60 Days Late	18.7 / 5.6	21.0 / 11.3	24.7 / 37.8	30.4 / 42.8	2.6 / 1.4	0.0 / 0.0	2.5 / 0.2	0.0 / 0.0	0.0 / 1.0
90+ Days Late	7.1 / 0.8	3.4 / 0.6	4.7 / 1.6	68.4 / 83.0	14.6 / 9.8	0.5 / 0.3	1.3 / 0.2	0.1 / 0.5	0.0 / 3.3
In Foreclosure	5.3 / 0.6	1.1 / 0.1	0.1 / 0.1	7.8 / 4.6	75.2 / 88.3	8.3 / 4.9	2.0 / 0.2	0.4 / 0.7	0.0 / 0.7
REO	0.0 / 0.0	0.1 / 0.0	0.0 / 0.0	0.8 / 0.4	0.6 / 0.3	87.3 / 90.3	0.1 / 1.3	11.1 / 7.7	0.0 / 0.0
Paid Off	0.0 / 0.0	0.0 / 0.0	0.0 / 0.0	0.0 / 0.0	0.0 / 0.0	0.0 / 0.0	100.0 / 100.0	0.0 / 0.0	0.0 / 0.0
Liquidated	0.0 / 0.0	0.0 / 0.0	0.0 / 0.0	0.0 / 0.0	0.0 / 0.0	0.0 / 0.0	0.0 / 0.0	100.0 / 100.0	0.0 / 0.0
Modified	0.0 / 0.0	0.0 / 0.0	0.0 / 0.0	0.0 / 0.0	0.0 / 0.0	0.0 / 0.0	0.0 / 0.0	0.0 / 0.0	100.0 / 100.0

2.2.5 Time Spent in Default

To handle the censoring issue in the data, we calculate the mortgage status transition matrix for each year. We then simulate the 'ergodic distribution' for this matrix using Monte Carlo simulation with several thousand mortgages over 35 years. Using this measure, the average time spent in default, regardless of termination type, went from 4 months up to 12 months. Figure 2.10 shows this change with the business cycles shaded along the axis.[11]

Figure 2.10: Delinquency Spells, Monte Carlo Simulations Based on LPS Transitions (Source: LPS and Author's Calculations)



[11]In Appendix 2.7.1.2, Figure 2.24 illustrates the increase in delays controlling for congestion/institutions, censoring, and the competing risk of curing.

2.3 Search Model with "Ins" and "Outs" of Default

2.3.1 Environment

Time, indexed by $t = 0, 1, 2, 3, \ldots$, is discrete and runs forever. The model economy is populated by a heterogeneous mass of risk averse and finitely-lived agents who are subject to both idiosyncratic and aggregate shocks. Each period agents may participate in up to three partial equilibrium markets: the labor market, the asset market, and the housing market.

The labor market is characterized by search frictions similar to Ljungqvist and Sargent (1998) and Krueger and Mueller (2010). Agents exert a search effort s_t at a utility cost $x(s_t)$ in order to increase their probability of receiving a wage offer. Wage offers are drawn from an exogenous and stationary distribution $F(\cdot)$, and agents are free to reject offers. This gives rise to a reservation wage profile $w^*(\cdot)$, a function of the state space of the agent. Once an offer is accepted, the wage will remain constant until the arrival of a random job destruction shock.

In the asset market, agents can save ($a_t > 0$) at a fixed risk free rate $\bar{r}$ in order to smooth their consumption.[12]

In the housing market, homeowners can sell their homes, but once an agent becomes a renter, they are a renter for the remainder of their life as in Corbae and Quintin (2009). Homeowners receive a flow utility from housing services given by z_h and renters receive a flow utility of housing given by z_r where $z_r < z_h$. In our model and similar to Chatterjee and Eyigungor (2009), every homeowner has a mortgage perpetuity and must either make the required payment or default; however, our major point of departure from existing models is that we treat default and foreclosure not as one period events, but as protracted and potentially reversible episodes that influence job search behavior.[13]

Given access to these three markets, agents seek to minimize their disutility from search

[12] It is standard in defaultable debt models to take the risk-free savings rate as exogenously given, see Eaton and Gersovitz (1981) or Benjamin and Wright (2009).

[13] This model is of the same general type explored in an earlier paper, Herkenhoff and Ohanian (2011), where mortgage default does not necessarily lead to eviction.

while maximizing their flow utility over non-durable consumption c_t and their flow from housing services z_{i_t} where $i_t \in \{h, r\}$ ('h' is for homeowner, 'r' is for renter). Let $\widehat{\beta} = (1-p_d)\beta$ be the death adjusted discount factor where p_d is the probability of dying and β is the household discount factor. The household objective function is then given by:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \widehat{\beta}^t \big(u(c_t, z_{i_t}) - x(s_t)\big)$$

Since we are interested in labor market recoveries and downturns, we include aggregate risk. We define θ_t to be the aggregate state at date t, where θ_t follows a Markov process over two states of the world, high (θ_H) and low (θ_L). We parametrize the model so that the aggregate state directly influences the job finding rate, job destruction rate, and house prices in such a way that when the aggregate state is high, the economy is in an expansion and when the aggregate state is low, the economy is in a contraction. The next few paragraphs elaborate on the role the aggregate state plays in each of the three markets described above.

In the labor market, the aggregate state indexes both the job finding rate and the job destruction rate. Recall that while unemployed, agents search for a job with intensity (s_t) at a weakly convex disutility ($x(s_t)$). The probability of obtaining an offer (which I will call the job finding probability) is a function of the aggregate state. In good times the job finding probability $\pi(s_t, \theta_t)$, which is weakly concave in s_t, improves ($\pi(s_t, \theta_H) > \pi(s_t, \theta_L)$). If the agent finds a job, the wage offer is drawn from a stationary distribution $F(w)$. The agent is free to turn down the job offer which gives rise to a reservation wage profile $w^*(x_t)$, where x_t is the state vector of the agent. While employed, there is an aggregate state contingent risk of being laid-off $\delta(\theta_t)$, such that in good times the probability of being laid off is lower than in bad times ($\delta(\theta_H) < \delta(\theta_L)$).

To keep the model tractable, mortgages are perpetuities and a fraction f_m of newly born agents are endowed with a mortgage. Mortgages have a constant required payment (c_h) denoted in units of consumption, and the house price ($p(\theta_t)$) parametrically depends on the aggregate state such that ($p(\theta_L) < p(\theta_H)$). We will always assume that in good times, a homeowner can break even ($p(\theta_H) = \frac{c_h}{r_b}$), where r_b is the fixed interest rate the bank charges on loans. In bad times, the homeowner is weakly underwater ($p(\theta_L) \leq \frac{c_h}{r_b}$) (see the parametrization section for more details).

A mortgagor that has made all past payments must make a discrete choice over 3 options at the start of the period: (i) make the payment c_h (ii) skip the payment c_h, or (iii) sell the house. In the event of a low wage draw or unemployment shock, the mortgagor may default to smooth consumption. In this world, since default is not synonymous with eviction, households may enter and exit default as they like; therefore we must keep track of time spent in default (n_t). A mortgagor that is already in default must make a discrete choice over 3 similar options at the start of the period: (i) make the two most delinquent payments (ii) remain in default, or (iii) sell the house.

For an agent who has spent n_t periods in default, the function $\lambda_F(n_t)$ describes the probability of being foreclosed upon as a function of the number of missed payments. As the time spent in default (n_t) increases, the odds of eviction and liquidation of the house increases, i.e. $\lambda_F(n) \leq \lambda_F(n') \quad \forall n' > n$ (see Figure 2.11 for an example of the foreclosure probability). If the homeowner sells or is foreclosed upon, they must rent. We will always assume that the mortgage payment is strictly greater than the rental payment ($c_h > c_r$), but the utility flow from owning a home strictly dominates the utility flow from renting ($z_h > z_r$). Rent is set such that the renter with the lowest possible unemployment benefits receives subsistence income, $\underline{b}$.

It is possible to stop foreclosure by paying twice, and to simplify the matter, the homeowner must pay the *two longest outstanding mortgage payments with interest* ($(1+r_b)^{n-1}c_h + (1+r_b)^n c_h$), where r_b is the interest rate banks charge on late payments. This payment behavior is consistent with the transitions observed in Figure 2.9 where homeowners slowly transit out of delinquency rather than curing entirely at once. Likewise, the fact that starting to self-cure stops the foreclosure process is consistent with anecdotal evidence about banks' preference to collect late fees (see Thompson (2010)).

In the event of a foreclosure, the house is sold at a discount of $1 - \chi$. If $\chi = .95$, this corresponds to a 5% discount and the house is sold for $\chi \cdot p(\theta_t)$. For homes sold at a loss L, $G(L)$ is a function which describes the potential deficiency judgement owed by the ex-homeowner.

The unique feature of this model is that over the course of the mortgage default episode the reservation wage and search effort of an agent change nontrivially. Upon initially defaulting, the foreclosure probability is low and thus agents will avoid wage cuts and hold out for high paying jobs. As foreclosure becomes more likely, they are willing to accept wage cuts so long as it covers their late payments and they can save the house. Likewise, when the probability of foreclosure is low, the agent economizes on search effort; in the later stages of default, eviction is imminent, and so the agent searches intensely trying to find any wage that will cover the mortgage payment.

We will focus on the recursive representation of this problem, and so from this point on we will drop time subscripts and use primes to denote tomorrow's values.

2.3.2 Employed Discrete Choices

The value function for the discrete choice faced by an employed homeowner with wage w, liquid assets a, with no late payments ($n = 0$), and in aggregate state θ is $VE_h(w, a, 0; \theta)$ (in general, if there is a V in front of a value function it involves a discrete choice, e.g. $VE_h(w, a, 0; \theta)$ is the discrete choice for an employed agent and $E_h^g(w, a, 0; \theta)$ is one particular option). An employed homeowner that is in good standing, which means no missed payments (n=0), has the following set of choices: pay ($E_h^g(w, a, 0; \theta)$), default and face the risk of foreclosure ($E_h^d(w, a, 0; \theta)$), or sell ($E_h^s(w, a, 0; \theta)$). Thus, the value of entering the period in good standing is given below:

$$VE_h(w, a, 0; \theta) = \max_{Pay,\ Default,\ Sell} \left\{ E_h^g(w, a, 0; \theta), E_h^d(w, a, 0; \theta), E_h^s(w, a, 0; \theta) \right\}$$

When $n \geq 1$, this means that the homeowner has skipped n payments and owes the lender multiple payments in order to stop foreclosure. The delinquent homeowner faces the choice of paying ($E_h^p(w, a, n; \theta)$), skipping another payment which introduces the risk of foreclosure that occurs with $\lambda_F(n)$ probability $(\lambda_F(n)E_h^f(w,a,n;\theta)+(1-\lambda_F(n))E_h^d(w,a,n;\theta))$, or selling the property $(E_h^s(w,a,n;\theta))$. Taking these options into account, the discrete choice for the employed homeowner who has missed at least one payment $(n \geq 1)$ is given below:

$$VE_h(w,a,n;\theta) = \max_{\textit{Pay Twice, Default, Sell}} \big\{E_h^p(w,a,n;\theta),\ \lambda_F(n)E_h^f(w,a,n;\theta) \\ + (1-\lambda_F(n))E_h^d(w,a,n;\theta),\ E_h^s(w,a,n;\theta)\big\}$$

Let $D_h(b,a,n;\theta)$ summarize the discrete choice decision for homeowners.

2.3.3 Employed Value Functions

An employed renter with wage w and liquid assets a has value function $E_r(w,a;\theta)$. The only choice made by an employed renter is next period's liquid asset holdings a'. At the end of the period, with probability $\delta(\theta')$, an employed renter is laid off and receives unemployment benefits of $b(w)$. The flow utility from renting is z_r, the rental payment is c_r, $\widehat{\beta}$ is the death adjusted discount factor, and $\bar{r}$ is the return on savings. Thus the problem solved by an employed renter is given below:

$$E_r(w,a;\theta) = \max_{a'}\ u(c,z_r) + \widehat{\beta}\mathbb{E}\big[(1-\delta(\theta'))E_r(w',a';\theta') + \delta(\theta')U_r(b(w),a';\theta')\big]$$

Such that

$$c + c_r + a' = w + (1+\bar{r})a$$

An employed homeowner with wage w, liquid assets a, current payments $n = 0$, and aggregate state θ that pays on time has a value function $E_h^g(w,a,0;\theta)$. The mortgage payment is c_h consumption units, z_h is the flow utility from living in the house, and $\delta(\theta)$ is the aggregate state contingent job destruction probability.

$$E_h^g(w,a,0;\theta) = \max_{a'}\ u(c,z_h) + \widehat{\beta}\mathbb{E}\big[(1-\delta(\theta'))VE_h(w',a',0;\theta') + \delta(\theta)VU_h(b(w),a',0;\theta')\big]$$

Such that

$$c + c_h + a' = w + (1 + \bar{r})a$$

An employed homeowner in default ($n > 0$) with wage w and liquid assets a that decides to make no payments solves the following problem:

$$\begin{aligned} E_h^d(w, a, n; \theta) = \max_{a'} \; & u(c, z_h) + \widehat{\beta}\mathbb{E}\big[(1 - \delta(\theta'))VE_h(w', a', n + 1; \theta') \\ & + \delta(\theta')VU_h(b(w), a', n + 1; \theta')\big] \end{aligned}$$

Such that

$$c + 0 + a' = w + (1 + \bar{r})a$$

Notice that the delinquency indicator ticks upwards $n' = n + 1$ and an unemployed person receives $b(w)$ in benefits.

An employed homeowner that is in default and begins to pay current ($E_h^p(w, a, n; \theta)$) is not subject to foreclosure. In this case the delinquency ticker moves down $n' = n - 1$. To simplify the matter, the homeowner must pay the *two longest outstanding mortgage payments with interest* ($(1 + r_b)^{n-1}c_h + (1 + r_b)^n c_h$). The full problem is written below:

$$\begin{aligned} E_h^p(w, a, n; \theta) = \max_{a'} \; & u(c, z_h) + \widehat{\beta}\mathbb{E}\big[(1 - \delta(\theta'))VE_h(w', a', n - 1; \theta') \\ & + \delta(\theta')VU_h(b(w), a', n - 1; \theta')\big] \end{aligned}$$

Such that

$$c + (1 + r_b)^{n-1}c_h + (1 + r_b)^n c_h + a' = w + (1 + \bar{r})a$$

An employed homeowner that sells has value function ($E_h^s(w, a, n; \theta)$). A seller becomes a renter and must payback all late fees with interest ($\sum_{i=1}^{n}(1 + r_b)^i c_h$) off of the top of the sale price (see Thompson (2010)), delinquent sales.

$$E_h^s(w, a, n; \theta) = \max_{a'} \; u(c, z_h) + \widehat{\beta}\mathbb{E}\big[(1 - \delta(\theta'))E_r(w', a'; \theta') + \delta(\theta')U_r(b(w), a'; \theta')\big]$$

Such that

$$c + a' = w + (1 + \bar{r})a + p(\theta) - \frac{c_h}{r_b} - \sum_{i=1}^{n}(1 + r_b)^i c_h$$

In the event of foreclosure, $\chi < 1$ is the discount on the house price $p(\theta)$. Once again, late fees $(\sum_{i=1}^{n}(1 + r_b)^i c_h)$ are taken off of the top of the discounted sale price $\chi p(\theta)$. $G(\cdot)$ is a function that reflects the institutional detail of foreclosure sale/sheriff sale. For example, if this were a non-recourse state, then the function would be $G(x) = \max\{0, x\}$. If there is recourse, the deficiency judgement is limited to wages and assets in excess of subsistence consumption, $\underline{c}$. An employed homeowner that is foreclosed upon solves the following problem:

$$E_h^f(w, a, n; \theta) = \max_{a'}\ u(c, z_h) + \widehat{\beta}\mathbb{E}\big[(1 - \delta(\theta'))E_r(w', a'; \theta') + \delta(\theta')U_r(b(w), a'; \theta')\big]$$

Such that

$$c + a' = \max\big\{w + (1 + \bar{r})a + G\Big(\chi p(\theta) - \frac{c_h}{r_b} - \sum_{i=1}^{n}(1 + r_b)^i c_h\Big), \underline{c}\big\}$$

2.3.4 Unemployed Discrete Choices

The problem of an unemployed agent closely mimics the problem of an employed agent. The main difference is in the search choice s and subsequent job finding probability $\pi(s; \theta)$ which parametrically depends on the aggregate state θ. An unemployed person in good standing, which means no missed payments (n=0), has to choose from paying, defaulting, or selling:

$$VU_h(b, a, 0; \theta) = \max_{Pay,\ Default,\ Sell} \big\{U_h^g(b, a, 0; \theta), U_h^d(b, a, 0; \theta), U_h^s(b, a, 0; \theta)\big\}$$

For $n > 1$, the unemployed person is in bad standing and owes the bank past mortgage payments. They must choose between making two payments to work towards a cure, continuing in default, or selling:

$$VU_h(b,a,n;\theta) = \max_{Pay\ Twice,\ Default,\ Sell} \big\{U_h^p(b,a,n;\theta),\ \lambda_F(n)U_h^f(b,a,n;\theta) + (1-\lambda_F(n))U_h^d(b,a,n;\theta),\ U_h^s(b,a,n;\theta)\big\}$$

2.3.5 Unemployed Value Functions

An unemployed renter must choose their search intensity s which has a convex utility cost $x(s)$. The job finding probability $\pi(s;\theta)$ is weakly concave which ensures an interior solution to the search choice. The variable b is the current unemployment benefit, a is the liquid asset holdings, and $\hat{w}$ is the wage drawn from $F(\hat{w})$. The timing is such that the wage is drawn and then the unemployed renter can choose to accept the offer $\hat{w}$ or reject the offer and keep benefits b' which stochastically expire. Let p_b be the probability benefits expire, and if benefits expire agents are given a minimum amount $\underline{b}$, where $\underline{b} = \frac{1}{2}\underline{w}$.

$$U_r(b,a;\theta) = \max_{a',s}\ u(c,z_r) - x(s) + \widehat{\beta}\mathbb{E}\Big[(1-\pi(s;\theta'))U_r(b',a';\theta') + \pi(s;\theta')\int_{\hat{w}} \max\big\{E_r(\hat{w},a';\theta'),\ U_r(b',a';\theta')\big\}dF(\hat{w})\Big]$$

Such that

$$c + c_r + a' = b + (1+\bar{r})a$$

The max operator implies a reservation wage for which an agent accepts or rejects a wage $w_r^*(b,a';\theta')$ (the star indicates this is a reservation wage, the subscript indicates the renter status). The upper bound for the support of w is $\bar{w}$:

$$\int_{\hat{w}} \max\big\{E_r(\hat{w},a';\theta'),\ U_r(b',a';\theta')\big\}dF(\hat{w}) = U_r(b',a';\theta_r'^*(b',a';\theta'))F(w_r^*(b',a';\theta')) + \int_{w_r^*(b',a';\theta')}^{\bar{w}} E_r(\hat{w},a';\theta')dF(\hat{w})$$

An unemployed homeowner with benefits b, liquid assets a, no late payments ($n = 0$)

that pays on time solves the following problem:

$$U_h^g(b,a,0;\theta) = \max_{a',s} u(c,z_h) - x(s) + \widehat{\beta}\mathbb{E}\Big[(1-\pi(s;\theta'))VU_h(b',a',0;\theta') \\ + \pi(s;\theta')\int_{\hat{w}} \max\big\{VE_h(\hat{w},a',0;\theta'),\ VU_h(b',a',0;\theta')\big\}dF(\hat{w})\Big]$$

Such that

$$c + c_h + a' = b + (1+\bar{r})a$$

An unemployed homeowner that is in default ($n \geq 1$) and makes no payments has their default indicator tick upward $n' = n+1$. Defaulters engage in search just like any other agent, but as explained below, the time spent in default will directly influence the search intensity and reservation wage. A defaulting non-payer solves the following problem:

$$U_h^d(b,a,n;\theta) = \max_{a',s} u(c,z_h) - x(s) + \widehat{\beta}\mathbb{E}\Big[(1-\pi(s;\theta'))VU_h(b',a',n+1;\theta') \\ + \pi(s;\theta')\int_{\hat{w}} \max\big\{VE_h(\hat{w},a',n+1;\theta'),\ VU_h(b',a',n+1;\theta')\big\}dF(\hat{w})\Big]$$

Such that

$$c + 0 + a' = b + (1+\bar{r})a$$

The reservation wage $w_d^*(b,a',n+1;\theta')$ is a key function to characterize, and we will characterize this reservation wage below both theoretically and numerically. The reservation wage is the point at which the value of taking a job during default is just equal to the value of continuing in default while unemployed.

$$VE_h(w_d^*(b',a',n+1;\theta'),a',n+1;\theta') = VU_h(b',a',n+1;\theta')$$

An unemployed homeowner in default that begins to pay current is not subject to foreclosure. As before, the mortgagor must pay the two longest outstanding mortgage payments

$((1+r_b)^{n-1}c_h + (1+r_b)^n c_h)$. The value function is given below:

$$U_h^p(b,a,n;\theta) = \max_{a',s} u(c,z_h) - x(s) + \widehat{\beta}\mathbb{E}\Big[(1-\pi(s;\theta'))VU_h(b',a',n-1;\theta')$$
$$+ \pi(s;\theta')\int_{\hat{w}} \max\big\{VE_h(\hat{w},a',n-1;\theta'),\ VU_h(b',a',n-1;\theta')\big\} dF(\hat{w})\Big]$$

Such that

$$c + (1+r_b)^{n-1}c_h + (1+r_b)^n c_h + a' = b + (1+\bar{r})a$$

An unemployed homeowner that sells becomes a renter forever more. They receive the state contingent house price $p(\theta)$, but they must pay off the remaining mortgage $\frac{c_h}{r_b}$ and the outstanding late payments $\sum_{i=1}^n (1+r_b)^i c_h$. Thus an unemployed agent that sells solves the following problem:

$$U_h^s(b,a,n;\theta) = \max_{a',s} u(c,z_h) - x(s) + \widehat{\beta}\mathbb{E}\Big[(1-\pi(s;\theta'))U_r(b',a';\theta')$$
$$+ \pi(s;\theta')\int_{\hat{w}} \max\big\{E_r(\hat{w},a';\theta'),\ U_r(b',a';\theta')\big\} dF(\hat{w})\Big]$$

Such that

$$c + a' = b + (1+\bar{r})a + p(\theta) - \frac{c_h}{r_b} - \sum_{i=1}^{n}(1+r_b)^i c_h$$

As above, χ is the discount on the house price $p(\theta)$ if foreclosed upon and $G(\cdot)$ reflects the institutional details of foreclosure sales. For instance, in a non-recourse state $G(x) = \max\big\{0, x\big\}$. Thus, an unemployed homeowner that is foreclosed upon solves the following problem:

$$U_h^f(b,a,n;\theta) = \max_{a',s} u(c,z_h) - x(s) + \widehat{\beta}\mathbb{E}\Big[(1-\pi(s;\theta'))U_r(b',a';\theta')$$
$$+ \pi(s;\theta')\int_{\hat{w}} \max\big\{E_r(\hat{w},a';\theta'),\ U_r(b',a';\theta')\big\} dF(\hat{w})\Big]$$

Such that

$$c + a' = \max\left\{b + (1+\bar{r})a + G\Big(\chi p(\theta) - \frac{c_h}{r_b} - \sum_{i=1}^{n}(1+r_b)^i c_h\Big), \underline{c}\right\}$$

2.3.6 Equilibrium

An equilibrium in this economy is a set of household policy functions for the savings decision $\left\{a_i^{j\prime}(b,a,n;\theta)\right\}_{i=h,r \quad j=E,U}$, the search intensity $\left\{s_i(b,a,n;\theta)\right\}_{i=h,r}$, the reservation wage, $\left\{w_i(b,a,n;\theta)\right\}_{i=h,r}$, and beginning of period default/tenure decisions $\left\{D_h^j(b,a,n;\theta)\right\}_{j=E,U}$ that solve the households' dynamic programming problem, where households take as given the parametric wage distribution $F(w)$, the interest rates $\bar{r}$ and r_b, house prices $p(\theta)$, and the law of motion for the aggregate state.

We recover aggregate dynamics by fixing the draws for the aggregate state, simulating a large (N=25,000) number of households for many periods (T=300), and then repeating this many times (R=10). We report steady state results by averaging outcomes over this period (we burn the first 100 periods), which includes both good and bad times. Agents that die are replaced by newly borns that are born in good standing with probability 1, begin with zero liquid assets, are randomly assigned to homeownership (f_m are born with a mortgage) and employment, and draw their wages from $F(w)$.

2.4 Calibration and Steady State Results

2.4.1 Calibration

We solved the dynamic programming problem by using value function iteration over a discrete state space. The grid for search effort is evenly spaced over the interval $[0,\frac{1}{2}]$ with 10 nodes. The asset grid is evenly spaced over the interval [0,1] with 20 nodes. Wages are evenly spaced from $[\underline{w},1]$ with 20 nodes. We set $\underline{w} = .2$ to ensure a minimum income level at benefit expiration of $\underline{b} = .1$ as in Krueger and Mueller (2010).

Each period in the model corresponds to 1 month. Krueger and Mueller (2010) fit a nearly identical labor market model to time use data (their model abstracts from asset accumulation and home tenure). We follow them closely and choose preferences and search technology functional forms as follows:

$$\textbf{Preferences for Consumption: } u(c,z) = \log(c) + \log(z)$$

$$\textbf{Disutility of Search: } x(s) = \alpha_s s^2$$

The function form for the probability of finding a job is also taken from Krueger and Mueller (2010), but we incorporate a state contingent coefficient since we are interested in business cycles:

$$\pi(s;\theta) = \alpha_f(\theta)s$$

The underlying aggregate state follows a transition matrix based on NBER business cycle dates (see Appendix 2.7.2). In good times $\alpha_f(H) = 2$ which ensures that maximum search effort results in an offer with probability 1 (while there is limited data on offers, both Krueger and Mueller (2010) and Ljungqvist and Sargent (1998) demonstrate that such an assumption is necessary to deliver plausible job finding rates). In bad times, the offer rate is multiplied by .761 to reflect the reduced job finding rate in downturns, $\alpha_f(L) = 2 \times .761 = 1.522$. Thus, the maximum search effort results in an offer with probability .76 during a downturn. This factor is measured using Shimer (2005a)'s post war database and taking the ratio of the average job finding rates in NBER dated expansions to the average job finding rates in NBER dated contractions. The layoff rate is measured using post-2000 business cycle dates which is all that is available from JOLTS. Our calculations yield $\delta(L) = 1.5$ and $\delta(H) = 1.3$ (since there is no on-the-job search, we use the layoff rate as opposed to the separation rate).

In the model, agents have a 42 Year Working Life, thus p_d=.002 as in Ljungqvist and Sargent (1998). We set the unemployment benefit replacement rate to be 50% based on the OECD database on Benefits and Wages, and unemployment benefits are capped above as they are in reality ($\bar{w}$ denotes the maximum wage draw): $b(w) = \frac{1}{2}\min\left\{w, \frac{1}{2}(\bar{w} + \underline{w})\right\}$. Benefits expire stochastically, and the average duration of benefits is 6 months.

We measure the exogenous wage distribution $F(w)$ as in Jolivet et al. (2006). We define job entrants to be workers who were just hired after a period of non-employment. We then calculate the empirical wage distribution $\widehat{F}(w)$ in levels for the new entrants in the 2005-2007 PSID panel.[14]

The flow utility of renting is normalized to one, $z_r = 1$, and the consumption cost of renting is set to zero, $c_r = 0$, to avoid any potential negative consumption traps. Both the flow utility to owning, z_h, and the consumption cost of owning, c_h, are set to match moments in the data.

The foreclosure completion probability function $\lambda_F(n)$ is linear and increasing after 3 months in default (recall n is the number of months in default). The incremental increase in the foreclosure completion probability is calculated using Lender Processing Services data (see Appendix 2.7.2). In the delay economy, foreclosures are completed after **month 12** with probability 1, whereas in the no-delay economy, foreclosures are completed after **month 3** with probability 1. While the foreclosure completion probability function $\lambda_F(n)$ is stylized along many dimensions, it captures the essence of what we are interested in, namely the large increase in foreclosure times since 2007.

As in Campbell and Cocco (2011), the price of a house, $p(\theta)$, is exogenously determined and depends on the underlying state of nature θ.[15] We set the price of the house in good times to be the discounted sum of all future mortgage payments, $p(H) = \frac{c_h}{r_b}$. In bad times, the price is set to be below the remaining mortgage payments. Thus everyone is underwater in the model when the aggregate state is low, $\theta = \theta_L$. In the data, this is strictly true for 30.7% of the mortgages covered in the 2011 LPS database; however, our effective negative equity estimates for 2011, which take into account the transaction costs of selling and equity extraction thresholds, are significantly higher at 43%. Thus, we set the price in bad times to be 1% underwater, $p(L) = .99 \cdot p(H)$. At the bottom of this section, we will show how

[14] Jolivet et al. (2006) define job entrants as follows: "Job entrants are workers who were just hired after a period of non-employment."

[15] Corbae and Quintin (2009) effectively fix the price by making the lenders the construction company and letting their technology for producing homes linear. Thus, in their model the price of a home is the inverse of the calibrated technology parameter.

these parameters influence the model.

Just as Corbae and Quintin (2009) argue, if foreclosed upon, the sale price of the house falls by an additional amount. We use a conservative discount of 5%, i.e. $\chi = .95$.[16] If the home is liquidated at a loss (and it will always be liquidated at a loss given the parametrizations above), a deficiency judgement equal to half the loss is enforced. More precisely, the function that governs the deficiency judgement $G(\cdot)$ is given by the following:

$$G(x) = \frac{1}{2} x \mathbb{I}(x < 0) + x \mathbb{I}(x > 0)$$

This deficiency judgement function is meant to capture the average behavior of the economy. Even in most states that are most popularly believed to be "non-recourse" such as California, all refinanced loans are recourse and subject to deficiency judgements (see Ghent and Kudlyak (2011)).

There are several parameters that remain to be calibrated. We will pick the discount factor β, the fixed mortgage payment c_h, the flow utility from housing z_h, the bank interest rate r_b, the savings rate $\bar{r}$, the fraction of newly born agents endowed with a mortgage f_m, and the disutility of search coefficient α_s in order to match the default rate, the average back end debt to income ratio, the cure rate for 30 days late mortgagors, the cure rate for 60 days late mortgagors, the homeownership rate, the unemployment rate, and the fraction the mortgagors with a liquid assets to income ratio between 0 and 5%.

We follow Chatterjee and Eyigungor (2009) in assuming that all homeowners are mortgagors and mortgages are perpetuities.[17] We therefore target a homeownership rate of 69% (Census, 2004) in the benchmark model, but we include an alternative calibration in which 45% of the population has a mortgage.[18]

[16] Chatterjee and Eyigungor (2009) use a 22% discount, and Corbae and Quintin (2009) use a more extreme discount of 44%.

[17] There is also a question of what exactly a "homeowner" is in the model as compared to the data. For the purposes of the experiments below, we only have two types of agents, homeowners and renters, and all homeowners have mortgages. In reality mortgagors have substantial costs of maintaining their homes, including sizeable property taxes. We do not model these facets of homeownership, but instead assume that all relevant payments related to owning a home are included in c_h. This is similar to Corbae and Quintin (2009) who do not distinguish between homeowners and mortgagors.

[18] According to the Census roughly 2/3 of homeowners have a mortgage.

We measure the average back end debt to income ratio in the PSID by applying NBER's Tax Sim program to the 2009 PSID dataset to generate after-tax income.[19] From after-tax income, we further subtract expenses for child care, medical bills, and other expenses not modeled here. The ratio of mortgage payments, including first and second mortgages, to this adjusted after-tax income number is what we call the back-end debt to income ratio. Since we do not model unsecured debt obligations, we will also include another measure of back end debt to income that imputes a 10% flow cost on the stock of other unsecured debts reported in the PSID in the numerator of the ratio described above.[20]

The ergodic unemployment rate target will vary across calibrations, but we will present models that target 7.5% unemployment, 8.0% unemployment.[21]. The cure rates are taken to be the lower triangular entries in Table 2.9, summed across columns to yield a model-equivalent measure. We target the cure rate from 30 days late (DL) to current and from 60 days late to 30 days late. Liquid assets are measured as in Section 2.2.2 and depicted in Figure 2.8. We target the fraction of homeowners with liquid assets to annual income between 0-5%.

2.4.2 Steady State Results

Table 2.1 shows that the model's steady state does quite well at matching various targeted features of the data. As is standard in any default model, in order to get reasonable default rates it is necessary to have a high discount rate: the β in the model corresponds to an annual discount rate of roughly 18%.[22] Even with a low discount factor, the default rate is well below the default rate in normal times implying that the reported results understate the importance of default as an insurance mechanism. The low default rate is largely attributable to the fact that the only shocks that can induce default are the job loss shock and the benefit

[19]This controls for marital status in filing, exemptions, and deductions, including mortgage deductibles, etc.

[20]The debts includes credit cards, student loans, auto loans, etc.)

[21]There is considerable debate over the natural rate of unemployment, but the Fed recently released a 6.5% unemployment rate target. We choose 1% above the federal reserve banks target unemployment rate to reflect the fact that our model has no participation margin and thus the unemployment rate in our model corresponds to a number more like U6.

[22]The discount rate cannot be too high since it also shifts the asset distribution.

expiration shock. By construction, it makes sense to interpret the model's default rate as the job-loss-induced default rate. The bank interest rate corresponds to an annual rate of 2.5%, and the savings rate corresponds to an annual yield of .72%. These interest rates primarily determine the cure rate and the fraction of liquid assets held by homeowners, respectively. The cure rate is quite high in the data, even in the recession, and thus the bank fees must be low; by omitting modifications we might be biasing downward the bank penalty rate since a large number of homeowners have had their mortgages recast or had late fees forgiven.[23]

The value of services derived from a home z_h, is roughly 4x greater than the value of services derived from renting. Such a high z_h is necessary to match the homeownership rate and cure rates observed in the data.[24] Another key parameter determining the homeownership rate is the fraction of agents starting as renters, $(1 - f_m)$.

The search disutility parameter is set to match the 7.5% ergodic unemployment rate.[25]The chosen value of α_s implies almost no movement along the search intensity margin.[26]

Table 2.2 shows that the benchmark calibration does quite well at matching several non-targeted moments. Defaulters have back end debt to income ratios in line with the data, and the mortgagor unemployment rate is identical to the data. Defaulters also have similar liquid asset holdings to the data.

Table 2.3 shows several alternative calibration results. The alternative models are set to match the back end debt to income ratio inclusive of imputed payments on unsecured debt (the column titled High Unemployment and High DTI) and a mortgage-per-capita ratio of 45% (the column titled Low Mortgagor Rate). In the data, the mean back end debt to income including imputed unsecured payments is 43.9%.

[23]In a working paper version of the model we include modifications as a random event that competes with foreclosure. Including means tested modifications distorts job taking behavior even more. See Mulligan (2008) and Herkenhoff and Ohanian (2011) for more.

[24]Corbae and Quintin (2009) find an additive premium of similar magnitude in their moment matching exercise.

[25]We choose 1% above the federal reserve banks target unemployment rate to reflect the fact that our model has no participation margin and thus the unemployment rate in our model corresponds to a number more like U6.

[26]Krueger and Mueller (2011) find evidence that search intensity and reservation wages are fairly flat over time, but their data are cross-sectional and do not control for homeownership status or delinquency status.

Table 2.1: Steady State: Targeted Moments

	Data	Source	Benchmark Model	Parameters	
Default Rate	1.50%	LPS 2001-2003	0.34%	$\widehat{\beta}$	0.98604
30+ DL Cure Rate	41.20%	LPS 2001-2003	44.26%	$\bar{r}$	0.000642
60+ DL Cure Rate	39.70%	LPS 2001-2003	44.99%	z_h	4.0804
Homeownership Rate	69.00%	Census	68.75%	c_h	0.22584
Unemployment Rate	7.50%		7.47%	α_s	6.9872
Mean Back-End-DTI	41.00%	2009 PSID	40.60%	r_b	0.002033
Fraction w/ 0-5% Liquid Assets to Income	45.00%	2009 PSID	44.87%	$1-f_m$	0.17315

Table 2.2: Steady State: Non-Targeted Moments

	Model	Data	Source
Homeowner Unemployment Rates	6.35%	6.29%	2009 PSID
Fraction of Defaulters with 0-5% Liquid Assets to Income	75.92%	84.55%	2009 PSID
DTI Defaulting Homeowners, mean	71.53%	77.60%	2009 PSID

Table 2.3: Steady State: Alternative Calibrations

	Alternative Calibrations		Parameters		
	High Unemployment, High DTI	Low Mortgagor Rate		High Unemployment, High DTI	Low Mortgagor Rate
Default Rate	0.29%	0.51%	$\widehat{\beta}$	0.98548	0.98557
30+ DL Cure Rate	41.55%	41.58%	$\bar{r}$	0.000642	0.001564
60+ DL Cure Rate	43.67%	41.34%	z_h	5.5741	2.4462
Homeownership Rate	68.21%	44.33%	c_h	0.22721	0.24614
Unemployment Rate	7.90%	8.05%	α_s	12.0944	9.0752
Mean Back-End-DTI	42.57%	41.98%	r_b	0.0018327	0.004432
Fraction w/ 0-5% Liquid Assets to Income	49.15%	44.99%	$1-f_m$	0.1982	0.1997

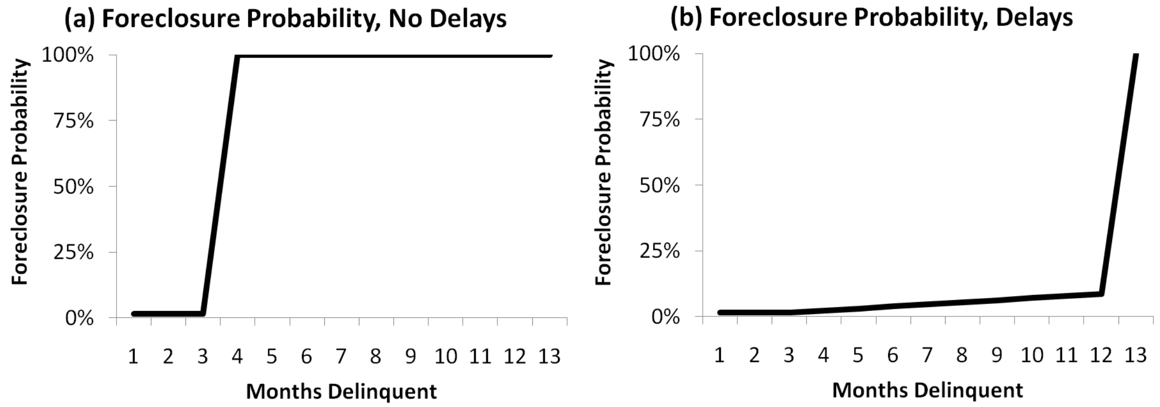
2.5 Turbulence Experiment

To capture the effect of foreclosure delays on the economy during the 2007-2009 recession and ensuing recovery, we run a turbulence experiment similar to Ljungqvist and Sargent (1998). In particular, we start two identical economies in their ergodic steady state with 3-month foreclosure delays. Both economies enter a recession characterized by elevated job destruction and low house prices, but in one economy we introduce unexpected 12-month foreclosure delays. The details are explained below:

- Prior to Date 1: Both economies are identical and are in steady state with a 3-month foreclosure delay.
- Date 1: There are three simultaneous events
  - Both economies enter a contractionary period for 12 months (i.e., the aggregate state is low during this time period $\theta = \theta_L$).
  - There is also an additional one-time doubling of the job destruction rate in both economies.
  - One economy introduces default protection through a 12-month foreclosure delay (**the delay economy**) whereas the other economy maintains a 3-month foreclosure delay (**the no delay economy**)
- After Date 12: Both economies begin to recover by entering the good aggregate state ($\theta = \theta_H$).

Figure 2.11 plots the foreclosure probabilities whose slopes were based on the data. In both economies, during months 1-3, there is a constant foreclosure rate of 1.5%. In the no delay economy, there is certain eviction in month 4 ($N = 3$ with the assumed grid structure). In the delay economy, this rate gradually increases after becoming 90+ days late until there is certain eviction in month 13 ($N = 12$). See the Appendix 2.7.2 for more information.

Figure 2.11: Foreclosure Probability $\lambda_F(n)$



2.5.1 Model Transition Matrix

Figure 2.12 has the model implied transition rates during the turbulence experiment. The black numbers correspond to the delay economy and should thus correspond to the data in Figure 2.9. The red underlined numbers correspond to the no-delay economy and are thus counterfactuals. The model predicts that with delays the monthly default rate is .1% (=.0041-.0031) higher in levels when there are foreclosure delays (this is roughly 33% higher relative to the no delay economy). Likewise, by introducing foreclosure delays the cure rates from 90+ days late to 60 days late drop by 26.24% (=.5553-.2929) which represents a 47% relative decline compared to the no delay economy. The interesting aspect of the experiment is that the foreclosure rate is actually higher in the delay economy. Since more homeowners default and more homeowners remain in the 90+ days late category for longer, they optimally endure more foreclosures. Thus with delays the foreclosure rate rises roughly 3.8% (=.1063-.0675), a 57% relative increase compared to the economy with no delays. This is an important implication for policy makers to consider. By incentivizing more homeowners to enter default and not cure, ultimately more people lose their homes.

Figure 2.12: Model Homeowner Transitions, (No Delay Economy=Red Underlined Entries, Delay Economy= Black Entries), Conservative Parametrization

	Current	30 DL	60 DL	90+ DL	Renter
Current	0.9969 / 0.9959	0.0031 / 0.0041	0 / 0	0 / 0	0 / 0
30 DL	0.4408 / 0.4547	0 / 0	0.5505 / 0.5377	0 / 0	0.0087 / 0.0075
60 DL	0 / 0	0.4202 / 0.3528	0 / 0	0.5713 / 0.6363	0.0085 / 0.0109
90+ DL	0 / 0	0 / 0	0.5553 / 0.2929	0.3772 / 0.6008	0.0675 / 0.1063
Renter	0 / 0	0 / 0	0 / 0	0 / 0	1 / 1

2.5.2 Model Aggregates

Figures 2.13 to 2.16 show how the aggregate economy responds to the turbulence. The model period is a month, but we aggregate the simulated data to a quarterly frequency for ease of interpretation. The unemployment rates are shown in Figure 2.13. The economy with delays peaks at an unemployment rate of 10.12% whereas the no delay economy peaks at an unemployment rate of 9.94%. In the experiment, the 4th quarter is the end of the recession, and thus the figure shows a marked decline in unemployment from that point forward. Figure 2.14 plots the gap between the two unemployment rate curves. As we will prove below, the greater the default protection (the longer the foreclosure delays) the bigger the difference in unemployment rates due to reduced search effort and raised reservation wages. The difference in unemployment rates between the two economies peaks at .37%.

Figure 2.15 plots the fraction of mortgagors in default. The stock of mortgages in default reaches its maximum two quarters after the recession since this is when the last large cohort of laid-off workers run out of unemployment benefits (in expectation). With foreclosure delays, delinquencies peak at 2.57% of the total stock of mortgages, well below the data counterpart shown in Appendix 2.7.1.2 in Figure 2.22. However, relative to the economy with no foreclosure delays, this is roughly a 25% larger delinquent stock.

Figure 2.16 shows that in the delay economy, homeownership is actually lower. With more people in delinquency for longer, there are many more evictions even with the foreclosure delays. When the foreclosure process is relative speedy, homeowners avoid default and thus the homeownership rate is 1.39% higher by the end of the experiment. This is the most important model-generated prediction for policy-makers. By protecting defaulters via housing moratoria, lawsuits, and mortgage modifications, ultimately more homeowners default and lose their homes.[27]

Table 2.4 shows that the delays actually result in higher take home pay by .1% (roughly the welfare cost of a business cycle). The extra self-insurance provided by the default protection has two effects: (i) on the extensive margin, fewer people are working (hence the

[27]It is important to note that there are no price-feedback effects in this model. If the delays prop-up house prices and incentivize homeowners to keep making payments, the effect becomes ambiguous.

Table 2.4: Turbulence Experiment: Output and Foreclosure Delays

	Delays	No-Delays
Output Per Capita	0.6775	0.6768
Output Gain from Delays	0.10%	

higher unemployment rate), but (ii) on the intensive margin, those who are working are better matched (in the sense of higher wages). What Table 2.4 shows is that after netting the two effects, the additional take home pay outweighs the effect of fewer workers.

Figure 2.13: Turbulence Experiment: Unemployment Rates

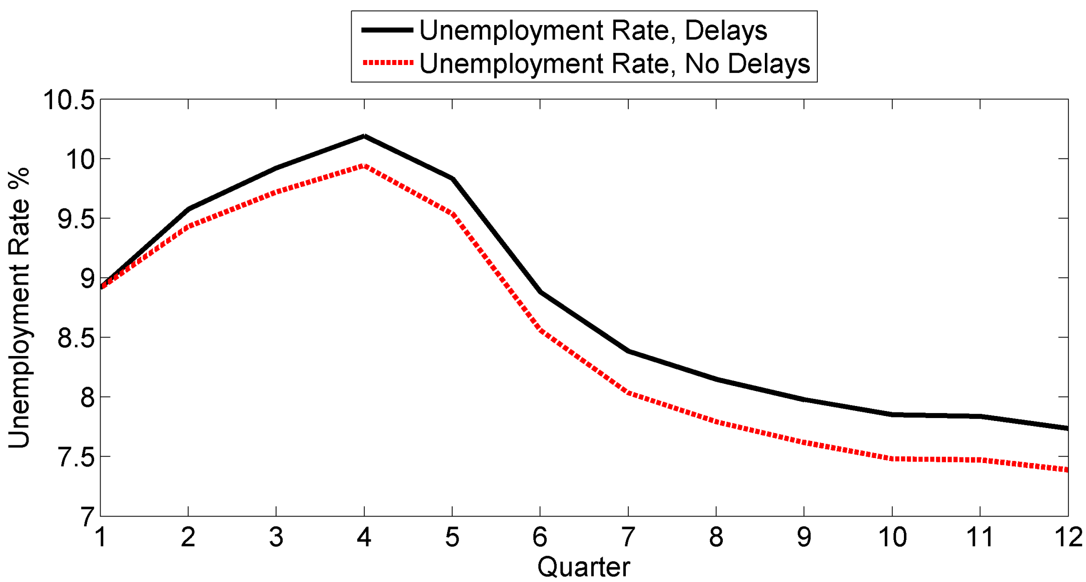


Figure 2.14: Turbulence Experiment: Difference in Unemployment Rates Across Economies

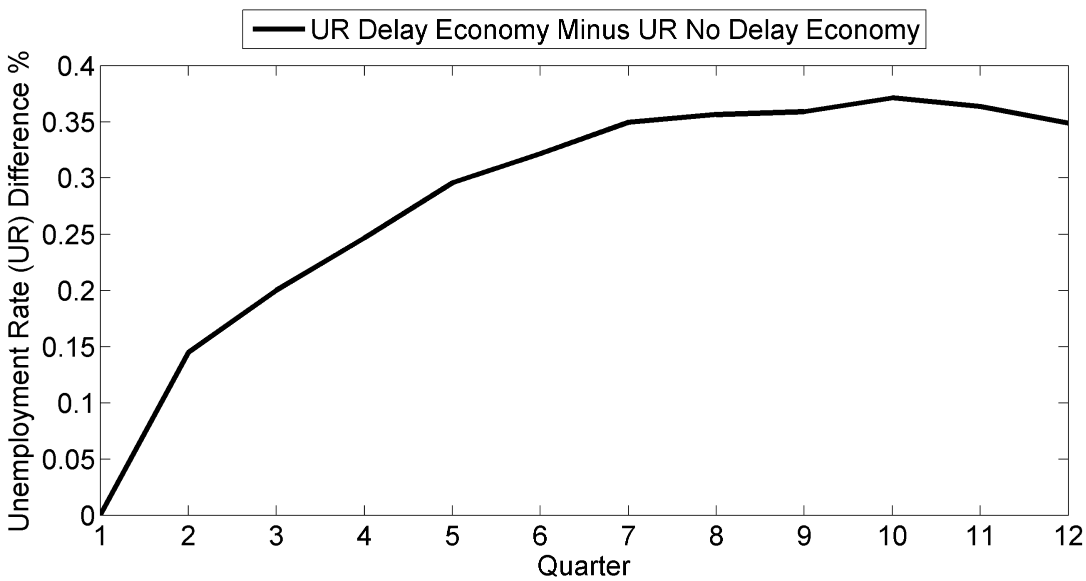


Figure 2.15: Turbulence Experiment: Delinquency Stock

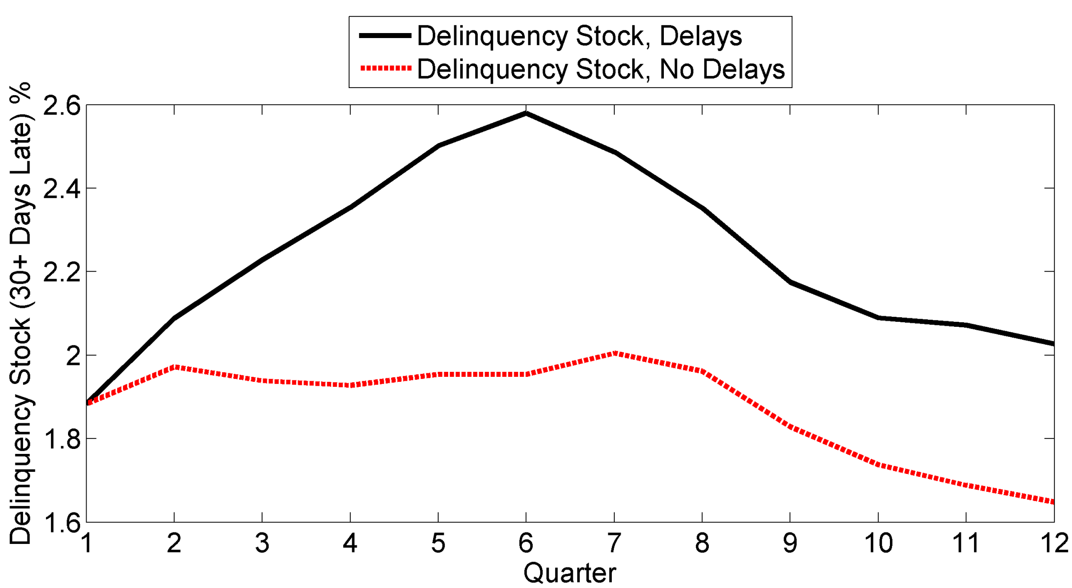
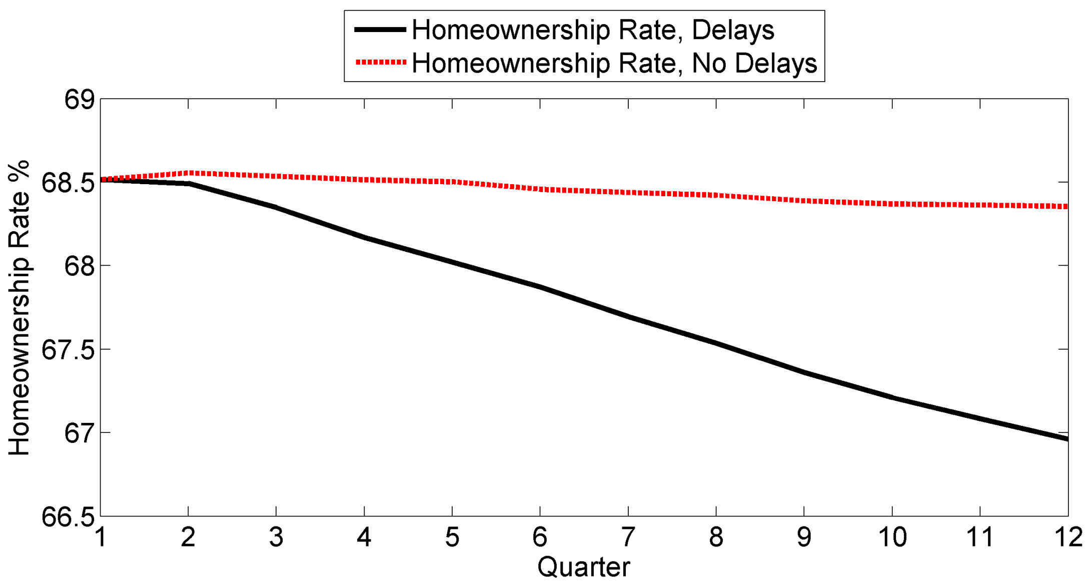


Figure 2.16: Turbulence Experiment: Homeownership



2.5.3 Robustness

Figure 2.17 shows the unemployment rate difference between the foreclosure delay economy and the no foreclosure delay economy under alternative calibrations. The foreclosure delay economy, when calibrated to match a high debt-to-income (DTI) and high unemployment rate (UR), peaks at an unemployment rate that is .501% greater than the economy with no delays. In the economy that matches the mortgage per-capita rate, the difference in unemployment rates peaks at .849%. The relatively large unemployment gap for this calibration is due to the low value of homeownership and relatively high mortgage payment, both of which make default an attractive state. Since each calibration has different fundamental parameter values, the steady states following the turbulence experiment differ. As explained above, search intensity is essentially a corner solution in the baseline calibration. In both of the alternative calibrations, the search intensity margin varies considerably over the business cycle and moves away from the corner in down times. Agents respond by lowering search effort more in down times in the delay economy versus the no-delay economy; in good times, both economies are back at the corner solution. The search intensity margin thus produces the hump-shaped difference in unemployment rates between the foreclosure delay economy and no foreclosure delay economy.

Figure 2.17: Turbulence Experiment: Difference in Unemployment Rates Across Economies

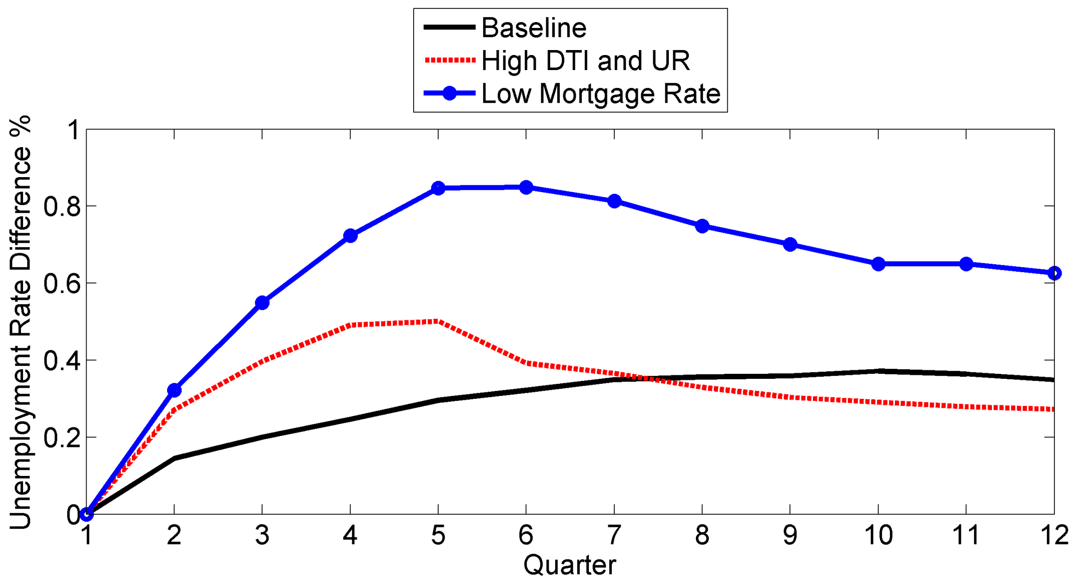


Table 2.5: Sensitivity to Price Decline and Enforcement

	Baseline	Low Enforcement	No House Price Decline
Peak Difference in Unemployment Rates	0.376%	0.384%	0.380%

Table 2.5 shows how the model's results change when there is only a 10% chance of the deficiency judgement being enforced (Low Enforcement Column) and when there is no house price decline (No House Price Decline Column). In either case, the results do not vary significantly.

2.5.4 Real Rate of Interest

A skipped payment is nothing more than a line of credit by the bank to the mortgagor. We define the real rate of interest on the "skipped payment loan" as the potential payment in consumption terms, which is a foreclosure-probability-weighted summation of the late payment and the consumption equivalent to the utility loss of foreclosure, over the loan amount (c_h). In symbols, the real rate of interest is given as a function of skipped payments (n):

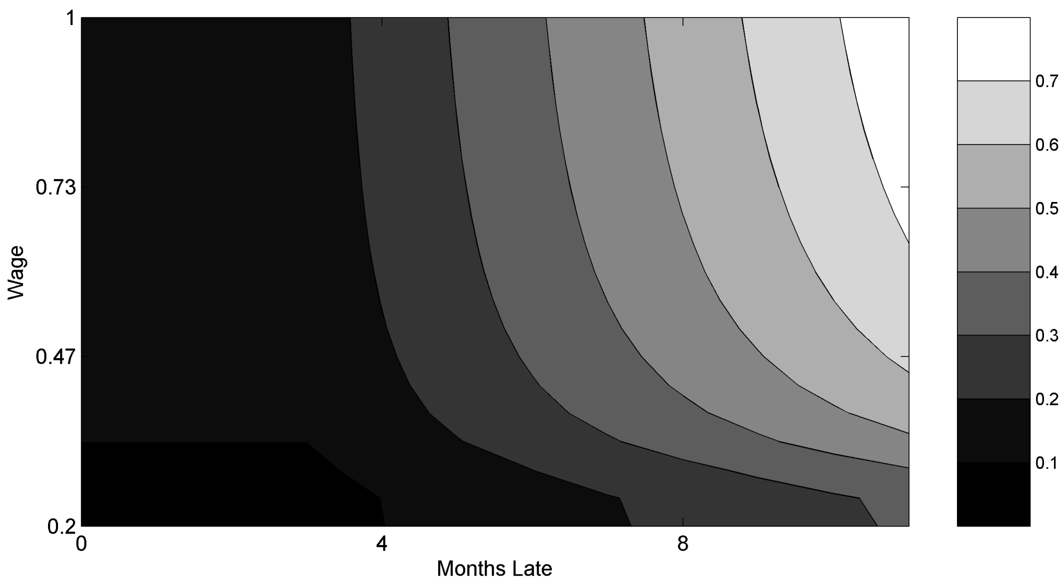
$$\hat{r}(n) = \frac{\lambda_F(n)\tilde{c} + (1 - \lambda_F(n))(1 + r_b)c_h}{c_h} - 1$$

Such that

$$\tilde{c} = e^{\left\{\frac{r_b + p_d}{1 + r_b}(E_h - E_r)\right\}}$$

The notation is the same as in the model where r_b is the late interest rate on the payment, p_d is the death probability, $(E_h - E_r)$ is the utility cost of becoming a renter if foreclosure happens, and $\lambda_F(n)$ is the chance of being foreclosed upon after having skipped n payments. Figure 2.18 plots this real rate for an unemployed person with low assets in good times. Figure 2.18 is a contour graph where colors correspond to interest rates. As depicted, the real rate varies from 6.8% to 77.05% depending on the state space. For high earners losing a house is costly- it provides a large flow utility at a relatively small cost (the mortgage payment to income ratio is very small). As a result, the gap between $E_h - E_r$ is larger and the real rate of interest is higher. As homeowners become more delinquent, the probability of foreclosure increases and the real rate of interest increases. That the implicit real rates are above 70% per month points to an efficiency argument in the way these 'informal unemployment benefits' are funded; when the government can borrow at real rate close to zero, it is hard to justify financing consumption via foreclosure delays.

Figure 2.18: Real Rate of Interest



2.5.5 Mechanisms in the Model and the Data

We illustrate the model mechanisms theoretically and then we demonstrate the features numerically. Lemma 2.5.1 shows how the reservation wage falls as protection increases and Lemma 2.5.2 shows how search effort declines and protection increases.

Lemma 2.5.1 *Define $\psi(n) = 1 - \lambda_F(n)$ as the degree of default protection (the probability of not being foreclosed upon). Let θ be constant, let δ be the constant job destruction rate, and let b be the constant benefit rate. Suppose that the domain of the household dynamic programming problem is convex and the return function $u(c,z) - x(s)$ is concave (i.e. the model satisfies the hypotheses of the Benveniste-Schienkman Theorem), then the optimal reservation wage $w_i^*(b,a,n;\theta),\quad i \in \{h,r\}$ is increasing in the degree of protection for any interior points of the state space.*

Proof. Consider an unemployed agent that is comparing the options of (i) turning down a wage draw equal to their reservation wage, i.e. remaining unemployed, and continuing to default, versus (ii) accepting a wage draw equal to their reservation wage and paying current. Suppressing the state space, denote the reservation wage $w^*(b) = w_i^*(b,a,n;\theta)$. Implicitly, the reservation wage depends on the degree of default protection, thus denote the reservation wage $w^*(b;\psi)$. Likewise, suppress the states for the value of defaulting while unemployed $U^d(b) = U^d(b,a,n;\theta)$ as well as paying and being employed $W^p(w) = W^p(b,a,n;\theta)$. Implicitly, the value of defaulting and being unemployed $(U^d(b;\psi))$ and the value paying and being employed $(W^p(w;\psi))$ depend on ψ (however, the value of realized and completed foreclosure $(U^f(b))$ does not depend on ψ, but rather on recourse enforcement etc.). By definition, the reservation wage makes the agent indifferent between option (i) and option (ii):

$$\psi U^d(b;\psi) + (1-\psi)U^f(b) = W^p(w^*(b,\psi);\psi)$$

Differentiating,

$$\psi \frac{\partial U^d(b;\psi)}{\partial \psi} + U^d(b;\psi) - U^f(b) = \underbrace{\frac{\partial W^p(w;\psi)}{\partial w}\bigg|_{w=w^*(b;\psi)} \frac{\partial w^*(b;\psi)}{\partial \psi}}_{\text{Indirect Effect}} + \underbrace{\frac{\partial W^p(w;\psi)}{\partial \psi}\bigg|_{w=w^*(b;\psi)}}_{\text{Direct Effect}}$$

and rearranging,

$$\frac{\partial w^*(b;\psi)}{\partial \psi} = \frac{\psi \frac{\partial U^d(b;\psi)}{\partial \psi} - \frac{\partial W^p(w^*(b;\psi);\psi)}{\partial \psi} + U^d(b;\psi) - U^f(b)}{\frac{\partial W^p(w^*(b;\psi);\psi)}{\partial w}} \tag{2.1}$$

Consider the effect of protection on a newly employed agent that pays current on the mortgage, $\frac{\partial W^p(w^*(b;\psi);\psi)}{\partial \psi}$. Since the agent is paying, the agent is not at risk of foreclosure. Thus, it must be the case that ψ matters only in the case that the agent loses their job and then begins defaulting again. This implies that the derivative is bounded in a convenient way (assume for simplicity that benefits are constant):

$$\frac{\partial W^p(w^*(b;\psi);\psi)}{\partial \psi} \leq \beta\delta\Big(\psi \frac{\partial U^d(b;\psi)}{\partial \psi} + U^d(b;\psi) - U^f(b)\Big) \tag{2.2}$$

Subbing (2.2) into (2.1) and grouping terms,

$$\frac{\partial w^*(b;\psi)}{\partial \psi} \geq \frac{(1-\beta\delta)\Big(\frac{\partial U^d(b;\psi)}{\partial \psi} + U^d(b;\psi) - U^f(b)\Big)}{\frac{\partial W^p(w^*(\psi))}{\partial w}} > 0$$

The value of default $\frac{\partial U^d(b;\psi)}{\partial \psi} > 0$ is strictly increasing in the degree of default protection, and the value of employment $\frac{\partial W^p(w^*(b;\psi))}{\partial w} > 0$ is strictly increasing in the wage. That the agent chooses default implies that $U^d(b;\psi) - U^f(b) > 0$. Thus the inequality holds. ■

Lemma 2.5.2 *As before, define $\psi(n) = 1 - \lambda_F(n)$ as the degree of default protection. Consider a version of the model that satisfies the hypothesis of Lemma 2.5.1. Under the additional assumptions that the disutility of search is increasing and strictly convex in search* *effort, $x'(s) > 0$ and $x''(s) > 0 \ \ \forall s > 0$, and $\pi(s,\theta)$ is linear in s with $\partial\pi(s,\theta)/\partial s = \alpha_s$, then the optimal search effort $s_i^*(b,a,n;\theta), \quad i \in \{h,r\}$ is decreasing in the degree of protection for any interior point in the state space.*

Proof. Suppressing all household states except for unemployment benefits, let $s^*(b;\psi) = s_i^*(b,a,n;\theta) \ \ i \in \{h,r\}$ be the optimal search decision. Implicitly, the search effort depends on the underlying degree of default protection ψ (see the first order conditions below). The assumptions in the hypothesis ensure that first order conditions suffice for search effort decisions. Consider a defaulting homeowner with $n \geq 1$, and let $VU_h(b;\psi) = VU_h(b,a,n+1;\psi)$ and $VE_h(b;\psi) = VE_h(b,a,n+1;\psi)$. Differentiating, the optimal search effort is implicitly given below:

$$\begin{aligned}\frac{\partial x(s^*(b;\psi))}{\partial s} =& \widehat{\beta}\mathbb{E}\Big[-\alpha_s VU_h(b;\psi) \\ &+ \alpha_s\Big(VU_h(b;\psi)F(w^*(\psi)) + \int_{w^*(\psi)}^{\bar{w}} VE_h(\hat{w};\psi)\ dF(\hat{w})\Big)\Big]\end{aligned}$$

To characterize the effects of protection on search effort, apply the envelope theorem:

$$\begin{aligned}\frac{\partial^2 x(s^*(b;\psi))}{\partial^2 s}\frac{\partial s^*(b;\psi)}{\partial\psi} &= \widehat{\beta}\mathbb{E}\Big[-\alpha_s\frac{\partial VU_h(b;\psi)}{\partial\psi} \\ &\quad + \alpha_s\Big(\frac{\partial VU_h(b;\psi)}{\partial\psi}F(w) + \int_w^{\bar{w}}\frac{\partial VE_h(\hat{w};\psi)}{\partial\psi}\ dF(\hat{w})\Big)\Big]\Big|_{w=w^*(\psi)} \\ &< \widehat{\beta}\mathbb{E}\Big[-\alpha_s\frac{\partial VU_h(b;\psi)}{\partial\psi} \\ &\quad + \alpha_s\Big(\frac{\partial VU_h(b;\psi)}{\partial\psi}F(w) + \frac{\partial VU_h(b;\psi)}{\partial\psi}(1-F(w))\Big)\Big]\Big|_{w=w^*(\psi)} \\ &= 0\end{aligned}$$

The last line follows from the inequality below:

$$0 < \frac{\partial VE_h(w;\psi)}{\partial\psi} \leq \beta\delta\frac{\partial VU_h(w;\psi)}{\partial\psi} < \frac{\partial VU_h(w;\psi)}{\partial\psi} \leq \frac{\partial VU_h(b;\psi)}{\partial\psi} \quad \forall w > b$$

The intuition behind the inequality is that the effect of protection is strongest for those who are unemployed with low benefits, as one would expect. Since benefits are constant, the reservation wage is at least the benefit amount, thus for all the wages above the reservation wage, the above inequality holds. ■

The two main mechanisms described in Lemma 2.5.1 and Lemma 2.5.2 are now demonstrated numerically across time spent in default. In the delayed foreclosure case, defaulters have higher reservation wages since they have the ability to maintain consumption while trying to find a better paying job. The reservation wage declines as foreclosure gets closer since foreclosure will potentially leave them with low consumption, and the curvature of the utility function means they will have a large marginal utility of consumption if this scenario is realized. Thus they lower their reservation wage to just above the minimum amount necessary to cover their mortgage payments. This behavior is numerically illustrated in Figure 2.19 which is the reservation wage profile in good times ($\theta = \theta_H$) for a given level of assets (a) in the model calibrated to match high debt to incomes and high unemployment.[28] Just as described above, as foreclosure becomes a higher probability event, the reservation wage falls. Moreover, the reservation wage always remains above the required mortgage payment (c_h). The no delay economy merely compresses the time it takes to for this process to occur.

Figure 2.20 shows how the search intensity changes over the default episode. Initially the search intensity is quite low as agents do not have strong incentives to find a job; they are still receiving the same flow utility from housing as well as a 50% replacement rate of their last wage which gives them an effective income that is in some cases greater than their effective income while working and making payments on the mortgage. In terms of the model, because the utility function is concave and these defaulting agents have the same effective consumption as before, their marginal utility of consumption is still relatively low, and thus the agents are not incentivized to find a job immediately. As the foreclosure probability increases, the search intensity dramatically rises because there is now a risk that the agent will potentially go through a costly foreclosure and lose the flow utility from housing.

[28]This calibration is chosen to illustrate the mechanisms most clearly.

Figure 2.19: Turbulence Experiment: Difference in Reservation Wages Between Economies

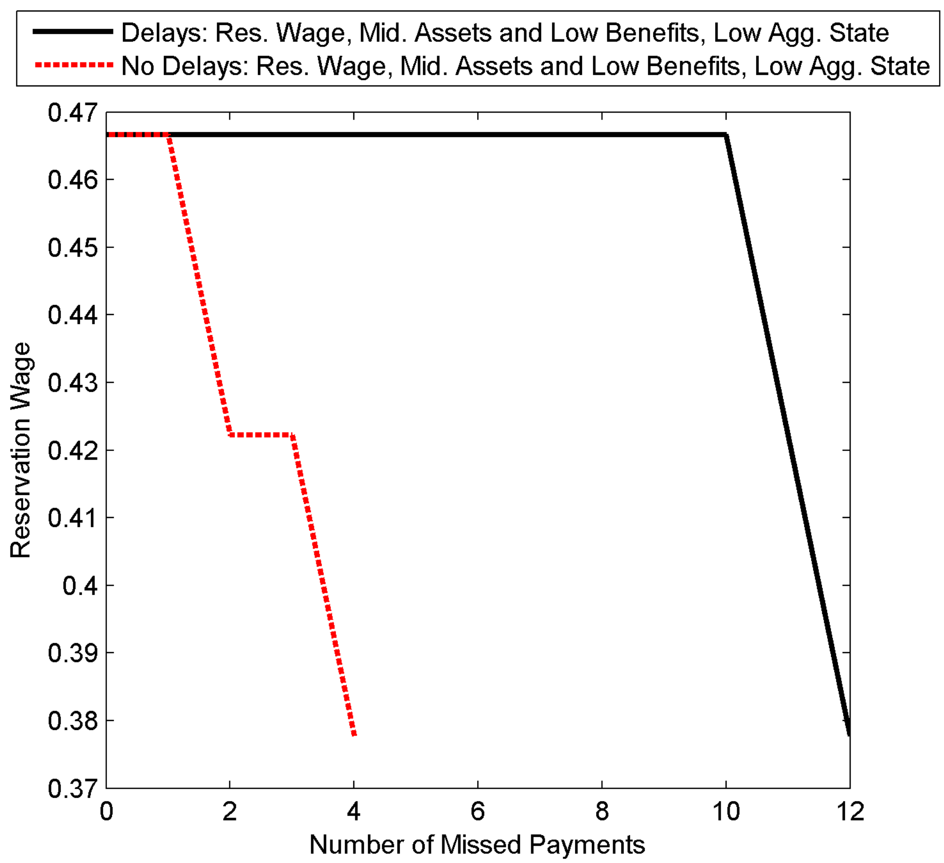


Figure 2.20: Turbulence Experiment: Difference in Search Effort Between Economies

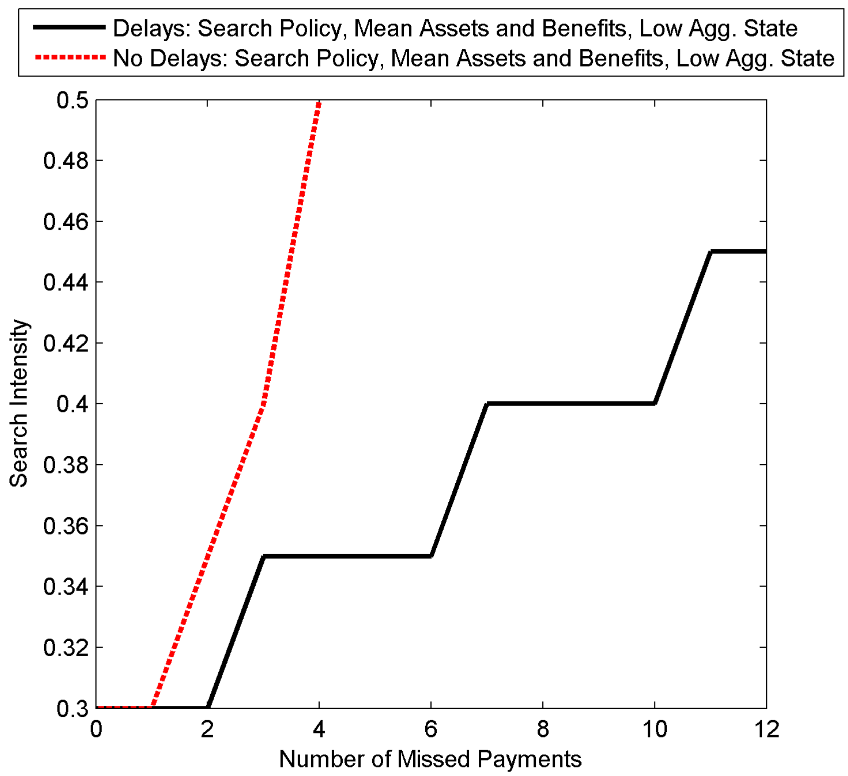


Figure 2.21 shows the unemployment rate by delinquency status. Due to the way the incentives to find a job increase as the foreclosure probability rises, the model generates a hump shaped unemployment rate by delinquency status, just as in Figure 2.2. It is important to note that the unemployment rate among defaulters is higher in our model than the data but this is due to the fact that the only shock that generates a default in this model is either job loss or benefit expiration. Since our default rate is significantly smaller than the data (.34% in the model as opposed to 1.5% in the data, see the Calibration Section), the model *does not* over-estimate the fraction of the population that is unemployed and in default.

Figure 2.21: Turbulence Experiment: Unemployment Rate by Delinquency Status

2.6 Conclusion

To our knowledge, we are the first to capture the interaction between employment and the "ins" and "outs" of default empirically as well as in a quantitative model. On the empirical side, we use both the PSID and SCF to document several new stylized facts including the spike in employment per capita among those involved in foreclosure. We argue that the incentives to find a job near foreclosure are considerably stronger than the incentives to find a job upon unemployment benefit expiration because of the potential forgone return to home tenure, the implications for credit access, the option value of owning a home, the potential deficiency judgement, etc. We draw a clear distinction between default and foreclosure and we document the way homeowners transit between these states.

On the quantitative side, the model captures the effect of prolonged default and allows us to consider how financial frictions can change job search and wage acceptance decisions. With plausible economic turbulence, we find significant and persistent effects from the foreclosure delays on the unemployment rate. Default is an implicit line of credit from banks to borrowers that begins with a missed payment and ends with a foreclosure or cure. By extending the duration of this line of credit via foreclosure delays, this extra self-insurance lets unemployed workers economize on search effort and avoid large wage cuts. As a direct effect, the economy with foreclosure delays has an unemployment rate that is $\frac{1}{3}\%$-$\frac{3}{4}\%$ higher in levels and a stock of delinquent loans that is nearly 25% larger in relative terms. However, because workers can find better matches, output actually increases by $\frac{1}{10}\%$. We find that defaulters borrow at extraordinarily high interest rates, and we show that the behavior in our model is consistent with observed facts from the data. While our analysis is entirely positive, it gives future researchers the opportunity to use the data in this paper to analyze the normative implications of foreclosure delay including whether or not this is the most efficient way to provide unemployment benefits.

In related work, Herkenhoff and Ohanian (2012b) suggest that aid to unemployed homeowners such as retraining subsidies and scholarships for secondary education will stem defaults more permanently and allow the housing market to recover. Delaying foreclosure is temporary relief, but helping workers obtain the skills required to find a job will provide them with the income necessary to be homeowners in the long run.

2.7 Appendix

2.7.1 Data

The mortgage data is randomly sampled from the Lender Processing Services (LPS) McDash database and is nationally representative. The database extends back to 1992:Q2 and covers roughly 2/3 of all mortgage until the present.

The wealth, wage, and asset data is taken from the Panel Study of Income Dynamics (PSID), and only household heads are considered.

2.7.1.1 Image Descriptions

Unemployment Rate Among Mortgagors: 2009 PSID Core/ Immigrant Sample, Non-Disabled Working Age Heads (24-65yr) with Mortgages.

LPS Negative Equity: First Residential Loans with non-missing Loan-to-Value and non-missing Corelogic Price Index from Origination Until Present. Corelogic Price Index at Zip Code Level is applied to the origination home value.

Unadjusted Employment/ Unemployment By Delinquency Status: 2009 PSID Core/ Immigrant Sample, Non-Disabled Working Age Heads with Mortgages (or Previously Had a Mortgage but was Foreclosed Upon)

Composition Adjusted Employment/Unemployment By Delinquency Status: 2009 PSID Core/ Immigrant Sample, Non-Disabled Working Age Heads with Mortgages (or Previously Had a Mortgage but was Foreclosed Upon), Linear Regression Employment Indicator on Host of Controls (Negative Equity, Judicial/ Non Judicial Indicators, Past Income, Age, Sex, Race, Unsecured Debt, Liquid Assets, Illiquid Assets, etc.) and Separate Indicators for 30 Days Late, 60 Days Late, 90+ Days Late, and Foreclosure. Restrict the sample to Labor

Force Participants for the Unemployment Adjustment. Apply indicator coefficients to the unadjusted baseline omitted group (homeowners that made all payments)

2.7.1.2 Unemployment by Delinquency, Composition Adjustment

Table 2.6: Unemployment Rates, 2009 PSID Supplement, Working Age Heads of House (Source: PSID)

Unemployment Rate (PSID, Working Age Heads)

	Renters	No Missed Payments	30 Days Late	60 Days Late	90+ Days Late	Foreclosed / In Foreclosure
All States, Unadj.	18.5%	7.0%	15.6%	18.4%	33.3%	16.1%
All States, Composition Adj.	NA	7.0%	14.5%	18.8%	35.3%	13.4%
Judicial States	17.8%	7.0%	20.7%	18.8%	50.0%	23.1%
Non Judicial States	19.0%	6.9%	12.5%	18.2%	24.4%	11.1%
Observations	3192	2958	77	49	69	31
Judicial Observations	1973	1794	48	33	45	18
Non-Judicial Observations	1219	1164	29	16	24	13

Employment Per Capita (PSID, Working Age Heads)

	Renters	Non-Defaulting Mortgagors	30 Days Late	60 Days Late	90+ Days Late	Foreclosed / In Foreclosure
All States, Unadj.	71.8%	86.1%	79.3%	80.0%	61.3%	74.3%
All States, Composition Adj.	NA	86.1%	79.7%	78.3%	61.6%	78.6%
Judicial States	72.2%	86.6%	71.9%	81.3%	44.4%	66.7%
Non Judicial States	71.6%	85.8%	84.0%	79.4%	70.8%	80.0%
Observations	3621	3196	82	50	75	35
Judicial Observations	1388	1249	32	16	27	15
Non-Judicial Observations	2233	1947	50	34	48	20

Notes: The sample includes all non-disabled 2009 PSID Core/Immigrant heads of household between 24 and 65. Mortgagors that miss one payment are considered 30 days late, and so on (see text for more details). Foreclosure includes those who have been foreclosed upon since the last survey in 2007 or have received the letter of foreclosure. Composition Adjustment described in the text.

Table 2.7: Basic Controls

PSID Controls

	Renters	No Missed Payments	30 Days Late	60 Days Late	90+ Days Late	Foreclosure
Median 2006 Income	37200	78000	58000	54500	59000	57104
Fraction with College Degree	22.3%	37.6%	20.8%	30.6%	18.8%	12.9%
Negative Equity	0.0%	10.3%	24.7%	32.7%	39.1%	25.8%

Table 2.8: Unemployment Rate and Employment Per Capita, Survey of Consumer Finances (SCF)

Unemployment Rate (SCF, Working Age Heads)

	Renters	No Missed Payments	30 Days Late	60+ Days Late	In Foreclosure/Foreclosed
Unemployment Rate, Unadj.	11.0%	5.8%	8.5%	21.1%	4.3%
Unemployment Rate, Composition Adj.	NA	5.8%	8.8%	19.7%	5.4%
Observations	1040	1482	130	90	47

Employment Per Capita (SCF, Working Age Heads)

	Renters	No Missed Payments	30 Days Late	60+ Days Late	In Foreclosure/Foreclosed
Employment Per Capita, Unadj.	74.6%	88.0%	86.2%	76.3%	91.8%
Employment Per Capita, Adj.	NA	88.0%	85.7%	76.1%	93.6%
Observations	1241	1587	138	93	49

Controls (SCF, Working Age Heads)

	Renters	No Missed Payments	30 Days Late	60+ Days Late	Foreclosure
Median Income in 2006	54000	100000	66000	55000	77500
Fraction with College Degree	45.9%	59.2%	40.8%	27.8%	51.1%
Fraction with Negative Equity	0.0%	17.5%	25.4%	31.1%	31.9%

Table 2.9: Logit Dependent Variable: Indicator if Employed. Average Marginal Effects Reported. PSID Heads.

	(1) Logit	(2) Logit	(3) Logit
30 Days Late	-0.0636	-0.0827*	-0.0755**
	(0.0422)	(0.0461)	(0.0376)
60 Days Late	-0.0777	-0.0795	-0.1186**
	(0.0598)	(0.0623)	(0.0580)
90+ Days Late	-0.2454***	-0.2988***	-0.2834***
	(0.0675)	(0.0710)	(0.0709)
Foreclosed Since 2007/In Foreclosure	-0.0748	-0.1273*	-0.0644
	(0.0608)	(0.0741)	(0.0533)
Negative Equity Indicator	-0.0012		0.0023
	(0.0208)		(0.0147)
Total Income in 2006	0.0060***		0.0032***
	(0.0013)		(0.0011)
College Degree Indicator	0.0153		0.0123
	(0.0136)		(0.0108)
Liquid Assets to Income < 5%	0.0160		-0.0087
	(0.0128)		(0.0100)
Illiquid Assets to Income < 5%	-0.0009		-0.0051
	(0.0173)		(0.0150)
Unsecured Debt to Income $\in [.25, .5]$	0.0570**		0.0343*
	(0.0234)		(0.0179)
Unsecured Debt to Income $\in [.5, .75]$	0.0043		0.0091
	(0.0318)		(0.0241)
Unsecured Debt to Income $\in [.75, \infty]$	-0.0597***		-0.0246*
	(0.0193)		(0.0147)
Judicial Indicator	0.0042		-0.0063
	(0.0128)		(0.0098)
Recourse Indicator	-0.0170		-0.0117
	(0.0143)		(0.0110)
Sub Sample	Working Age Population	Working Age Population	Labor Force Participants
Demographic Controls (Age, Race, Sex, Education, Divorce)	Yes	No	Yes
State Law Controls (Judicial, Recourse)	Yes	Yes	Yes
P-Value, Test for Equality of Coefficients B(Foreclosure)=B(90+ Days Late)	0.150	0.294	0.026
Observations	3129	3196	2897

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 2.10: Logit Dependent Variable: Indicator if Employed. Average Marginal Effects Reported. SCF Heads.

	(1) Logit	(2) Logit	(3) Logit
30 Days Late	-0.0231	-0.0261	-0.0300
	(0.0294)	(0.0306)	(0.0231)
60+ Days Late	-0.1185***	-0.1249***	-0.1392***
	(0.0432)	(0.0449)	(0.0412)
Foreclosed Since 2007/In Foreclosure	0.0564*	0.0347	0.0044
	(0.0331)	(0.0435)	(0.0299)
Negative Equity Indicator	-0.0176		-0.0052
	(0.0217)		(0.0154)
Total Income in 2006	-0.0005**		-0.0003**
	(0.0002)		(0.0001)
College Degree Indicator	0.0729***		0.0435***
	(0.0167)		(0.0136)
Liquid Assets to Income < 5%	0.0267		-0.0032
	(0.0338)		(0.0300)
Illiquid Assets to Income < 5%	-0.0162		-0.0198
	(0.0233)		(0.0190)
Unsecured Debt to Income $\in [.25, .5]$	-0.0359		-0.0035
	(0.0367)		(0.0287)
Unsecured Debt to Income $\in [.5, .75]$	-0.1093**		-0.0476
	(0.0540)		(0.0421)
Unsecured Debt to Income $\in [.75, \infty]$	-0.0801***		-0.0141
	(0.0306)		(0.0265)
Sub Sample	Working Age Population	Working Age Population	Labor Force Participants
Demographic Controls (Age, Race, Sex, Education, Divorce)	Yes	No	Yes
State Law Controls (Judicial, Recourse)	No	No	No
P-Value, Test for Equality of Coefficients B(Foreclosure)=B(60+ Days Late)	0.0095	0.0429	0.0317
Observations	1587	1587	1482

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 2.11: Dependent Variable: Employment Indicator As of 2009 SCF Survey Date

	(1) LPM	(2) LPM	(3) Logit	(4) Logit
Foreclosure	0.437***	0.393**	0.493**	0.454*
	(0.163)	(0.158)	(0.228)	(0.241)
Negative Equity Indicator	-0.218		-0.218	
	(0.143)		(0.135)	
Income in 2006	-3.07e-07		-3.73e-07	
	(1.46e-06)		(2.48e-07)	
College Degree Indicator	0.105		0.104	
	(0.152)		(0.145)	
Age	-0.00580		-0.00545	
	(0.00669)		(0.00592)	
Observations	63	63	63	63
R-squared	0.113	0.061		

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

2.7.1.3 Small Sample Analysis

Restricted Sub-Sample: Working age heads of household who were at least 60+ days late over the last 12 months, reported a positive unemployment spell over the last 12 months, and have a mortgage in 2009 or previously had a mortgage in 2007 but were foreclosed upon and thus no longer a mortgagor.

Treatment Group: Unemployed delinquent heads that were involved in a foreclosure. 7 received the treatment and 6 subsequently found jobs.

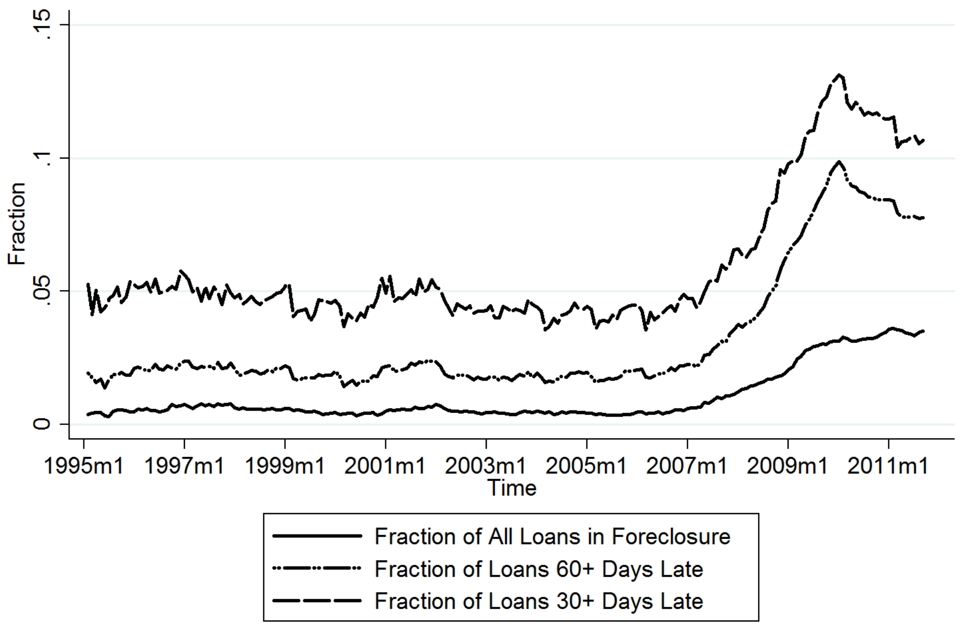
Control Group: Unemployed delinquent heads that were not involved in a foreclosure. 56 were in the control group and 26 subsequently found jobs.

Due to the small sample, I include a limited set of controls; the selection of controls is based on significance in the composition analysis. All errors below are bootstrapped using the entire sample with replacement, repeated 5000 times.

2.7.1.4 Default Data

Figure 2.22 shows default stocks across all states. Figure 2.23 shows delinquency stocks for January 2011 by MSA.

Figure 2.22: Delinquency Stock and Foreclosure Stock (Source: LPS)



2.7.1.5 Competing Risks Model

The main problem associated with measure foreclosure delay is the severe incidence of right censoring and the presence of competing risks. We also want to distinguish between congestion and the effects of policies. To correct for these issues and discipline our study of foreclosure delays we estimate risk-specific sub hazards, similar to Gerardi et al. (2011). True censoring is easy to correct, simply replace the hazard times the survivor function in the likelihood function with just the survivor function for censored observations. To correct for competing risks is more difficult and requires the estimation of a subhazard. To understand why this is important, the problem with treating cures (almost half the observations) as censors is that censored observations can still eventually be foreclosed upon. If these cures are treated as censoring the foreclosure delays will be grossly magnified and over estimated. It is important to note that Figure 2.3 does not suffer from the problem of censoring and cures.

We compare two times periods, 1992-1998 which is the period following the savings and loan recession in which there were limited policies affecting mortgage foreclosure versus the policy laden period of time, 2009-2011. A loan enters the study when it begins foreclosure and exits the study via cure or completed foreclosure. True censoring is the only reason either of these outcomes would not be observed. The controls include whether the mortgage is in a judicial state or non-judicial state, the cumulative number of loans currently in the foreclosure process (congestion), and the loan to value of the loan. Figure 2.24 plots the cumulative incidence function of foreclosure completion, *holding congestion constant*. The curves can be read as the fraction of loans that have had a foreclosure completed t periods from the initial foreclosure letter. As is clear from the image, the policies had large effects on the foreclosure process, and most of the policy delay occurs around 3 months after the initial foreclosure letter. Both judicial and non-judicial states had a similar change in cumulative incidence in levels due to the policies.

Figure 2.23: Fraction Delinquent (30+ Days Late, Compare to Model) (Source: LPS)

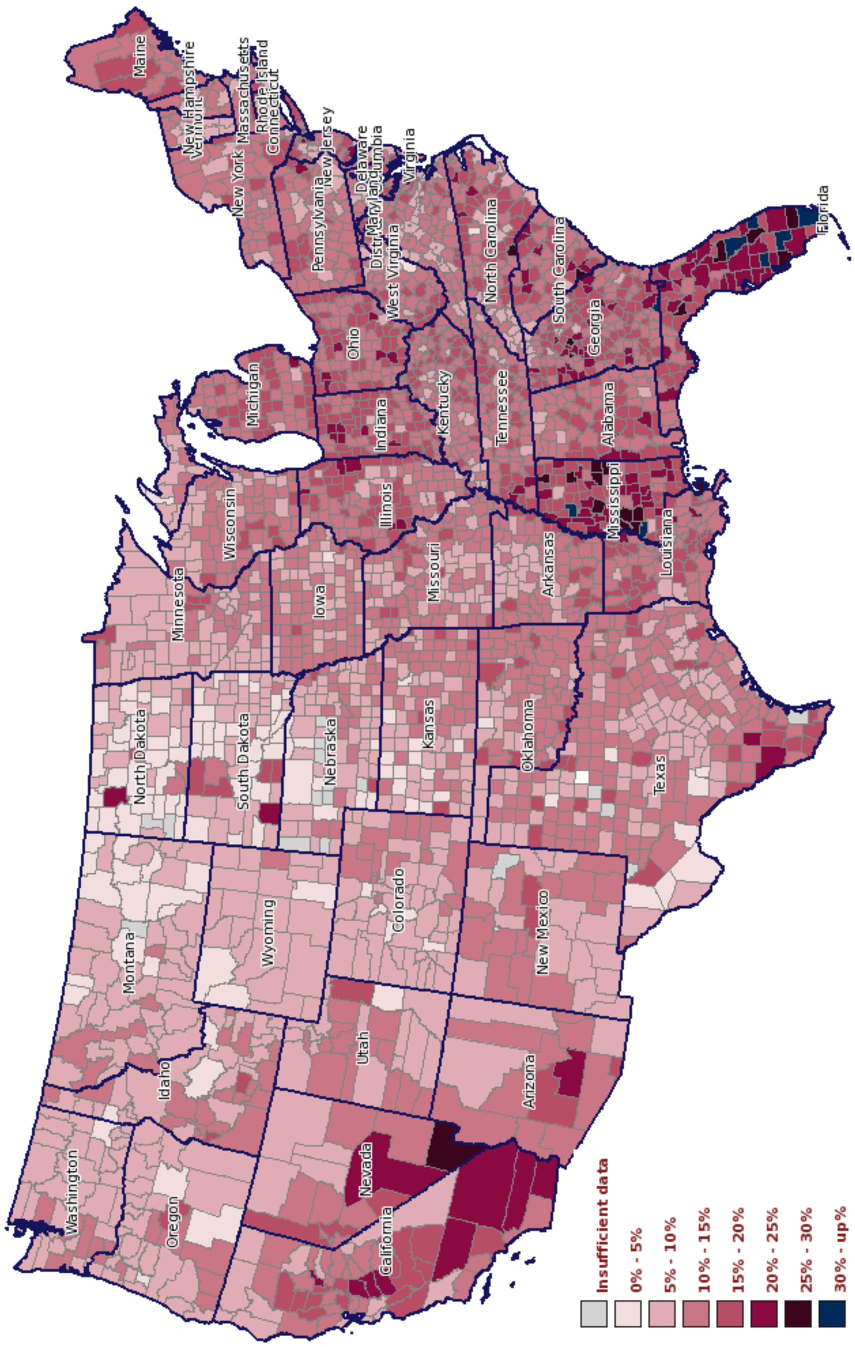
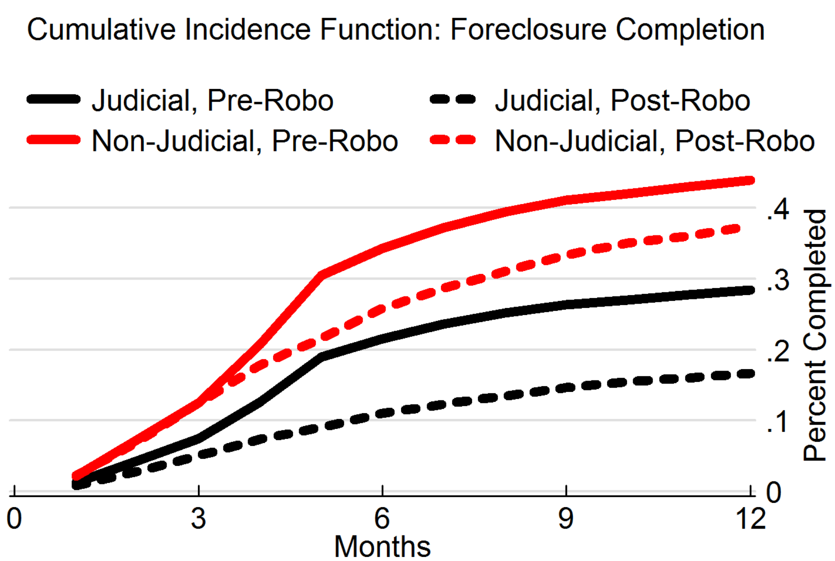


Figure 2.24: Competing Risks Model (Source: LPS and Author's Calculations)



Competing Risks Model, (1) Completed Foreclosure competes with (2) Self-Cure.
Pre-Robo: 1992 to 1998, Post-Robo Cohort: 2009 to 2011.
Cohorts followed from foreclosure letter until either outcome.
Corrected for Censoring, and Controls for Congestion and LTV.
Interpretation: Fraction with completed foreclosure t months after initial foreclosure letter.
Does not asymptote to unity due to competing event (cure).

2.7.2 Parameterization Regressions and Aggregate State Transition Matrix

For non-censored observations, we estimated a few simple linear hazard regressions. In Table 2.12 the dependent variable is an indicator that takes the value 1 when the person is asked to leave the house.[29] Our estimates look at the probability of being asked to leave the home conditional on being 90+ days late.

This table says, that for each missed payment after having already skipped 3 payments,

Table 2.12: Estimation results : Dependent variable is indicator of eviction $\mathbb{I}(\mathit{Eviction\ Occurred})$, sample is conditional on being 90 days late (Source: LPS)

Variable	Coefficient	(Std. Err.)
Time Since 90 Days Late	0.00797	(0.00028)
Intercept	0.07992	(0.00563)

the probability of eviction goes up by .797%.

Table 2.13 shows the estimates for how likely it is to be modified as a function of skipped payments. These hazards are easy to interpret, which is the reason we used this simple setup for our preliminary results. In later versions we will use Cox proportional hazard models that can correct for censoring.

Table 2.13: Dependent variable is indicator of modification $\mathbb{I}(Modification\ Occurred)$, sample conditional on being 30+ days late (Source: LPS)

Variable	Coefficient	(Std. Err.)
Time Since 30 Days Late	-0.00002	(0.00004)
Intercept	0.00556	(0.00058)

We also constructed the monthly good-times-bad-times transition matrix from business cycle data on the NBER webpage; the probability of transiting from good times to bad times is .0146 and the probability of staying in good times is .9854:

[29]The "paid-off" state can indicate many outcomes, but we count all of those outcomes as evictions- if this were not the case, and if we took into account censoring, the delay periods would look much longer

$$\theta_{Transition} = \begin{bmatrix} 0.9854 & 0.0146 \\ 0.0833 & 0.9167 \end{bmatrix}.$$

2.7.3 Congestion or Policy Driven Foreclosure Delay and Its Impact on Default Decisions

Table 2.14 explains the variables used in this empirical portion of the paper. The robo-signing indicator, which takes a value of 1 after October 2010, is the first variable of interest.[30] To see what the effects were of foreclosure delay, we use a natural experiment to conduct an event study by looking at loans in the foreclosure process between 2009 and 2011, and comparing their chances of being foreclosed upon before and after the robo-singing lawsuit was initiated. Figure 2.25 shows the break in the series, plotted quarterly; clearly after the robo-signing lawsuit, the probability of being foreclosed upon fell substantially (where "foreclosed upon" means liquidated via foreclosure sale). To formalize this event study, we regress an indicator of whether or not a loan was foreclosed (either successful or unsuccessful foreclosure sale) on the robo signing indicator, as well as a host of other controls. Panel (A) of Table 2.15 shows that the probability of being foreclosed in any given month declined by roughly 2.41% after the robo-signing lawsuit was passed. To put this in perspective, this is equivalent to an additional six month delay (simply take the ratio of the months in foreclosure and robo-signing coefficients 6.67=.0036/.0241). This is only one of many events that impacted the ability of banks to foreclose, and thus represents a potentially small part of the issue at hand. We therefore conclude that policy interventions have caused a decent portion of the foreclosure delays.The role of congestion is also important; one percent more loans in foreclosure in the given state decreases the probability of being foreclosed upon by .92%.

Panel (B) of Table 2.15 shows the effect of general foreclosure delay on the decision to default. To capture this effect, we regress an indicator that equals one when the loan first becomes 60+ days late on the relevant state's foreclosure delay along with other covariates. Even after controlling for a time trend, foreclosure delay impacts the decision to default,

[30]The robo-signing lawsuit was originally given to the 5 largest services on this date; these servicers handle a disproportionate share of loans, so we treat this as a national event.

increases the probability of default by about .1-.2% at roughly 1 year's worth of delays ($.0013 \times 12 - .0001 \times 12^2$). To put this into perspective, the foreclosure delay effect on the hazard of defaulting is about 1/15th-1/10th as important as being 30% underwater (being underwater by 30% or more increases chances of defaulting by 1.52%).

Figure 2.25: Foreclosure Completion Rate, Event Study (Robo Signing Date, Vertical Line) (Source: LPS)

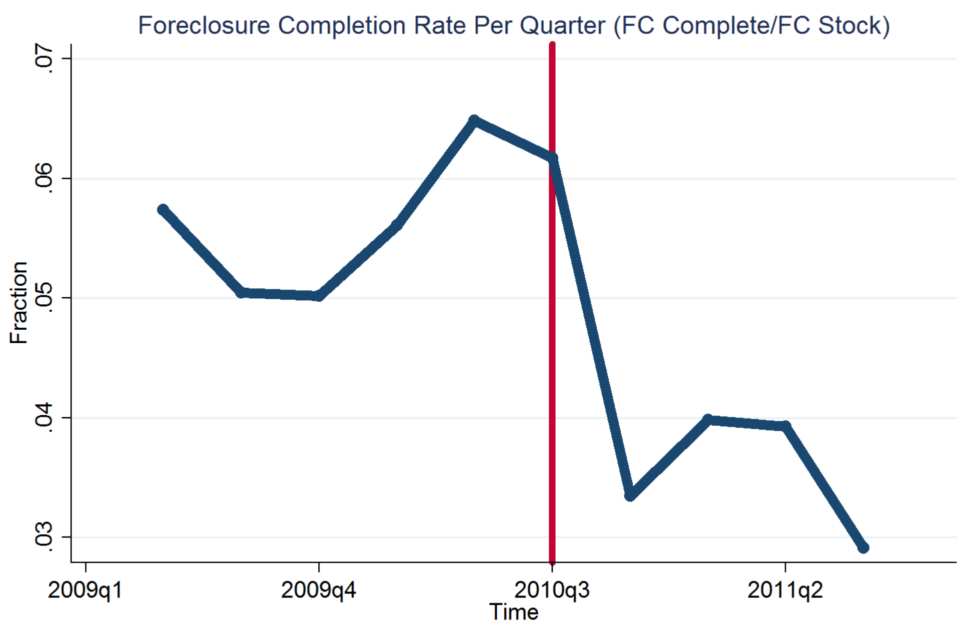


Table 2.14: Definitions (Source: LPS)

Variable	Description
Robo	Indicator=1 if Date > October 2010
Months in Foreclosure	Months spent in foreclosure, by month and by loan
Percent of Loans in Foreclosure, by State	Fraction of all loans in foreclosure proceedings, by month and by state
Principal Remaining in 10,000s	Principal Remaining in $ 10,000s
Foreclosure Delay, by State	Average time spent in foreclosure proceedings, by month and by state
(Foreclosure Delay)^2, By State	
1.1 $\geq$Current LTV$>$ 1	Principal Remaining/Current Home Value (Estimated using OFHEO All Transations Index)
1.2 $\geq$Current LTV$>$ 1.1	
1.3 $\geq$Current LTV$>$ 1.2	
Current LTV$>$ 1.3	
Mortgage Characteristics	FICO, DTI, Interest Rate, Mortgage Type, Loan Type, Investor Type, Document Type, Purpose Type

Table 2.15: Linear Probability Model (Source: LPS)

Panel (A)		**Panel (B)**	
Dependent Variable:	**Foreclosed Indicator**	Dependent Variable:	**60 Days Late Indicator**
Robo	-0.0241**		
	(0.0104)		
Principal Remaining in 10,000s	-0.0064***	Principal Remaining in 10,000s	0.0001**
	(0.0006)		(0.0000)
Months in Foreclosure	0.0036***	Foreclosure Delay	0.0013***
	(0.0005)		(0.0005)
Percent of Loans in Foreclosure, by State	-0.0092**	(Foreclosure Delay)^2	-0.0001***
	(0.0046)		(0.0000)
$1.1 \geq$Current LTV> 1	-0.0140	$1.1 \geq$Current LTV> 1	0.0087***
	(0.0186)		(0.0028)
$1.2 \geq$Current LTV> 1.1	-0.0156	$1.2 \geq$Current LTV> 1.1	0.0138***
	(0.0225)		(0.0047)
$1.3 \geq$Current LTV> 1.2	-0.0051	$1.3 \geq$Current LTV> 1.2	0.0182***
	(0.0274)		(0.0070)
Current LTV> 1.3	-0.0079	Current LTV> 1.3	0.0152**
	(0.0309)		(0.0068)
Mortgage Characteristics	Yes	Mortgage Characteristics	Yes
State Fixed Effects	Yes	State Fixed Effects	Yes
Time Trend	Yes	Time Trend	Yes
State Unemployment Rate	Yes	State Unemployment Rate	Yes
Observations	3792	Observations	98590

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

2.7.4 Literature Review

We find similar behavioral effects as Mulligan Mulligan (2008, 2010, 2011) who looks at means-tested subsidies, including mortgage modifications, and their role in slowing employment growth.[31] Our paper also builds on our earlier work, Herkenhoff and Ohanian (2011), where we explored the interaction between labor markets and housing markets in a partial equilibrium setting with frictional employment, skill loss and means-tested mortgage subsidies.[32] The model predicts agents use the modification "option" at the last possible moment to lock-in low payments and potentially avoid eviction. In order to qualify for a modification, agents must become at least 1 month delinquent; the novelty of that model was that the initial delinquency did not result in foreclosure- instead the agent had free rent for one period. This changes the model economic agents' incentives to relocate to relatively better labor markets, and as a result, unemployment reaches .5% higher in the world with modifications. Our work is also related to Mulligan (2008, 2011) who considers the impact of mortgage modifications and means testing on labor supply decisions. Mulligan shows that the replacement rate of income has increased substantially since the onset of the recession and that this replacement rate manifests itself as a labor wedge. This is consistent with the diagnosis in Mulligan (2010) and Ohanian (2010).

On the empirical side of the literature, Gerardi et al. (2011) consider whether or not foreclosure delay actually helps a borrower; they find that foreclosure delay merely stalls the ultimate outcome of eviction. Pace and Zhu (2011) find that borrowers are more likely to default if there is a longer period of free rent during foreclosure delay. They find that an additional 3 month delay increases the default hazard by 30%, for a subset of loans. Calomiris and Higgins (2010) provide some thought experiments on foreclosure delay. They walk through the costs of the delays including (i) bank lending reduction, (ii) uncertain and transitory affect on income, (iii) less housing construction, (iv) neighborhood blight and

[31] Mulligan's models were the first to look at the incentive effects of mortgage modifications in a creative principal agent setting, and his subsequent work is in an RBC model which has voluntary unemployment due to increased payments to non-employed household members.

[32] In that model, agents were living hand-to-mouth and given one tool to keep their home, mortgage modification (for a general equilibrium treatment of modifications in an endowment economy see Chatterjee and Eyigungor (2009) and for empirical facts of modifications see Adelino et al. (2009).

the benefit of (i) stabilizing house prices, and (ii) keeping people in their homes. Calomiris et al. (2011) apply a similar thought experiment to the mortgage servicer settlement that mandates modifications; similar to Herkenhoff and Ohanian (2011), these authors argue that modifications are merely another foreclosure delay that slows down the economy. While not modeled endogenously in our exercise, the price effects from actual foreclosures which are carefully documented in Calomiris et al. (2008).

On the structural real estate economics side, the norm in the literature is to model default and foreclosure as immediate eviction, and in general this allows authors to focus on the mechanism of interest. Examples include Garriga and Schlagenhauf (2009), Corbae and Quintin (2009), Hatchondo et al. (2012) and Campbell and Cocco (2011); each of these papers contributes substantially to the work on mortgage innovation, but omits the role of protracted default and foreclosure. Chatterjee and Eyigungor (2011) use an endowment economy to model the effect of the construction boom on home prices and foreclosure. As a subsection of their paper, they look at foreclosure delay which is modeled as a one period delay between default and foreclosure. In essence, a homeowner picks between paying, inviting eviction (with 1 period of free rent), or selling. They find that this one period delay is important in generating a large incidence of foreclosure (it also allows them to keep the discount factor lower). However, they find that this has no impact on house prices. Herkenhoff and Ohanian (2011) include a similar foreclosure delay in which agents skip one payment before either modifying a loan or being foreclosed upon, and in related work, Herkenhoff, Ohanian, and Sanchez (2011) consider the delinquency interactions across unsecured debt and secured debt, including long term contracts, in a life-cycle consumption smoothing model. The idea of delays in defaultable debt models is not new, however. Benjamin and Wright (2009) were the first to model protracted sovereign default episodes for nations using renegotiation delays and Benjamin and Mateos-Planas (2011) apply the same structure as Benjamin and Wright to look at protracted renegotiation over unsecured consumer credit in an endowment economy where agents have the option to file for bankruptcy.

In terms of labor and housing, Head and Lloyd-Ellis (2012) were one of the first to consider housing markets, labor markets, and mobility in a general equilibrium matching model. Their focus is on the relocation effect, similar to Herkenhoff and Ohanian (2011). They find that there are important interactions between the labor market and the housing market, but that the effects are a wash in aggregate.

As mentioned above, this paper contributes along a data dimension and modeling dimensions. The model allows households to enter and exit default regularly in times of crises in order to smooth consumption. With frictional employment, these ins and out of default correspond to unemployment spells. On the data side, we find similar behavior. Default episodes are often times serially correlated, and often times do not result in eviction (the sheriff sale of foreclosure).

2.7.5 Additional Comments on the Model

2.7.5.1 Unsecured Credit and Other Debts

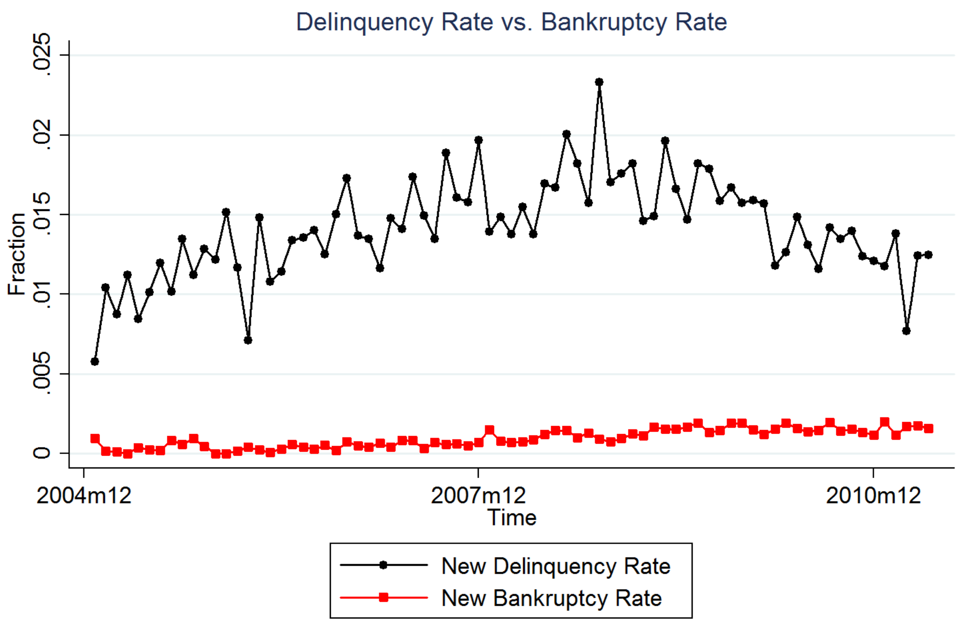
Agents are given access to a riskless savings technology, but for those with limited savings, agents choose to default because it is the best available technology to smooth their consumption. The typical trigger for default is unemployment. Aside from the initial mortgage endowment, agents are not allowed to borrow to smooth consumption. We lump credit card debt service payments into the model's fixed mortgage payment in our parameterization, but we do note that credit card debt outstanding is 1/11th of mortgage debt outstanding and is a relatively small share of household debt (see the Federal Reserve Bank of New York's 2011-II Credit Report, Total Debt Outstanding). The inability to readily obtain new unsecured lines of credit is also consistent with the standard credit crunch hypotheses.[33] While we do not model bankruptcy, the work done by Li and White (2009) suggests that after the 2005 bankruptcy reform, households substituted away from bankruptcy into default and foreclosure.[34] Figure 2.26 documents the fact that while bankruptcies are important, they are a relatively small pandemic compared to a generic measure of delinquencies, defined by

[33] Mian and Sufi (2010) use Equifax data to study these regional credit crunches

[34] In general, they find that default and foreclosure predict bankruptcy, and vice versa. They are unable to isolate causation, but they do plot similar graphs to us that show bankruptcy applies to a small fraction of delinquent households.

those who have skipped one or more payments.

Figure 2.26: Delinquency and Bankruptcy Rates (Source: LPS)



2.7.6 Wage Process

Following Shimer (2005b), we compute the fraction of job-to-job flows that are voluntary and involuntary.[35] We interpret voluntary job-to-job transitions as moving up the wage ladder one position, and involuntary job-to-job transitions as moving down the wage ladder one position. Using the same numbers, we set $f_t = .61$ (job finding rate), $f_t^e = .0915$ (employment to employment rate), $s_t = .035$ (separation rate) and then calculate the attributable shares of job transitions that are voluntary and involuntary using the formulas in Shimer (2005b). Our calculations yield that the monthly probability of a wage increase via voluntary job-to-job transition is 8.7% and the probability of a wage decrease via an involuntary job-to-job transition is .88%.[36]

[35] Job-to-job flows which are involuntary means that there was a layoff within the month and a new job found within the month.

[36] This is similar to Ljungqvist and Sargent (1998)'s wage process which allowed for a movement up the wage ladder in any given month with a 10% probability.

CHAPTER 3

Unemployment, Negative Equity, and Strategic Default

3.1 Introduction

The question of what exactly drives mortgage defaults is of central importance in the aftermath of the 2008 U.S. financial crisis and subsequent Great Recession. In order to begin to design policies to alleviate the still-elevated levels of delinquencies and foreclosures, and prevent a future mortgage foreclosure crisis, we need to understand the exact sources of the problem. There is a large and growing literature that studies the empirical determinants of mortgage default.[1] Within this literature, there is broad agreement that a number of factors may potentially contribute to default, including negative equity, employment/unemployment status of the mortgagor, and the net wealth and liquidity position of the mortgagor. Quantifying the relative importance of these factors is important because they have very different implications for understanding default incentives and actions, and also for the design of economic policy. Specifically, if negative equity in and of itself plays a quantitatively important role, then many defaulters may be engaging in what is called strategic, or ruthless default, in which borrowers stop paying when they have a large negative equity position. In contrast, if unemployment plays a key role, then default by many borrowers may simply reflect an inability to make mortgage payments, rather than exercising an option value on an asset whose price has fallen, as would be the case with strategic default.

Despite many studies, there is no definitive answer as to the quantitative importance of these different factors in default decisions.[2] This reflects the fact that existing studies have

[1] Foote et al. (2008), Haughwout et al. (2008), Mayer et al. (2009), Gathergood (2009), Goodman et al. (2010), Elul et al. (2010), Bhutta et al. (2011), and Mocetti and Viviano (2013) among others.

[2] For example, Goodman et al. (2010), Bhutta et al. (2011), and Foote et al. (2008) argue that negative equity is the most important factor explaining the rise in defaults during the crisis, Elul et al. (2010) argues

not used a dataset that simultaneously provides measures of mortgage status, borrower employment/unemployment status, and the asset and liability position of borrowers. Instead, borrower employment status is typically proxied in studies by using the state, county, or MSA unemployment rate. Gyourko and Tracy (2013) shows that this proxy can lead to quantitatively important attenuation bias that substantially understates the role of unemployment in default. Indeed, as we discuss in more detail below, many of the prior studies that have included aggregate unemployment rates have found only a weak correlation with default. Moreover, measures of wealth are omitted in most studies due to the lack of such information in the typical loan-level datasets used by researchers.

Consequently, relatively little is known about the contribution of job loss and borrower net worth positions on default. And this in turn has important implications for assessing the contribution of negative equity, not only because the impact of these other factors is not measured, or not measured well, but also because little is known about the interaction of negative equity with these other factors. As a result, the impact of negative equity as a "single trigger" for default, as would be the case of strategic default, or whether negative equity is important in conjunction with another factor as a "double trigger", is uncertain.

In this paper we begin to disentangle the causes of default using the Panel Study of Income Dynamics (PSID), which includes relatively precise measures of mortgage delinquency, negative equity, employment status, and wealth. In a simple, transparent, reduced-form analysis, we assess the relative importance of these factors in explaining household-level mortgage defaults. We find in contrast to many prior studies that focused on regional unemployment rates, an individual's unemployment status and liquid asset positions are important (and nearly always the most important) determinants of default. To be more precise, we find that individual unemployment increases the probability of default by 8 to 13 percentage points, ceteris paribus, which is a very large effect considering that the unconditional, average default rate in the PSID is only 3.9%. Consistent with prior work by Bhutta et al. (2011), we also find that severe negative equity of -20% or worse increases the probability of default

that illiquidity in the form of high credit card utilization rates in combination with negative equity are the main factors triggering default, while Mayer et al. (2009) argues that it is a combination of house price stagnation, loose underwriting, and poor employment prospects.

by 5 to 18 percentage points, ceteris paribus. Finally, we find a strong, negative correlation between a household's level of liquid assets and default behavior. Households who report a ratio of liquid assets to annual gross income of over 5% default 3 to 8 percentage points less than households with a ratio under 5%, in line with the liquidity results of Elul et al. (2010). We corroborate these results in the Survey of Consumer Finances (SCF), which has a similar level of information at the household-level.

In addition, we present suggestive evidence of the importance of double trigger events in causing mortgage defaults. For example, the simple unconditional default rate of unemployed households with negative equity in the PSID is approximately 30%, whereas employed households with negative equity have an unconditional default rate of just over 10%, which implies that unemployment produces a difference in default rates of approximately 20% among those with negative equity. In contrast, the unconditional default rate for an unemployed household with positive equity in the PSID is 10.6% while an employed household with positive equity has a default rate of only 2.1%, which implies that unemployment produces a difference of roughly 8.5% in default rates among those with positive equity. Thus, the simple interaction effect, or the "double trigger" effect, between unemployment *and* negative equity is to raise the unconditional default rate by approximately 11.5% (20% - 8.5%) over and above either trigger on its own. While the sample size in the PSID is too small to precisely estimate the interaction between employment and equity with controls, the large magnitude of the unconditional measure of the double trigger effect of unemployment and negative equity suggests that future research on the double trigger hypotheses is vital.

Finally, with both detailed data on households' balance sheets and home equity positions, we are able to provide some new suggestive measures of strategic default to the literature. We find that in the PSID, less than 14% of defaulters have both negative equity and enough liquid (broadly defined) or illiquid assets to make 1 month's mortgage payment. In the SCF, which deliberately over-samples high-net-worth individuals and provides more disaggregated measures of wealth, only 6% of all defaulters (where default is measured during the 12 months prior to the survey date and includes default on all types of debt) have both negative equity and enough money in their savings or checking accounts to make 1 month's mortgage payment. Such evidence calls into question the importance of ruthless default during the 2007-2009 recession and may suggest that policies designed to promote employment, such as payroll tax cuts, are most likely to stem defaults in the long run.

Section 3.2 discusses the related literature. Section 3.3 describes the data. Section 3.4 describes both the single trigger and double trigger results. Section 3.5 discusses measures of strategic default using both PSID and SCF data, and finally, Section 3.6 concludes.

3.2 Related Literature

The early theoretical literature modeled mortgage default as an option using the contingent claims framework pioneered by Black and Scholes (1973).[3] In that framework the sole determinants of mortgage default are interest rates and home values. There is no role for unemployment or other cash-flow or wealth shocks in the borrower's default decision. However, many early empirical studies found that other variables such as income, unemployment rates, and divorce rates seemed to predict mortgage default rates.[4]

Riddiough (1991) was one of the first papers in the theoretical mortgage default literature to model so-called "trigger events" such as divorce, job loss, health shock, or other accident.[5] Kau et al. (1993) incorporated transactions costs and what they referred to as "suboptimal default," which is just another name for trigger events, and concluded that these events must have a large and important role in option-based models in order to match the data. After this finding, numerous studies began incorporating various proxies for trigger events into their empirical default models, with varying degrees of success. For example, Deng et al. (1996) used a competing risk survival framework to model default and prepayment and included regional unemployment rates and divorce rates as proxies for trigger events. However, they

[3] Asay (1979) was the first to apply the Black and Scholes methods to mortgage pricing. See Kau and Keenan (1995) for an overview of that literature.

[4] Campbell and Dietrich (1983) in a sample of privately insured mortgages (held by the Mortgage Guaranty Insurance Corporation) found that both income and unemployment rates were important determinants of mortgage default. Thibodeau and Vandell (1985), using data from a Savings & Loan association found similar results, and also found that wealth levels seemed to predict default. See Vandell (1995) for an overview of this early literature.

[5] He used a stochastic jump process to model the trigger event and was successful in replicating actual default behavior in simulations.

concluded that regional unemployment was not an important factor in their model as the sign of the regional unemployment coefficient was mixed and statistically insignificant in several cases.[6] In contrast, other studies such as Deng et al. (2000) argued that unobserved heterogeneity such as job loss and divorce, are important determinants of mortgage default.

Coinciding with the mortgage default and foreclosure crisis that started in 2007, the literature on the determinants of mortgage default resumed in earnest. Due to the dramatic decline in house prices that precipitated the huge increase in defaults and foreclosures and the severe recession characterized by double-digit unemployment rates at the national level, the recent literature has focused on the roles of negative equity and unemployment in causing mortgage defaults. This literature was kicked off by Foote et al. (2008) who used mortgage data from Massachusetts in the early 1990s as well as in the early part of the recent financial crisis to assess the role of negative equity in the mortgage default decision. In line with their theoretical model, they found that the majority of people with negative equity do not default. They argued that the low default rates by homeowners likely reflected price expectations and that those who actually did default likely defaulted because of a double trigger event—negative equity and some adverse life event like job loss or health problems. In an attempt to capture these trigger effects, the authors used a local unemployment indicator, which has now become a standard in the literature.

Many interpreted this finding as evidence against the concept of widespread "strategic" or "ruthless" default—the idea that mortgage borrowers default solely based on the decline in the value of their property relative to their remaining mortgage balance—which is related to the predictions of the option-theoretic literature on mortgage default discussed above. This prompted numerous additional studies on the determinants of default and specifically on the importance of strategic default versus default due to trigger events, or as the literature refers to it as the "double-trigger" explanation of mortgage default.[7] For example, Bhutta et al. (2011) used data on non-agency, securitized mortgages and documented that default

[6]Capozza et al. (1997) also used regional unemployment and divorce rates to proxy for trigger events and found that they had little economic impact on default propensities.

[7]Double trigger refers to the combination of negative equity and job loss (or some other type of trigger like a divorce, death of a spouse, etc.)

rates increase dramatically for borrowers in positions of severe negative equity. The authors interpreted these results as evidence that people only strategically default when there is considerable negative equity (-60% or lower), and posited that for more moderate levels of negative equity, the role of trigger events is likely important. Another highly cited study by Guiso et al. (2010) used a different approach to assess the importance of strategic default. The authors conducted a household survey that asked homeowners under what conditions they would strategically default on their mortgages. The study found that the most important driver of strategic default is severe negative equity, with race, gender, expectations about future employment, and views about fairness and morality also having importance.[8] Goodman et al. (2010) tried to disentangle the relative importance of negative equity and unemployment in driving defaults using data on non-agency securitized mortgages and unemployment rates at the county-level. The authors concluded that negative equity predicts default behaviour more so than regional unemployment, but explicitly discussed the limits of using a regional unemployment rate and the bias it might induce towards negative equity:

> "It is important to realize that we cannot tie the employment status of an individual loan to a particular borrower; we can only tie the unemployment rate of that MSA to a resident borrower. While we use a similar methodology to derive mark-to-market CLTV from original CLTV, the distortion is likely to be less dramatic for CLTVs. *That is, if the unemployment rate in a particular area is only 10%, a particular borrower is only 10% likely to be unemployed. However, if homes in a given area have depreciated by 40%, that borrowers house is likely to have dropped a relatively similar amount.*" (p. 4)

Recent work by Gyourko and Tracy (2013) seems to confirm this intuition. The authors show using simulations that empirical research attempting to uncover the relationship between unemployment shocks and mortgage defaults likely suffers from severe attenuation

[8]While this paper contributed significantly to the literature and provided unique insights into strategic default, a major drawback of the study is the fact that it is a hypothetical survey, so that it is impossible to determine whether mortgage borrowers would actually behave in a manner that is consistent with their reported answers.

bias. That is, by aggregating unemployment (which is an extreme form of measurement error), and regressing the precise default status on the imprecise unemployment rate one introduces a downward bias in the estimate of the effect of unemployment on default. Thus, using local unemployment rates as proxies for individual unemployment shocks can result in severely underestimating the role of unemployment in the default decision. This could explain the tendency of many empirical default studies to find an insignificant role for unemployment, as discussed above.[9]

The attenuation bias illustrated in Gyourko and Tracy (2013) is a result of not observing employment status at the individual level. The datasets used in the existing literature have simply not contained such information, and as a result, researchers were forced to proxy for individual employment status with aggregate rates. This study is one of the first to incorporate information on individual unemployment spells in a model of mortgage defaults, and our findings regarding the importance of unemployment in causing default complements the Gyourko and Tracy (2013) study and suggests that their simulation exercise is accurate.

Another shortcoming of the datasets used in the existing empirical mortgage default literature is the lack of information regarding borrowers' overall financial situation. The level of a household's precautionary savings and liquid assets as well as illiquid assets, and the size of other debt payments may also factor into its decision to default.[10] Elul et al. (2010) is one of the only studies to our knowledge that used information on certain aspects of household balance sheets to predict mortgage default. The authors used credit bureau data from Equifax combined with loan-level mortgage data, and found that high credit card utilization rates (i.e. those who borrow up to their credit limits), large combined loan-to-value ratios (the first mortgage payment plus second mortgage payment divided by income) and negative equity are the most important factors in determining default. The authors also found that county-level unemployment rates have some predictive power, but less than high credit card utilization rates. We will refer to these findings as the illiquidity results,

[9]There is a considerable amount of research in addition to the studies mentioned above, such as Mayer et al. (2009), and Haughwout et al. (2008), which also find that local unemployment rates are only weakly correlated with default rates.

[10]See the two-period model developed by Foote et al. (2008) for an example of how wealth could play an important role in the default decision.

since people who borrow over their limits at punitive interest rates must necessarily be cash constrained.

While no U.S. studies of mortgage default have been able to incorporate individual unemployment shocks, there are a few studies that have done so using various European micro datasets. For example, Böheim and Taylor (2000) used the British Household Panel Survey (BHPS) to study the role of unemployment and financial stress in the decision to default. In contrast to the PSID data used in this study, the timing of the questions in the BHPS is similar to the SCF in which the degree of default over the past 12 months is reported but the date of default is not.[11] Böheim and Taylor (2000) find a similar ordinal relationship between negative equity and unemployment, with an unemployment coefficient roughly double the negative equity coefficient, but they stop short of looking at interactions.[12] Finally, Mocetti and Viviano (2013) used Italian annual tax records and unemployment records to look at the role of job loss in default. They found that job loss over the tax-year is a strong predictor of default, more so than changes in county-level home prices.

While these European-based empirical studies are important, none of them address the trigger hypotheses central to the negative equity policy debate. Moreover, our study exploits the precise timing in the PSID of unemployment and default questions as well as the survey-date measurements of wealth. By using a dataset with each of these variables, we are able to precisely test the drivers of mortgage default and test the relevance of trigger events versus stragic default based solely on the degree of negative equity.

3.2.1 Recent Advances in Theory

In the aftermath of the U.S. foreclosure crisis, there have also been advances in the theoretical mortgage default literature. Specifically, there have been attempts to integrate mortgage default into more general, equilibrium models of consumer behavior in order to study the

[11] For example, the BHPS asks, "In the last twelve months have you ever found yourself more than two months behind with your rent/mortgage?"

[12] Gathergood (2009) conducted a similar analysis using the BHPS, except it focuses on the 5 years following an initial mortgage purchase. The study finds that burdensome credit payments, long term sickness, divorce, and negative equity are all better predictors of default than unemployment.

interplay between the mortgage default decision and various aspects of consumption portfolio choice. These studies have focused on foreclosure, and not necessarily default.[13] In this section we briefly describe the main findings of this literature, which guide some of our variable choices in the empirical analysis below.

In a partial equilibrium setting, Campbell and Cocco (2011) modeled mortgage foreclosure structurally and found that: (i) negative equity alone; (ii) borrowing constraints in combination with negative equity; (iii) high debt to income ratios in combination with negative equity; (iv) remaining term and type of mortgage in combination with negative equity; and (v) expected income growth rates are all important determinants of foreclosure. In Garriga and Schlagenhauf (2009), negative equity alone is never the lone cause of foreclosure. Households decide to sell for some reason other than equity, typically a decline in income in combination with low savings, because equity is only realized after the house is on the market. Thus every default is necessarily a double-trigger default.

Corbae and Quintin (2009) focused on housing stock shocks which are two-for-one shocks, reducing equity and the flow utility from housing. In equilibrium, there are only 'strategic' foreclosures in the sense that the housing stock shock induces default, but the homeowner could still afford to make the payments. In the case where there is positive equity and the mortgagor has experienced a series of bad income shocks and cannot afford the payments, the mortgagor simply sells the property. Both Garriga and Schlagenhauf (2009) and Corbae and Quintin (2009) found roles for mortgage innovation on foreclosure rates via increased susceptibility to negative equity.[14]

Foote et al. (2008) used a much simpler, two-period model to show that households choose to default and lose their homes to foreclosure if the net implicit rents from owning plus the *expected* net equity position over their tenure horizon is positive.[15] In fact, the

[13]Foreclosure is quite unique from default in the sense that lenders initiate the foreclosure process only after a borrower chooses to default. Foote et al. (2008) argue that negative equity is a necessary condition for foreclosure to occur, but Herkenhoff and Ohanian (2012a) show that negative equity is not a necessary condition for default.

[14]Both Hatchondo et al. (2012) and Corbae and Quintin (2009) also argued that recourse laws increase defaults.

[15]In their model there is no distinction between default and foreclosure

contemporaneous value of equity does not factor into the default/foreclosure decision in the model. In sum, they find that expected house price appreciation, the flow utility from owning, and the mortgage payment size are the main factors in determining whether or not a household chooses to default and experience foreclosure.

Herkenhoff and Ohanian (2012b) is the only existing model that includes both mortgage default and foreclosure. Based on the relationship between employment and mortgage default in the PSID, they build a high-frequency model with three partial equilibrium markets: (i) a labor market, (ii) an asset market, and (iii) a mortgage market. In this framework, they find that job loss and unemployment benefit expiration are the main causes of default. Moreover, they find that the strength of these factors is nearly independent of equity status, a direct implication of their calibration strategy. Since they calibrate the flow utility from housing to match observed large defaulter cure rates, the resulting flow utility from housing dwarfs the role of negative equity. In other words, every default is involuntary and occurs because of job loss induced liquidity constraints or benefit-expiration induced liquidity constraints.

3.3 PSID Data

The primary data used in this study come from the 2009 PSID Supplement on Housing, Mortgage Distress, and Wealth Data. The 2009 PSID survey was divided into 12 sub-waves, and was conducted over the course of the year. There were 8,690 households surveyed in the 2009 PSID, however in the empirical analysis we impose a few restrictions that reduces the sample size. In particular, we eliminate from our sample disabled households and households that are not of working-age (younger than 24 or older than 65), which reduces the sample to 6,820 households. In addition, we eliminate renters as well as households that are homeowners but who report not having a mortgage, which further reduces the sample to 3,037 households. Finally, in our regression analysis below we only include households whose head reports being in the labor force.

Our analysis focuses on the determinants of mortgage default, and specifically on the role of negative equity, unemployment, and wealth status. In the next section we describe the key PSID variables in the analysis.

3.3.1 PSID Variable Definitions and Summary Statistics

The top panel of Table 3.1 displays summary statistics of demographic characteristics of the households in our estimation sample. Statistics are provided for all households in the sample as well as the sample of households that have defaulted on their respective mortgages. In this section we will focus on summary statistics for all households, and postpone a discussion of the corresponding statistics for defaulters until section 3.4.

The average age of the household heads in our sample is approximately 44 years, and as mentioned above, we restrict the sample to households with a head between the ages of 24 and 65 years. Approximately 85% of the household heads in our sample are male, 72% are white, and 22% are black. The majority of households are married (73%) and the majority of household heads (about 58%) have at least some college education, which is not surprising given that we are restricting the sample to homeowners.

The bottom panel of Table 3.1 displays summary statistics regarding the financial situation of the households in our sample at the time of the survey. Specifically the table contains information on the distribution of total household income, liquid and illiquid assets, unsecured debt, and outstanding hospital bills. We present summary statistics for both variable levels and ratios with respect to income. In some of the empirical models below we specify these variables as sets of indicators, and thus we include summary statistics for the indicator variables as well in the table. Average household income is approximately $110 thousand in our sample of homeowners with a mortgage. Households hold $18 thousand in liquid assets and $110 thousand in illiquid assets on average,[16] and report, on average, approximately $16 thousand in unsecured debt and about $900 in outstanding hospital bills.[17] Finally, almost

[16]Liquid assets are defined as the sum of all checking or savings accounts, money market funds, certificates of deposit, government savings bonds, and Treasury bills. Illiquid assets are defined as the sum of equity and bond holdings, the value of automobiles, retirement accounts, and business income. These variables are measured only once, as of the survey date.

[17]Unsecured debt is defined as credit card charges, student loans, medical or legal bills, and loans from relatives. Hospital bills includes outstanding debt owed to a hospital or nursing home.

6% of households report having declared bankruptcy before 1995.[18]

The top panel of Table 3.1 also contains summary statistics regarding mortgage delinquency, unemployment, and negative equity. Households were asked how many months they were behind on their mortgage payments at the time of the PSID interview.[19] Approximately 6.5% were at least one month behind (30+ days delinquent), while 3.9% were at least two months behind (60+ days delinquent). In the remainder of the paper we will adopt the definition of default that corresponds to two or more payments behind (i.e. at least 60+ days delinquent), as this is the convention in the literature. The 30+ day and 60+ day delinquency rates that we calculate in the PSID are lower than delinquency rates in the broader U.S. population according to various sources (see Table 3.13 in Appendix 3.7.1 for more details). The Board of Governors, for example, publishes delinquency rates among FDIC insured banks, and they report an average 30+ day delinquency rate of 9.1% averaged over 2009. According to the National Delinquency Survey conducted by the Mortgage Bankers Association (MBA), the average 30+ day delinquency rate in 2009 was 9.4%, while the average 60+ day delinquency rate was 5.8%. One possible explanation for the lower delinquency rates in the PSID is an under-representation of subprime mortgages. The subprime segment of the market drove mortgage default rates in the crisis period (for example, according to the MBA, the average 30+ day delinquency rate for subprime mortgages in 2009 was 25.5%). There is some indirect evidence of the under-representation of subprime mortgages in our sample. The majority of subprime mortgages originated before the crisis carried an adjustable interest rate (according to the MBA, 67% of subprime originations in the first half of 2006 were adjustable rate mortgages), and in our sample, only 9.1% of loans are ARMs (see the bottom panel of Table 3.1).

In our sample 7% of households report being unemployed, while 3.6% report having lost their job within 6 months of the date of the interview. Unfortunately, the mortgagor unemployment rate in the PSID is not readily comparable to any other national unemployment rate. However, we note that the mortgagor unemployment rate is lower than the headline

[18] 1995 is the most recent PSID survey to collect bankruptcy information.

[19] In Appendix 3.7.1 we provide the exact PSID survey question on mortgage delinquency.

BLS unemployment rate for ages 16+, which was 9.3% averaged over 2009.[20]

12.6% of the households in the sample are in a position of negative equity. We construct the negative equity variable using the reported home value (HV) less the reported first mortgage principal balance outstanding (PR_1) and the reported second mortgage principal outstanding (PR_2). Keeping with the literature, we express equity as one minus the combined loan-to-value ratio (CLTV):

$$Equity = 1 - CLTV = 1 - \frac{PR_1 + PR_2}{HV}, \tag{3.1}$$

although in our estimation below we use CLTV itself.

The top panel of Figure 3.1 displays the distribution of equity in our sample, while the bottom panel shows the equity distribution estimated by Corelogic in the third quarter of 2009. [21] Although the shapes of the equity distributions are quite similar across datasets, the level of overall negative equity reported by Corelogic is approximately twice as high as it is in our PSID sample. According to Corelogic, slightly more than 10% of properties had greater than 25% negative equity, while slightly less than 4% do so in the PSID. While there could be many reasons for the divergence in equity estimates between the two databases, households tend to over-report house values as compared to actual selling prices by 5% to 10% (see Benítez-Silva et al. (2008)). Thus, a self-reported CLTV ratio of 90% is on the verge of realizing negative equity in the event of a sale.

While the PSID clearly seems to understate the amount of negative equity in the economy relative to Corelogic estimates, we do not view this as a significant drawback of our analysis. To determine the dual roles that negative equity and unemployment have in causing mortgage delinquency and default, we believe that self-reported equity is the most appropriate equity

[20]The overall unemployment rate in the 2009 PSID for ages 16+ is 13.7%, which is significantly higher than the BLS figure.

[21]The bottom panel of Figure 3.1 comes from the August 13, 2009 report entitled "Summary of Second Quarter 2009 Negative Equity Data from First American CoreLogic." Corelogic uses a national database of property transactions that covers 43 states to come up with their equity estimates, and thus should be quite representative of the U.S. population. Corelogic uses administrative data on outstanding mortgage balances and estimates of housing values to compute equity, while we use reported mortgage balances and housing values in the PSID.

measure. In choosing whether or not to default, households take into account their own perceived valuation of their home, which may or may not be derived in part from a third-party estimate (such as Corelogic or Zillow). To put it another way, the value of using self-reported equity values is that only those households who believe that they are in positions of negative equity are given negative equity, and this is the group of households whom we expect to be most sensitive to negative equity in terms of their default behavior.[22]

Figure 3.2 displays unconditional default rates across the equity distribution in our PSID sample. The non-linear relationship between equity and default that has been documented in the literature (Foote et al. (2008)) is apparent. The default rate associated with households with equity values above -5% is between 2% and 3%. However, the default rate increases significantly for equity values below -5%, reaching more than 25% for households with equity below -25%. This pattern is often interpreted as evidence of strategic default, and we will come back to this issue in our analysis below. To capture the non-linear relationship between equity and default in our empirical analysis and to maintain consistency with the previous literature, we use indicator variables for different levels of the CLTV ratio.

Finally, Table 3.1 also displays summary statistics of certain mortgage terms of interest. In our empirical analysis below, we control for various mortgage characteristics including the type of mortgage, the interest rate, the remaining term, the presence of a second mortgage, and whether or not the mortgage is a refinance of a previous loan.[23] In addition, we control for whether the state of residence allows lender recourse, whether the state is characterized by a judicial foreclosure process (as opposed to power-of-sale), and whether the state of residence is AZ, CA, FL, or NV, which are often to referred to as the "sand states."[24] Finally, we add controls for recent house price appreciation (HPA) at the state-level (using

[22] In addition it is likely the case that many households have information about the condition of their home and the state of their local housing market that is not captured in data-based estimates such as the Corelogic numbers, which use zip-code-level or county-level house price indices to estimate property values.

[23] An oft forgotten facet of real estate law is the only purchase money mortgages (i.e. mortgages used to buy a home directly) are non-recourse loans, whereas refinanced mortgages (which are mortgages taken out to pay off another mortgage) are typically treated as recourse loans. Therefore, it is more important to control for the refinance status than for the recourse status of a state.

[24] Ghent and Kudlyak (2011) provide evidence that default rates are higher in states that do not allow lender recourse. Gerardi et al. (2011) find that at any given point in time, default rates are higher in judicial states compared to power-of-sale states.

house price indices estimated by the Federal Housing Finance Administration (FHFA)), to capture household-level expectations of future house price movements to the extent that households form expectations in an adaptive manner, and also recent growth in the state-level unemployment rate. We use the growth rate in state-level house prices and unemployment rates from 2008 to 2009, but our results are similar if we use growth rates from 2006 to 2009 or 2007 to 2009.

3.4 Results

In this section we present results on the importance of various default triggers in the PSID. We begin by describing the characteristics of PSID households in default and then present results from our empirical models. In Appendix 3.7.2 we also conduct a parallel analysis using data from the 2007 and 2009 Survey of Consumer Finances (SCF), in order to externally validate the results from the PSID analysis. The results from the SCF data are broadly consistent with the PSID results.[25]

3.4.1 Characterizing Defaulters

Our first set of results is a descriptive characterization of defaulters in the PSID. The questions asked in the PSID regarding mortgage delinquency, employment, and the household balance sheet allow us to uniquely characterize defaulters in a degree of detail that is new to the literature. Table 3.1 provides a comparison of the average mortgagor (including all mortgage observations) and the average defaulter (only those 60+ days delinquent as of the survey date) within our restricted mortgagor sample. Most notably, defaulters have an unemployment rate of 25% as compared to the average mortgagor who has an unemployment rate of 7%. This strong correlation between unemployment and default persists in every model that we consider below, regardless of the breadth of controls. Defaulters are also significantly different along many demographic margins. For example, only 17% of defaulters attained a college degree versus 32% of all mortgagors, and 58% of households

[25] Appendix 3.7.1 includes details of the questions used as well as a discussion about weighting.

that default are married compared to 73% of all mortgagors. Furthermore, defaulters are relatively low-income households with a mean income in 2009 of almost $40,000 less than the average mortgagor, and are also more than three times likely to have suffered a severe income loss of -50% or worse.

In terms of mortgage characteristics, 28% of defaulters have negative equity of -20% or worse versus 4% of all mortgagors. As we will see below, this correlation between severe negative equity and default also persists with the addition of various controls. The mortgage product mix is also skewed with 33% of defaulters reporting adjustable rate mortgages (ARMs) versus 9% of all mortgagors. The defaulters have much higher mortgage debt-to-income (DTI) ratios, reflecting their lower incomes as well as their larger remaining principal balances.[26] Defaulters have, on average, $60,000 more in outstanding mortgage debt and live in states that experienced a larger drop in home prices over the previous year. Geographically, 33% of defaulters reside in the sand states of AZ, CA, FL, and NV, whereas only 15% of all mortgagors reside in these states.

As mentioned above, the PSID is unique in providing household-level balance sheet data and mortgage repayment information. Table 3.1 shows that households in default have much larger unsecured debt positions, roughly $12,000 more in unsecured debts compared to the average mortgagor, and defaulters have almost $6,600 less in terms of net auto assets. Defaulters have significantly less business assets, and less "other housing" assets which include second residences, vacation homes, and investment properties. Defaulters have almost zero retirement savings ($800 on average) and approximately $15,000 less in liquid assets than the average mortgagor (liquid assets include checking and savings accounts, money market funds, certificates of deposit, government savings bonds, or Treasury bills). Defaulters also have almost $12,000 less in stock holdings than the average mortgagor.

The resounding message from this comparison is that households in default are far from the average mortgagor along almost every measurable dimension, particularly in terms of employment and wealth, which are unobservables in most loan-level data sets. To further

[26]The DTI ratio is simply the ratio of the household's reported annual mortgage payment to its reported annual income.

exploit the unique nature of this data, in Section 3.5 we will use this information to conduct a descriptive analysis of strategic default in the PSID.

3.4.2 Suggestive Evidence of Double Trigger Events

Table 3.2 contains information regarding the double trigger event of job loss and negative equity as well as other types of financial shocks and negative equity. The table contains a comparison of default rates for various categories of borrower income and financial characteristics, stratified by whether a borrower has negative equity or positive equity and also whether a borrower has severe negative equity ($CLTV \geq 120\%$) or not. The table shows that unemployed households in the PSID with negative equity have an unconditional default rate of 30.0%, whereas employed households with negative equity have an unconditional default rate of 10.2%, which means that unemployment produces a difference in default rates of 19.8% among those with negative equity. In contrast, an unemployed household with positive equity has a 10.6% default rate, whereas an employed household with positive equity has a 2.1% default rate, which means that unemployment produces a difference of 8.5% in default rates among those with positive equity. The simple interaction effect between unemployment *and* negative equity on the default rate is therefore 11.3% (= 19.8% - 8.5%), which implies that the double trigger effect of job loss and negative equity is to increase the default rate by 11.3% over and above either trigger on its own (i.e. this is the differential effect on the default rate induced by a unemployment shock among those with negative equity versus those with positive equity).

Likewise, unemployed households with severe negative equity have an unconditional default rate of 41.7%, whereas employed households with negative equity have an unconditional default rate of 22.5%, a difference of 19.2%. Unemployed households with non-severe negative equity have an unconditional default rate of 12.0%, whereas employed households with non-severe negative equity have an unconditional default rate of 2.3%, a difference of 9.7%. Thus the simple interaction effect between severe negative equity and unemployment is to raise the default rate by 9.5% (= 19.2% - 9.7%) over and above either trigger on its own.

A similar pattern holds among those with a liquid asset to income ratio less than 5%. The simple interaction between low liquid assets and negative equity is quite large at 5.7% (=(15.2%-5.7%)-(4.6%-.8%)). We also see the same type of result for DTI ratios, as well as income loss (calculated between 2007 and 2009). Unfortunately, the sample size used to compute each of these default rates is relatively small which makes it difficult to obtain power in any formal test of interaction effects with controls. Nonetheless, we attempt such tests below.

3.4.3 Unemployment and Default

The top panel of Table 3.3 illustrates the basic relationship between unemployment, recent job loss, and default using both a linear probability model (LPM) and a logit model. The first column shows the results from a simple unconditional regression of default (defined as 60+ days delinquent) on an indicator variable for being unemployed at the time of the PSID interview. The coefficient estimate implies that unemployed households are about 11 percentage points more likely to default compared to employed households. This is a huge effect, considering the fact that the default rate across all households in our sample is only 3.9%. The corresponding logit regression (column 4) produces an identical average marginal effect.[27] Columns (2) and (5) add an indicator variable of recent job loss (within 6 months of the interview). Households that are unemployed, but who have experienced a relatively recent job loss are less likely to default compared to households who have been unemployed for longer period of time, however this effect is not statistically significant in either the LPM or logit models.[28]

[27]For dummy variables, evaluation of the logit at the mean produces meaningless results, i.e. $P(Y = 1 \mid Z = 1 \cap X = \bar{X}) - P(Y = 1 \mid Z = 0 \cap X = \bar{X})$ makes little sense when X is an indicator and $\bar{X}$ is the average in the population of that indicator. Instead, we report average marginal effects which is averaging the marginal effect over individuals evaluated at their actual value of $X = X_i$ for each $i \in \{1, \cdots, N\}$. Thus we report the average marginal treatment effect of Z (negative equity, job loss, etc.) on outcome Y (default):

$$AME(Z) = \sum_i (P(Y = 1 \mid Z = 1 \cap X = X_i) - P(Y = 1 \mid Z = 0 \cap X = X_i))/N$$

[28]According to the LPM estimates, a household that has been unemployed for less than 6 months is approximately 8 percentage points more likely to default compared to an employed household, while a household that has been unemployed for more than 6 months is almost 14 percentage points more likely to

Finally, columns (3) and (6) add demographic controls along with some state-level controls.[29] The estimates associated with the unemployment variables do not significantly change. There are a few notable patterns among the controls. Default rates among black households are approximately 3 percentage points higher than default rates among white households. Households with at least a college degree have lower default rates than households that did not graduate from high school (about 3 - 5 percentage points). Households living in states that experienced higher rates of house price appreciation in the previous year are significantly less likely to be in default. A one standard deviation increase in HPA (about 7%) is associated with a 3 percentage point decrease in the probability of default. Finally, we find a weak correlation between state-level changes in unemployment rates and default rates, which is consistent with the previous literature. In particular, the finding that individual unemployment status is strongly correlated with default while aggregated unemployment rates are not confirms the findings in Gyourko and Tracy (2013).[30]

3.4.4 Equity and Default

The bottom panel of Table 3.3 illustrates the basic relationship between equity and default in our PSID sample. In column (1) we display the estimate from a simple unconditional LPM of default on CLTV expressed as a decimal (i.e. a value of 0.9 is a CLTV of 90%), and in column (4) we display the average marginal effect from an unconditional logit model. The CLTV coefficient estimate from the LPM implies that a one-standard deviation increase in CLTV (approximately 35 percentage points) is associated with a 4.6 (=.132*.35*100) percentage point increase in the probability of default.

default. These results are consistent with the predictions of the model in Herkenhoff and Ohanian (2012b) in which the long term unemployed are the most likely to be liquidity constrained and default on mortgage payments. However, the difference between long-term and short-term unemployment in Table 3.3 are not statistically significant, and the magnitudes are sensitive to the particular model used in the estimation

[29]Specifically, we add a set of race dummies, a gender dummy, a marriage dummy, dummies for educational levels, dummies for whether the state allows lender recourse and judicial foreclosure, and an indicator for whether the household lives in AZ, CA, FL, or NV, the states that experienced the largest house price declines and worst foreclosure problems. In addition we add variables that measures state-level house price growth from 2008-2009 and the change in the state-level unemployment rate over the same period. For space considerations we only show the estimates associated with the statistically significant control variables.

[30]Taking out individual employment status does not materially affect the correlation between aggregate unemployment rates and default.

We know from Figure 3.2 that the relationship between equity and default is highly non-linear, so in columns (2) and (5) we specify CLTV in terms of a series of indicator variables with the baseline case corresponding to households with CLTV < 70%. The results are consistent with the pattern observed in Figure 3.2. There is a positive correlation between CLTV and default that becomes stronger with higher CLTV values (greater negative equity positions). Households with CLTVs between 100% and 120% (negative equity up to -20%) have default rates that are 3.4 percentage points higher than households with CLTVs less than 70%, ceteris paribus. But even more striking is the finding that households with CLTVs above 120% (negative equity worse than -20%) are 22.6 percentage points more likely to default as compared to their counterparts with CLTVs less than 70%. The corresponding default probability in the logit specification is 10 percentage points. Columns (3) and (6) include our demographic and state-level controls. The coefficient magnitudes associated with the higher CLTV ranges slightly decrease, but otherwise the results do not significantly change.

It is clear from Figure 3.2 and Table 3.3 that default rates are significantly higher for households in positions of negative equity or near-negative equity (i.e. CLTVs above 90%), than for households with significantly positive equity, which is completely consistent with findings in the existing literature. As a result, in the remainder of our analysis we will focus on negative equity as a trigger for mortgage default. In addition to focusing on the exact negative equity threshold (i.e. CLTV=100%), we will also look at alternative thresholds of CLTV=90% and CLTV=120%. Moving costs and realtor fees could easily add up to 10% of the property value, so that a household that needs to sell could effectively have negative equity even with a CLTV as low as 90%. Prior research has found significantly higher default rates for households in positions of deep negative equity (as we also find in Table 3.3) versus only moderate negative equity, so that a threshold of 120% will allow us to focus on these households.[31]

[31] Prior studies like Bhutta et al. (2011) have considered even higher negative equity thresholds like CLTV=150%. However, we simply do not have enough observations in the PSID with such deep negative equity values to be able to obtain any degree of precision with such a high threshold.

3.4.5 Trigger Analysis: Unemployment and Negative Equity

Having established that both unemployment and negative equity are important determinants of household-level default behavior on their own, we now estimate models with both variables included to determine the relative strength of each predictor. In Table 3.4 we report estimation results from LPM and logit models that include both variables. We include the same set of demographic and state covariates, and add a set of mortgage characteristics to the set of control variables. These include an indicator for a second mortgage, an indicator for whether the first mortgage is a refinance loan, an indicator for whether the first mortgage is an ARM or a FRM, the current interest rate associated with the first mortgage, and an indicator for whether the maturity of the first mortgage is greater than 15 years.[32]

The estimates from the LPM reported in columns 1-3 in Table 3.4 indicate that long term unemployment is more strongly correlated with default compared to the lower negative equity thresholds of CLTV=90% and and CLTV=100%. However, the CLTV=120% threshold is a stronger predictor of default in the LPM, as households with CLTV≥120% are almost 18 percentage points more likely to default than borrowers with CLV¡120%. This is not the case in the logit model however, The estimated marginal effects from the logit (columns 4 - 6), suggest that households who have been unemployed for more than 6 months are approximately 9 to 10 percentage points more likely to default compared to employed households. In contrast, households with negative equity or near negative equity (CLTV≥100 and CLTV≥90, respectively) are approximately 4 percentage points more likely to default than households with positive equity, while households with deeper negative equity (CLTV≥120) are about 6 percentage points more likely to default. Thus, according to the logit results, long-term unemployment is a slightly stronger default trigger than negative equity. Given, the well-documented econometric issues with the LPM,[33] we place more weight on the logit

[32] In all of the empirical models we also include a set of indicator variables to deal with missing observations. For discrete variables, we simply add an indicator to the model that takes the value of one if the observation has a missing value and zero otherwise. For continuous variables, we add such an indicator to the model and set the value of the continuous variable to zero. We do not report the estimates associated with these variables for space considerations.

[33] One important drawback of the LPM is the fact that it does not restrict fitted probabilities to lie within the unit interval

results, and thus conclude that while unemployment and negative equity are both important triggers of default, unemployment appears to be the stronger of the two.

3.4.6 Other Triggers

As mentioned above, previous studies in the empirical mortgage default literature have found some evidence that other triggers, such as divorce, death of a spouse, adverse medical shocks, and negative income shocks, in general, are correlated with default. Of course these studies did not have information on household-level shocks, and instead were forced to use aggregate proxies, such as divorce rates at the county-level. The PSID contains information on divorce and medical shocks at the household-level, which we can use to test their importance as triggers of mortgage default.

We identify heads of households that either went through a divorce or lost a spouse between the 2007 and 2009 PSID surveys.[34] In addition, we use information on outstanding hospital bills to proxy for an adverse medical shock. We construct an indicator variable to identify households that have outstanding hospital bills in excess of 10% of annual income.[35] Finally, we also construct a negative income shock trigger using information on income from the 2007 PSID survey. We calculate the percentage change in reported total household income between the 2007 and 2009 surveys, and form indicator variables for households in the bottom 25th percentile of the distribution of income growth (approximately a -10% change or worse) and households in the bottom 5th percentile of the distribution of income growth (approximately a -50% change or worse).

Table 3.5 reports results on the importance of these additional potential triggers. In the top panel of the table we consider the more moderate income shock trigger of -10% or worse, while in the bottom panel we consider the more extreme income trigger of -50%

[34] Specifically we consider a divorce to have taken place if the head of household reported being married in the 2007 survey and divorced or separated in the 2009 survey, and we consider a death of a spouse to have taken place if the head of household reported being married in the 2007 survey and being a widower in the 2009 survey.

[35] Approximately 1.8% of households in our sample report outstanding hospital and nursing home bills in excess of 10% of income. Thus, this variable captures the few households in the PSID that have been hit with severe medical issues. We also tried using the level of hospital bills outstanding, and this variable had essentially zero correlation with mortgage default.

or worse. Divorce or loss of spouse does not appear to be an important determinant of mortgage default in our PSID sample.[36] The point estimates from the LPMs and logits are small and not statistically different from zero. There is slightly more evidence in support of adverse medical shocks as a default trigger, but that evidence is only weak at best. The point estimates associated with the hospital bill indicator are relatively large (between 5 and 7 percentage points depending on the model and negative equity specification), but they are rarely statistically significant at the 10 percent level.

There is evidence that negative income shocks serve as default triggers, especially severe income shocks. According to the top panel of the table, households that experienced at least a 10% drop in income were between 2.4 and 3.1 percentage points less likely to default compared to households that experienced a rise in income or a less severe drop. Households that experienced at least a 50% drop in income were between 7.2 and 9.3 percentage points less likely to default. This effect is larger than most of the negative equity triggers. It is a little surprising that the inclusion of these income shock indicators has little effect on the magnitude of the correlation between unemployment and default. Thus, it is not the case that the income shock indicators are simply picking up the income loss associated with job loss.

3.4.7 Wealth and Prior Bankruptcy

Previous studies in the literature have stressed the potential importance of wealth in a household's decision to default on a mortgage.[37] We have information regarding assets and liabilities in the PSID, but we only have that information at the time of the survey date. Thus, we cannot make any causal inference regarding the relationship between wealth and default. For example, a negative correlation between wealth and default could be causal in the sense that a negative wealth shock (such as a fall in the stock market, or failed business

[36]The difference in sample sizes between columns (1)-(3) and columns (4)-(6) is due to the fact that a missing divorce indicator perfectly predicts non-default. These 59 missing values are not correlated with any observables, and are thus dropped to provide for well-defined coefficients in the logit MLE estimations. The point estimates in the linear probability model are unaffected by the inclusion of these observations.

[37]For example, see the discussion and model in Gerardi et al. (2007).

venture) leads directly to default. However it could simply be the result of other shocks, such as an unemployment shock leading a household to draw down savings and increase unsecured debt in an effort to put off default for as long as possible. We cannot distinguish between those two scenarios with our PSID data. With this caveat in mind, in this section we will characterize the relationship between the likelihood of mortgage default and asset and debt positions. We focus on three variables in particular: the ratio of liquid assets to income, the ratio of illiquid assets to income, and the ratio of unsecured debt to income.

Table 3.6 displays estimation results, where the wealth variables are each expressed as a series of indicator variables to capture potential nonlinearities in the relationship between the variables and mortgage default. The estimates suggest that households with extremely low levels of liquid and illiquid assets (less than 5% of income) are the most likely to default. The evidence is stronger for liquid assets, as most of the illiquid asset indicator variables are not statistically different from zero. Households with a liquid asset to income ratio of less than 5% are between 3 and 8 percentage points less likely to default compared to households with ratios of more than 50%. There is also evidence that households with extremely high levels of unsecured debt (over 50% of income) are much more likely to default compared to households with moderate-to-very low levels of unsecured debt. For example, households with outstanding debt levels above 50% of income, on average, default approximately 2.6 to 5.1 percentage points more often than households with debt levels below 5% of income.

It is also noteworthy that the estimated marginal effects associated with the unemployment indicator in the logit models decrease with the addition of these wealth variables (this is not the case in the LPMs). If we compare the estimates in Table 3.6 to the estimates in Table 3.5, the unemployment marginal effects decrease by about 50%, while the negative equity marginal effects are largely unaffected. This is consistent with our story above, in which households that lose their jobs run down their assets and increase their debt levels before finally defaulting. If this were the case, then we would expect that adding wealth variables into the default regression would take away some of the explanatory power of unemployment, which is exactly what we observe.

The literature has consistently found that prior credit history is an important determinant of mortgage default. Information regarding credit scores is not available in the PSID, but there is a limited amount of information regarding previous bankruptcy declarations. Specifically, households were asked in the 1996 PSID survey whether they had ever declared bankruptcy, and thus, we have information on household bankruptcies that took place before 1996.[38] Panel A of Table 3.7 shows that surprisingly, almost 6% of the PSID sample declared bankruptcy prior to 1996. There is some debate regarding the information content of previous negative credit events like bankruptcy in the literature. According to federal law, bankruptcies must be removed from credit reports after 10 years, so that pre-1996 bankruptcies would not have shown up on credit reports at the time of the 2009 PSID survey. Musto (2004) argues that this information loss has important implications for the market:

> "Federal law mandates the removal of personal bankruptcies from credit reports after 10 years. The removal's effect is market efficiency in reverse. The short term effect is a spurious boost in apparent creditworthiness, especially for the more creditworthy bankrupts, delivering a substantial increase in both credit scores and the number and aggregate limit of bank cards. The longer term effect is lower scores and higher delinquency than initial full information scores predict. These findings relate to both the debate over the bankruptcy code and the wisdom of influencing market clearing by removing information."

The bottom panel of Table 3.7 shows the unconditional default rate for the households that previously declared bankruptcy and the households that did not. In contrast to Musto (2004)'s assertion, default rates are actually 1 percentage point lower among the households that declared bankruptcy prior to 1996. To ensure that this relationship is robust, we include a pre-1996 bankruptcy indicator into the LPMs and logit models estimated in Table 3.2. The results are displayed in Table 3.8, and are consistent with the unconditional results. We find no evidence of a positive correlation between prior bankruptcy declarations and mortgage default.

[38]The PSID did not ask questions about bankruptcy after 1996.

3.4.8 Double Triggers

We now turn to a test of what we will call the "double trigger hypothesis," or the DTH. The idea of the DTH is that the *combination* of job loss and negative equity is instrumental in driving mortgage defaults, as opposed to unemployment or negative equity by themselves. We will measure the importance of the DTH using the following estimated statistic:

$$\Big[P(D = 1 \mid I_{\{Neg.\ Eq.\}} = \mathbf{1} \cap I_{\{Unemploy\ 2009\}} = \mathbf{1})$$
$$- P(D = 1 \mid I_{\{Neg.\ Eq.\}} = \mathbf{1} \cap I_{\{Unemploy\ 2009\}} = \mathbf{0})\Big]$$
$$- \Big[P(D = 1 \mid I_{\{Neg.\ Eq.\}} = \mathbf{0} \cap I_{\{Unemploy\ 2009\}} = \mathbf{1})$$
$$- P(D = 1 \mid I_{\{Neg.\ Eq.\}} = \mathbf{0} \cap I_{\{Unemploy\ 2009\}} = \mathbf{0})\Big]$$

This is the additional effect of unemployment on default for those with negative equity versus those with positive equity.[39] In the LPM, this statistic corresponds exactly to the estimated coefficient on an unemployment and negative equity interaction term. In the logit model, this statistic is slightly more complicated to compute due to the inherent non-linearity of the model.

Table 3.9 displays estimation results for the unemployment and negative equity interaction term. For ease of interpretation, we do not distinguish between short and long term unemployment spells (i.e. we leave out the indicator for job loss within the previous 6 months). There is some evidence of a double trigger effect, but it is very sensitive to the negative equity threshold. The interaction term is large and statistically significant for the CLTV>90 threshold in the LPM (at the 5% significance level), but is not statistically significant in the logit. The combination of near-negative equity and unemployment increases

[39]This is exactly equivalent to the additional effect of negative equity for those who are unemployed versus those that are employed.

the probability of default by over 14 percentage points in the LPM and almost 8 percentage points in the logit. This is a huge effect considering the fact that the unconditional default rate in the data is only 3.5 percentage points. However, for the other negative equity thresholds, the estimated interactions are smaller in magnitude and not statistically different from zero. The lack of statistical significance could be due to the small PSID sample, as we only have 13 households that are unemployed with CLTV>90%, 9 unemployed households with CLTV>100%, and 5 unemployed households with CLTV>120%. Thus, in general we conclude that there is mixed evidence regarding the importance of the double trigger of unemployment and negative equity. For near-negative equity and moderate negative equity the interaction appears to be quite important (at least in the LPMs), and quantitatively more important than negative equity as a default trigger by itself. However, for households with severe negative equity, negative equity is a very important trigger by itself, and the interaction with unemployment does not appear to be very important.

3.5 Evidence for Strategic Default

The concept of strategic default has been a topic of much debate in the commentary on the U.S. mortgage and foreclosure crisis. There have been a significant number of anecdotal stories, mostly in newspaper articles, about individuals who stop paying their mortgages and walk away from their homes due to severe negative equity, despite the financial capability of continuing to make payments.[40] In addition, there are a few academic studies that claim to indirectly identify strategic default. For example, Guiso et al. (2010) find evidence from a survey that many homeowners would be willing to strategically default under certain conditions. Bhutta et al. (2011) find a strong correlation between severe negative equity (-60% or worse) and default among non-agency securitized mortgages, and interpret it as evidence of the importance of strategic default.

There are at least two difficult issues that must be confronted in an analysis of strategic default. First, one must define exactly what a strategic default is, which is not so straight-

[40]See for instance the WSJ article entitled "American Dream 2: Default, Then Rent," by Mike Whitehouse.

forward, and second, one needs detailed data on both mortgage payment histories as well as information on income and wealth. There is no consensus on a single, coherent definition, and economic theory provides little guidance, as in the context of an optimization problem, all mortgage defaults are to some degree "strategic." We believe that what most commentators mean by the term strategic default is the decision by a borrower to stop making payments despite the financial ability to continue to do so at little cost. By little cost, we mean that a borrow has enough liquid savings or a large, stable source of income to meet monthly mortgage obligations without having to borrow at high interest rates and/or make a considerable sacrifice in terms of current consumption. While this is by no means a precise definition, our goal in this section is not to identify behavior that can unambiguously be characterized as evidence of strategic default, but rather to describe the basic patterns of wealth holdings for borrowers that choose to default and let the reader draw his or her own conclusions about what can be inferred about strategic default. In terms of data, while the PSID is certainly not a perfect dataset to study aspects of strategic default, it does contain information on both mortgage default and wealth holdings, which is not the case in virtually all administrative loan-level datasets.

Table 3.10 shows the reported wealth holdings of households that were at least 60-days delinquent on their mortgages at the time of the 2009 PSID survey. We focus on liquid assets (defined above) as well as less liquid forms of wealth such as stock and bond holdings and retirement account assets, as well as unsecured debt. The table shows the distribution of assets and debt across all households that default (Panel A), households that default with negative equity (Panel B), and households that default with severe negative equity (Panel C). Since the entire concept of strategic default is based on increasing net worth by eliminating negative equity, we will focus on households that default with negative equity, but we add a panel for all defaulters for comparison purposes. It is clear from the table that the vast majority of negative equity defaulters have extremely low levels of liquid and illiquid assets. Three-quarters of severe negative equity defaulters have less than $2k in liquid assets and 90% have less than $10k in liquid assets. In addition, 90% of severe negative equity defaulters have zero holdings of stocks, bonds, and retirement account assets. A significant number of these households have non-trivial values of outstanding unsecured debt. Half of negative equity defaulters have over \$10k of unsecured debt, while half of severe negative equity defaulters have over \$4k of unsecured debt.

Finally, in each panel of Table 3.10 we display the distribution of the ratio of liquid assets to the monthly mortgage payment and the ratio of illiquid assets (defined to include stocks, bonds, and retirement accounts) to the monthly mortgage payment. Almost three-quarters of negative equity defaulters do not have enough liquid assets to make a single mortgage payment, while three-quarters of severe negative equity defaulters do not have enough liquid assets to make two payments. At the bottom of each panel we show the number and fraction of households in default that have a liquid asset-to-payment ratio *or* an illiquid asset-to-payment ratio greater than 1, 2, 6, and 12. According to the table, over 60% of severe negative equity defaulters report having neither enough liquid assets or illiquid assets to make one month's mortgage payment. It is unlikely that these households would qualify as strategic defaulters under virtually any definition, and thus we interpret 40% as an upper bound for potential strategic defaults in the PSID among those with severe negative equity. In contrast, approximately 13% of severe negative equity defaulters report having liquid or illiquid asset holdings greater than 12 months worth of mortgage payments. One could make the case that these borrowers fit a reasonable definition of strategic default in the sense that even without factoring in income, they have enough assets to continue making mortgage payments for at least one year, but choose to default instead.

Let us step back and broaden the scope of our analysis to include all delinquent mortgagors (not just those with severe negative equity). Among *all* defaulters, only 13.9% (=16/115) have negative equity (CLTV>100%) and enough liquid or illiquid assets to make 1 payment. That is, only 13.9% of all defaulters are underwater and would be able to make one month's mortgage payment out of their savings and financial wealth (a result that echoes Gruber (2001)).

3.5.1 Strategic Default in the SCF

Table 3.11, which is based on the SCF, confirms the PSID patterns illustrated in Table 3.10: a large fraction of defaulters have insufficient liquid assets to cover 1 month's mortgage payment, especially those with severe negative equity. In the SCF, we measure liquid assets as the sum of savings, checking accounts, and CDs. Since the SCF collects detailed account information, Table 3.12 computes liquid assets to mortgage payment ratios excluding CDs.

In the first panel of Table 3.11, 54.9% of SCF defaulters have enough liquid assets to make 1 mortgage payment. The next line shows that 42.5% of defaulters have enough liquid and illiquid assets to make 2 payments, 24.8% of defaulters have enough for 6 payments, and 13.3% of defaulters have enough for one year's worth of payments. The second panel looks at defaulters with negative equity and shows that over $\frac{3}{4}$ of defaulters with negative equity have insufficient liquid assets to make 1 month's payment. A similar pattern emerges in the third panel which looks at defaulters with severe negative equity of -20% or worse.

Table 3.12 shows that of all defaulters, only 6 percent have negative equity and enough money in their checking and savings account to make 1 mortgage payment. Since the SCF over-samples high-income and wealthy households, if strategic default accounted for a significant fraction of mortgage defaults, we would expect to see evidence of it in these data. We believe that these results, in conjunction with the results in Table 3.10 may call into question the role of strategic default in the 2007-2009 financial crisis.

3.6 Conclusion

Previous studies of the empirical determinants of mortgage default have been limited by the fact that loan-level databases have no data on mortgagor employment status and net worth. This study provides to our knowledge the first direct evidence on the impact of employment status, net worth, as well as negative equity on mortgage default by exploiting data from the PSID.

We find that job loss is the main "single trigger" determinant of default in the PSID, and the quantitative importance of job loss is robust to several different specifications of our reduced-form model. Specifically, we find that job loss increases the probability of default between 5 to 13 percentage points. Severe negative equity (-20% or more) also increases the probability of default by 5 to 18 percentage points. The impact of severe negative equity on default drops significantly in magnitude when liquid asset positions are taken into account. Furthermore, we find evidence for the "double trigger" event of job loss and negative equity, as well as job loss and severe negative equity. Specifically, we find that the joint occurrence of both job loss and negative equity raises the unconditional default rate by 11.3% over and above either trigger on its own.

A striking finding of the empirical analysis is on the frequency of strategic default, which is typically defined as default by mortgagors who have sufficient resources to make the mortgage payment. As a suggestive measure, we look at whether or not defaulting households with negative equity have enough liquid assets to make their mortgage payment. We find that strategic default is rare in the PSID. In particular, only 13.9 percent of defaulters in the PSID have sufficient liquid assets to make a mortgage payment. We confirm the rarity of strategic default using data from the SCF which shows that only 6 percent of defaulters have sufficient liquid assets to make one mortgage payment. These findings suggest that strategic default is not a major factor in understanding recent mortgage default decisions, but rather that defaulters may have few options other than to default. These findings have important policy implications. In particular, they suggest that temporary mortgage modifications do not provide a long-term solution to default. Rather, the key to stemming mortgage defaults is developing policies that promote re-employment and higher earnings, such as payroll tax cuts.

Table 3.1: Summary Statistics: Demographics, Income, and Wealth

Panel A: Fraction of All Mortgagors and Defaulters (60+ Days Delinquent)

	All	Defaulters		All	Defaulters
Unemployment	7.0%	24.8%	Missing Term Remaining	4.0%	3.7%
Job Loss in Last 6mo.	3.6%	10.1%	Recourse	24.3%	28.4%
Black	21.9%	37.6%	Judicial	39.2%	31.2%
White	71.6%	45.9%	Sand State	15.4%	33.0%
Age	43.7	44.3	HPA (2008-2009)	-7.4%	-11.5%
Male	84.8%	72.5%	Unempl. Rate 2009 (whole %)	9.3	9.8
Married	73.3%	57.8%	Unempl. Growth (2008-2009)	59.5%	61.3%
Recently Divorced	3.1%	5.5%	Hospital Bills/Inc > 10%	1.8%	4.6%
Less than HS Education	9.0%	21.1%	Hospital Bills Outstanding?	32.9%	33.3%
High School Education	27.2%	35.8%	Hospital Bills to Income	2.4%	2.6%
Some College Education	25.7%	18.3%	Pre-1995 Bankruptcy	5.6%	3.7%
College Grad+ Education	32.2%	16.5%	Unsecured Debt ($ thousands)	16.0	27.8
Education Missing	5.9%	8.3%	Auto Debt ($ thousands)	18.1	11.5
Second Mortgage Dummy	19.4%	23.9%	Business Assets ($ thousands)	44.0	1.7
Missing info on Second Mortgage	0.2%	0.9%	IRA ($ thousands)	22.9	0.8
Refinance	47.0%	49.5%	Other Housing ($ thousands)	32.4	2.9
Missing Refinance	0%	0%	Home Value ($ thousands)	243.8	224.7
ARM	9.1%	33.0%	Liquid Assets ($ thousands)	18.2	2.9
Interest Rate on Mortgage (whole %)	5.2	5.7	Stocks ($ thousands)	16.4	4.6
Missing Interest Rate on Mortgage	9.3%	17.9%	Bonds ($ thousands)	13.5	21.3
Term Remaining > 15yrs	68.0%	80.7%	Principal Remaining ($ thousands)	151.8	211.6
30+ Days Delinquent	6.5%	100%	60+ Days Delinquent	3.9%	100%
Observations	2,830	109			

Panel B: Distribution of Wealth Variables of All Mortgagors and Defaulters

Liquid Assets/Income	Mean	≤ 0.05	$0.05 < x \leq 0.10$	$0.10 < x \leq 0.20$	$0.20 < x \leq 0.50$	> 0.50	Missing
All	13.1%	52.1%	16.3%	14.1%	11.8%	5.6%	5.5%
Defaulters	4.1%	84.4%	6.4%	4.9%	3.7%	0.9%	1.8%
Illiquid Assets/Income							
All	61.7%	27.0%	9.2%	15.7%	22.2%	25.9%	17.6%
Defaulters	46.0%	33.0%	11.9%	20.2%	18.3%	16.5%	11.9%

Unsecured Debt/Income	Mean	≤ 0.05	$0.05 < x \leq 0.25$	$0.25 < x \leq 0.50$	$0.50 < x \leq 0.75$	> 0.75	Missing
All	20.8%	51.7%	28.2%	11.3%	3.7%	5.0%	2.5%
Defaulters	96.0%	34.9%	29.4%	12.8%	8.3%	14.7%	1.8%

Debt to Income	Mean	≤ 0.07	$0.07 < x \leq 0.15$	$0.15 < x \leq 0.32$	$0.32 < x \leq 0.40$	> 0.40	Missing
All	18.0%	9.9%	38.3%	42.2%	4.9%	4.7%	2.0%
Defaulters	30.7%	4.6%	12.8%	42.2%	21.1%	19.3%	1.8%

CLTV	Mean	≤ 0.80	$0.80 < x \leq 0.90$	$0.90 < x \leq 1.00$	$1.00 < x \leq 1.20$	> 1.20	Missing
All	65.1%	63.5%	12.5%	11.4%	8.2%	4.4%	8.4%
Defaulters 100.0%	35.8%	12.8%	12.8%	11.0%	27.5%	9.2%	

	Total Income		Income Growth (2007-2009)			
	2007	2009	< -50%	< -10%	$-10\% \leq x < 5\%$	> 5%
All	$99,184	$109,738	3.9%	22.8%	21.2%	56.0%
Defaulters	$74,449	$71,423	13.8%	43.1%	6.4%	50.5%

Table 3.2: Default Rate by Income and Wealth Status

	CLTV < 100%	CLTV ≥100%	CLTV < 120%	CLTV ≥120%
Unemployed	10.6% (N = 166)	30.0% (N = 30)	12.0% (N = 184)	41.7% (N = 12)
Employed	2.1% (N = 2,308)	10.2% (N = 323)	2.3% (N = 2,520)	22.5% (N = 111)
Liquid Assets < 5%	4.6% (N = 1,242)	15.2% (N = 230)	4.9% (N = 1,397)	30.7% (N = 75)
Liquid Assets ≥ 5%	0.8% (N = 1,232)	5.7% (N = 123)	0.8% (N = 1,307)	14.6% (N = 48)
Illiquid Assets < 5%	3.5% (N = 652)	11.6% (N = 112)	3.8% (N = 731)	24.2% (N = 33)
Illiquid Assets ≥ 5%	2.4% (N = 1,822)	12.0% (N = 241)	2.6% (N = 1,973)	24.4% (N = 90)
Debt-to-Income ≥ 40%	11.1% (N = 99)	30.3% (N = 33)	11.2% (N = 116)	50.0% (N = 16)
Debt-to-Income < 40%	2.4% (N = 2,375)	10.0% (N = 320)	2.6% (N = 2,588)	20.6% (N = 107)
Inc. Growth < -10%	5.1% (N = 553)	21.3% (N = 89)	5.8% (N = 606)	33.3% (N = 36)
Inc. Growth ≥ -10%	2.0% (N = 1,921)	8.7% (N = 264)	2.1% (N = 2,098)	20.7% (N = 87)
Inc. Growth < -50%	12.8% (N = 94)	20.0% (N = 15)	12.6% (N = 103)	33.3% (N = 6)
Inc. Growth ≥ -50%	2.3% (N = 2,380)	11.5% (N = 338)	2.5% (N = 2,601)	23.9% (N = 117)

Table 3.3: Basic Unemployment and Equity Results, Dependent Variable is 60+ Days Late Default Indicator as of 2009 Survey Date, PSID

Panel A: Basic Unemployment Results

	Linear Probability Model			Logit		
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployed (d)	0.107***	0.137***	0.127***	0.107***	0.136***	0.102***
	(4.29)	(3.56)	(3.38)	(4.29)	(3.63)	(3.37)
Job Loss in Last 6 Months (d)		-0.060	-0.060		-0.015	-0.014
		(-1.21)	(-1.23)		(-1.43)	(-1.28)
Black (d)			0.028***			0.030***
			(2.59)			(2.71)
HS Education (d)			-0.024			-0.013
			(-1.26)			(-1.36)
Some College Education (d)			-0.043**			-0.028***
			(-2.33)			(-3.13)
College Grad+ Education (d)			-0.047***			-0.033***
			(-2.61)			(-3.71)
HPA (2008-2009)			-0.419***			-0.422***
			(-2.84)			(-3.06)
Unemp. Growth (2008-2009)			0.022			0.041
			(0.71)			(1.23)
Other Demographic Controls?	NO	NO	YES	NO	NO	YES
Observations	2,827	2,827	2,820	2,827	2,827	2,820
R^2 / Pseudo R^2	0.020	0.021	0.059	0.039	0.041	0.140

Panel B: Basic Equity Results

	Linear Probability Model			Logit		
	(1)	(2)	(3)	(4)	(5)	(6)
CLTV	0.132***			0.072***		
	(6.65)			(5.93)		
$70\% \leq$ CLTV $< 80\%$		0.002	0.006		0.005	0.004
		(0.27)	(0.58)		(0.28)	(0.24)
$80\% \leq$ CLTV $< 90\%$		0.021*	0.023**		0.028**	0.028**
		(1.93)	(2.03)		(2.28)	(2.32)
$90\% \leq$ CLTV $< 100\%$		0.025**	0.028**		0.031**	0.033**
		(2.10)	(2.08)		(2.54)	(2.49)
$100\% \leq$ CLTV $< 120\%$		0.034**	0.027*		0.038***	0.032**
		(2.25)	(1.73)		(2.92)	(2.40)
CLTV $\geq 120\%$		0.226***	0.203***		0.100***	0.084***
		(5.80)	(5.34)		(8.17)	(7.20)
Black (d)			0.028**			0.029***
			(2.49)			(2.72)
HS Education (d)			-0.032*			-0.020**
			(-1.67)			(-2.08)
Some College Education (d)			-0.050***			-0.034***
			(-2.73)			(-3.88)
College Grad+ Education (d)			-0.052***			-0.038***
			(-2.95)			(-4.47)
HPA (2008-2009)			-0.344**			-0.366***
			(-2.37)			(-2.66)
Unemp. Growth (2008-2009)			0.019			0.033
			(0.62)			(0.95)
Other Demographic Controls?	NO	NO	YES	NO	NO	YES
Observations	2,827	2,827	2,820	2,827	2,827	2,820
R^2 / Pseudo R^2	0.049	0.056	0.083	0.105	0.095	0.173

Notes. Robust t-statistics in parentheses. Asterisk legend: *** pval<0.01, ** pval<0.05, * pval<0.1. PSID Restricted sample (See above). Demographic controls include, age, race, sex, marital status, education. Coefficient estimates from LPM reported in columns (1)-(3). Average marginal effects from logit model reported in columns (4)-(6). Sample size is reduced by 7 observations in column (6) due to missing demographic controls. Variables followed by (d) are indicator variables.

Table 3.4: Unemployment and Negative Equity Triggers Results, Dependent Variable is 60+ Days Late Default Indicator as of 2009 Survey Date, PSID

	Linear Probability Model			Logit		
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployed (d)	0.128***	0.126***	0.126***	0.099***	0.091***	0.092***
	(3.45)	(3.37)	(3.39)	(3.12)	(2.95)	(3.10)
Job Loss in Last 6 Months (d)	-0.070	-0.069	-0.072	-0.020**	-0.019*	-0.019*
	(-1.49)	(-1.48)	(-1.53)	(-1.99)	(-1.86)	(-1.87)
CLTV $\geq$ 90%	0.043***			0.035***		
	(3.92)			(4.19)		
CLTV $\geq$ 100%		0.065***			0.036***	
		(4.06)			(4.56)	
CLTV $\geq$ 120%			0.175***			0.058***
			(4.64)			(5.74)
Black (d)	0.024**	0.026**	0.027**	0.024**	0.025**	0.027**
	(2.15)	(2.35)	(2.46)	(2.27)	(2.40)	(2.56)
HS Education (d)	-0.023	-0.024	-0.021	-0.016*	-0.016	-0.014
	(-1.25)	(-1.26)	(-1.16)	(-1.65)	(-1.62)	(-1.50)
Some College Education (d)	-0.039**	-0.037**	-0.036**	-0.026***	-0.025***	-0.025***
	(-2.17)	(-2.06)	(-2.00)	(-2.81)	(-2.73)	(-2.65)
College Grad+ Education (d)	-0.045**	-0.043**	-0.040**	-0.034***	-0.033***	-0.031***
	(-2.53)	(-2.43)	(-2.32)	(-3.79)	(-3.68)	(-3.39)
HPA (2008-2009)	-0.340**	-0.320**	-0.291**	-0.365***	-0.340**	-0.308**
	(-2.39)	(-2.25)	(-2.09)	(-2.67)	(-2.53)	(-2.29)
Unemp. Growth (2008-2009)	0.013	0.016	0.010	0.027	0.033	0.028
	(0.43)	(0.51)	(0.34)	(0.79)	(0.96)	(0.82)
Refinance (d)	0.016**	0.015**	0.015*	0.011	0.011	0.011
	(1.99)	(1.97)	(1.93)	(1.49)	(1.46)	(1.40)
ARM (d)	0.090***	0.091***	0.085***	0.060***	0.063***	0.058***
	(4.30)	(4.40)	(4.07)	(3.66)	(3.84)	(3.51)
Mortgage Term > 15 years (d)	0.015**	0.018**	0.019**	0.013	0.016**	0.018**
	(2.09)	(2.37)	(2.54)	(1.57)	(2.06)	(2.22)
Other Demographic Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Other Mortgage Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,820	2,820	2,820	2,820	2,820	2,820
R^2 / Pseudo R^2	0.094	0.097	0.118	0.216	0.216	0.233

Notes. Robust t-statistics in parentheses. Asterisk legend: *** p<0.01, ** p<0.05, * p<0.1. PSID Restricted sample (See above). Demographic controls include, age, race, sex, marital status, education. Mortgage controls include presence of second mortgage, prior refinance, variable rate mortgage dummy, mortgage term greater than 15 years dummy, and whole interest rate. Coefficient estimates from LPM reported in columns (1)-(3). Average marginal effects from logit model reported in columns (4)-(6). Variables followed by (d) are indicator variables.

Table 3.5: Other Triggers Results, Dependent Variable is 60+ Days Late Default Indicator as of 2009 Survey Date, PSID

Panel A: Moderate Income Loss

	Linear Probability Model			Logit		
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployed (d)	0.120***	0.118***	0.119***	0.083***	0.075***	0.077***
	(3.23)	(3.17)	(3.19)	(2.89)	(2.70)	(2.83)
Job Loss in Last 6 Months (d)	-0.063	-0.063	-0.066	-0.017	-0.016	-0.017
	(-1.37)	(-1.36)	(-1.43)	(-1.63)	(-1.43)	(-1.55)
CLTV $\geq$ 90% (d)	0.043***			0.035***		
	(3.91)			(4.24)		
CLTV $\geq$ 100% (d)		0.065***			0.036***	
		(4.05)			(4.63)	
CLTV $\geq$ 120% (d)			0.175***			0.057***
			(4.65)			(5.77)
Recently Divorced (d)	0.003	0.005	0.003	0.009	0.008	0.007
	(0.12)	(0.17)	(0.09)	(0.50)	(0.42)	(0.36)
Hospital Bills/Income > 10% (d)	0.052	0.053	0.059	0.049	0.057	0.068*
	(1.28)	(1.29)	(1.46)	(1.43)	(1.56)	(1.82)
Income Loss < -10% (d)	0.031***	0.030***	0.029***	0.027***	0.026***	0.025***
	(3.00)	(2.93)	(2.85)	(2.93)	(2.84)	(2.70)
Demographic Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Mortgage Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,820	2,820	2,820	2,820	2,820	2,820
R^2 / Pseudo R^2	0.101	0.104	0.125	0.235	0.235	0.251

Panel B: Substantial Income Loss

	(1)	(2)	(3)	(4)	(5)	(6)
Unemployed (d)	0.124***	0.122***	0.123***	0.091***	0.083***	0.085***
	(3.33)	(3.25)	(3.27)	(2.84)	(2.66)	(2.77)
Job Loss in Last 6 Months (d)	-0.067	-0.067	-0.069	-0.019*	-0.018*	-0.019*
	(-1.45)	(-1.44)	(-1.50)	(-1.90)	(-1.71)	(-1.84)
CLTV $\geq$ 90% (d)	0.042***			0.033***		
	(3.84)			(3.99)		
CLTV $\geq$ 100% (d)		0.064***			0.035***	
		(3.99)			(4.39)	
CLTV $\geq$ 120% (d)			0.175***			0.057***
			(4.63)			(5.54)
Recently Divorced (d)	-0.006	-0.005	-0.007	0.003	0.003	0.001
	(-0.20)	(-0.16)	(-0.23)	(0.19)	(0.16)	(0.06)
Hospital Bills/Income > 10% (d)	0.051	0.052	0.059	0.055*	0.063*	0.071**
	(1.33)	(1.33)	(1.50)	(1.67)	(1.78)	(1.97)
Income Loss < -50% (d)	0.093***	0.092***	0.091***	0.076***	0.076**	0.074**
	(2.95)	(2.91)	(2.88)	(2.59)	(2.57)	(2.46)
Demographic Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Mortgage Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,820	2,820	2,820	2,820	2,820	2,820
R^2 / Pseudo R^2	0.105	0.108	0.129	0.238	0.238	0.255

Notes. Robust t-statistics in parentheses. Asterisk legend: *** p<0.01, ** p<0.05, * p<0.1. PSID Restricted sample (See above). Demographic controls include, age, race, sex, marital status, education. Mortgage controls include presence of second mortgage, prior refinance, variable rate mortgage dummy, mortgage term greater than 15 years dummy, and whole interest rate. Coefficient estimates from LPM reported in columns (1)-(3). Average marginal effects from logit model reported in columns (4)-(6). Variables followed by (d) are indicator variables.

Table 3.6: Wealth Results, Dependent Variable is 60+ Days Late Default Indicator as of 2009 Survey Date, PSID

	Linear Probability Model			Logit		
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployed (d)	0.118***	0.117***	0.117***	0.085***	0.078***	0.078***
	(3.22)	(3.17)	(3.18)	(3.23)	(3.04)	(3.14)
Job Loss in Last 6 Months (d)	-0.065	-0.065	-0.068	-0.017*	-0.017*	-0.018*
	(-1.41)	(-1.41)	(-1.49)	(-1.75)	(-1.65)	(-1.83)
CLTV $\geq$ 90% (d)	0.035***			0.026***		
	(3.16)			(3.05)		
CLTV $\geq$ 100% (d)		0.058***			0.030***	
		(3.56)			(3.77)	
CLTV $\geq$ 120% (d)			0.174***			0.057***
			(4.63)			(5.55)
Recently Divorced (d)	-0.006	-0.005	-0.007	0.001	0.000	-0.000
	(-0.21)	(-0.18)	(-0.24)	(0.04)	(0.02)	(-0.03)
Hospital Bills/Income > 10% (d)	0.043	0.044	0.049	0.037	0.044	0.048
	(1.09)	(1.10)	(1.23)	(1.24)	(1.40)	(1.49)
Income Loss < -50% (d)	0.093***	0.092***	0.090***	0.083***	0.084***	0.077**
	(3.02)	(2.99)	(2.93)	(2.62)	(2.70)	(2.50)
0.05 < Liquid Assets/Inc < 0.10 (d)	-0.027***	-0.028***	-0.028***	-0.026***	-0.026***	-0.026***
	(-3.24)	(-3.27)	(-3.31)	(-3.34)	(-3.53)	(-3.38)
0.10 < Liquid Assets/Inc < 0.20 (d)	-0.023***	-0.024***	-0.027***	-0.023***	-0.024***	-0.027***
	(-2.69)	(-2.76)	(-3.20)	(-2.79)	(-3.05)	(-3.73)
0.20 < Liquid Assets/Inc < 0.50 (d)	-0.025***	-0.026***	-0.027***	-0.023***	-0.024***	-0.026***
	(-2.85)	(-2.96)	(-3.18)	(-2.59)	(-2.67)	(-3.15)
Liquid Assets/Inc > 0.50 (d)	-0.035***	-0.035***	-0.035***	-0.035***	-0.036***	-0.035***
	(-3.40)	(-3.40)	(-3.37)	(-4.40)	(-4.60)	(-3.56)
0.05 < Illiquid Assets/Inc < 0.10 (d)	-0.017	-0.014	-0.020	-0.003	-0.002	-0.006
	(-0.79)	(-0.68)	(-0.94)	(-0.27)	(-0.18)	(-0.50)
0.10 < Illiquid Assets/Inc < 0.20 (d)	-0.019	-0.017	-0.018	-0.006	-0.005	-0.004
	(-0.99)	(-0.89)	(-0.91)	(-0.61)	(-0.53)	(-0.42)
0.20 < Illiquid Assets/Inc < 0.50 (d)	-0.030*	-0.029	-0.033*	-0.016*	-0.015	-0.017*
	(-1.67)	(-1.59)	(-1.81)	(-1.81)	(-1.63)	(-1.92)
Illiquid Assets/Inc > 0.50 (d)	-0.026	-0.025	-0.028	-0.020**	-0.019**	-0.020**
	(-1.47)	(-1.38)	(-1.59)	(-2.25)	(-2.13)	(-2.26)
0.05 < Unsecured Debt/Inc < 0.10 (d)	0.008	0.008	0.009	0.012	0.012	0.015
	(1.02)	(1.01)	(1.12)	(1.29)	(1.27)	(1.55)
0.10 < Unsecured Debt/Inc < 0.20 (d)	0.009	0.011	0.014	0.020	0.022	0.026
	(0.72)	(0.89)	(1.16)	(1.29)	(1.38)	(1.58)
0.20 < Unsecured Debt/Inc < 0.50 (d)	0.030	0.030	0.030	0.029	0.032	0.035
	(1.12)	(1.14)	(1.18)	(1.30)	(1.43)	(1.57)
Unsecured Debt/Inc > 0.50 (d)	0.045*	0.043*	0.051**	0.033*	0.032*	0.041**
	(1.87)	(1.78)	(2.15)	(1.80)	(1.71)	(2.03)
Demographic Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Mortgage Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,820	2,820	2,820	2,820	2,820	2,820
R^2 / Pseudo R^2	0.117	0.120	0.143	0.284	0.287	0.310

Notes. Robust t-statistics in parentheses. Asterisk legend: *** p<0.01, ** p<0.05, * p<0.1. PSID Restricted sample (See above). Demographic controls include, age, race, sex, marital status, education. Mortgage controls include presence of second mortgage, prior refinance, variable rate mortgage dummy, mortgage term greater than 15 years dummy, and whole interest rate. Coefficient estimates from LPM reported in columns (1)-(3). Average marginal effects from logit model reported in columns (4)-(6). Variables followed by (d) are indicator variables.

Table 3.7: Summary Statistics: Pre-1996 Bankruptcies and Defaults, PSID

Panel A: Pre-1996 Bankruptcies

	Observations	Fraction (%)	Avg. Age
No Bankruptcy History	2,859	94.14	44.26
Pre-1996 Bankruptcies	178	5.86	45.48

Panel B: Default Fractions

	Observations	60-Day Delinquency (%)	30-Day Delinquency (%)
No Bankruptcy History	2,859	3.85	6.44
Pre-1996 Bankruptcies	178	2.81	6.18

Table 3.8: Pre-1996 Bankruptcy and Mortgage Default Results, Dependent Variable is 60+ Days Late Default Indicator as of 2009 Survey Date.

	Linear Probability Model			Logit		
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployed (d)	0.123***	0.121***	0.122***	0.089***	0.082***	0.084***
	(3.31)	(3.24)	(3.26)	(2.81)	(2.63)	(2.74)
Job Loss in Last 6 Months (d)	-0.066	-0.066	-0.069	-0.018*	-0.017	-0.018*
	(-1.43)	(-1.42)	(-1.49)	(-1.79)	(-1.62)	(-1.74)
CLTV $\geq$ 90% (d)	0.043***			0.034***		
	(3.90)			(4.04)		
CLTV $\geq$ 100% (d)		0.064***			0.035***	
		(4.00)			(4.38)	
CLTV $\geq$ 120% (d)			0.175***			0.057***
			(4.62)			(5.55)
Recently Divorced (d)	-0.005	-0.004	-0.007	0.003	0.003	0.001
	(-0.19)	(-0.15)	(-0.23)	(0.18)	(0.15)	(0.06)
Hospital Bills/Income > 10% (d)	0.052	0.053	0.059	0.057*	0.065*	0.074**
	(1.35)	(1.35)	(1.51)	(1.69)	(1.79)	(2.00)
Income Loss < -10% (d)	0.094***	0.093***	0.091***	0.077***	0.077**	0.075**
	(2.97)	(2.93)	(2.90)	(2.58)	(2.56)	(2.46)
Pre-1995 Bankruptcy (d)	-0.024*	-0.021	-0.016	-0.017	-0.015	-0.014
	(-1.88)	(-1.65)	(-1.25)	(-1.56)	(-1.30)	(-1.13)
Demographic Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Mortgage Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,820	2,820	2,820	2,820	2,820	2,820
R^2 / Pseudo R^2	0.105	0.109	0.129	0.239	0.240	0.256

Notes. Robust t-statistics in parentheses. Asterisk legend: *** p<0.01, ** p<0.05, * p<0.1. PSID Restricted sample (See above). Demographic controls include, age, race, sex, marital status, education. Mortgage controls include presence of second mortgage, prior refinance, variable rate mortgage dummy, mortgage term greater than 15 years dummy, and whole interest rate. Coefficient estimates from LPM reported in columns (1)-(3). Average marginal effects from logit model reported in columns (4)-(6). Variables followed by (d) are indicator variables.

Table 3.9: Double Trigger Results, Dependent Variable is 60+ Days Late Default Indicator as of 2009 Survey Date.

	Linear Probability Model			Logit		
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployed (d)	0.057**	0.073***	0.082***	0.064***	0.060***	0.061***
	(2.45)	(3.05)	(3.50)	(3.22)	(3.04)	(3.12)
CLTV $\geq$ 90%	0.032***			0.037***		
	(2.95)			(3.50)		
CLTV $\geq$ 100%		0.056***			0.045***	
		(3.41)			(3.52)	
CLTV $\geq$ 120%			0.167***			0.104***
			(4.24)			(3.66)
Unemployed*CLTV $\geq$ 90% (d)	0.143**			.079		
	(2.06)			(1.50)		
Unemployed*CLTV $\geq$ 100% (d)		0.093			.009	
		(1.13)			(0.17)	
Unemployed*CLTV $\geq$ 120% (d)			0.075			-.014
			(0.54)			(-0.19)
Hospital Bills/Income > 10% (d)	0.049	0.051	0.058	0.052	0.059*	0.065*
	(1.30)	(1.30)	(1.48)	(1.64)	(1.73)	(1.87)
Income Loss < -50%	0.095***	0.095***	0.092***	0.078***	0.077***	0.077***
	(3.03)	(2.99)	(2.92)	(2.67)	(2.64)	(2.62)
Demographic Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Mortgage Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,820	2,820	2,820	2,820	2,820	2,820
R^2	0.109	0.108	0.127	0.256	0.256	0.256

Notes. Robust t-statistics in parentheses. Asterisk legend: *** p<0.01, ** p<0.05, * p<0.1. PSID Restricted sample (See above). Demographic controls include, age, race, sex, marital status, education. Mortgage controls include presence of second mortgage, prior refinance, variable rate mortgage dummy, mortgage term greater than 15 years dummy, and whole interest rate. Coefficient estimates from LPM reported in columns (1)-(3). Average marginal effects from logit model reported in columns (4)-(6). Variables followed by (d) are indicator variables.

Table 3.10: Evidence on Strategic Default: PSID

Panel A: All Defaulters

	Obs.	Mean	1	5	10	25	50	75	90	95	99
						Percentile of Distribution					
Liq Assets ($ thousands)	112	2.8	0	0	0	0	0	2	5	10	35
Stocks ($ thousands)	112	4.4	0	0	0	0	0	0	0	0.05	200
Bonds ($ thousands)	115	20.3	0	0	0	0	0	0	0	50	550
Retirement ($ thousands)	115	0.8	0	0	0	0	0	0	0	4	16
Unsecured Debt ($ thousands)	113	26.6	0	0	0	0.5	10	30	50	100	300
Liq Assets / Monthly Payment	110	1.4	0	0	0	0	0.3	1.1	4.5	5.4	15.9
Illquid Assets / Monthly Payment	113	9.7	0	0	0	0	0	0	3.8	49.4	261.2
LA / Payment > 1 *or* ILA / Payment > 1						41 (35.7%)					
LA / Payment > 2 *or* ILA / Payment > 2						31 (27.0%)					
LA / Payment > 6 *or* ILA / Payment > 6						17 (14.8%)					
LA / Payment > 12 *or* ILA / Payment > 12						14 (12.2%)					

Panel B: Negative Equity (CLTV > 100%) Defaulters

	Obs.	Mean	1	5	10	25	50	75	90	95	99
						Percentile of Distribution					
Liq Assets ($ thousands)	44	2.8	0	0	0	0	0.7	2	10	12	35
Stocks ($ thousands)	44	7.0	0	0	0	0	0	0	0	2	300
Bonds ($ thousands)	44	26.4	0	0	0	0	0	0	0	50	800
Retirement ($ thousands)	44	0.5	0	0	0	0	0	0	0	0	14
Unsecured Debt ($ thousands)	43	34.7	0	0	0	1	10	30	46	100	500
Liq Assets / Monthly Payment	44	1.3	0	0	0	0	0.4	1.1	4.5	4.7	15.9
Illquid Assets / Monthly Payment	44	9.8	0	0	0	0	0	0.0	12.8	22.7	262.3
LA / Payment > 1 *or* ILA / Payment > 1						16 (36.4%)					
LA / Payment > 2 *or* ILA / Payment > 2						12 (27.3%)					
LA / Payment > 6 *or* ILA / Payment > 6						6 (13.6%)					
LA / Payment > 12 *or* ILA / Payment > 12						5 (11.4%)					

Panel C: Severe Negative Equity (CLTV > 120%) Defaulters

	Obs.	Mean	1	5	10	25	50	75	90	95	99
						Percentile of Distribution					
Liq Assets ($ thousands)	31	3.6	0	0	0	0	0.8	3	10	15	35
Stocks ($ thousands)	31	9.7	0	0	0	0	0	0	0	0	300
Bonds ($ thousands)	31	37.1	0	0	0	0	0	0	0	300	800
Retirement ($ thousands)	31	0.6	0	0	0	0	0	0	0	6	14
Unsecured Debt ($ thousands)	30	37.8	0	0	0	0	4.2	20	68	300	500
Liq Assets / Monthly Payment	31	1.7	0	0	0	0	0.4	1.9	4.6	6.5	15.9
Illquid Assets / Monthly Payment	31	13.5	0	0	0	0	0	0	14.7	115.4	262.3
LA / Payment > 1 *or* ILA / Payment > 1						12 (38.7%)					
LA / Payment > 2 *or* ILA / Payment > 2						11 (35.5%)					
LA / Payment > 6 *or* ILA / Payment > 6						5 (16.1%)					
LA / Payment > 12 *or* ILA / Payment > 12						4 (12.9%)					

Notes. For more observations, this table includes all non-disabled working age (24 to 65) heads of households in the PSID with no restrictions on loan to values or labor force participation. Liquid assets include checking or savings accounts, money market funds, certificates of deposit, government savings bonds, or Treasury bills. Payment includes both first and second mortgage payments. Illiquid assets include stocks, retirement savings, and bonds.

Table 3.11: Measures of Strategic Default, SCF

Panel A: All Defaulters

			Percentile of Distribution								
	Obs.	**Mean**	**1**	**5**	**10**	**25**	**50**	**75**	**90**	**95**	**99**
Liquid Assets ($ thousands)	113	6.02	0	0	0.01	0.15	0.6	2	6.98	15.1	116.9
Stocks ($ thousands)	113	0.91	0	0	0	0	0	0	0.57	1.6	27
Bonds ($ thousands)	113	0.02	0	0	0	0	0	0	0	0	1
IRA ($ thousands)	113	8.80	0	0	0	0	0	0	12	30	150
Unsecured Balance ($ thousands)	113	13.23	0	0	0	0	0.52	9	40	80	175
Liquid Assets/ Monthly Payment	113	2.36	0	0	0.01	0.12	0.57	1.39	4.29	5.89	39.58
Illiquid Assets/ Monthly Payment	113	8.90	-27.78	-11.11	0	0	0	5.63	14.58	50.00	128.93
	1356	-692.54	0	0.32	0.88	2.98	9.70	34.03	117.59	205.07	666.25
LA / Payment > 1 or ILA / Payment > 1						62 (54.9%)					
LA / Payment > 2 or ILA / Payment > 2						48 (42.5%)					
LA / Payment > 6 or ILA / Payment > 6						28 (24.8%)					
LA / Payment > 12 or ILA / Payment > 12						15 (13.3%)					

Panel B: All Defaulters with Negative Equity (CLTV>100%)

			Percentile of Distribution								
	Obs.	**Mean**	**1**	**5**	**10**	**25**	**50**	**75**	**90**	**95**	**99**
Liquid Assets ($ thousands)	39	5.71	0	0	0	0.1	0.44	1.5	6.98	11.4	173
Stocks ($ thousands)	39	0.09	0	0	0	0	0	0	0.57	0.75	1.1
Bonds ($ thousands)	39	0.04	0	0	0	0	0	0	0	0	1.6
IRA ($ thousands)	39	2.31	0	0	0	0	0	0	12	20	30
Unsecured Balance ($ thousands)	39	9.47	0	0	0	0	0.3	9	32	50	100
Liquid Assets/ Monthly Payment	39	0.84	0	0	0	0.07	0.30	0.61	3.49	4.75	8.83
Illiquid Assets/ Monthly Payment	39	4.67	-27.78	-11.11	0	0	0	3.23	8.06	62.56	106.43
LA / Payment > 1 or ILA / Payment > 1						17 (43.6%)					
LA / Payment > 2 or ILA / Payment > 2						13 (33.3%)					
LA / Payment > 6 or ILA / Payment > 6						5 (12.8%)					
LA / Payment > 12 or ILA / Payment > 12						2 (5.1%)					

Panel C: All Defaulters with Severe Negative Equity (CLTV>120%)

			Percentile of Distribution								
	Obs.	**Mean**	**1**	**5**	**10**	**25**	**50**	**75**	**90**	**95**	**99**
Liquid Assets ($ thousands)	18	1.37	0	0	0	0.06	0.54	1.50	6.98	9	9
Stocks ($ thousands)	18	0.00	0	0	0	0	0	0	0	0.05	0.05
Bonds ($ thousands)	18	0.09	0	0	0	0	0	0	0	1.6	1.6
IRA ($ thousands)	18	1.00	0	0	0	0	0	0	6	12	12
Unsecured Balance ($ thousands)	18	10.93	0	0	0	0	0.41	6	50	100	100
Liquid Assets/ Monthly Payment	18	0.68	0	0	0	0.03	0.28	0.55	3.49	3.75	3.75
Illiquid Assets/ Monthly Payment	18	-0.25	-27.78	-27.78	0	0	0	1.45	6.07	8.06	8.06
LA / Payment > 1 or ILA / Payment > 1						7 (38.9%)					
LA / Payment > 2 or ILA / Payment > 2						5 (27.8%)					
LA / Payment > 6 or ILA / Payment > 6						2 (11.1%)					
LA / Payment > 12 or ILA / Payment > 12						0 (00.0%)					

Notes. SCF Restricted sample (See above). Illiquid assets include stocks, bonds, and retirement savings. Liquid assets include checking, savings, and CDs. Monthly payment includes both first and second mortgage payments.

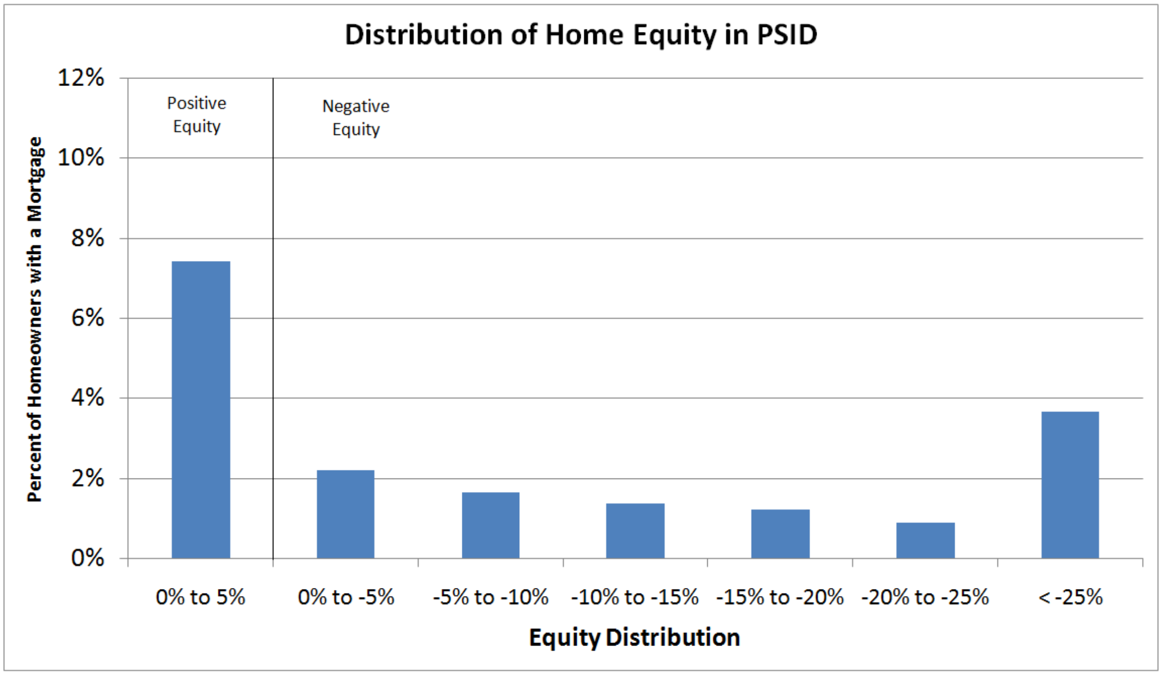
Table 3.12: Additional Measures of Strategic Default Among Mortgagors who were 2mo+ Delinquent over Last 12 Months, SCF

Among Defaulters over Prior 12 mo.		
	Fraction	Observations
Fraction of Defaulters with Insufficient Checking and Savings to Cover 1 Mo. Mortgage Payment and Credit Constrained	0.23	113
Fraction of Defaulters who have Sufficient Checking and Savings to Cover 1 Mo. Mortgage Payment and who have $CLTV > .9$	0.097	113
Fraction of Defaulters who have Sufficient Checking and Savings to Cover 1 Mo. Mortgage Payment and who have $CLTV > 1$	0.061	113

Notes. SCF Restricted sample (See above). Liquid assets include checking and savings only. Credit denial refers to denial between 2007 and 2009. Monthly payment includes both first and second mortgage payments.

Figure 3.1: Equity Distribution

(a) PSID



(b) Corelogic

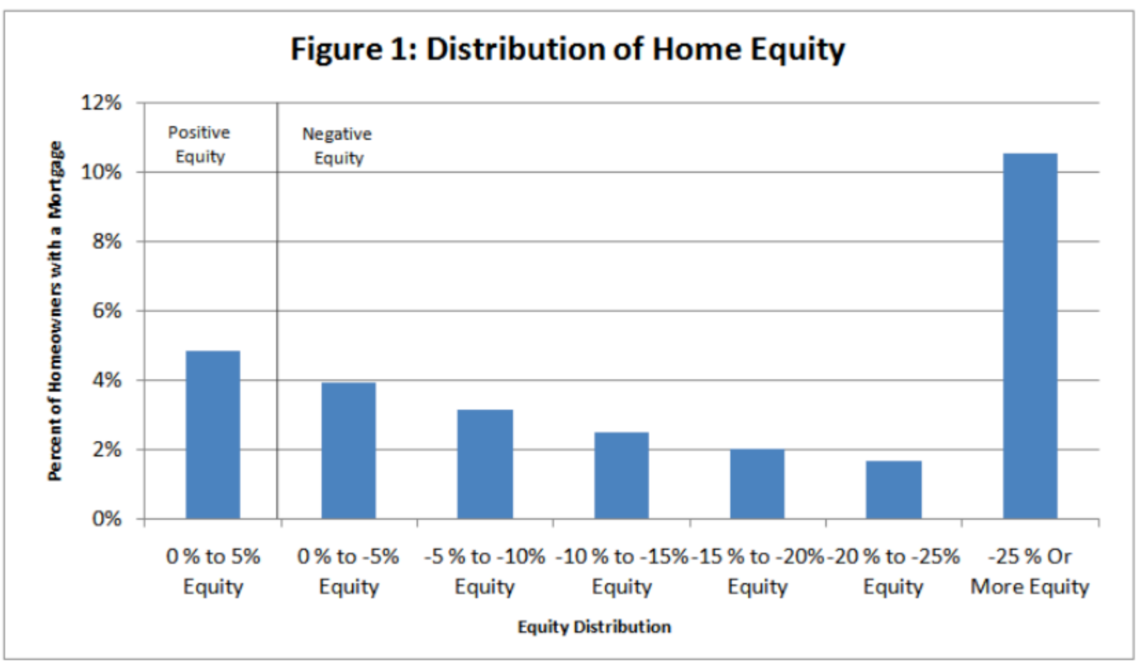
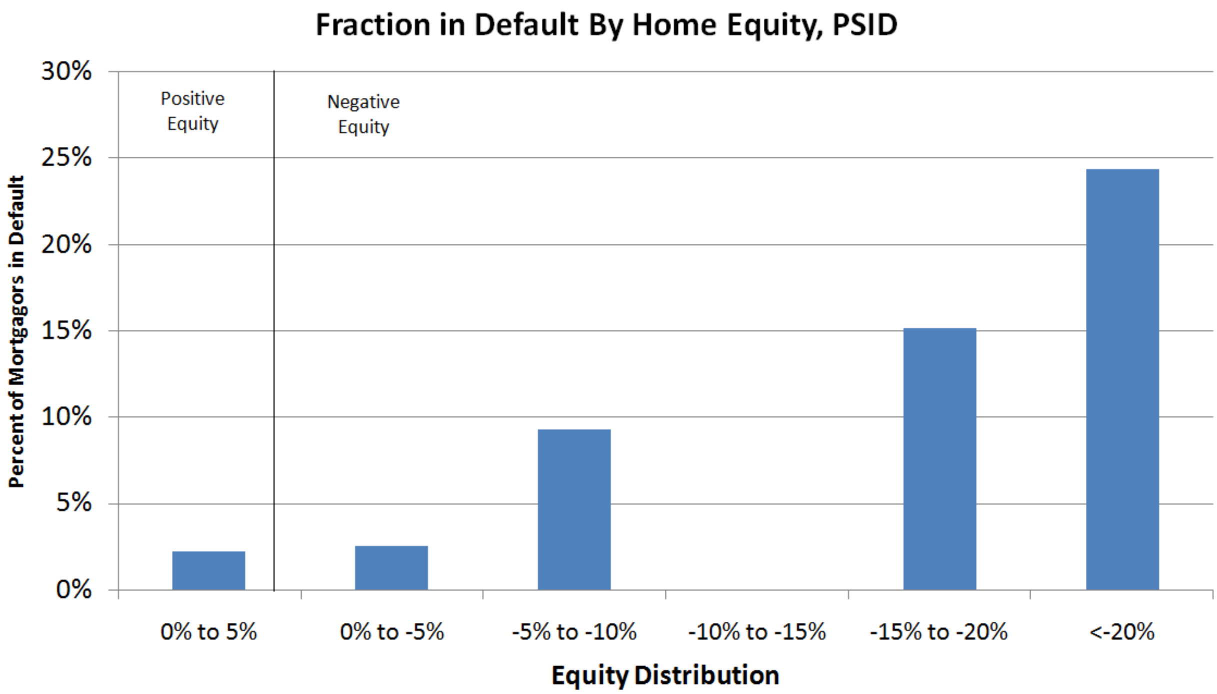


Figure 3.2: Default Rates and Negative Equity



3.7 Appendix

3.7.1 Data Details

3.7.1.1 PSID Interview Questions

The home value is self-reported: "A20. Could you tell me what the present value of your (house/apartment) is–I mean about how much would it bring if you sold it today?" The remaining principal is also self-reported: "A24. About how much is the remaining principal on this mortgage?" The mortgage default information is measured as of the survey date and also self-reported: "A27FOR2. How many months are you behind?"

3.7.1.2 SCF Interview Questions

The survey asks various questions regarding credit constraints, default, and house prices. They ask directly about credit constraints: "In the past [two] years, has a particular lender or creditor turned down any request you or your (husband/wife/partner) made for credit, or not given you as much credit as you applied for?" The question regarding default is about all loans: "Now thinking of all the various loan or mortgage payments you made during the last year, were all the payments made the way they were scheduled, or were payments on any of the loans sometimes made later or missed?" There is a follow up default question that asks whether or not the respondent was ever two or more months late. The house value is self-reported and so is the remaining principal, similar to the PSID.

3.7.1.3 Discussion of Weights

We do not weight the observations due to the fact that default outcomes are not post-stratum in the PSID. The point is best made with an important example. The Office of Thrift Supervision (OTS) publishes a mortgage delinquency report every quarter based on nationally representative data. They report that in 2009-Q3, roughly 6.2% of mortgages were delinquent. In the 2009 PSID, the unweighted default rate among mortgagors is 3.86%. However, the default rate in the 2009 PSID, weighted using the family weights, is only 3.15%. The weights significantly lower the default rate compared to the unweighted default rate and yield a default rate roughly half the magnitude of the population default rate. A similar set of outcomes is also true in the SCF.

3.7.2 Robustness Checks

3.7.2.1 SCF Data

We use the 2007-2009 Survey of Consumer Finances (SCF) panel dataset to double check our PSID results. Similar to the PSID, the SCF collected default information in the 2009 wave of interviews. However, the confounding factor in the SCF is the timing and precision of the questions. The main problems include, (i) the default question in the SCF refers to default over the last 12 months and is not confined to simply secured debt (let alone mortgages), (ii) there is no separate category for health expenses (the closest is medical loans which are included with "other" loans), (iii) there is no data on consecutive unemployment spells, and lastly, and (iv) since the default status at the survey date is unknown and since they record negative equity, wealth, and employment as of the survey date, causal inference is nearly impossible.[41] There are some benefits however, since the SCF includes measures of credit limits as of the survey date (see Elul et al. (2010)) and credit denial between the 2007 and 2009 survey dates. Unfortunately, in any study with prior default over the last 12 months as the dependent variable and credit utilization as the independent variable, there is severe endogeneity.

In terms of observations, the overall sample size is also considerably smaller, but the SCF specifically samples high-net-worth individuals which is useful in the discussion of strategic default. For the purposes of comparability, we restrict the sample to working age heads of households (24yrs to 65yrs) who are labor force participants and have a mortgage in 2009.

3.7.2.2 SCF Summary

Table 3.14 summarizes the SCF variables of interest. While there are only 1,482 observations, we have 113 default observations, where default is defined to be 60+ days late over the prior 12 months on any debt, which is roughly the same number of default observations as the PSID (however the PSID measure of default is different). Similar to the PSID, in the SCF

[41] See Herkenhoff (2013) for an IV correction to this problem based on the panel aspect of the dataset.

88% of the heads are male and the average age is 46 which is comparable to the sample in Table 3.1. Mean income is significantly higher (roughly $30,000 higher) in the SCF sample compared to the PSID sample.

In terms of financial health, 8% of the entire sample has a combined loan to value ratio over 100%, and 3% of the entire sample has a combined loan to value ratio over 120%. Almost 49% of SCF mortgagors have a ratio of liquid assets (which includes savings, checking, and CDs) to annual gross income of less than 5%. Moreover, 12% of the sample has a ratio of unsecured debt balances (which includes credit card, retail card, and other unsecured balances) to annual gross income of over 75%. Only 3% of mortgagors have gone over their credit limit, i.e. they have a credit utilization rate greater than 100%.

3.7.3 SCF Defaulter Characterization

Turning to the defaulter versus average mortgagor comparison, the SCF exhibits the same unemployment pattern as the PSID: only 6% of the entire mortgage sample is unemployed, whereas 17% of defaulters are unemployed. Likewise, 3% of the entire mortgage sample has severe negative equity of -20% or worse while over 16% of defaulters have severe negative equity of -20% or worse. Of importance is the fact that defaulters in the SCF have *significantly* lower incomes than the average SCF mortgagor, roughly $78,000 lower.

There is also an interesting correlation between credit denial and default; roughly 40% of defaulters were denied credit between 2007 and 2009 versus 16% for the entire mortgagor sample. The typical story is that defaulters have low credit scores, and thus are denied credit more often. A more interesting question is whether or not credit denial leads to default.[42]

3.7.4 Unemployment and Default in the SCF

Table 3.15 reports both linear probability (LPM) and logit results for a regression of the SCF default indicator on unemployment as of the survey date. Columns (1)-(3) are identical linear probability models except for the varying negative equity cutoffs. For comparability

[42] See Herkenhoff (2013) for more on this topic.

with the PSID, column (1) uses a combined loan to value (CLTV) cutoff of 90%, column (2) uses a CLTV>100% cutoff, and column (3) uses a CLTV>120% cutoff. Likewise, columns (4)-(6) are logit models with the same set of negative equity cutoffs. The controls included each regression include balance sheet controls for liquid assets, illiquid assets, and unsecured debt; demographic controls for age, rage, sex, marital status, and education; and mortgage controls for the presence of a second mortgage, whether there is 15 or more years remaining on the term of the loan, a prior refinancing, and whether the mortgage is an ARM.

Unemployment in every specification is a strongly correlated default (however, the interpretation here is far from causal), as in the PSID study. We interpret the linear probability model results in column (3) as follows: an unemployed person is 12.7% more likely to have defaulted on any of their debts over the prior 12 months than an employed person, and a mortgagor with severe negative equity of -20% or worse is 23.1% more likely to have defaulted on any of their debts over the prior 12 months than a mortgagor with a better equity position. To discipline the model's fit, we include an identical logit specification in column (6). The logit results reveal that an unemployed mortgagor is 9.9% more likely to have defaulted their debts over the prior 12 months relative to an employed mortgagor. A mortgagor with severe negative equity of -20% or worse is 13.1% more likely to have defaulted their debts over the prior 12 months than a mortgagor with a better equity position. The logit model in column (6) corrects for the well known deficiencies of the linear probability model and is thus our preferred specification.

As in the PSID, medical payments (proxied by other loan payments which includes medical loan payments) is not a strong predictor of default, and neither is recent divorce (the recent divorce point estimate is large, but not significantly different from zero). We do not include credit card utilization rates or credit denial status due to the inherent endogeneity induced by the survey timing.

3.7.5 Trigger Analysis: Unemployment and Negative Equity in the SCF

Table 3.16 provides more mixed evidence for the double trigger event of unemployment and negative equity. In every column , the point estimates for the coefficients on unemployment *alone* and negative equity *alone* are of the same magnitude as Table 3.15 (based on the PSID), suggesting a limited role for interactions between unemployment and negative equity. For example, in column (6), an unemployed mortgagor is 9.8% more likely to have defaulted their debts over the prior 12 months relative to an employed mortgagor (versus 9.9% in Table 3.15). Similarly, a mortgagor with severe negative equity of -20% or worse is 13.1% more likely to have defaulted their debts over the prior 12 months than a mortgagor with a better equity position, the exact same point estimate as in Table 3.15. The lack of an interaction effect is likely due to the fact that there are only 18 default observations in the SCF with severe negative equity of -20% or worse. With such limited variation, it becomes nearly impossible to obtain precise point estimates. We do note however, that the point estimates for the interaction term between unemployment and severe negative equity is large even though is is not statistically different from zero.

Table 3.13: PSID Sample Comparison: Unrestricted vs. Restricted vs. External Data

	PSID				Population	
Variable	Full Sample		Restricted Sample			
	Mean	N	Mean	N	Mean	Source
30+ Days Late (d)	0.064	3349	0.062	2814	0.114	2009-Q4 Mortgage Metrics Report
60+ Days Late (d)	0.039	3349	0.035	2814	0.052	2009-Q4 Mortgage Metrics Report
90+ Days Late (d)	0.023	3349	0.019	2814	0.032	2009-Q4 Mortgage Metrics Report
Unemployment (d)	0.060	3342	0.070	2814	0.093	BLS All 16+
$90\% < \text{CLTV} \leq 100\%$ (d)	0.127	3349	0.138	2814	See Chart	CoreLogic
$100\% < \text{CLTV} \leq 110\%$ (d)	0.034	3349	0.035	2814	See Chart	CoreLogic
$110\% < \text{CLTV} \leq 120\%$ (d)	0.023	3349	0.025	2814	See Chart	CoreLogic
$\text{CLTV} > 120\%$ (d)	0.042	3349	0.038	2814	See Chart	CoreLogic
60+ Days Late if $90\% < \text{CLTV} \leq 100\%$ (d)	0.047	426	0.039	387		
60+ Days Late if $100\% < \text{CLTV} \leq 110\%$ (d)	0.070	114	0.061	99		
60+ Days Late if $110\% < \text{CLTV} \leq 120\%$ (d)	0.066	76	0.072	69		
60+ Days Late if $\text{CLTV} > 120\%$ (d)	0.252	139	0.178	107		
60+ Days Late if Unemployed and $90\% < \text{CLTV} \leq 100\%$ (d)	0.263	19	0.278	18		
60+ Days Late if Unemployed and $100\% < \text{CLTV} \leq 110\%$ (d)	0.250	8	0.250	8		
60+ Days Late if Unemployed and $110\% < \text{CLTV} \leq 120\%$ (d)	0.143	7	0.143	7		
60+ Days Late if Unemployed and $\text{CLTV} > 120\%$ (d)	0.417	12	0.333	9		
60+ Days Late if Employed and $90\% < \text{CLTV} \leq 100\%$ (d)	0.037	407	0.027	369		
60+ Days Late if Employed and $100\% < \text{CLTV} \leq 110\%$ (d)	0.057	106	0.044	91		
60+ Days Late if Employed and $110\% < \text{CLTV} \leq 120\%$ (d)	0.058	69	0.065	62		
60+ Days Late if Employed and $\text{CLTV} > 120\%$ (d)	0.238	126	0.163	98		

Table 3.14: Summary Statistics and Defaulter Comparison: SCF

	Means	
Demographics	All Mortgagors	Defaulters
Unemployed at Survey Date, 2009 (d)	0.06	0.17
Male Indicator (d)	0.88	0.81
Married (d)	0.76	0.69
Age	46.11	43.70
Black (d)	0.06	0.12
College Educated (d)	0.59	0.34
Recently Divorced 2007-2009 (d)	0.03	0.05
	Means	
Income	All Mortgagors	Defaulters
Total Income 2007	137,231	59,265
Total Income 2009	156,307	58,458
5% $\leq$ Income Loss $<$ -10% from 2007 to 2009 (d)	0.04	0.02
Income Loss $<$ -10% from 2007 to 2009 (d)	0.25	0.36
Income Loss $<$ -50% from 2007 to 2009 (d)	0.09	0.12
	Means	
Mortgage	All Mortgagors	Defaulters
60 + Days Late on Any Debt over Prior 12 Months (d)	0.08	1.00
CLTV $<$ .7 (d)	0.60	0.32
.7 $\leq$ CLTV $<$ .8 (d)	0.08	0.08
.8 $\leq$ CLTV $<$ .9 (d)	0.08	0.13
.9 $\leq$ CLTV $<$ 1 (d)	0.06	0.11
1 $\leq$ CLTV $<$ 1.2 (d)	0.05	0.13
1.2 $\leq$ CLTV (d)	0.03	0.16
Loan Term $>$ 15 years (d)	0.06	0.08
Refinanced (d)	0.17	0.13
Variable Rate Mortgage (d)	0.15	0.22
Second Mortgage Presence (d)	0.08	0.12
	Means	
Financial	All Mortgagors	Defaulters
Liquid Assets to Income $<$ 5% (d)	0.49	0.82
Illiquid Assets to Income $<$ 5% (d)	0.14	0.33
25% $<$ Unsecured DTI $\leq$ 50% (d)	0.04	0.04
50% $<$ Unsecured DTI $\leq$ 75% (d)	0.01	0.03
75% $<$ Unsecured DTI (d)	0.12	0.19
Other Loan Payments (Including Medical) to Income $>$ 1% (d)	0.01	0.01
Other Loan Payments (Including Medical) to Income	0.10	0.11
Difference in Other Loan Payments (Including Medical) from 2007 to 2009	320	47
.8 $\leq$ Credit Utilization Rate $<$ .9 (d)	0.03	0.10
.9 $\leq$ Credit Utilization Rate $<$ 1 (d)	0.01	0.04
1 $\leq$ Credit Utilization Rate (d)	0.03	0.16
Denied Credit Between 2007 and 2009 (d)	0.16	0.40
Discouraged Borrower Between 2007 and 2009 (d)	0.12	0.42
Observations	1482	113

Notes. SCF Restricted Sample.

Table 3.15: Single Trigger Results, Dependent Variable is 60+ Days Late Indicator on All Debts over Prior 12 Months to 2009 Survey Date, SCF

	Linear Probability Model			Logit		
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployed at Survey Date, 2009 (d)	0.127***	0.126***	0.127***	0.101***	0.099***	0.099***
	(3.06)	(3.04)	(3.11)	(3.12)	(3.15)	(3.17)
CLTV > .9 (d)	0.110***			0.073***		
	(3.93)			(3.32)		
CLTV > 1 (d)		-0.005			-0.002	
		(-0.15)			(-0.07)	
CLTV > 1.2 (d)			0.231***			0.131**
			(3.25)			(2.48)
Recently Divorced 2007-2009 (d)	0.046	0.048	0.057	0.032	0.039	0.048
	(0.87)	(0.90)	(1.07)	(0.70)	(0.78)	(0.98)
Other Loan Payments (Including Medical) to Income > 1% (d)	-0.055	-0.046	-0.056	-0.046	-0.043	-0.047*
	(-0.76)	(-0.61)	(-0.93)	(-1.42)	(-1.25)	(-1.80)
Income Loss < -50% from 2007 to 2009 (d)	0.008	0.008	0.006	0.006	0.004	0.002
	(0.31)	(0.31)	(0.23)	(0.28)	(0.19)	(0.08)
Balance Sheet Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Demographic Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Mortgage Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,482	1,482	1,482	1,482	1,482	1,482
R-squared / Pseudo R-Squared	0.122	0.105	0.125	0.212	0.194	0.209

Notes. Robust t-statistics in parentheses. Asterisk legend: *** p<0.01, ** p<0.05, * p<0.1. SCF Restricted sample (See above). Demographic controls include, age, race, sex, marital status, education. Mortgage controls include presence of second mortgage, prior refinance, variable rate mortgage dummy, and mortgage term greater than 15 years dummy. Balance sheet controls include low liquid assets, low illiquid assets, and unsecured debt dummies. Coefficients reported in columns (1)-(3). Average marginal effects reported in columns (4)-(6).

Table 3.16: Double Trigger Results, Dependent Variable is 60+ Days Late Indicator on All Debts over Prior 12 Months to 2009 Survey Date, SCF

	Linear Probability Model			Logit		
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployed at Survey Date, 2009 (d)	0.116***	0.089**	0.115***	0.101***	0.098***	0.098***
	(2.69)	(2.06)	(2.78)	(3.16)	(3.11)	(3.15)
CLTV > .9 (d)	0.106***			0.072***		
	(3.71)			(3.29)		
CLTV > 1 (d)		-0.016			-0.002	
		(-0.46)			(-0.08)	
CLTV > 1.2 (d)			0.208***			0.131**
			(2.83)			(2.49)
Unemployed*CLTV>.9 (d)	0.069			-.019		
	(0.51)			(-.203)		
Unemployed*CLTV>1 (d)		0.182			.032	
		(1.54)			(.434)	
Unemployed*CLTV>1.2 (d)			0.278			.155
			(1.28)			(.82)
Recently Divorced 2007-2009 (d)	0.045	0.045	0.055	0.034	0.038	0.048
	(0.84)	(0.83)	(1.04)	(0.73)	(0.78)	(0.98)
Other Loan Payments (Including Medical) to Income > 1% (d)	-0.055	-0.044	-0.055	-0.047	-0.043	-0.046*
	(-0.75)	(-0.58)	(-0.89)	(-1.45)	(-1.24)	(-1.78)
Income Loss < -50% from 2007 to 2009 (d)	0.009	0.010	0.007	0.005	0.005	0.002
	(0.35)	(0.40)	(0.28)	(0.21)	(0.21)	(0.09)
Balance Sheet Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Demographic Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Mortgage Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,482	1,482	1,482	1,482	1,482	1,482
R-squared /Pseudo R2	0.123	0.109	0.127	0.213	0.194	0.209

Notes. Robust t-statistics in parentheses. Asterisk legend: *** p<0.01, ** p<0.05, * p<0.1. SCF Restricted sample (See above). Demographic controls include, age, race, sex, marital status, education. Mortgage controls include presence of second mortgage, prior refinance, variable rate mortgage dummy, and mortgage term greater than 15 years dummy. Balance sheet controls include low liquid assets, low illiquid assets, and unsecured debt dummies. Coefficients reported in columns (1)-(3). Average marginal effects reported in columns (4)-(6).

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