The Impact of Consumer Credit Access on Unemployment*

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Abstract

Unemployed households' access to unsecured revolving credit more than tripled over the last three decades. This paper analyzes how both cyclical fluctuations and trend increases in credit access impact the business cycle. The main quantitative result is that credit expansions and contractions have contributed to moderately deeper and more protracted recessions over the last 40 years. As more individuals obtained credit from 1977 to 2010, cyclical credit fluctuations affected a larger share of the population and became more important determinants of employment dynamics. Even though business cycles are more volatile, newborns strictly prefer to live in the economy with growing, but fluctuating, access to credit markets.

The fraction of unemployed households with access to unsecured revolving credit (e.g. credit cards) increased from 13% in 1977 to 45% in 2010. Such access to credit is quantitatively important for the unemployed. Low asset unemployed households replace approximately 15% of lost income through unsecured borrowing (Sullivan [2008]) while nearly 40%

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of households self-report defaulting on non-mortgage payments in response to job loss (Hurd and Rohwedder [2010]). Moreover, recent work by Herkenhoff, Phillips, and Cohen-Cole [2015] has shown that the ability to borrow significantly prolongs unemployment durations and raises replacement wages. At the same time that self-insurance opportunities expanded through credit markets, employment recoveries slowed (*inter alia* Bachmann [2009]). 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 growth and fluctuations in households' access to credit markets since the 1970s have affected the way employment evolves over the business cycle.

To address this question, the paper develops a general equilibrium search and matching model with defaultable debt. Relative to existing defaultable debt models such as Chatterjee, Corbae, Nakajima, and Ríos-Rull [2007], Livshits, MacGee, and Tertilt [2007], and Nakajima and Ríos-Rull [2014], the framework generates interactions between heterogeneous employment outcomes and heterogeneous credit histories. The model allows me to measure how consumer credit growth and consumer credit fluctuations have affected employment recoveries and welfare from 1977 to 2010 in the United States. There are three main results. First, credit expansions and contractions have contributed to moderately deeper and more protracted recessions. As more individuals obtained credit access from 1977 to 2010, credit fluctuations affected a larger share of the population and became more important determinants of employment dynamics. Second, even though business cycles are more volatile, newborn agents are willing to give up a positive amount of lifetime consumption in order to live in the economy in which credit is stochastically expanding to 2010 levels of credit, as opposed to the economy with fixed 1977 levels of credit. And finally, in the absence of procyclical credit fluctuations, slow-moving trend credit growth may actually *dampen* business cycle dynamics.

There are two opposing forces generating these results. When credit access expands in the short run, before households adjust their saving behavior, this acts like a safety net and households optimally search for better-paying but harder-to-find jobs knowing that if the job search fails they can use credit to smooth consumption. If credit grows coming out of a recession, this may lead to elevated unemployment in the short run and a slower recovery; this is what I call the *expansion effect* of credit. On the other hand, if households have a larger but constant level of credit access, they may actually respond less to productivity changes. The reason is that with greater long-run levels of credit access, more individuals dissave and enter recessions indebted. With a tighter labor market in a recession, indebted agents avoid default by disproportionately cutting their reservation wages in order to maintain a higher job finding rate. This force tends to dampen employment volatility over the business cycle, and it is what I call the *level effect* of credit. Which of these two forces dominates business cycle dynamics depends on the path of credit access before, during, and after recessions. The estimated path of credit access is highly procyclical along the benchmark transition path from 1977 to 2010. Strong credit growth tends to occur coming out of recessions and thus the *expansion effect* of credit dominates the *level effect* of credit, and as a result, employment recoveries slow. If credit expansions are weak, for example in an economy with a slow rate of trend credit growth, the *level effect* of credit wins, and business cycles become dampened. Regardless of which force wins, households have better self-insurance opportunities and are unambiguously better off.

Underlying these results is a general equilibrium business cycle model in which households search for both jobs and borrowing opportunities.[1] 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 applies for a loan and 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.

To generate both the trend growth and cyclical fluctuations in credit observed since the 1970s, the model incorporates stochastic, exogenous expansions and contractions to the aggregate efficiency of matching lenders to households. The empirical counterpart of trend growth of credit matching efficiency is credit scoring, the digitization of the banking sector, and the availability of online loans, among other numerous innovations (see Livshits, MacGee, and Tertilt [2016] for more discussion) while the cyclical fluctuations of credit matching efficiency map closely to movements in lending standards. The cyclical component plays the most important role in the quantitative analysis, and therefore I discuss various sources of evidence on the procyclicality of match efficiency. 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

[1] Related and innovative work by Drozd and Nosal [2008] model search in consumer credit markets and Wasmer and Weil [2004] and Petrosky-Nadeau [2014] consider search in the business loan market. New work by Raveendranathan [2018] has integrated generalized Nash bargaining into the credit market.

household job finding behavior.

The main experiment is then to feed band-pass filtered output per worker deviations into two identical economies from 1977 to 2010, except one economy receives a stochastic path of 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, procyclical credit expansions generate up to an additional one percentage point decline in employment that persists throughout the recovery. Compared to the economy with 1970s levels of credit access, the economy with stochastically expanding credit access brings employment deviations 23.5% closer to the data two years after the initial onset of the 1990, 2001, and 2007 recessions, on average. What drives the slower recoveries are procyclical expansions and contractions of credit along the transition path; I demonstrate this by showing that linearly expanding credit access actually dampens business cycles since the *level effect* of credit dominates. Despite the slower recoveries, newborn households would be willing to sacrifice between .05% and .2% of lifetime consumption in order to be born in the economy with stochastically expanding credit access as opposed to the economy with 1970s levels of credit access. Lastly, the timing of the revolving credit boom and its effect on employment make it a potentially important component of the jobless recovery phenomenon, although the mechanism in the present paper should largely be viewed as complementary, not mutually exclusive, to other explanations (e.g. Bachmann [2009], Schaal [2017], Jaimovich and Siu [2012], Berger [2012], and Mitman and Rabinovich [2012] among many others). What makes credit fluctuations more important in recent years is that there are simply more people using credit markets. In the 1980s, when the level of credit access is very low, large declines and rebounds in match efficiency have little impact on employment dynamics because there were just very few people who rely on credit markets (e.g. see Online Appendix P). This interaction between the level and cycle is absent from neoclassical growth models which are scale invariant (i.e. the level of technology does not impact the response of the economy to technology shocks).

While much is known both theoretically and empirically about the way unemployment insurance and saving decisions impact employment incentives (*inter alia* Hansen and İmrohoroğlu [1992], Ljungqvist and Sargent [1998], Acemoglu and Shimer [1999], and Chetty [2008]), 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 [2015], Herkenhoff and Ohanian [2015] among others), mortgage modifications (Mulligan

[2008] and Herkenhoff and Ohanian [2011]), and various combinations of spousal labor supply and assets (see Blundell, Pistaferri, and Saporta-Eksten [2016] and citations therein).

Several other studies including Athreya and Simpson [2006], Rendon [2006], Crossley and Low [2011] 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, Mukoyama, and Şahin [2010] and Nakajima [2012] find moderate effects of saving on labor markets. In an important extension, Nakajima [2012] modifies his model to allow for borrowing and finds little impact on aggregates. There are several reasons the present paper yields different conclusions. The main reason is that the present paper targets gross debt positions and the fraction of agents borrowing, implying much more credit use than Nakajima [2012]. Nakajima [2012]'s approach targets all types of wealth, which largely depends on the right-tail of the wealth distribution. The present paper is primarily focused on matching the left-tail of the wealth distribution, and focuses on liquid wealth since only this form of wealth can be drawn down by job losers with little penalty. The second reason is that Nakajima [2012] considers the stochastic steady state of the economy, which can produce strong offsetting forces. These offsetting effects are the main source of tension along the transition path, and the focus of the present analysis. And lastly, the present paper considers a model in which agents make job search decisions, and so their assets directly affect the submarkets in which they search. This allows credit access to affect the search behavior of an individual. Concurrent and innovative work by Bethune, Rocheteau, and Rupert [2015] provides a steady state analysis of the way consumer credit affects labor markets through firm productivity, and they find that through this channel, consumer credit can boost an economy. New work by Bethune [2015] extends this framework to think about aggregate risk. Recent work by Nakajima and Ríos-Rull [2014] finds that bankruptcy protection can actually increase the volatility of business cycles, and Athreya, Sánchez, Tam, and Young [2015] find that bankruptcy protection can actually increase delinquencies in a model with partial equilibrium labor markets. Lastly, recent work by Lise [2012], Chaumont and Shi [2017], and Griffy [2017] have integrated risk aversion and savings into random and directed search settings, respectively, to assess the impact of asset markets on inequality through on-the-job search.

The present paper contributes to this research agenda along three dimensions. First, the paper develops a general equilibrium search and matching model with defaultable debt. Second, the paper 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 1977 to 2010. Third, the paper constructs aggregate time series for unemployed households' access to credit and use of credit from the 1970s onwards, where the earlier data come from an archived predecessor survey to the Survey of Consumer Finances (made available in Online Appendix D).

Section 1 presents evidence on unemployed credit use and evidence of the procyclicality of lending standards and borrowing by the unemployed. Section 2 describes the model environment. Section 3 describes the calibration and steady state differences between the economy with 1977 levels of credit access and 2010 levels of credit access. Section 4 explores the model's mechanisms. Section 5 includes the main transition experiment. Section 6 concludes.

1 Empirical Evidence

In this section, I discuss three pieces of empirical evidence that are important for the model's mechanism: (1) unemployed households' credit access increased enormously from the 1970s to 2010, (2) unemployed households borrow and default, and (3) various measures of lending technology have improved over time, (4) access to credit, measured by lending standards, unemployed borrowing, and denial rates has been procyclical over the last 40 years.

1.1 Unemployed Access to Credit

This section complements the existing empirical work on access to credit among low income individuals (e.g. Livshits et al. [2016]) by computing historic credit access and credit use among the unemployed. Table 1 includes unsecured revolving credit access rates among all households as well as the unemployed. These statistics are based on the Survey of Consumer Finances (SCF, 1983 to 2010) and its predecessor, the Survey of Consumer Credit (SCC, 1977 and earlier). Unsecured revolving credit refers to the fraction of households with bankcards that have a revolving feature (when I discuss credit cards, I am referring to bankcards). Between 1977 and 2010, unsecured revolving credit access rates among the unemployed increased from 13% to 45%. Among all households including those without credit access, Table 1 shows that the fraction of unemployed households carrying positive balances tripled between 1977 and 2010, going from 12% to 33%. Likewise, gross unsecured debt to annual family income ratios (DTIs) increased from .6% to 5%. These statistics will ultimately inform the model's mechanisms. See Online Appendix D for time series and additional measures of self-insurance among the unemployed.

1.2 Borrowing by the Unemployed

While Table 1 describes the stock of unemployed borrowers, what about the flow? Do the unemployed borrow more? Evidence that the unemployed borrow to replace income is provided by Sullivan [2008], Hurd and Rohwedder [2010], Collins, Edwards, and Schmeiser [2015], and Braxton, Herkenhoff, and Phillips [2018]. In an important article, Sullivan [2008] finds that unemployed households with low assets increase unsecured debt by 11-13 cents per dollar of lost income in both the Panel Study of Income Dynamics and Survey of Income and Program Participation. To augment the existing body of evidence, I update Hurd and Rohwedder [2010] and use the RAND American Life Panel's (ALP) direct questions about borrowing in response to job loss from 2009-IV to 2015-IV. Table 2 shows that among the 1,600 unemployed households surveyed in that time period, 25.3% report borrowing in order to replace unemployment related income losses. Likewise 36.1% report skipping obligated non-mortgage payments (including consumer credit payments) in response to job loss.[2] This evidence directly supports the claim that unemployed households use credit cards to replace income, and among those who are already indebted or have other obligated payments, many become delinquent (I will also refer to this as default). The option to default is unique to consumer credit relative to unemployment insurance or welfare, and this evidence shows that default is a common method of consumption smoothing among the unemployed.

1.3 Lending Standards and Credit Matching Efficiency

The way credit access expands in the model is through the matching efficiency between lenders and consumers. The thought experiment is to imagine that a borrower and lender are put in the same room; matching efficiency includes all unobserved factors that affect the odds that a lending relationship is formed between the borrower and lender. This measure of matching efficiency includes both slow moving components such as the adoption of credit scoring as well as procyclical components such as lending standards and default rates.

[2] Online Appendix D includes more discussion of the RAND ALP.

1.3.1 Trend Movements

Regarding the slow moving component of credit match efficiency, Livshits et al. [2016] provide an excellent discussion of the various technological innovations that have occurred in the lending market. Livshits et al. [2016] provide supporting evidence and discuss the roles that (1) credit scoring, (2) IT innovation, and (3) securitization played in the large consumer credit run-up over the last 40 years. Related work by Drozd and Nosal [2008], Narajabad [2012], Athreya et al. [2012], and Sánchez [2018] also provides additional evidence that the cost of screening customers has dropped rapidly over the last 40 years.

1.3.2 Cyclical Movements

Regarding the cyclical component of match efficiency, this section provides evidence of procyclical credit expansions using (i) the Senior Loan Officer Opinion Survey and (ii) composition corrected borrowing and denial rates from the Survey of Consumer Finances.

One of the few high-frequency and long-running measures of lending standards is 'willingness to lend' from the Senior Loan Officer Opinion Survey (SLOOS). Figure 1 plots the net fraction of loan officers in the SLOOS who have an increased willingness to extend installment loans.[3] While the quantitative magnitudes are difficult to interpret (since the index does not reflect quantities), the general pattern is that willingness to lend tapers leading up to the business cycle, and then expands during recoveries. This echoes a large literature, *inter alia* Lown and Morgan [2006], DellAriccia et al. [2012] and references therein, which uses the SLOOS as well as proprietary mortgage data to show that lending standards are procyclical.

There are two additional time series that are informative of the mechanisms in this paper: (i) borrowing by the unemployed, and (ii) credit denial rates among the unemployed. In what follows, I show that both time series exhibit significant fluctuations even after controlling for individual determinants of borrowing and denial rates. The recovery years (1992, 2004, and 2010) exhibit above-trend borrowing, and the 2007-2009 crisis featured above-trend denial rates.

[3]This refers to Question 17 on the Senior Loan Officer Opinion Survey. They survey approximately 80 bank managers and ask, "Please indicate your bank's willingness to make consumer installment loans now as opposed to three months ago." The possible responses include "1. Much more willing / 2. Somewhat more willing / 3. About unchanged/ 4. Somewhat less willing / 5. Much less willing." The net percent willing to lend more is what is reported. From 1968 to the present they asked about installment loans and from 1990 to the present they asked specifically about credit cards. Both time series exhibit similar patterns.

To control for the demand factors and the composition of unemployed borrowers, Table 3 includes logit regressions of a dummy indicator for whether an unemployed agent borrows on various demographic, income, and asset controls as well as year dummies. The idea is that by including individual determinants of borrowing, such as education and position in the lifecycle, these regressions parse out demand-driven and composition-driven motives for borrowing. Table 3 reports average marginal effects, and Column (1) includes no controls. Column (2) shows that there are significant movements of unemployed borrowing even after including controls for age, income, education, liquid assets as well as other demographics. Columns (3) and (4) fit a linear trend through the time series for unemployed borrowing and test whether unemployed borrowing is above or below trend during the post-recession survey dates. The coefficients reveal that unemployed borrowing is significantly larger during post-recession survey dates even after controlling for demographics, income, and assets. These results are consistent with procyclical subprime credit expansions.

To remove individual-driven components of denial rates, Table 4 regresses two different definitions of denial rates, all denials (even if the loan was eventually obtained) and strict denials (loan was not obtained), over the time period in which those variables were collected in the SCF (1998 onwards) on various demographic, income, and asset controls as well as year dummies. Table 4 reports average marginal effects for a logit regression of all denials (Columns 1 and 2) and strict denial (Columns 3 and 4) on various controls. Controlling for age, income, education, liquid assets as well as other demographics, Columns (2) and (4) show that denial rates were elevated during the SCF surveys which covered crisis years (1996-2001 and 2005-2010) and dropped thereafter. Due to the limited sample sizes as well as potential recall bias, the only significant fluctuation in denial rates occurs during the 2007-2009 recession. However, it is important to note that the presence of controls amplifies the fluctuations as opposed to dampening the fluctuations (e.g. comparing Columns (3) and (4)). Table 4 provides suggestive evidence that lenders alter loan standards independent of age, income, education, and assets over the business cycle.

Online Appendix I includes two additional long-running public time series on household lending standards. Both time series, (i) the Home Mortgage Disclosure Act (HMDA) mortgage approval rates (1998 onwards), and (ii) matching efficiency A inferred from the free-entry condition in the lending market (1991 onwards), exhibit strong procyclicality. Online Appendix I also includes additional time series evidence on the cyclicality of technology adoption.

2 Model

The goal of building the model is to measure the impact of credit access on employment recoveries during periods of both trend credit growth and cyclical fluctuations in credit (i.e. 1977 to 2012 in the United States). To understand the interaction between individual employment and credit histories, the model must depart from standard lottery and large family assumptions and incorporate an extensive margin of credit. The model drops these two assumptions by drawing elements from the search literature (e.g. Mortensen and Pissarides [1994]) and defaultable debt literature (e.g. Eaton and Gersovitz [1981]). The model includes several additional elements including a discrete application stage in order to match flows into credit access, long-term lending relationships in order to match flows out of credit access, and expense shocks to match the fact that not all defaults are income driven.

2.1 Household Problem

Time is discrete and runs forever. As in Menzio, Telyukova, and Visschers [2016], there are $T \geq 2$ overlapping generations of risk averse households that face both idiosyncratic and aggregate risk.[4] 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. In the final stage of every period, expense shocks are realized (e.g. Livshits, MacGee, and Tertilt [2010]).

Similar to Dubey, Geanakoplos, and Shubik [2005], consumers maximize the present discounted value of utility 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.[5] Additionally, agents search for credit at utility cost χ_C, and I assume that labor is indivisible as well as separable from consumption. Let t be age and t_0 index birth cohort. Let h_{t,t_0+t} equal one if the agent is employed and let S_{t,t_0+t} be an indicator of whether the agent searches for credit. Then c_{t,t_0+t}, $\eta \cdot (1-h_{t,t_0+t})$, D_{t,t_0+t}, and $\chi_C S_{t,t_0+t}$ respectively denote the consumption,

[4] The overlapping generation setup is used for two reasons: (1) to generate borrowing (which is primarily among the young), and (2) to simplify computation and proofs.

[5] Unlike bankruptcy which is acyclical, Herkenhoff [2012] 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 [2012] 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.

leisure, default, and credit search outcomes of an age t agent at date $t_0 + t$. The goal of a newly born in cohort t_0 is to maximize

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

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, and their credit access status $a \in \{C, N\}$ where a=C indicates the individual has credit access and is synonymous with being matched to a lender and a=N indicates no credit access. The state vector also contains their current wage $w \in \mathcal{W}$ if employed or unemployment benefits $z \in \mathcal{Z}$ if unemployed, where $z = \gamma w$ and $\gamma \in (0, 1)$ is the replacement rate. It also includes their net assets $b \in \mathcal{B}$, their age $t \in \mathbb{N}_T$, and the aggregate state Ω.[6]

The aggregate state Ω includes three components. The first component is aggregate productivity y, the second component is the aggregate credit matching efficiency 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 choose whether or not to look for credit.[7] Looking for credit entails a utility cost χ_C. Lenders then view the entire state-space of potential borrowers and send credit offers to maximize profits. If a credit offer successfully reaches a searching 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 a limiting case of Nash-Bargaining which results in a bond price that is similar to competitive models such as Chatterjee et al. [2007].

A household remains matched to a lender until the household defaults (defined as $D > 0$) or the match is destroyed exogenously (the exogenous breakup rate is given by $\bar{s}$). Through-

[6]More formally, their current wage lies in the set $w \in \mathcal{W} \equiv [\underline{w}, \overline{w}] \subseteq \mathbb{R}_+$ if employed and UI lies in the set $z \in \mathcal{Z} \equiv [\gamma\underline{w}, \gamma\overline{w}] \subseteq \mathbb{R}_+$ where $\gamma \in (0, 1)$ is the replacement rate if unemployed, and their net assets lie in the set $b \in \mathcal{B} \equiv [\underline{b}, \overline{b}] \subseteq \mathbb{R}$. 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. Aggregate productivity lies in the set $y \in \mathcal{Y} \subseteq \mathbb{R}_+$ and aggregate credit matching efficiency lies in the set $A \in \mathcal{A} \subseteq \mathbb{R}_+$.

[7]Online Appendix D.3 provides evidence on sequential search in credit markets based on the SCF questions (loosely quoted): 'were you denied credit,' and 'were you subsequently able to obtain credit if initially denied credit.'

out the paper, I will make the assumption of *universal default* which means that default results in the immediate severance of all lending relationships.[8] The assumption of universal default means that today's bond price depends on the current default decision of the household. Let $s(D)$ describe the credit relationship breakup probability which is assumed to be contingent on the default choice D:

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

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. 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 and the household has made default decision D at the start of the period, the resulting bond price for an age t unemployed household (U) with unemployment benefits z who is requesting a loan of size b' is $q_{U,t}(z, b', D; \Omega)$ (Section 2.2 provides more details about lenders).

Because I assume that lenders can direct their search toward households, the probability a household successfully obtains credit is a function of their state-space. I define $A\psi_{U,t}(z, b; \Omega)$ 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, conditional on that household searching for credit. Section 2.2 will explain the credit market in more detail. Let $U_t^C(z, b; \Omega)$ be the value function of an unemployed household matched with a lender and $U_t^N(z, b; \Omega)$ be the value function of an unemployed household without credit access. Let χ_C be the time cost of searching for credit. Using this notation, the Bellman equation for an unemployed agent that must decide whether or not to look for a lender, $U_t(z, b; \Omega)$, is

$$U_t(z, b; \Omega) = \max\{A\psi_{U,t}(z, b; \Omega)U_t^C(z, b; \Omega) + \big(1 - A\psi_{U,t}(z, b; \Omega)\big)U_t^N(z, b; \Omega) - \chi_C, U_t^N(z, b; \Omega)\} \quad \forall t \leq T$$

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

After the asset market closes, the aggregate state is realized, and then unemployed agents

[8]This assumption allows me to rule out model behavior such as a household defaulting on a prior lender because they found a new lender. This assumption is empirically relevant during the time period studied (1977 to 2012), as Universal Default rules were common practice until the CARD Act of 2009. Lenders would charge penalty rates or revoke credit on non-delinquent lines of credit in response to delinquency on another credit card of a customer.

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 $p_t(\tilde{w}; \Omega')$ is the probability of successfully matching with an employer paying $\tilde{w}$. In this section the wage is fixed while employed, but this is relaxed in Online Appendix H.2 when on-the-job-search is allowed. 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 2.3 will explain the labor market in more detail.

With no further shocks, the only trigger for default is job loss. To disconnect default from employment status, agents are subject to expense shocks (e.g. Livshits et al. [2010]). With probability p_x, the household begins the next period with an additional debt burden (or a reduction to their asset stock) of x.[9] These expense shocks are designed to capture unmodeled out-of-pocket expenses associated with health, divorce, spousal job loss etc. Agents either pay, roll over, or default upon this additional obligation. These expense shocks occur at the end of the period are captured by the 'hatted' value functions.

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

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

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

subject to the budget constraint,

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

and for each continuation Bellman equation $V \in \{W, W^C, U, U^C\}$, households incur ex-

[9]Online Appendix E includes details about the types of shocks included in the expense shock.

pense shocks with probability p_x,

$$\widehat{V}(\tilde{w}, b'; \Omega') = p_x V(\tilde{w}, b' - x; \Omega') + (1 - p_x) V(\tilde{w}, b'; \Omega')$$

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

$$\begin{aligned} \Omega' &= (\mu', A', y'), \qquad \mu' = \Phi(\Omega, A', y') \\ y' &\sim F(y' \mid y), \qquad A' \sim G(A' \mid A). \end{aligned} \tag{1}$$

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, $b' \geq 0$,

$$\begin{aligned} U_t^N(z,b;\Omega) = &\max_{b' \geq 0, D \in [0,1]} u(c) - x(D) + \eta \\ &+ \beta \mathbb{E}\left[\max_{\tilde{w} \in \mathcal{W}} \; p_{t+1}(\tilde{w}; \Omega') \widehat{W}_{t+1}(\tilde{w}, b'; \Omega') + \big(1 - p_{t+1}(\tilde{w}; \Omega')\big) \widehat{U}_{t+1}(z, b'; \Omega') \right] \;\; \forall t \leq T \end{aligned}$$

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

such that the budget constraint holds

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

and taking as given the aggregate law of motion (1).

Employed agents in this economy face a similar credit constraint to unemployed agents. The only difference is that with probability δ they are laid off and must search for a new job. In order to have a reasonable unemployment rate with a quarterly calibration, I allow laid-off workers to search for jobs within the period. Online Appendix A contains these additional Bellman equations.

2.2 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, where r_f is exogenous. With free entry, the yield on savings offered to consumers is this risk free rate r_f. Lending institutions on the other hand send out credit offers to potential borrowers based on the borrower's characteristics. Each set of characteristics is a different submarket, where the cost of sending a credit offer to any submarket is κ_C. Once matched with a borrower, the relationship is long lived.

It is important to note that a credit offer is an invitation to bargain. If a lender successfully meets a household who wants to borrow, the lender and household bargain over the bond price schedule. 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 per-period 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.[10] These assumptions yield a bond price that is identical to competitive models such as Livshits et al. [2007].[11]

Let $b' = b'_{e,t}(w, b; \Omega)$ and $D = D^C_{e,t}(w, b; \Omega)$ be the present-period bond and default choices of the household. Let $\widehat{D}^{a'}_{e',t+1}(w', b'; \Omega')$ be the expected 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 b', the aggregate state Ω', and the expense shock,

$$\widehat{D}^{a'}_{e',t+1}(w', b'; \Omega') = p_x D^{a'}_{e',t+1}(w', b' - x; \Omega') + (1 - p_x) D^{a'}_{e',t+1}(w', b'; \Omega')$$

The equation for lender profit is in Online Appendix A.1. After imposing the bargaining structure between households and lenders, the bond price is given by,

$$q_{e,t}(w, b', D; \Omega) = \begin{cases} \frac{\bar{s}\mathbb{E}\left[1-\widehat{D}^{a'}_{e',t+1}(w',b';\Omega')\right]+(1-\bar{s})\mathbb{E}\left[1-\widehat{D}^{C}_{e',t+1}(w',b';\Omega')\right]}{(1+r_f+\tau)}, & b' \in \mathcal{B}_-, \quad D = 0 \\ 0, & b' \in \mathcal{B}_-, \quad D > 0 \\ \frac{1}{(1+r_f)}, & b' \in \mathcal{B}_+ \end{cases} \tag{2}$$

[10] The spread τ could be endogenized as a choice by the household but at the expense of tractability. In the model, the contact rate between households and lenders adjust such that τ exactly covers the cost of sending a credit offer. Without τ there would be no incentives for the lender to send a credit offer if the household makes take-it-or-leave-it offers. In the literature, imposing this wedge τ is common; see Livshits et al. [2007] for an example.

[11] Since lenders and households bargain each period, and the household has all of the bargaining weight, lenders do not have an incentive to send households with existing credit a new offer, since the terms of credit would remain the same.

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 exogenous aggregate credit matching efficiency. Then, the credit-filling rate, which is the probability a lender matches with a household, is given by,

$$A\phi_{e,t}(w,b;\Omega) = \frac{A \cdot M_C(u_{C,t}(e,w,b;\Omega), v_{C,t}(e,w,b;\Omega))}{v_{C,t}(e,w,b;\Omega)}$$

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

$$A\psi_{e,t}(w,b;\Omega) = \frac{A \cdot M_C(u_{C,t}(e,w,b;\Omega), v_{C,t}(e,w,b;\Omega))}{u_{C,t}(e,w,b;\Omega)}$$

The free entry condition will ensure that the contact rate between households and lenders adjusts so that the spread τ exactly covers the cost of sending a credit offer. The free entry condition for lenders binds for every submarket of consumers that takes loans:

$$\kappa_C = A\phi_{e,t}(w,b;\Omega)Q_t(e,w,b;\Omega) \tag{3}$$

2.3 Firms

As in Shi [2009], Menzio and Shi [2010, 2011], Karahan and Rhee [2011], and Menzio et al. [2016], I assume that firms post fixed wage contracts and there is free entry of firms, subject to a vacancy cost κ_L. In particular, firms post vacancies in certain submarkets that are indexed by wage $w \in \mathcal{W} \subset \mathbb{R}_{++}$ and age t. The posted wage w is fixed once an employee is found.[12] Let $v_t(w;\Omega)$ be the number of vacancies posted in the (w,t) submarket and $u_t(w;\Omega)$ be the number of unemployed households in that submarket. 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 $f_t(w;\Omega) = \frac{M(u_t(w;\Omega),v_t(w;\Omega))}{v_t(w;\Omega)}$ and let the job finding rate be given by $p_t(w;\Omega) = \frac{M(u_t(w;\Omega),v_t(w;\Omega))}{u_t(w;\Omega)}$. With free entry it must be the case that profits are competed away. Let the submarket tightness be given by $\theta_t(w;\Omega) = \frac{v_t(w;\Omega)}{u_t(w;\Omega)}$. Then free entry determines the active submarkets,

$$\kappa_L = f_t(w;\Omega)J_t(w;\Omega) \ \text{ iff } \theta_t(w;\Omega) > 0 \tag{4}$$

[12] Online Appendix H.2 allows for on the job search.

To characterize $J_t(w;\Omega)$, I assume that firms operate a linear technology and are subject to an exogenous job destruction rate δ. The firm value of an ongoing match to a worker of age t being paid wage w in aggregate state Ω is given below:

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

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

where the aggregate law of motion for Ω' given by (1) is taken as given.

2.4 Equilibrium, Existence and Uniqueness

In order to solve the problem numerically, I will focus on a subset of competitive equilibria called *Block Recursive Equilibria* (see Shi [2009] and Menzio and Shi [2010, 2011]). 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. Online Appendix C defines a block recursive equilibrium and provides an existence proof.

3 Stochastic Steady State: Calibration and Welfare

The parameters are calibrated so that the model's stochastic steady state is consistent with 2010 moments. Stochastic steady state means that aggregate labor productivity (y) still fluctuates but that aggregate credit matching efficiency (A) is constant forever.[13] 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:

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

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

[13] A long sequence of productivity shocks is drawn according to the AR(1) process for y and large number of agents (N=60,000) is then simulated for a large number of periods (T=280 quarters, where we discard the first 100 quarters). Averages are reported over the remaining 180 quarters.

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. I set the job destruction rate to a constant 10% per quarter as in Shimer [2005], and so $\delta = .1$ across all states. The labor vacancy posting cost κ_L is chosen to target a mean unemployment rate of 5.82% which is the average postwar BLS unemployment rate. For the labor market matching function, I follow den Haan et al. [2000] and use a constant returns to scale matching function that yields well-defined job finding probabilities, $M(u, v) = \frac{u \cdot v}{(u^\zeta + v^\zeta)^{1/\zeta}} \in [0, 1)$. The matching elasticity parameter is chosen to be $\zeta = 1.6$ as in Schaal [2017].

I set the the risk free rate to 4% per annum as in Livshits et al. [2007]. Analogous to Livshits et al. [2010], I directly target a 5.19% gross debt-to-annual-income ratio of unemployed households in the 2010 SCF, yielding a quarterly household discount factor of $\beta = .974$. This corresponds to an annual discount rate of 10.8%. As I discuss in Appendix K, to capture the full extent to which individuals utilize credit markets to smooth consumption, I choose to target the fraction of unemployed individuals with positive gross credit balances. This calibration strategy differs from Nakajima [2012] and Krusell et al. [2010] but captures the left-tail of the *liquid* wealth distribution well. Table 8 illustrates the wealth distribution in the model and data, using two different definitions of liquid wealth. A drawback of the benchmark calibration strategy is that it under-predicts wealth at the 90th percentile of the liquid wealth distribution (and therefore the benchmark model also under-predicts mean liquid wealth, since the bulk of liquid wealth is held by the right-tail). To address these concerns, I include a version of the model with heterogeneous discount factors, β, in Online Appendix K. The heterogeneous β version of the model can match the right tail of the wealth distribution but ultimately produces a very similar result to the benchmark model.

The aggregate credit matching efficiency A_{2010} is chosen to match the new-borrower credit approval rate of 67.2%, which can only be calculated from public data in the 2007-2009 SCF panel.[14] I then 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 den Haan et al. [2000]:[15] $M_C(u_C, v_C) = \frac{u_C \cdot v_C}{(u_C^{\zeta_C} + v_C^{\zeta_C})^{1/\zeta_C}} \in [0, 1)$. Based on empirical work by Agarwal et al. [2017], I set the proportional minimum servicing fee to τ =4.9% per annum.[16]

[14]This new-borrower credit approval rate is the approval rate among individuals who did not previously have a credit card. This statistic is only availably publicly from the 2007-2009 SCF panel. In order to calculate this approval rate, I must isolate individuals who have no existing credit in 2007 and applied for a loan between the two survey dates.

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

[16]This corresponds to the sum of the 1.4% rewards and fraud expense plus 3.5% for operational costs,

I set the exogenous credit separation rate $\bar{s} = .01$ based on the lower bound of the 2010 estimates from Fulford [2015]. Fulford [2015] calculates the rate at which individuals transition from a positive credit limit to a zero credit limit from quarter to quarter; this statistic can be interpreted as the rate at which individuals lose credit access and therefore it directly maps to $\bar{s}$.

The utility cost of obtaining credit, χ_C, is set to match the fraction of unemployed individuals borrowing (holding positive balances from month-to-month), which is 33.1% in the 2010 SCF. Following an analogous strategy to Shimer [2005], 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].[17]

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

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

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 (see Online Appendix C).[18] I set κ_D to match the average quarterly credit card chargeoff rate of 1.06% in the flow of funds from 1985-2007.

To guarantee boundedness of returns, I take ϵ_D 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.[19] The life span is set to $T = 120$ quarters (30 years), and newly born agents are born unemployed, with zero assets, and a uniform random draw of unemployment benefits.[20]

To calibrate the expense shock, I use the new expenditure data in the PSID from 2005 to 2013. I estimate $p_x = .022$ and $x = .2625$ in order to match the frequency of unmodeled shocks (e.g. disability, divorce, spousal layoff, or a medical shock) and the resulting increase in debt observed in the data. Online Appendix E includes details of this estimation.

discussed in their online appendix.

[17] As a proxy for the tightness, I use the ratio of credit card mail volume (Synovate) to SCF loan applicants from 1995 to 2007.

[18] This particular choice of utility penalty does not impact the main quantitative results.

[19] This parameter is important for governing business cycle dynamics; however, I am not directly targeting unemployment volatility

[20] Online Appendix O considers alternate newborn initial conditions.

3.1 Stochastic Steady State Comparison, 1977 vs. 2010: Business Cycles and Welfare Gains

I begin the analysis by considering the stochastic steady state of two economies with different levels of credit access. Recall that stochastic steady state means that aggregate labor productivity still fluctuates but that aggregate credit matching efficiency is constant forever. I calibrate the 1977 steady state by holding all other parameters fixed and estimating $A_{1977} = 0.482$ to match the fraction of unemployed households with positive balances in 1977.

Table 7 illustrates the stochastic steady state results. The model predicts that the unemployment rate is .3 percentage points higher in the economy with 2010 levels of credit access. The mechanism driving this difference is that credit acts as a safety net allowing households to search for better-paying and harder-to-find jobs. While a *constant* but greater credit safety-net increases the level of unemployment, it has a dampening effect on the dynamics of the economy. Business cycles, when measured by employment volatility, are actually *less* volatile in the 2010 stochastic steady state. I explore the mechanisms behind this result in Section 4.

To calculate the welfare gains from expanding access to credit markets, I follow Lucas [1987] and consider the fraction of ex-ante lifetime consumption newborn agents living in an economy with 1977 levels of credit access would give up in order to be born in the economy with 2010 levels of credit access. The middle row of Table 7 shows that newborn agents would be willing to give up .12% of lifetime consumption to move from the economy with 1977 levels of credit access to 2010 levels of credit access. Among the greater population, inclusive of newborns and non-newborns, the welfare gains of increased credit access vary. The last two rows of Table 7 show that unemployed agents are willing to give up .15% of lifetime consumption to live in an economy with 2010 levels of credit access, whereas the employed are willing to give up roughly .11% of lifetime income. There are two forces preventing the greater population from enjoying larger welfare gains: (i) the large chargeoff rate and utility penalties associated with greater amounts of default, and (ii) the increased credit application rate, which directly lowers utility through the search cost.

4 Exploring the Model's Mechanisms

To understand the way differences in both the levels and the growth of credit can impact business cycles, I start with a series of impulse response experiments. These experiments illustrate (i) how steady-state level differences in credit can dampen business cycle dynamics (I will refer to this as the *level effect*), and (ii) how procyclical credit growth can slow recoveries through a short-run loosening of the budget constraint and decrease in job finding rates (I will refer to this as the *expansion effect*). The experiments have the following setup:

i. Consider 2 economies in good times in which productivity is equal to $y = 1.015$.

ii. Both economies endure the same temporary productivity drop ($y = .985$ 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_0 to A_1.

iv. I assess two timing assumptions:

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

   B. The credit expansion occurs *after* the recession

In order to make the magnitudes of the impulse response experiments interpretable, I will study expansions from 1989 levels of credit to 1992 levels of credit (as calibrated in Section 5). I therefore choose the initial credit level, A_0, such that $A_0 = A_{1989} = 0.63$ and the new credit level, A_1, such that $A_1 = A_{1992} = 0.74$. Let $\Delta A = A_1 - A_0 = A_{1992} - A_{1989}$ denote the size of the credit expansion for the impulse response experiments. I assume that all agents have the same beliefs about transitions between A_0 and A_1 given by

$$P_{\mathcal{A}} = \begin{bmatrix} 0.75 & 0.25 \\ 0 & 1 \end{bmatrix}$$

This transition matrix implies that agents expect the credit expansion to occur within 4 quarters, and once it occurs, it is permanent.

4.1 Credit Expands Before Recession: Shallower Business Cycles

The first impulse response experiment illustrates how business cycles are dampened by a higher, but constant, level of credit access. This is the *level effect*. Panel (A) of Figure 2 illustrates the productivity decline and the time path for the credit technology, A. In this experiment, credit expands 5 years prior to the recession in one economy, and remains fixed in the other, so the two economies are essentially in their respective steady states when the business cycle occurs.

Panel (B) of Figure 2 plots the percent change in employment for each economy. Panel (B) reveals that the economy with greater access to credit has dampened employment dynamics. Aggregate employment falls by nearly .5% *less* than in the economy with fixed access. The economy with fixed access has a slower employment recovery, taking an additional quarter to reach pre-recession levels of employment.

To understand why this is the case, Panel (C) of Figure 2 shows that in the economy with greater credit access, agents optimally choose to dissave and search in higher wage submarkets with lower job finding rates *before the recession begins*. Before the recession, the aggregate job finding rate is 1.1 percentage points lower in the economy with greater credit access. Job finding rates fall by 8.2 percentage points in the economy with greater credit access during the recession; in the economy with fixed credit, job finding rates drop by 9.6 percentage points, a 15% larger decline. The reason is that in the economy with greater credit access, 30.3% of individuals are indebted going into the recession, whereas only 26.2% are indebted in the fixed access economy. When the recession occurs and the labor market tightens, indebted job losers avoid default by cutting their reservation wage disproportionately to maintain a high and stable job finding rate (see Online Appendix G for additional discussion). Therefore, in the long-run after a credit expansion, more individuals borrow and enter recessions indebted, leading to a less responsive aggregate job finding rate. As a consequence, employment dynamics are dampened.

4.2 Credit Expands After Recession: Slower Recoveries

In this section, I show that employment recoveries are slower if credit grows during a recovery. This is the *expansion effect*. This experiment, which highlights the role of persistent procyclical credit expansions, is particularly relevant for US employment dynamics over the last 40 years.

Panel (A) of Figure 3 illustrates the inputs for this experiment, which are identical to the prior experiment, except for the timing of the credit expansion. Credit now expands *after* the recession.

Panel (B) of Figure 3 plots the percentage change in employment following the recession.

When credit expands, on impact, employment is depressed by an additional .25 percentage points. The slow employment recovery persists throughout the sample period. Panel (C) of Figure 3 illustrates how the short-run mechanism works through job finding rates. In response to a credit expansion, households have a larger safety-net and begin to search for higher-paying but harder to find jobs; this depresses job finding rates and slows down the business cycle recovery.

Figure 4 repeats the same exercise for one economy with lower initial credit access and one economy with higher initial credit access. Both economies receive the same sized credit expansion (Panel (A)). In the economy with greater initial credit access, the credit expansion depresses employment by more (Panel (B)). Employment drops by .25 percentage points in the economy with low initial credit access and by .5 percentage points in the economy with high initial credit access, nearly twice as large. Figure 4 is important for understanding why credit fluctuations become larger determinants of employment dynamics from the 1970s to the present. As the level of credit grows, as it did in the U.S. from the 1970s onwards, similar magnitude credit fluctuations affect a larger fraction of the population and the *expansion effect* becomes a more important determinant of employment dynamics.

5 Main Quantitative Experiment

The main experiment quantifies the impact of credit fluctuations on employment dynamics between 1977 and 2010. I compare two economies: (1) an economy with credit access that remains fixed at 1977 levels (the 'fixed access' economy), and (2) an economy in which credit access stochastically expands and contracts between 1977 and 2010 (the 'benchmark timing' economy).

In the benchmark timing economy, credit matching efficiency linearly expands and contracts each year in order to match the fraction of unemployed individuals borrowing at each SCF survey date from 1977 to 2010.[21] Let $\mathcal{A} = [A_{1977}, A_{1978}, \ldots, A_{2009}, A_{2010}]$ denote the vector of estimated credit matching efficiencies. $\mathcal{A}$ is a 34 state Markov chain, where each element corresponds to one matching efficiency level per year from 1977 to 2010, and the vector $\mathcal{A}$ is potentially non-monotone (e.g. A_{2009} may be greater than, less than, or equal to

[21] The SCF survey dates are 1977, 1983, 1989, 1992, 1995, 1998, 2001, 2004, 2007, 2010. This path of credit matching efficiency is obtained by solving the transition experiment repeatedly under various guesses for the entire time-path of credit matching efficiency, updating the time-path of credit at each iteration to make the model replicate, as close as possible, the fraction of unemployed borrowers in the SCF at each survey date (the model is averaged over all quarters within the relevant year when compared to the SCF survey data).

A_{2010}). The transition probabilities are given by $P_{\mathcal{A}}$, described in detail below.

Both economies begin with the same initial conditions in 1977, where A_{1977} is calibrated to match the fraction of unemployed individuals borrowing in 1977. Both economies face the same Markov chain over credit match efficiencies, described by the vector $\mathcal{A}$ and transition probabilities $P_{\mathcal{A}}$. In the economy with fixed access, the realized shocks are such that credit matching efficiency remains fixed at A_{1977} from 1977 to 2010. In the benchmark economy, the realized shocks are such that the credit matching efficiency follows the path $\mathcal{A}$ from 1977 to 2010.

For computational tractability, credit expansions and contractions occur annually from 1977 to 2010 in the benchmark economy. Since the model period is quarterly, agents understand that on average, once every four quarters (with a 25% chance per quarter), credit matching efficiency will change. Therefore the Markov transition probabilities are given by the following matrix:

$$P_{\mathcal{A}} = \begin{array}{c} \\ A_{1977} \\ \\ A_{2009} \\ A_{2010} \end{array} \begin{array}{c} \begin{array}{ccccc} A_{1977} & A_{1978} & & A_{2009} & A_{2010} \end{array} \\ \begin{bmatrix} 0.75 & 0.25 & \dots & 0 & 0 \\ & \ddots & & & \\ 0 & 0 & \dots & 0.75 & 0.25 \\ 0 & 0 & \dots & 0 & 1 \end{bmatrix}_{34\times 34} \end{array}$$

Even though the transition matrix may appear to impose monotonicity, the vector of credit matching efficiencies is not necessarily monotone and thus credit may increase or decrease over time (i.e. transiting from A_{2009} to A_{2010} does not mean credit matching efficiency at in 2010 is greater than 2009).[22]

Table 9 summarizes how well the path for credit matching efficiency under the benchmark timing assumption matches the targeted values of unemployed borrowing at each SCF survey date.[23] Panel (A) of Figure 5 illustrates the estimated path for credit matching efficiency under the benchmark timing assumption. Panel (B) illustrates the grid-approximation to

[22] Consider a stylized example in the benchmark economy: A_{1998} is .5, A_{1999} is .4, and A_{2000} is .6. Agents living in 1998 understand that each quarter, with a 25% chance, matching efficiency will *contract* to 1999 levels. Agents living in 1999 understand that each quarter, with a 25% chance, matching efficiency will *expand* to 2000 levels.

[23] The transition path begins at $A_{1977} = .45$. This is lower than the 1977 stochastic-steady state value of $A = .48$ reported in Section 3 due to differences in expectations (agents believe they will exit the steady state with a high probability). Along the transition path, the slow moving nature of borrowing and the large fluctuations in productivity imply that credit matching efficiency reaches levels that are higher than the 2010 stochastic steady state value of A.

productivity (band-pass filtered output per employee, as described in Section 3). Lastly, Panel (C) graphically demonstrates that the credit matching efficiency process correctly replicates the fraction of unemployed borrowers at each SCF survey date.

Before turning to the main results, it is worth noting that the benchmark timing for credit matching efficiency is procyclical. As Section 1 discusses, the few publicly available measures of consumer credit access from 1977 to 2012 are procyclical, and exhibit large contractions around the 2007-2009 crisis, even after controlling for 'demand-side' factors such as changing incomes, education levels, and assets (e.g. Table 3). The large decline in matching efficiency leading up to the 2007-2009 crisis can be interpreted as tighter lending standards and a reduction in credit supply.[24] Section 5.4 shows that the benchmark model's credit matching efficiency process is capable of generating unemployed DTI dynamics and Synovate Credit Offer dynamics that are close to the data.

Finally, Online Appendix H considers perfect foresight transitions as well as quarterly expansions, and Online Appendix I.5 uses the Federal Reserve Board's Senior Loan Officer Opinion Survey in conjunction with the free-entry condition in the credit-market to directly measure credit matching efficiency.[25]

5.1 Main Quantitative Results

There are four findings from the benchmark transition experiment: (1) credit growth coming out of the 1990, 2001, and 2007 recessions increases the severity of each downturn (measured as the employment loss from peak to trough) (2) in the 2001 and 2007 recessions, credit growth reduces the speed of recovery (measured as the amount of time it takes the economy to reach pre-recession employment levels), (3) at every point along the transition path, newborns would prefer to live in the world with fluctuating, but growing, credit access, even though the unemployment rate is more volatile, and lastly (4) credit fluctuations, as opposed to trend credit growth, are primarily responsible for generating slower recoveries.

1980 Recession – Panel (A) of Figure 6 illustrates the employment response to the 1980-I recession (I combine the two 1980s recessions). The model actually generates employment

[24] The rapid rebound in credit matching efficiency is consistent with Synovate data (see Section 5.4); however, several important caveats of the Synovate series are discussed in the paper (importantly, it does not measure online offers and likely understates the size of the rebound). In Online Appendix I.4, I provide several sources of evidence that suggest subprime unsecured credit expanded rapidly following the 2007-2009 recession.

[25] The insight is to infer matching efficiency as a residual from the free entry condition by using proxies for credit demand (mortgage applications) and credit supply (Synovate credit offers). Appendix I.5 provides more details on this 'residual' method.

fluctuations that are too large relative to the data. The economies with and without credit access respond to the recession similarly, with employment dropping by roughly 3 percentage points from peak to trough. 16 quarters after the onset of the recession, both model economies are approximately .8 percentage points below pre-recession employment levels, whereas the data exhibits an approximately full recovery by that point.[26]

1990 Recession – Panel (B) of Figure 6 illustrates the employment response to the 1990-III recession. From peak to trough, employment drops by 1.36 percentage points in the data, 1.10 percentage points in the economy with fixed access, and 1.32 percentage points in the economy with growing credit access. What is striking about the 1990 recession is that the economy with growing credit access actually recovers at a *faster* rate than the economy with fixed credit access. This is because credit growth slows and actually becomes negative during the recovery years of 1992 and 1993 (see Figure 5), leading to a tightening of constraints, and less ability to self-insure.

2001 Recession – Panel (C) of Figure 6 illustrates the employment response to the 2001-I recession. In the 2001 recession, credit increases the severity of the recession, and the credit boom following the recession leads to a slower recovery. From peak to trough, employment drops by 1.86 percentage points in the data, 1.18 percentage points in the economy with fixed access, and 1.69 percentage points in the economy with growing credit access.

The credit boom coming out of the 2001 recession generates a strong, short-run self-insurance effect that swamps the dampening *level effect* of credit. As a result, Figure 6 (C) shows that 16 quarters after the onset of the recession, the economy with fixed credit predicts a full recovery to prior peak employment, whereas in the economy in which credit expands, employment is still .77 percentage points below prior peak employment. The mechanism is that during the post-recession credit boom, unemployed households search for higher-paying, but harder-to-find jobs.

2007 Recession – Panel (D) of Figure 6 shows that under the benchmark timing assumption for match efficiency, similar to the 2001 recession, the credit expansion coming out of the 2007 recession deepens the trough of employment by over 1 percentage point. The path of credit matching efficiency during the 2007-2009 crisis implies a near shut-down of credit cards to new borrowers (i.e. young individuals with no credit), with a strong recovery following the recession. Similar to the 2001 recession, the strong recovery of consumer credit

[26]Since there are relatively few SCF surveys around the 1980 recession, credit is quite stable in the benchmark economy. Online Appendix P considers an extreme path for credit fluctuations in the 1980s and demonstrates that because so few individuals were borrowing, credit shocks in the 1980s do not alter employment dynamics. Section 4.2 and Section 5.3 discuss this point in more detail.

following the 2007-2009 recession leads to a short-run self-insurance effect that dominates the dampening *level effect* of credit, and the result is a slow employment recovery. Table 11 summarizes these findings, showing that allowing for credit growth and contractions closes the gap between the model with fixed credit access and the data by 20.5% on average, two years after the 1990, 2001, and 2007 recessions.

To formalize this graphical analysis and make the model's moments comparable to other studies, Table 10 computes business cycle moments along the model's transition path and compares those moments to the data as well as the Shimer [2005] and Hagedorn and Manovskii [2008] calibrations of the Diamond-Mortensen-Pissarides (DMP) model. Relative to the fixed-access model, the benchmark model generates greater unemployment volatility (measured relative to productivity volatility), marginally greater persistence of unemployment, and the credit shocks dampen the correlation between productivity and unemployment. The reason the model with growing credit access dampens the correlation between productivity and unemployment is that in a typical business cycle with constant credit, when productivity recovers, vacancies increase and unemployment drops rapidly; with a procyclical credit expansion, vacancies and productivity still recover, but the unemployment rate remains elevated since the greater ability to self-insure allows workers to take longer to find jobs. Therefore the economy with credit growth disconnects the employment recovery from the productivity recovery.

While not the focus of this paper, I include other calibrations of search and matching models in Table 10. The model generally outperforms the standard baseline DMP calibration, but under performs along several dimensions against the Hagedorn and Manovskii [2008] calibration. The present calibration, however, succeeds in generating large amounts of unemployment volatility and reducing the correlation between productivity and the unemployment rate, while preserving a negative relationship between unemployment and vacancies.[27]

5.2 Welfare Gains from 1977 to 2010

Business cycles are more volatile and protracted along the transition path. Are agents better off? Figure 7 illustrates the welfare gains of newly born individuals along the transition path. The gains are computed in 5-year rolling cohort windows, i.e. the welfare gain reported in 1982 Q-1 (which corresponds to 1982.13 on the graph) is what a typical newly born agent, born between 1982-Q1 and 1987-Q1, would give up in order to live in a world

[27] In Online Appendix H, I consider an economy with on-the-job search (OJS). OJS allows the model fit the Beveridge closer.

with growing credit access (subject to the benchmark timing of credit expansions and contractions). During the late 2000s, individuals are willing to give up approximately .2% of lifetime consumption to live in an economy with greater credit access, even though business cycles are more volatile. There are larger welfare gains along the transition path than across stochastic steady states for two reasons. First, in order to match unemployed borrowing along the transition path, credit matching efficiency reaches higher levels than steady-state credit matching efficiency. Second, credit is more valuable during recessions, and thus the welfare gains are higher for cohorts born during the 2007-2009 crisis.

5.3 The Trend Versus The Cycle

To isolate the role of credit fluctuations relative to trend credit growth, this section considers the 'linear timing' economy which assumes that credit matching efficiency expands at a constant rate from A_{1977} to A_{2010} between 1977 and 2010. The initial and terminal values of credit matching efficiency in 1977 and 2010 are the same as the benchmark timing economy. The initial and terminal values of credit matching efficiency determine the linear growth rate of credit between 1977 and 2010. Expectations about the timing of the credit matching efficiency expansions are determined by the same $P_{\mathcal{A}}$ as Section 5.

To isolate how credit matching efficiency fluctuations and trend credit growth differentially affect the business cycle, Figures 8 and 9 compare employment fluctuations between the *benchmark* economy, in which credit is volatile, and the *linear credit growth* economy, in which credit slowly and positively expands from 1977 to 2010. Panel (A) of Figure 8 illustrates the credit matching efficiency path, while Panel (B) plots the model's fraction of unemployed individuals who borrow.

The linear timing model generates very different employment dynamics than the benchmark economy, especially during the 2007-2009 recession. Panel (D) of Figure 9 demonstrates that during the recovery of the 1990 recession, the linear timing model has a slower recovery. This is because credit tightens in the benchmark model after the 1990 recession but continues to slowly expand under linear timing. Panel (F) shows that in the 2001 recession, the linear timing model predicts a full employment recovery 16 quarters after the recession. This discrepancy between the benchmark model and linear timing model is due to the fact that a slow linear expansion of credit does not capture the 2000s credit boom. For the 2007-2009 recession, Panel (H) shows that the linear timing model actually predicts a shallower business cycle. To put this into the terms used in Section 4, under linear timing, the *expansion* effect of credit is very weak and the *level effect* of credit dominates. As a result, business cycle dynamics become dampened. Figure 9 makes it clear that the cyclical component of credit matching efficiency is the main driver of slower recoveries along the *benchmark* transition path, and the trend-component of credit matching efficiency is actually working in the opposite direction, lowering employment volatility.

While trend growth in credit dampens the economy's response to productivity fluctuations, greater initial levels of credit access amplify the economy's response to *credit fluctuations*. If credit access is extremely low, and therefore few people use credit, cyclical movements in credit matching efficiency have a much weaker impact on employment dynamics (see Section 4.2). For example, in the 1980s, when a small share of the population has credit, large declines and rebounds in match efficiency have little impact on employment dynamics (see Online Appendix P). This interaction between the level and cycle is absent from neoclassical growth models which are scale invariant (i.e. the level of technology does not impact the response of the economy to technology shocks). As the level of credit grew from the 1970s onwards, procyclical credit fluctuations affected a larger fraction of the population and became more important determinants of employment dynamics.

5.4 Assessing the Model's Mechanisms

This section provides both micro and macro assessments of the model mechanisms. I first discuss the micro implications: (i) how credit affects unemployment durations and wage dynamics, and (ii) default behavior of unemployed agents. Herkenhoff et al. [2015] study the impact of credit access on unemployment duration and replacement wages of displaced workers by merging the Longitudinal Employer-Household Dynamics (LEHD) data and individual credit reports. They find that being able to replace 10% of prior annual income with revolving credit allows displaced workers to take between .33 and 2 weeks longer to find a job but their replacement wages are about .5% to 3.9% greater, conditional on finding a job, consistent with a reservation wage mechanism. They show that even if workers do not draw down the credit line, the *ability to borrow* affects every unemployed workers' search behavior.

To compare the calibrated model's predictions to the data, Panel (A) of Table 12 includes the model's responses of duration and replacement rates to credit access. To remove productivity fluctuations from the calculation, I compute duration and replacement rate elasticities between the 2010 and 1977 steady states. Following Herkenhoff et al. [2015], the duration elasticity is the change in unemployment duration, measured in weeks, across steady states divided by the change in the credit-to-income ratio across steady states.[28] Likewise, the replacement rate elasticity is the change in the ratio of the wage 1 year after layoff to the wage 1 year before layoff divided by the change in the credit-to-income ratio. following Herkenhoff et al. [2015], this is computed among job finders. Appendix J includes detailed formulas for the computation of these elasticities.

Panel (A) of Table 12 compares the model's elasticities to three measures of the duration and replacement rate elasticities corresponding to (i) the elasticity implied by a raw OLS regression of duration on credit-to-income, (ii) an instrumental variable (IV) approach using Gross and Souleles [2002]'s account-age instrument as an IV for credit-to-income, and lastly (iii) Musto [2004]'s bankruptcy-flag removal as an instrument for credit-to-income. The model's duration elasticity is 1.16, and the model's replacement wage elasticity is .01. These estimates mean that agents take 1.39 weeks longer to find a job if they can replace 10% more of their prior annual income with credit, and agents find jobs that pay .1% greater if they can replace 10% more of their prior annual income with credit. The duration elasticity lies between the data estimates, whereas the replacement wage elasticity is toward the low-end of the data estimates.

These numbers are also in line with existing studies of UI, and a majority of the US evidence supports the claim that a greater UI safety net tends to improve wage outcomes including Ehrenberg and Oaxaca [1976], Feldstein and Poterba [1984], Addison and Blackburn [2000], and Hagedorn et al. [2013].[29] While this search mechanism is very similar to unemployment insurance in the static sense (i.e. a credit limit increase is an increase in liquid resources available to a household just like an increase in unemployment insurance), the main difference between unemployment insurance and credit is in the dynamics: (1) loans must be repaid or defaulted upon (2) unemployment claimant rates have been very stable over the last 3 decades (Auray et al. [2012]) whereas credit access has grown enormously, and (3) the line of credit can be drawn down before a household ever loses its jobs (in which case the household begins the unemployment spell indebted and is forced to find a job faster than if it had never borrowed to begin with).

The way unemployed agents use credit to smooth consumption is not limited to borrowing; those with existing debts can default to smooth consumption. This is also an important mechanism in the model, and it is not targeted in the calibration. Panel (B) of Table 12 illustrates the fraction of defaulters (defined as any type of chargeoff) in the model who are

[28]The credit-to-income ratio is computed using annual income in the denominator. In the numerator, available credit is proxied by the average approval rate multiplied by the largest loan observed in each steady state, $|\hat{\psi} b_{min}|$.

[29]Online Appendix J provides more discussion.

unemployed relative to the PSID (which only measures mortgage delinquency), and the SCF (which measures general delinquencies over the 12 months prior to the SCF survey date). Roughly 10.2% of the agents in the model defaulted because of an unemployment spell.[30] Between 23% and 24% of mortgage defaulters in the PSID had an unemployment shock over the prior year, and roughly 23% of defaulters in the SCF had an unemployment spell over the prior 12 months. These statistics suggest that the model is capturing (although somewhat understating), the link between unemployment and delinquency, which is a crucial form of self-insurance for indebted, constrained agents.

I now turn to macro implications of the model's mechanisms: (i) debt to income dynamics of the unemployed, (ii) credit offers, and (iii) the cyclicality of chargeoffs. In Online Appendix L, I demonstrate that the model is also consistent with the rise in unemployment duration, the rise in bankruptcies, and the decline in savings observed from 1977 to 2010. On the intensive margin, Figure 10 shows that the benchmark model does well at matching how much the unemployed borrow over time, not just the fraction that borrow. While the 2010 Gross Debt to Income (DTI) ratio of unemployed agents was targeted, no other SCF DTI survey data point was targeted along the transition path. This provides an important test of the calibrated transition path, as well as the model's mechanism. The model successfully captures the rise in DTI among the unemployed after the 2001 and 2007 recessions, and while the levels are off in the early 1990s, the model also successfully predicts a rise in DTI among the unemployed following the 1990 recession.

As an additional assessment of the credit matching efficiency paths, Figure 11 compares the model's credit offers per capita to Synovate/Mintel Comperemedia data.[31] There are several caveats about using Synovate as a benchmark measure of credit supply: (i) direct-mail marketing has been in steep decline, which may severely bias time series comparisons (ii) the Synovate mail monitor data does not include actual credit approval rates, which declined in 2005 and 2006 (e.g. Figure 16 in Online Appendix I), (iii) Synovate data only provides a simple count of *pieces* of credit mail, and (iv) Synovate's sampling procedure is not publicly available, nor do they provide weights, and the series is subject to major revisions.[32] With

[30] The remainder default due to the expense shock or exogenous lender separations.

[31] To construct a similar series to the data, which includes offers to all existing cardholders as well as new cardholders, I assume that individuals who already have access to credit receive X offers per annum in the model. This number of X offers is chosen so that the model series exactly matches the Synovate series in 2011 (for the benchmark model X=14.1, and X=9.59 in the linear timing model). Then I add that to the offers received by newly applying individuals in the model (i.e. those who apply for initial credit access), to arrive at the total number of offers in the model.

[32] E.g. between 2013, when this paper was written, and 2016, Mintel Comperemedia (who bought Synovate) adjusted the historic credit offer series upwards by 2 billion additional offers per annum in 2006, to 8.1 billion, on a prior estimate of 6 billion offers for 2006, with no explanation of the reweighting or sampling adjustments.

these caveats in mind, Figure 11 shows that the benchmark timing assumption for credit matching efficiency captures the general upward trend in credit offers, as well as the 2000s credit boom, and it comes close to generating the credit supply dynamics observed during the 2007 recession.

Lastly, Figure 12 illustrates that the baseline economy produces a strong countercyclical chargeoff rate which closely mirrors the data over the last 30 years. Since the benchmark timing assumption bases credit dynamics on low-income unemployed individuals, and since those individuals are the most likely to default (in both the model and data, e.g. Gerardi et al. [2017]), the benchmark model naturally generates a close correlation with chargeoffs.

6 Conclusions

Unemployed households' access to unsecured revolving credit has grown remarkably since the 1970s, 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 and welfare.

There are three main results. First, the quantitative analysis reveals that credit expansions and contractions are partly responsible for deepening and protracting recessions from 1990 to 2010. As the level of credit access increased from the 1970s onwards, credit shocks affected a larger fraction of the population and became more important determinants of employment dynamics. Second, even though business cycles are more volatile, later cohorts of newborn agents are willing to give up .2% of lifetime consumption in order to live in the economy in which credit is stochastically expanding to 2010 levels of credit, as opposed to the economy with fixed 1977 levels of credit. And finally, in the absence of procyclical credit fluctuations, trend credit growth may actually dampen business cycle fluctuations.

This paper is the first step in a broader research agenda to understand the interaction between consumer credit markets and employment. We have already begun the next phase of the research agenda which is to use employer-employee records linked to credit reports by social security number to empirically address the relationship between consumer credit and employment. Several important questions are being addressed: (1) What is the impact of credit access on job finding rates and wages? (2) 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 (e.g. Braxton et al. [2018])? (3) Does consumer credit access impact the decision to become an entrepreneur?

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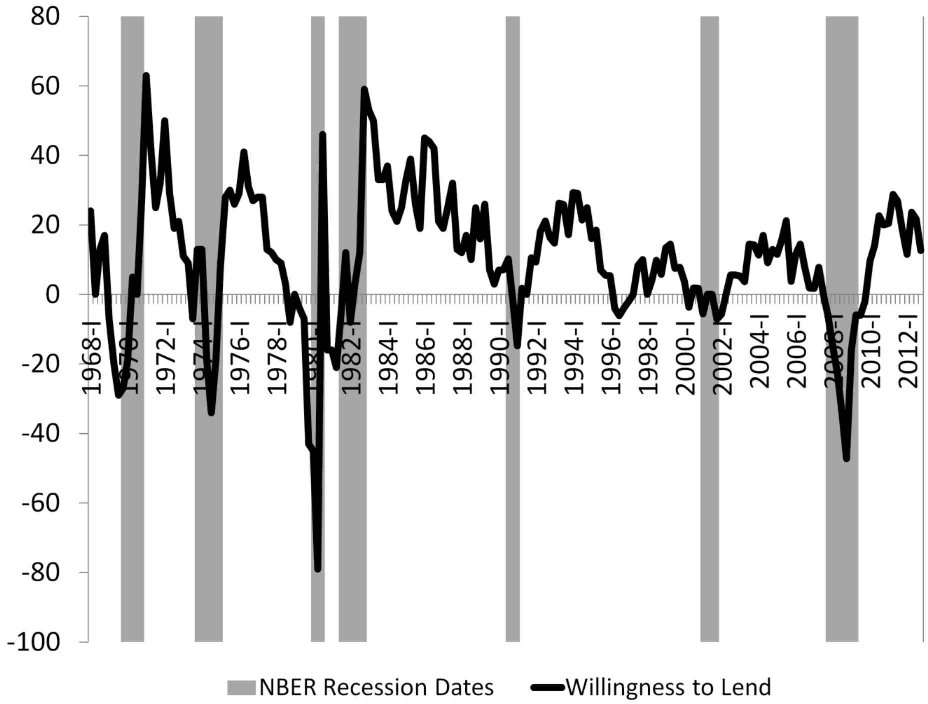
Figure 1: Net Percent of Banks with More Willingness to Make Installment Loans from 1966 to 2013 (Source: Federal Reserve Board, Senior Loan Officer Opinion Survey 1966-2012)



Notes: historic willingness to lend data available here https://www.federalreserve.gov/boarddocs/snloansurvey/199802/febdata.txt*. Recent willingness to lend data available here:* https://fred.stlouisfed.org/series/DRIWCIL*.*

Figure 2: Impulse Response Experiment: Credit Expansion Before Recession

(A) **(B)** **(C)**

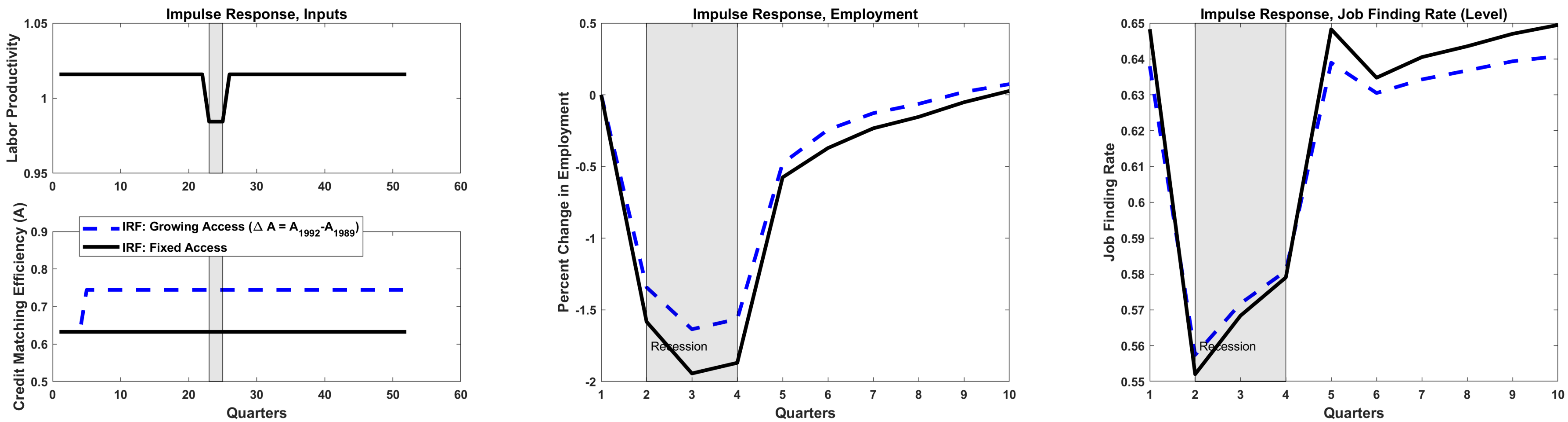


Figure 3: Impulse Response Experiment: Credit Expansion After Recession

(A) **(B)** **(C)**

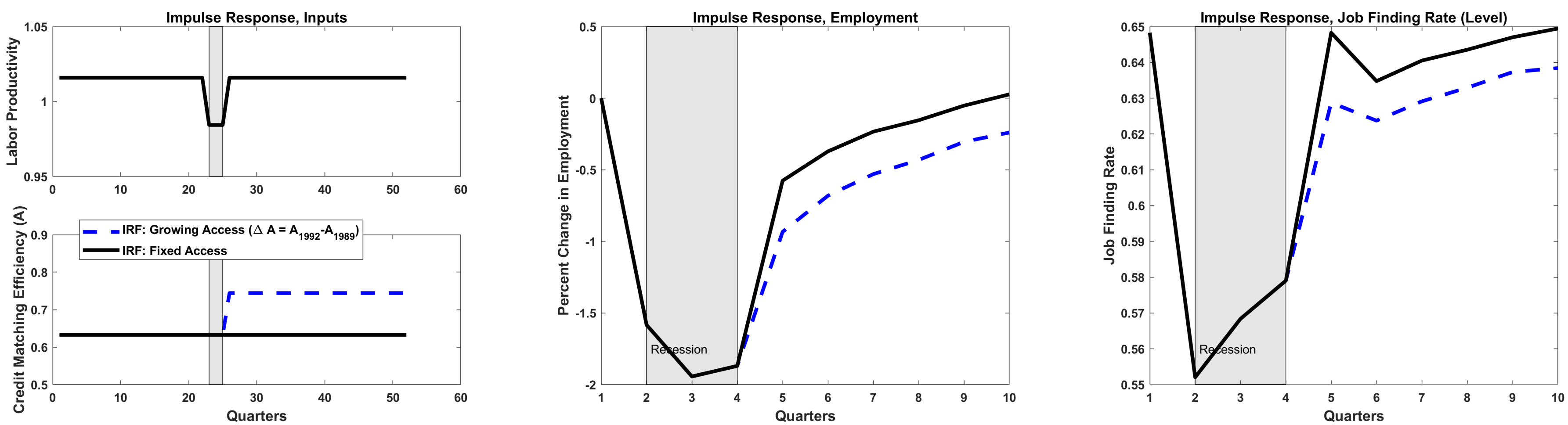


Figure 4: Impulse Response Experiment: Larger Fraction Borrowing Amplifies Credit Shocks

(A) **(B)**

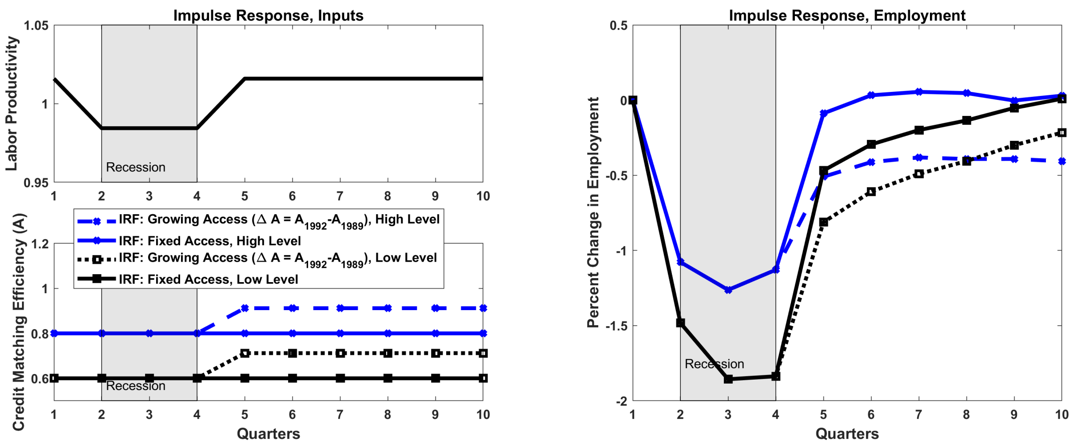


Figure 5: Transition Experiment: Calibration Targets and Credit Matching Efficiency Path

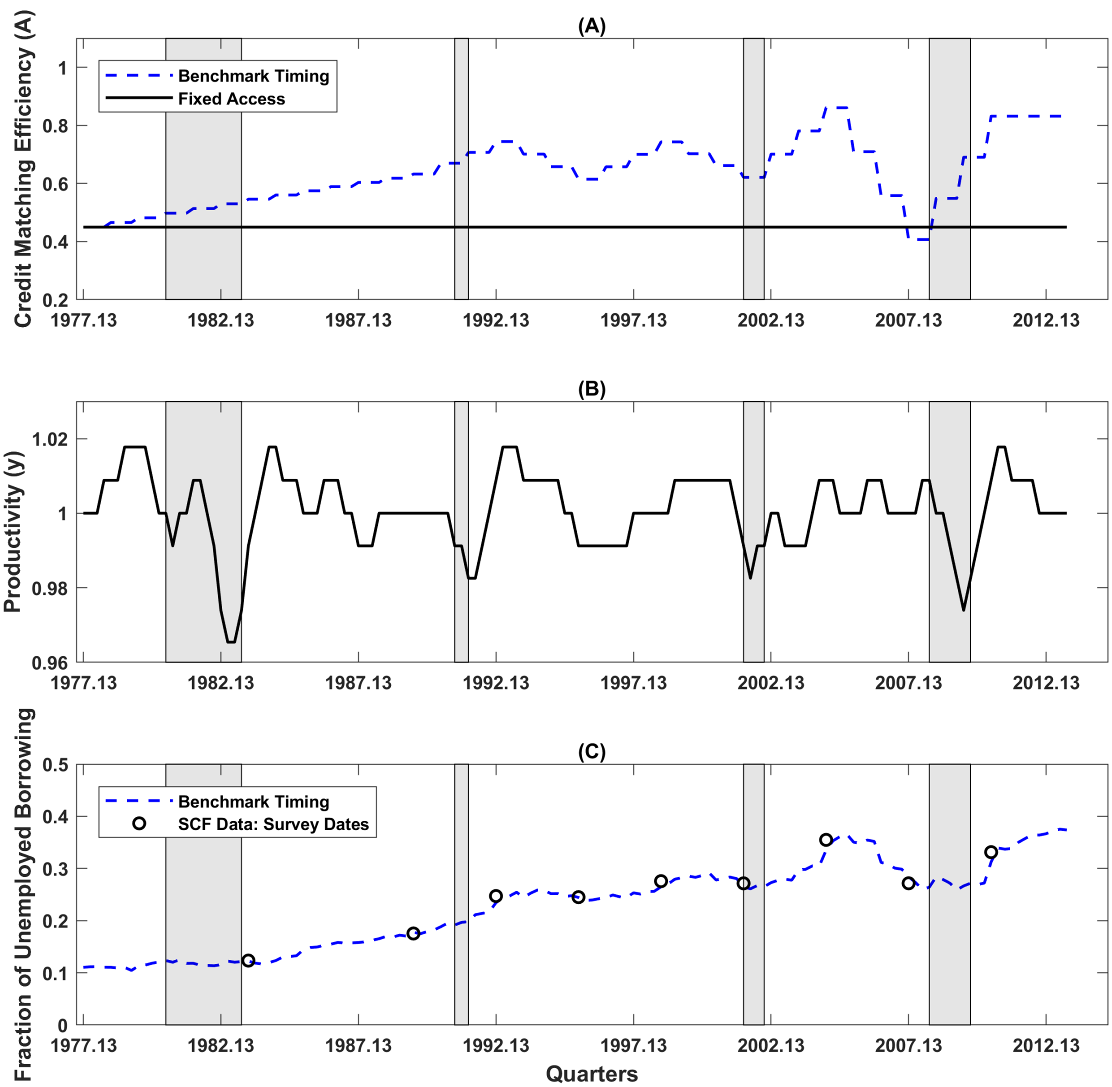


Figure 6: Transition Experiment: Employment Fluctuations

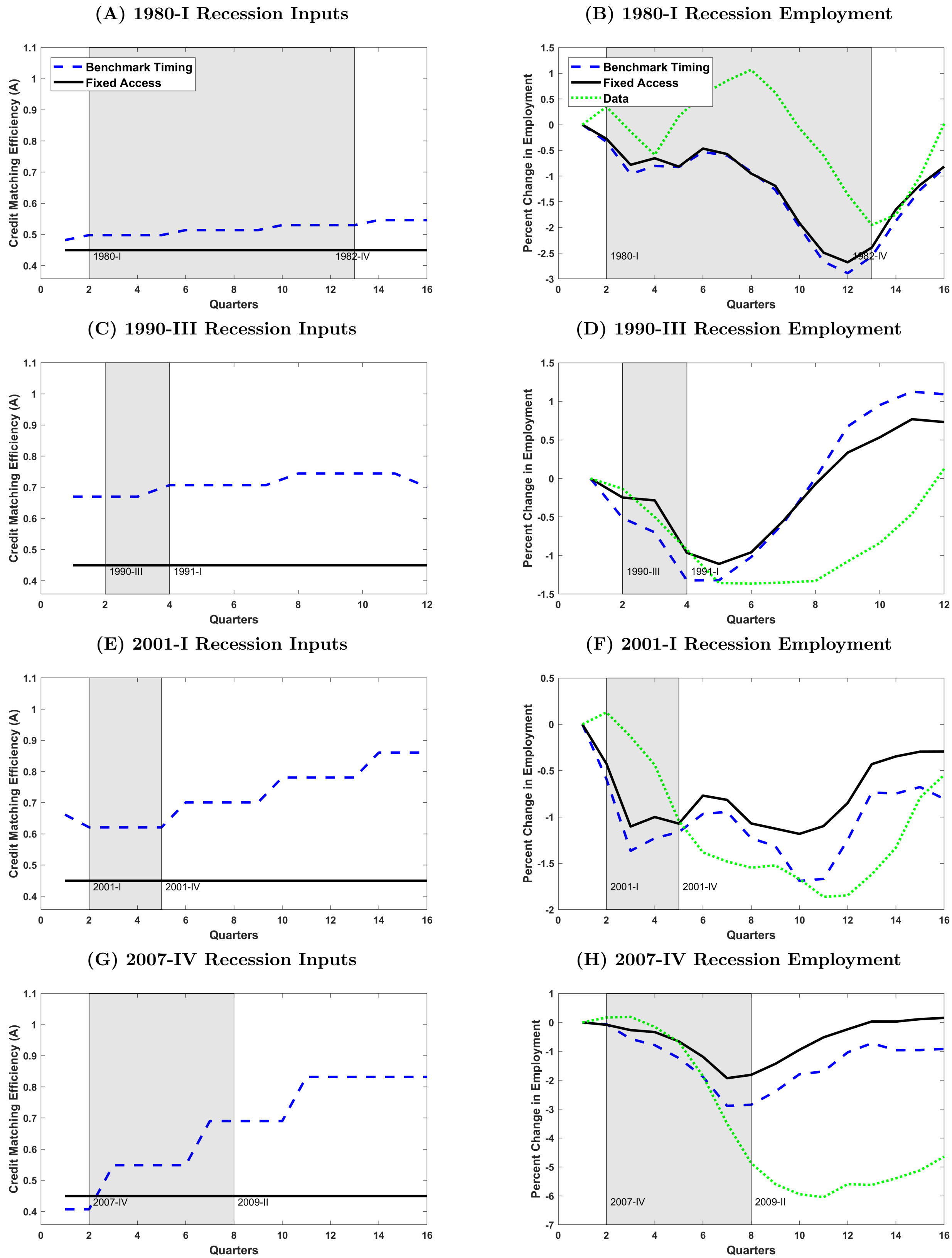


Figure 7: Welfare Along Transition Path

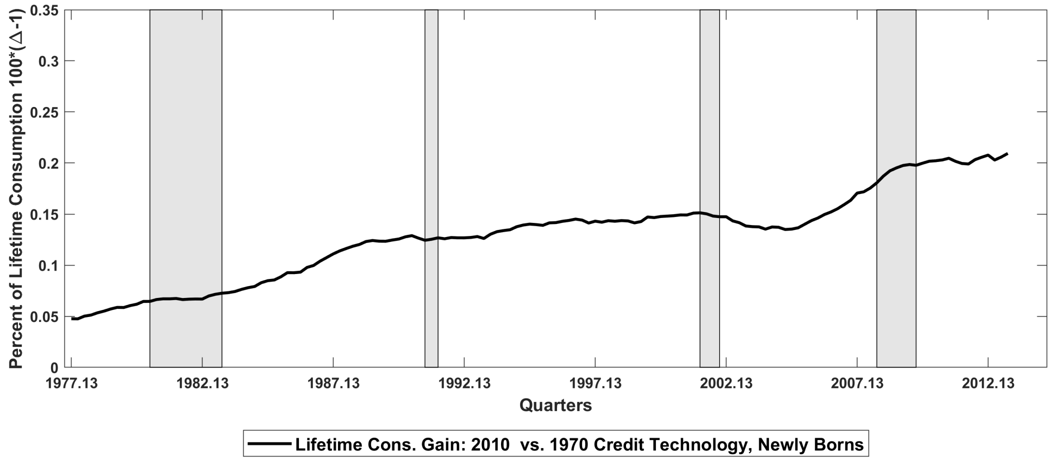


Figure 8: Trend vs. Cycle: Calibration Targets and Credit Matching Efficiency Path

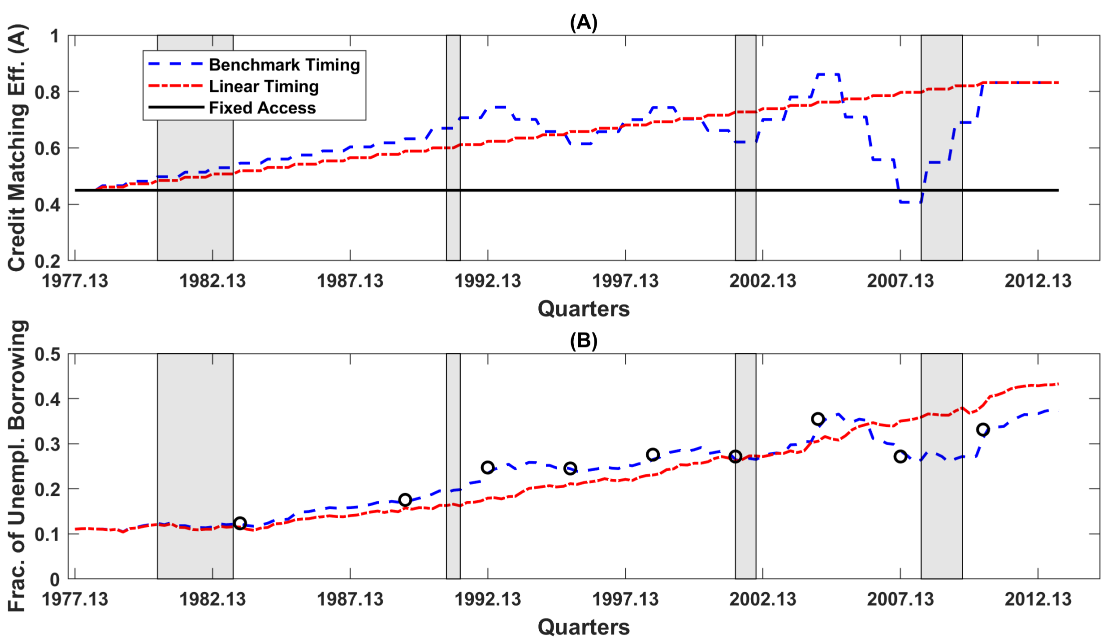


Figure 9: Trend vs. Cycle: Employment Fluctuations

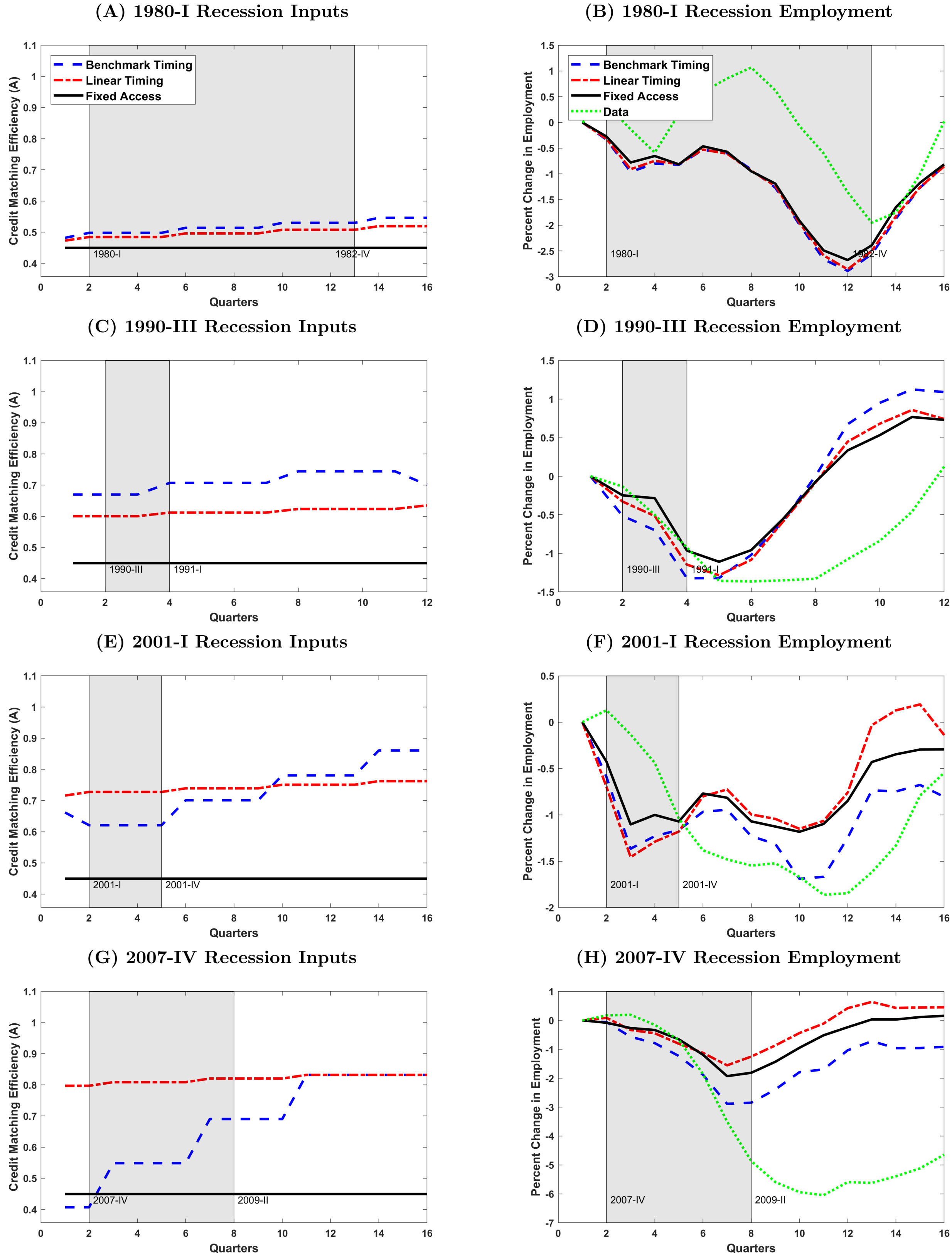


Figure 10: Transition Experiment: Gross DTI of Unemployed

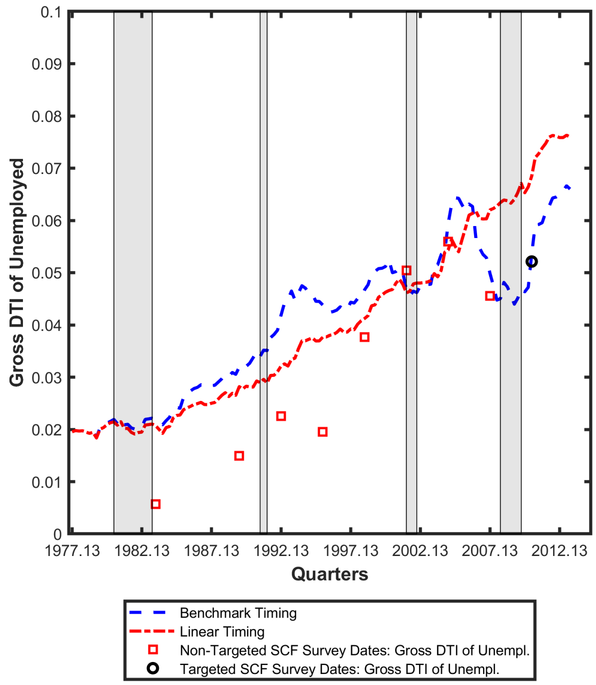


Figure 11: Credit Card Offers, Model v. Data (Source: Synovate and Mintel)

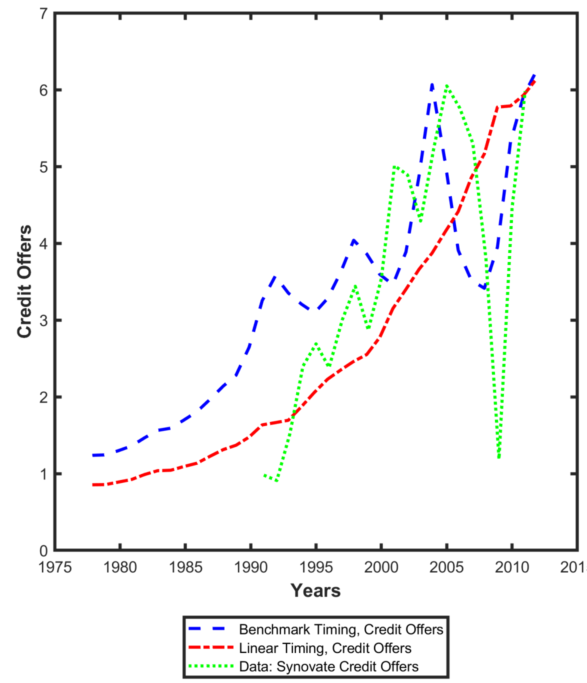


Figure 12: Chargeoff Dynamics, Deviations from Trend (HP Filter, $\lambda = 1600$)

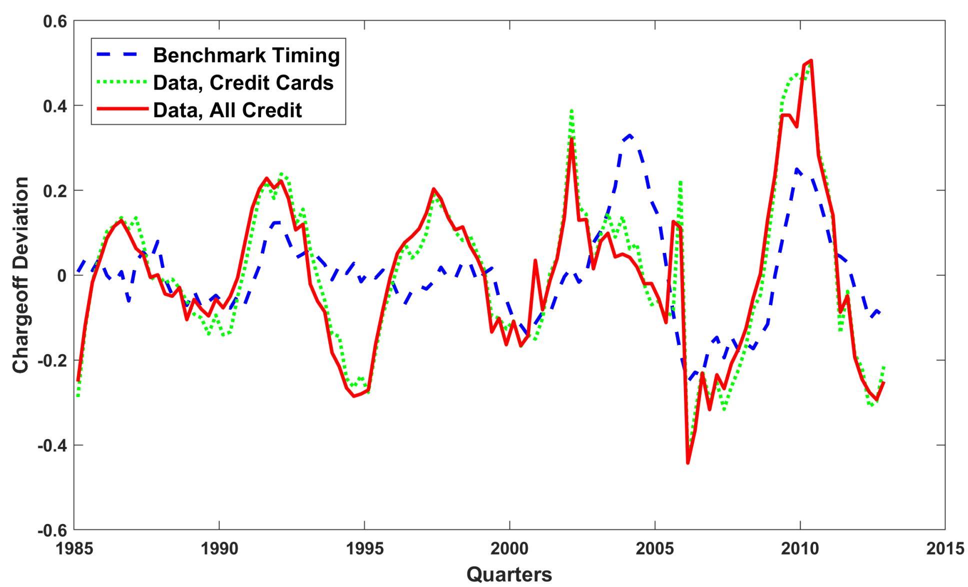


Table 1: Credit Access and Credit Use Among the Unemployed and All Households (Source: 1977 SCC and 2010 SCF)

	Unemployed Households		All Households	
	1977	**2010**	**1977**	**2010**
Fraction with Unsecured Revolving Credit Access	12.8%	45.0%	37.6%	65.0%
Fraction Borrowing (Positive Balance)	11.5%	33.1%	15.7%	34.1%
Gross DTI	0.6%	5.2%	0.6%	3.9%
N	78	416	2563	6482

Notes. See Online Appendix D for more details.

Table 2: Borrowing by the Unemployed (Source: RAND ALP, 2009-IV to 2015-IV)

	In response to job loss, percent who...
Borrow	25.3%
Skip payments (non-mortgage related)	36.1%
N	1680

Notes. See Online Appendix D for more details.

Table 3: SCF Composition Corrected Time Series for Unemployed Borrowing. Logit Regressions. Average Marginal Effects Reported (Source: SCF 1970-2013)

	(1)	(2)	(3)	(4)
Dependent Variable:	Borrowing (d)	Borrowing (d)	Borrowing (d)	Borrowing (d)
1977 (d)	0.0884**	0.129***		
	(0.0393)	(0.0484)		
1983 (d)	0.0965***	0.118***		
	(0.0259)	(0.0267)		
1989 (d)	0.148***	0.193***		
	(0.0501)	(0.0550)		
1992 (d)	0.220***	0.238***		
	(0.0378)	(0.0369)		
1995 (d)	0.218***	0.251***		
	(0.0375)	(0.0373)		
1998 (d)	0.249***	0.280***		
	(0.0424)	(0.0428)		
2001 (d)	0.244***	0.259***		
	(0.0458)	(0.0467)		
2004 (d)	0.328***	0.319***		
	(0.0445)	(0.0421)		
2007 (d)	0.245***	0.248***		
	(0.0445)	(0.0445)		
2010 (d)	0.304***	0.275***		
	(0.0290)	(0.0268)		
2013 (d)	0.253***	0.224***		
	(0.0309)	(0.0287)		
Year			0.00601***	0.00423***
			(0.000838)	(0.000868)
Post-Recession Dummy (1992, 2004, 2010)			0.0526**	0.0420**
			(0.0212)	(0.0209)
Demographic and Income Controls	N	Y	N	Y
Pseudo-R2	0.0364	0.0984	0.0291	0.0853
Observations	2,209	2,169	2,209	2,169

*Notes. Robust Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Sample includes unemployed individuals as of the survey date. (d) denotes dummy. Dependent variable is dummy of positive credit card balance. Demographic and income controls include age, income, liquid assets, as well as race, sex, and education dummies. Regressions are weighted using SCF survey weights. 1970 and 1977 observations are equally weighted since no weights are available in those years.*

Table 4: SCF Unemployed 5-Year Credit Denial Probabilities. Logit Regression. Average Marginal Effects Reported (Source: 1998-2013 SCF)

Dependent Variable:	**(1)** Denied (d)	**(2)** Denied (d)	**(3)** Strict Denial (d)	**(4)** Strict Denial (d)
1996-2001 (d)	0.0490	0.0979	0.000953	0.0568
	(0.0894)	(0.0833)	(0.0784)	(0.0781)
1999-2004 (d)	0.0335	0.0652	-0.0128	0.0180
	(0.0798)	(0.0758)	(0.0695)	(0.0648)
2002-2007 (d)	0.0304	0.0516	0.0525	0.0810
	(0.0837)	(0.0778)	(0.0769)	(0.0713)
2005-2010 (d)	0.167**	0.203***	0.116*	0.153***
	(0.0684)	(0.0649)	(0.0622)	(0.0589)
2008-2013 (d)	0.123*	0.124*	0.0864	0.0955
	(0.0707)	(0.0674)	(0.0641)	(0.0626)
Demographic and Income Controls	N	Y	N	Y
Total Balance Control	N	Y	N	Y
Observations	719	706	719	706
Pseudo R2	0.0115	0.0862	0.00963	0.0920

*Notes. Robust Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Sample includes unemployed individuals as of the survey date. (d) denotes dummy. Dependent variable in columns (1) and (2) is a dummy for any type of credit denial in the past 5 years. Dependent variable in columns (3) and (4) is a dummy for a credit denial in which the household was unable to eventually obtain the full amount in the past 5 years. Demographic and income controls include age, income, liquid assets, as well as race, sex, and education dummies. Total balance control includes total credit balance. Regressions are weighted using SCF survey weights. 1970 and 1977 observations are equally weighted since no weights are available in those years.*

Table 5: Summary of Parameters, 2010 Stochastic Steady State Calibration

Parameter	Value	Description
Non-Calibrated		
$\bar{s}$	0.01	Exogenous credit separation rate
r_f	0.04	Annualized Risk Free Rate
τ	0.049	Annualized Proportional Servicing Fee
δ	0.1	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
p_x	0.022	Probability of expense shock
x	0.263	Size of expense shock
Calibrated		
κ_L	0.021	Vacancy Posting Cost
κ_D	0.184	Disutility of Default
χ_C	0.210	Utility cost of applying
η	0.604	Flow Utility of Leisure
A_{2010}	0.718	Credit Matching Efficiency
β	0.974	Discount Factor

Table 6: Simulated Moments, 2010 Stochastic Steady State Calibration

Parameter	Target	Model	Data	Source
κ_L	Unemployment Rate	0.0586	0.0582	BLS (1948-2013)
κ_D	Chargeoff Rate	0.0107	0.0106	Flow of Funds (1985-2007)
χ_C	Fraction of Unemployed Borrowing	0.3316	0.3310	SCF (2010)
η	Autocorrelation of Unemployment	0.9045	0.9360	Shimer (2005)
A_{2010}	Approval Rate	0.6769	0.6720	SCF Panel (2007-2009)
β	Gross Unempl. DTI	0.0576	0.0519	SCF (2010)

Table 7: Stochastic Steady State Comparison

	2010	**1977**	**Ratio (2010/1977)**
Fraction Unemployed Borrowing	0.33	0.13	2.56
Avg. Unemployment Rate	5.87%	5.56%	1.06
Unemployment Volatility	14.0	14.4	0.97
Credit Matching Efficiency (A)	0.72	0.48	1.49
Newborns: Fraction of Lifetime Consumption Willing to Forego to Move from 1977 to 2010 SS			0.12%
Employed Newborns and Non-newborns: Fraction of Lifetime Consumption Willing to Forego to Move from 1977 to 2010 SS			0.11%
Unemployed Newborns and Non-newborns: Fraction of Lifetime Consumption Willing to Forego to Move from 1977 to 2010 SS			0.15%

Table 8: 2010 Liquid Asset Distribution: Model v. Data

Ratio of Liquid Wealth to Annual Income (2010)				
	Benchmark Model	**Model with Heterogeneous** β (Online Appendix K)	**Data 1: SCF 2010**	**Data 2: SCF 2010**
Definition	Net Liquid Assets (b)	Net Liquid Assets (b)	Most Liquid Assets (Checking +Saving +Money Market -Credit Card Debt)	Net Worth Excluding Pensions and Home Equity (Checking +Saving +Money Market +CDs +Mutual funds +Bonds +Stocks -Credit Card Debt)
p10	-0.038	-0.028	-0.056	-0.060
p25	0.000	0.000	0.000	0.000
p50	0.038	0.057	0.025	0.031
p75	0.095	0.131	0.109	0.211
p90	0.160	1.415	0.365	1.405
Mean	0.047	0.325	0.204	0.509

Table 9: Credit Matching Efficiency Along Transition Path

	1977	1983	1989	1992	1995	1998	2001	2004	2007	2010
Credit Matching Efficiency (A_t)	0.450	0.546	0.633	0.744	0.615	0.743	0.621	0.861	0.407	0.832
Model: Unemployed Borrowing	0.116	0.124	0.177	0.245	0.242	0.272	0.267	0.356	0.269	0.331
Data: Unemployed Borrowing	0.115	0.123	0.175	0.247	0.245	0.276	0.271	0.355	0.272	0.331

Table 10: Transition Experiment: Summary of Labor Market Moments

Growing Access, Benchmark Timing						**Baseline DMP (Shimer 2005), [Hagedorn-Manovskii (2008) in Square Brackets]**				
Variable $\mathbf{x}$ =	u_1	v	θ	y	UE Rate	u_1	v	θ	y	UE Rate
SD(x)/SD(y)	11.430	3.686	4.697	1.000	4.815	0.45 [11.2]	1.35 [13.0]	1.75 [22.5]	1 [1]	0.5
Autocorr(x)	0.903	0.504	0.784	0.832	0.846	0.94 [.83]	0.94 [.56]	0.94 [.75]	0.89 [.77]	0.91
Corr(u,$\mathbf{x}$)	1.000	-0.163	-0.868	-0.778	-0.972	1 [1]	-0.93 [-.72]	-0.96 [-.92]	-0.96 [-.89]	-0.96
Fixed Access						**Data (Shimer 2005)**				
Variable $\mathbf{x}$ =	u_1	v	θ	y	UE Rate	u_1	v	θ	y	UE Rate
SD(x)/SD(y)	9.677	3.055	3.646	1.000	3.984	9.50	10.10	19.10	1.00	5.90
Autocorr(x)	0.896	0.567	0.801	0.832	0.840	0.94	0.94	0.94	0.88	0.91
Corr(u,$\mathbf{x}$)	1.000	-0.110	-0.878	-0.845	-0.972	1.00	-0.89	-0.97	-0.41	-0.95

Notes: Model data are logged, and then HP filtered with smoothing parameter 10^5 to be consistent with Shimer [2005]. To be consistent with 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.

Table 11: Reduction in Employment Discrepancy Between Model and Data by Including Credit Matching Efficiency Expansions

	Percentage Change in Employment 8Q Since Peak			
	No Access	Access	Data	Reduction in Employment Discrep.
1990 Recession	-0.07	0.00	-1.33	-6.1%
2001 Recession	-1.07	-1.23	-1.55	33.8%
2007 Recession	-1.81	-2.85	-4.86	33.9%
Average	–	–	–	20.5%

Notes. Data is Nonfarm Business Sector Employment. E(t) is employment in period t after recession. Percentage change formula: 100*(E(8)/E(0)-1) where E(0) is employment in period prior to NBER dated recession. *Reduction in Employment Discrep. stands for "the reduction in employment discrepancy between the model and the data by including credit expansions." The formula for calculating the reduction in employment discrepancy between the model and the data by including credit expansions is given by: (E(Fixed Access)-E(Access))/(E(Fixed Access)-E(Data)) where $E(\cdot)$ is employment.

Table 12: Comparison of model to data: unemployment duration, wage replacement rate, and default rate. (Sources: Herkenhoff et al. [2015], PSID 2009-2013, and SCF 1998-2013)

Panel (A)	Model	Data: OLS (HPC)	Data: IV-GS (HPC)	Data: Bankruptcy Flag Removal (HPC)
Duration Elasticity	1.16	0.279***	0.442***	1.696*
Replacement Elasticity	0.01	0.0605***	0.134***	0.398**
Panel (B)	Model	Data: 60 Days Late Mortgage (PSID)	Data: Foreclosure (PSID)	Data: Minor delinquency (SCF)
Fraction Unemployed within 1 Year of Default	10.2%	22.9%	23.8%	22.8%

*Notes: *** p<0.01, ** p<0.05, * p<0.1. HPC Notes: Sample includes LEHD from 2001 to 2008. Estimates from Herkenhoff, Phillips, Cohen-Cole 2015 (HPC) (see Appendix J for additional details). PSID Notes: Sample includes heads from 2009 to 2013. 60 Days Late Mortgage refers to fraction of Heads Unemployed within 1 Year of 60 day Mortgage Delinquency (including date of default). Foreclosure refers to fraction of Heads Unemployed within 1 Year of Foreclosure Start (including date of default). SCF Notes: Sample includes heads from 1998 to 2013. Minor delinquency refers to fraction of Heads Unemployed within 1 Year of Minor Delinquency (including date of default). Model Notes: Benchmark Timing (Pooled, 1977-2012).*

Online Appendix

The Impact of Consumer Credit Access on Unemployment

by Kyle Herkenhoff

November 14, 2018

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A Employed Bellman Equations

At the start of the period, employed agents are able to obtain access to credit markets with probability $A\psi_{W,t}(w,b;\Omega)$ which depends on the vector of household attributes. Let $W_t^C(w,b;\Omega)$ be the value function for an employed agent that successfully matches with a lender, and $W_t^N(w,b;\Omega)$ be the value function for an employed agent that is unable to match with a lender. Let χ_C be the time cost of searching for credit. Using this notation, the Bellman equation for an employed household that must decide whether or not to look for credit, $W_t(w,b;\Omega)$, is

$$W_t(w,b;\Omega) = \max\{A\psi_{W,t}(w,b;\Omega)W_t^C(w,b;\Omega) + \big(1 - A\psi_{W,t}(w,b;\Omega)\big)W_t^N(w,b;\Omega) - \chi_C, W_t^N(w,b;\Omega)\} \quad \forall t \leq T$$

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

Let δ be the job separation rate.[33] Also let $q_{W,t}(w,b',D;\Omega)$ 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, net assets b, in aggregate state Ω, is given by,

$$\begin{aligned} W_t^C(w,b;\Omega) = \max_{b'\in\mathcal{B},D\in[0,1]} u(c) - x(D) + \beta\mathbb{E}\Big[&(1-\delta)\widehat{W}_{t+1}(w,b';\Omega') \\ &+ \delta \max_{\tilde{w}\in\mathcal{W}} \Big\{p_{t+1}(\tilde{w};\Omega')\widehat{W}_{t+1}(\tilde{w},b';\Omega') + \Big(1 - p_{t+1}(\tilde{w};\Omega')\Big)\widehat{U}_{t+1}(\gamma w,b';\Omega')\Big\}\Big] \end{aligned}$$

subject to the expense shocks (i.e. $\widehat{W}_{t+1}(w,b';\Omega') = p_x W_{t+1}(w,b'-x;\Omega') + (1-p_x)W_{t+1}(w,b';\Omega')$) and the budget constraint,

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

and taking as given the aggregate law of motion (1).

[33] The state contingent separation rate can be used to bound the firm continuation value away from zero. It will be set to a constant for computations.

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, $b' \geq 0$,

$$W_t^N(w,b;\Omega) = \max_{b'\geq 0, D\in[0,1]} u(c) - x(D) + \beta\mathbb{E}\Big[(1-\delta)\widehat{W}_{t+1}(w,b';\Omega') + \delta \max_{\tilde{w}\in\mathcal{W}} \big\{p_{t+1}(\tilde{w};\Omega')\widehat{W}_{t+1}(\tilde{w},b';\Omega') + \Big(1-p_{t+1}(\tilde{w};\Omega')\Big)\widehat{U}_{t+1}(\gamma w,b';\Omega')\big\}\Big]$$

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).

A.1 Lender Profit

Since lenders are separated from households in the case of default (on any debt), the current default decision, D, is relevant for the lender. The universal default rule is summarized by $\Xi(D)$.

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

The expression for lender profit is a value function since matches are long lived. The workers' asset position matters for the continuation value, and it is assumed that defaults are equally borne on all types of debt, including the 'expense shock' debt. The expected profits accruing to a matched lender, $Q_t(e,w,b;\Omega)$, are given by,[34]

$$\begin{aligned} Q_t(e,w,b;\Omega) =& (1-\Xi(D))\Big\{ q_{e,t}(w,b',D;\Omega)b' - \frac{\bar{s}}{1+r_f}\mathbb{E}\big[(1-(p_x D^{a'}_{e',t+1}(w',b'-x;\Omega') + (1-p_x)D^{a'}_{e',t+1}(w',b';\Omega')))\cdot b'\big] \\ & - \frac{(1-\bar{s})}{1+r_f}\mathbb{E}\big[(1-(p_x D^{\mathbf{C}}_{e',t+1}(w',b'-x;\Omega') + (1-p_x)D^{\mathbf{C}}_{e',t+1}(w',b';\Omega')))\cdot b'\big] \\ & + \frac{(1-\bar{s})}{1+r_f}\mathbb{E}\big[p_x Q_{t+1}(e',w',b'-x;\Omega') + (1-p_x)Q_{t+1}(e',w',b';\Omega')\big]\Big\} \end{aligned}$$

[34] To simplify the expectations below, there is a slight abuse of notation: Credit access, a', is actually realized after the expense shock.

B Welfare Calculation

This section explains the details of Table 7, which includes the distribution of consumption equivalent welfare gains (Δ) from leaving an economy with 1970s levels of credit technology and entering an economy with 2010 levels of credit technology. Let $\{c_{t,t_0+t}(A_{1970}, N)\}_{t=a_0,\ldots,T}$ be the consumption path of an agent if aggregate credit matching efficiency is held fixed at 1970s levels (A_{1970}) and the individual has no credit access, N, at age a_0. $\{c_{t,t_0+t}(A_{2010}, N)\}_{t=a_0,\ldots,T}$ is the corresponding consumption path if the individual lives in a world with 2010 levels of credit technology and the individual does not have credit access at age a_0.

$$\mathbb{E}_0 \sum_{t=a_0}^{T} \beta^t \Big[u((1+\Delta)c_{t,t_0+t}(A_{1970}, N)) + \eta \cdot (1 - h_{t,t_0+t}(A_{1970}, N)) - x(D_{t,t_0+t}(A_{1970}, N)) - \chi_C S_{t,t_0+t}(A_{1970}, N) \Big]$$

$$= \mathbb{E}_0 \sum_{t=a_0}^{T} \beta^t \Big[u(c_{t,t_0+t}(A_{2010}, N)) + \eta \cdot (1 - h_{t,t_0+t}(A_{2010}, N)) - x(D_{t,t_0+t}(A_{2010}, N)) - \chi_C S_{t,t_0+t}(A_{2010}, N) \Big]$$

There are two welfare gains presented in the paper. The welfare gain, Δ, amongst newborns is calculated at $a_0 = 0$, before agents draw their initial conditions. To compute welfare gains among the employed and unemployed, it is necessary to look at agents other than newborns, since all newborns are born without a job. The welfare gain among the employed and unemployed is calculated within bins of the state space (age, assets, credit access, employment status). For a given employment status, averaging across bins yields the employment-specific welfare gain in Table 7.

C Equilibrium Definition and Existence Proofs

Before defining an equilibrium, let $S^a_{e,t}(z, b; \Omega)$ denote the credit search policy function of an agent.

Definition of a Recursive Competitive Equilibrium: Let asterisks denote optimal policy functions. A recursive competitive equilibrium for this economy is a list of household policy functions for assets $\{b'^{*}_{e,a,t}(w, b; \Omega)\}$, credit search decisions $\{S^{*;a}_{e,t}(z, b; \Omega)\}$ wage search decisions $\{\tilde{w}^*_{a,t}(w, b; \Omega)\}$, and the fraction of debt to default upon $\{D^{*,a}_{e,t}(w, b; \Omega)\}$, a bond price $\{q_{e,t}(w, b, D; \Omega)\}$, a labor market tightness function $\{\frac{v_t(w;\Omega)}{u_t(w;\Omega)}\}$, a credit market tightness function $\{\frac{v_{C,t}(e,w,b;\Omega))}{u_{C,t}(e,w,b;\Omega)}\}$, 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 (4).

iii. The credit market tightness is consistent with free entry equation (3) .

iv. Debt is priced consistent with households making take-it-or-leave-it proposals according to equation (2).

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

C.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 $x'' > 0$, $x' > 0$, $\lim_{D\to\overline{D}} x'(D) = \infty$, $\lim_{D\to 0} x'(D) = 0$.

I follow a similar strategy of Menzio et al. [2016] 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.

Proposition C.1. *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. [2016].

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 pays the cost χ_C and searches for 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 $\theta_T(w; y)$ from the free entry condition and using the fact that $J_T(w; \Omega) = J_T(w; y) = y - w$.

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

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 ($\theta^C_{e,T}(w, b, D; A, y) = 0$), the household makes new take-it-or-leave-it bond proposals $q_{e,T-1}(w, b, D; y, A)$ based on the date T default policies.

v. Solve HH problem at date $T - 1$ (I only show the unemployed problem to save space):

$$
\begin{aligned}
U^C_{T-1}(z,b;A,y) = & \max_{b'\in\mathcal{B},D\in[0,1]} u(c) - x(D) + \eta \\
& + (1-s(D))\cdot\beta\mathbb{E}\Big[\max_{\tilde{w}\in\mathcal{W}} p(\theta_T(\tilde{w};A',y'))\Big(p_x W^C_T(\tilde{w},b'-x;A',y') + (1-p_x)W^C_T(\tilde{w},b';A',y')\Big) \\
& + \Big(1-p\big(\theta_T(\tilde{w};A',y')\big)\Big)\Big(p_x U^C_T(z,b'-x;A',y') + (1-p_x)U^C_T(z,b';A',y')\Big)\Big] \\
& \underbrace{+ \quad s(D)}_{Lose\ Credit}\cdot\beta\mathbb{E}\Big[\max_{\tilde{w}\in\mathcal{W}} p(\theta_T(\tilde{w};A',y'))\Big(p_x W_T(\tilde{w},b'-x;A',y') + (1-p_x)W_T(\tilde{w},b';A',y')\Big) \\
& + \Big(1-p\big(\theta_T(\tilde{w};A',y')\big)\Big)\Big(p_x U_T(z,b'-x;A',y') + (1-p_x)U_T(z,b';A',y')\Big)\Big]
\end{aligned}
$$

subject to the budget constraint,

$$c + q_{U,T-1}(z,b',D;A,y)b' \le z + (1-D)b,$$

and taking as given the law of motion for the aggregate states that matter to the household (notice no μ process is required to solve the above problem),

$$y' \sim F(y' \mid y), \qquad A' \sim G(A' \mid A).$$

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.

vi. The choice to search for credit will therefore be independent of the aggregate state,

$$
\begin{aligned}
U_{T-1}(z,b;A,y) = \max\{& A\psi(\theta^C_{U,T-1}(z,b;A,y))U^C_{T-1}(z,b;A,y) \\
& + \big(1 - A\psi(\theta^C_{U,T-1}(z,b;A,y))\big)U^N_{T-1}(z,b;A,y) - \chi_C, U^N_{T-1}(z,b;A,y)\}
\end{aligned}
$$

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

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

Such that

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

and the shock follows the process

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

viii. Obtain the labor market tightness $\theta_{T-1}(w;y)$ from the free entry condition:

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

ix. 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:

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

x. 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. $\square$

D Data Appendix

Appendix D.1 includes the time series for Table 1 in Section 1 of the main text. Appendix D.2 provides more facts from the SCF on unemployed households' credit use, emphasizing the lack of liquid assets among unemployed borrowers. Appendix D.3 discusses the importance of search in the credit market and empirical evidence in support of such an assumption. Appendix D.4 includes discussion of the RAND American Life Panel (ALP) questions used to construct Table 2.

D.1 Data on Unemployed Households & Credit Use Over Time

Table 13 includes detailed data on the time series for credit card use presented in the main body. Specifically, the time series concern bankcards such as Visa, Mastercard, and American Express which represent the vast majority of credit cards (Evans and Schmalensee [2005]). The sample is restricted to heads of household who are labor force participants; there are no age restrictions. The data from 1983 and onward are taken from the Survey of Consumer Finances. The data from 1970-1983 are taken from the Survey of Consumer Credit. The Survey of Consumer Credit is available from the Michigan Survey Research Center and has consistent questions with the SCF regarding employment, credit, and assets. The Survey of Consumer Credit did not provide weights in 1970 and 1977. Gross debt to annual family income ratios (DTIs) are constructed as $Fraction\ Borrowing * \frac{1}{12} Monthly\ DTI$.

D.2 Charges, Balances, and Limits of the Unemployed

To provide a snapshot of credit use among wealthy households, Table 14 shows the monthly bankcard charges (new credit card charges as of the survey date), balances (current balance less most recent payments as of the survey date), and limits (aggregate limit across all cards as of the survey date) by household heads in the 1989 and 2007 Survey of Consumer Finances.[35] Table 14 yields a few stylized facts: (i) 34% of unemployed households used their credit cards in 2007 as opposed to 17% in 1989, (ii) of those unemployed using their cards, on average they had charges equal to 25% of their average prior monthly income in 2007, (iii) 53% were carrying a credit balance in 2007 (which actually declined relative to

[35] An important note is that 'charges' refers to the new amount charged to the credit card on the most recent bill as of the SCF survey date. This is not the same as the increase in the balance of the credit card which is unobserved. 1989 was the first year in which charge data, default data, and credit limit was collected.

Table 13: Time Series Data from Herkenhoff (2013)

Fraction of Unemployed Households with Bankcards				Fraction of All Households with Bankcards			
Year	Wtd.	Unwtd.	Obs.	Year	Wtd.	Unwtd.	Obs.
1970	0.13	0.13	111	1970	0.18	0.18	3434
1977	0.13	0.13	78	1977	0.38	0.38	2563
1983	0.20	0.20	276	1983	0.41	0.45	4262
1989	0.25	0.29	105	1989	0.56	0.67	3143
1992	0.38	0.39	177	1992	0.62	0.72	3906
1995	0.32	0.38	176	1995	0.66	0.76	4299
1998	0.41	0.40	153	1998	0.68	0.75	4305
2001	0.49	0.48	124	2001	0.73	0.79	4442
2004	0.48	0.48	152	2004	0.71	0.77	4519
2007	0.44	0.45	128	2007	0.70	0.77	4417
2007p	0.47	0.49	101	2007p	0.74	0.81	3857
2009p	0.57	0.60	219	2009p	0.72	0.79	3857
2010	0.45	0.44	416	2010	0.65	0.68	6482
Fraction of Unemployed with Positive Balance				Fraction of All Households with Positive Balance			
Year	Wtd.	Unwtd.	Obs.	Year	Wtd.	Unwtd.	Obs.
1970	0.03	0.03	111	1970	0.07	0.07	3434
1977	0.12	0.12	78	1977	0.16	0.16	2563
1983	0.12	0.12	276	1983	0.21	0.20	4262
1989	0.18	0.17	105	1989	0.29	0.25	3143
1992	0.25	0.23	177	1992	0.33	0.27	3906
1995	0.25	0.26	176	1995	0.37	0.31	4299
1998	0.28	0.25	153	1998	0.37	0.31	4305
2001	0.27	0.26	124	2001	0.39	0.32	4442
2004	0.35	0.33	152	2004	0.40	0.32	4519
2007	0.27	0.28	128	2007	0.41	0.34	4417
2007p	0.32	0.34	101	2007p	0.46	0.38	3857
2009p	0.36	0.36	219	2009p	0.39	0.32	3857
2010	0.33	0.31	416	2010	0.34	0.30	6482
Balance Among Unemployed with Positive Balances				Balance Among All Households with Positive Balances			
Year	Wtd.	Unwtd.	Obs.	Year	Wtd.	Unwtd.	Obs.
1970	300	300	3	1970	202	202	224
1977	268	268	9	1977	330	330	402
1983	1100	977	32	1983	786	810	839
1989	1282	1136	18	1989	1822	2020	794
1992	2811	2481	41	1992	2199	2493	1070
1995	3913	4419	45	1995	2972	3389	1338
1998	5656	5958	39	1998	4081	4806	1316
2001	6031	7386	32	2001	3897	4577	1433
2004	7124	7406	50	2004	5084	5880	1462
2007	6419	7242	36	2007	7169	8498	1496
2007p	5670	6279	34	2007p	7337	8707	1463
2009p	6316	7691	78	2009p	8417	10923	1221
2010	6250	6451	128	2010	6957	7787	1934
DTI Among Unemployed with Positive Balances				DTI Among All Households with Positive Balances			
Year	Wtd.	Unwtd.	Obs.	Year	Wtd.	Unwtd.	Obs.
1970	0.26	0.26	3	1970	0.23	0.23	224
1977	0.61	0.61	9	1977	0.47	0.47	384
1983	0.55	0.51	32	1983	0.34	0.32	839
1989	1.02	0.68	18	1989	0.63	0.57	794
1992	1.10	1.00	41	1992	0.86	0.80	1067
1995	0.96	1.03	44	1995	1.01	0.96	1326
1998	1.64	1.65	39	1998	1.27	1.29	1308
2001	2.23	2.23	32	2001	1.07	1.06	1431
2004	1.89	1.96	49	2004	1.32	1.30	1456
2007	2.01	2.22	35	2007	1.50	1.43	1483
2007p	1.54	1.44	32	2007p	1.51	1.43	1452
2009p	1.90	1.93	78	2009p	1.60	1.66	1204
2010	1.89	1.91	127	2010	1.38	1.37	1919

1989), and (iv) 16% did not have enough liquid assets to pay off that balance.

Table 14: Credit Card Charges, Credit Card Balances, and Credit Card Limits

	Mean		Obs.	
	1989	**2007**	**1989**	**2007**
Charges				
Fraction of All Households with Positive Charges Last Month	0.40	0.53	3143	4417
Fraction of Unemployed Households with Positive Charges Last Month	0.17	0.34	105	128
Last Month's Charges for Unemployed Households with Charges>0 (Nominal)	231	840	20	44
Last Month's Charges to Monthly Income for Unemployed Households with Charges>0	0.19	0.25	20	44
Fraction of Unemployed Households Carrying Positive Balance with Charges>0	0.78	0.53	20	44
Balance to Monthly Income for Unemployed Households with Charges>0	0.99	1.18	20	44
Fraction of Unemployed Households with Less Liquid Assets Than Last Month's Charges	0.04	0.16	20	44
Balances				
Fraction of All Households Carrying Positive Balance	0.29	0.41	3143	4417
Fraction of Unemployed Households Carrying Positive Balance	0.18	0.27	105	128
Avg. Balance for Unemployed Households with Balance>0 (Nominal)	1282	6419	18	36
Avg. Balance to Monthly Income for Unemployed Households with Balance>0	1.02	2.01	18	36
Fraction of Unemployed Households with Less Liquid Assets Than Monthly Balance	0.43	0.61	18	36
Credit Limit				
Credit Limit to Annual Income, All Bankcard Holders	0.16	0.40	2107	3417
Credit Limit to Annual Income, Unemployed Bankcard Holders	0.18	0.41	30	58
Unused Credit Limit, Unemployed Bankcard Holders (Nominal)	2626	21593	30	58
Unused Credit Limit to Annual Income, Unemployed Bankcard Holders	0.12	0.34	30	58
Maximum Available Liquid Assets				
Unused Credit Limit Plus Liquid Assets to Annual Income Ratio, All Households Including those Without Bankcards	0.79	0.93	3143	4417

Notes. 1989 and 2007 SCF heads of household who are labor force participants. Charges refer to prior month's charges as of the survey date. Balance refers to current month's balance after all payments and charges. Monthly income computed as monthly average of total gross family income. Credit limit computed as aggregate sum of credit limits, unused credit is the credit limit less the balance. Liquid assets computed as the sum of cash, checking, money market funds, CDS, corporate bonds, government saving bonds, stocks, and mutual funds less credit card debt. Observations are weighted.

Table 14 also shows that (i) 27% of unemployed households are carrying balances from month to month in 2007 as opposed to 18% in 1989, (ii) those monthly balances doubled to 201% of monthly income from 1989 to 2007, and (iii) of those unemployed households carrying balances in 2007, 61% did not have enough liquid assets to pay off that balance. In total, 16% (=.27*.61) of the unemployed have liquid assets less than their monthly balance.

To measure potential self-insurance opportunities, Table 14 also measures credit limits. Unemployed households have an unused credit limit to annual income ratio of 34%, meaning that they could charge 34% of their annual income to their credit cards before having to pay overage fees.[36] Even though the mean liquid asset to income ratio has declined considerably from .67 in 1989 to .59 in 2007, the maximum available amount of liquid assets increased (i.e. the sum of liquid assets plus unused credit limits increased). The ratio of unused credit

[36] Credit limits are not strict. Herkenhoff [2012] provides estimates of the fraction of households over their credit limit using Equifax data.

limits plus liquid assets to income went from an average of 79% in 1989 to 93% in 2007.[37]

D.3 Sequential Search in Credit Markets

Search in the credit market allows the model to match two measurable moments that are crucial to answer the question in this paper: (i) the probability an agent receives credit access (a flow measure), and (ii) the fraction of agents with credit access (a stock measure). The approval rate determines the strength of the mechanism for households who lose their job with no existing credit lines, and without it, the model would overstate the importance of credit. Likewise the stock of households with credit access determines how many job losers are impacted by the mechanism. Apart from a non-trivial set of agents being denied credit, and a non-trivial set of agents lacking credit access, Table 15 shows that households engage in sequential search for credit. About 66% of households applied for credit in the 5 years preceding the 2007 SCF. About 15% were denied credit in that time period, and nearly 50 % of those denied credit were able to eventually obtain credit. This is exactly the type of behavior a sequential search model reproduces.

In addition to empirical support for search in the credit market, the directed search structure of the credit also allows one to compute the model (by admission of a block recursive equilibrium).

Table 15: Sequential Search in Credit Markets (Source 2007-2009 SCF Panel)

	Fraction of Population	Observations
Denied Credit b/w 02-07	15.38	2,828
	Fraction of those Denied	Observations
Obtained Credit Eventually	46.9	204
Did Not Reapply	25.98	113
Unable to Obtain Credit	27.13	118
	Fraction of Population	Observations
Denied Credit b/w 07-09	12.06	2,828
	Fraction of those Denied	Observations
Obtained Credit Eventually	28.74	98
Did Not Reapply	29.33	100
Unable to Obtain Credit	41.94	143

[37] Let L be liquid assets, I be annual income, U be unused credit, then this ratio is constructed as $\frac{L+U}{I}$.

D.4 RAND American Life Panel

The RAND American Life Panel includes several direct questions on borrowing. Hurd and Rohwedder [2010] describe the sampling in detail, and these questions are based on their survey. I condition on a 'Yes' answer to question "Did your family income go down as a result of [fill for having lost job] losing a job?" and I tabulate "How did [You and your spouse/partner] adjust to the loss of income? (please check all that apply) 1. Reduced spending 2. Reduced amount going into savings 3. Fell behind on mortgage payments 4. Fell behind on rent 5. Skipped or postponed paying some other bills 7. Increased debt 6. None of the above." I combine the responses 'fell behind on rent' and 'skipped or postponed paying some other bills' as a non-mortgage default, which includes delinquency on credit card payments, etc.

E Measuring Expense Shocks

Using the new comprehensive expenditure data in the PSID (2005-2013), I construct various expense shocks. From 2005-2013, the PSID coverage of consumption is as comprehensive as the Consumer Expenditure Survey (CEX). The unmodeled expense shocks include (1) spousal unemployment (2) recent divorce, (3) disability, (4) medical expense shock equal to 5% or more of annual income. In the PSID, I identify expense shocks to be a medical bill shock (5% or more of annual income – about 7% of families have this shock over any 2 year period), a recent divorce shock (about 1.6% of households have this shock over a given 2 year period), the development of a new physical or mental disability (nearly 6% of household heads and 3% of spouses, have this shock over any given two year period – note that these are not necessarily permanent disabilities, and the transition rate out of this state is quite high, and many continue to work), or spousal unemployment (about 3.3% of households have a spousal unemployment spell over a given 2 year period).

The baseline, weighted results indicate that 19% of households suffer one of these shocks every 2 years. This translates to a ($1.19^{1/8}$=1.0219) to a $\sim$2.2% per quarter probability of a shock. These shocks are associated with a level increase in debt of \$2,023. For those who receive the shocks, I compute $\frac{\Delta Debt}{Prior\ Year\ After\text{-}Tax\ Income}$, and on average, the expense shock is equivalent to 7.1% of annual after-tax household income (28% of quarterly after-tax income). After-tax household income is calculated using TAXSIM. Both the after-tax income and expenditure data are benchmarked against the CEX in Gerardi et al. [2017]. To map this to the model, the expense shock is equivalent to 28% of 1 quarter's wage, and the average quarterly wage in the model is approximately ~ 1. With no discreteness of grids, the expense shock is given by $x = .28 * 1 = .28$, but due to the discreteness of the grid, $x = .2625$.

F 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 ($f_{c,t}$).[38] 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 question regarding credit denial to obtain the probability a household received credit $p_{c,t}$.[39]

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:

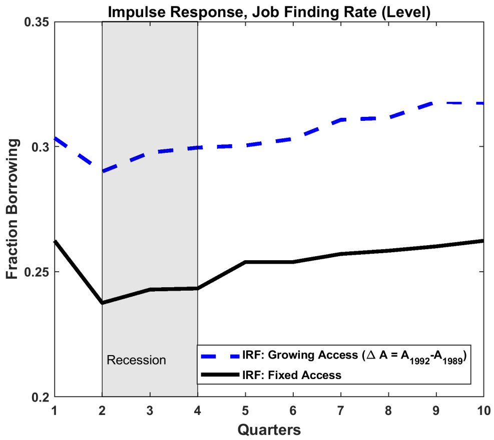
$$p_{c,t} = A_c \theta_{C,t} (1 + \theta_{C,t}^\gamma)^{\frac{-1}{\gamma}} + \epsilon_t$$

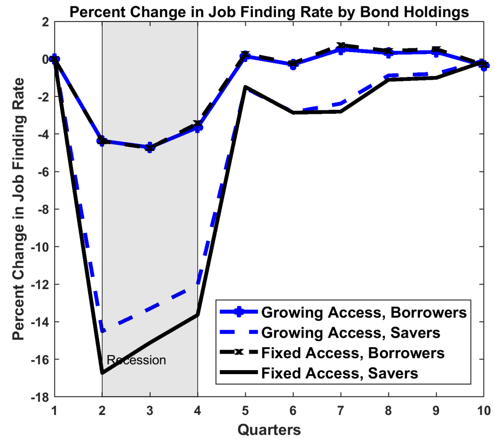
Estimation yields $A_c = .974$ (significant at 1%), $\gamma = .383$ (significant at 1%), with a goodness of fit of .99. The relatively few observations (N=5) provided by the SCF limit my ability to estimate A_c dynamically, let alone as a static parameter. Estimating the match elasticity after imposing $A_c = 1$ implies $\gamma = .372$ (significant at 1%) with a goodness of fit of .99.

[38] 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.

[39] 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 13: Impulse Response Experiments: Level Effect





G Impulse Response Experiments: Job Finding Rates by Indebtedness

In the main text, Panel (C) of Figure 2 shows that in the economy with greater credit access, agents optimally choose to search in higher wage submarkets with lower job finding rates *before the recession begins*. Before the recession, the aggregate job finding rate is 1.1 percentage points lower in the economy with greater credit access. Job finding rates fall by 8.2 percentage points in the economy with greater credit access during the recession; in the economy with fixed credit, job finding rates drop by 9.6 percentage points, a 15% larger decline. Panel (A) of Figure 13 shows that in the economy with greater credit access, 30.3% of individuals are indebted on the eve of the recession, whereas only 26.2% are indebted in the fixed access economy. Panel (B) of Figure 13 shows that when the recession occurs and aggregate job finding rates fall, indebted job losers avoid default by cutting their reservation wage disproportionately to maintain a high and stable job finding rate (reservation wages and job finding rates are proportional and move in opposite directions). As a result, the job finding rate is more stable in the economy with greater credit access, and therefore employment and output dynamics are dampened.

H Robustness

Appendix H.1 computes the model's transition path under perfect foresight and higher-frequency credit expansions. Appendix H.2 then extends the model to allow for on-the-job search. In both cases, the main results persist, but with a marginally smaller impact of credit on employment.

H.1 Perfect Foresight and Higher-Frequency Credit Expansions

This section computes the transition path under perfect foresight with quarterly credit expansions. In order for agents to know exactly when credit expand, and what value it will take, in each quarter, I must have one credit grid point per quarter. This requires increasing the state-space by a factor of 4. To make the problem feasible, I must partition the transition path into intervals and then solve the transition path over the intervals. From peak-to-peak is a natural partition over the sample period, 1977 to 2012.

Figure 14 plots the perfect foresight transition paths for each of the 4 partitions of the transition path. The 1990 recession, 2001 recession, and 2007 recession produce employment dynamics that are stronger than the stochastic case. Agent's borrow more during the recession knowing that with certainty credit will expand during the expansion. Therefore, these results suggest that the benchmark timing and beliefs produce results that are robust to perfect foresight.

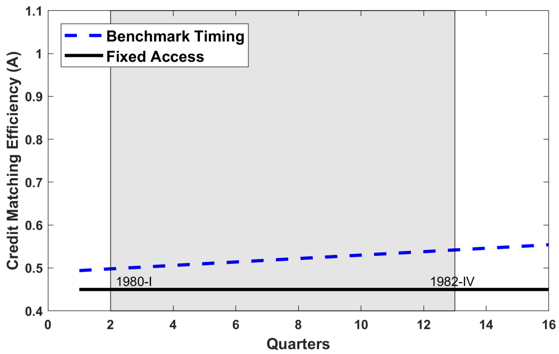
H.2 On The Job Search Extension

For notational ease, I omit the expense shocks from the equations below; however, the computed OJS model includes them. 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 $\Omega = (\mu, y, A)$.

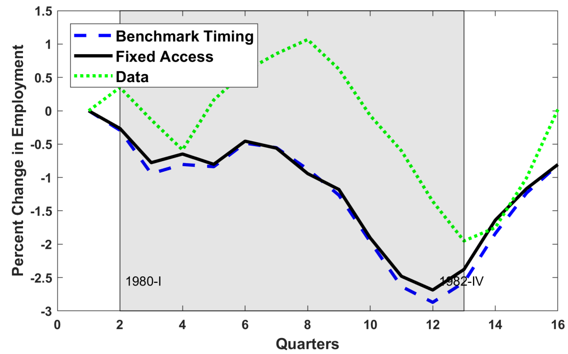
The submarket tightness is therefore given by $\theta_t(a, w, b; \Omega) = \frac{v_t(a,w,b;\Omega)}{u_t(a,w,b;\Omega)}$ where $v_t(a, w, b; \Omega)$ is the number of vacancies posted in the $(a, w, b, t; \Omega)$ submarket and $u_t(a, w, b; \Omega)$ is the number of unemployed people in that submarket. The corresponding vacancy-filling rate

Figure 14: Perfect Foresight Transition Path: Employment Fluctuations

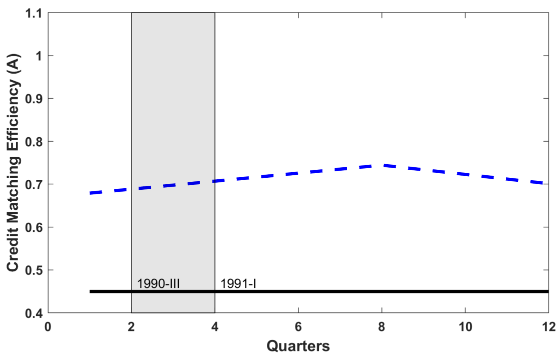
(A) 1980-I Recession Inputs



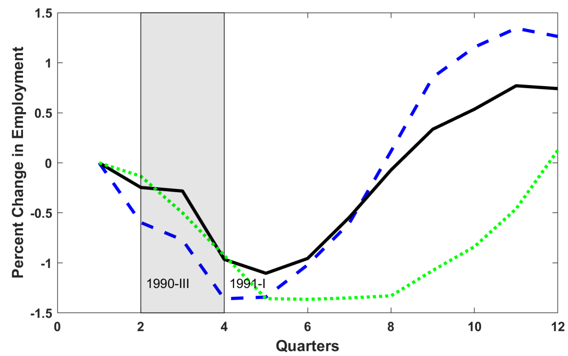
(B) 1980-I Recession Employment



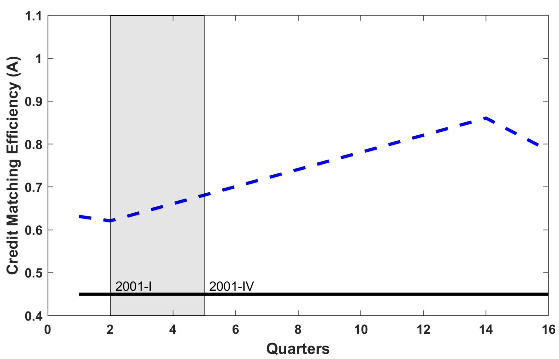
(C) 1990-III Recession Inputs



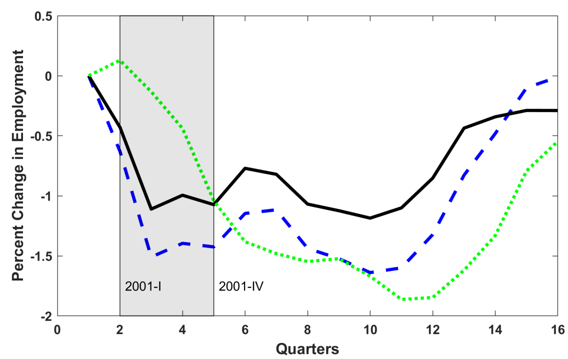
(D) 1990-III Recession Employment



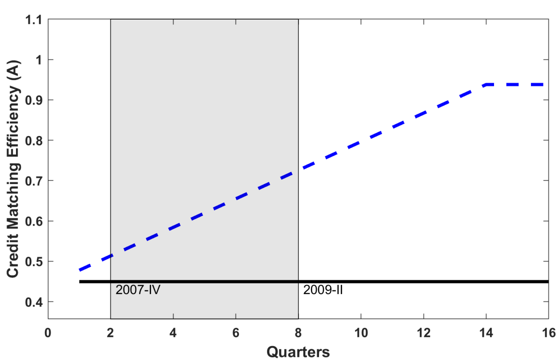
(E) 2001-I Recession Inputs



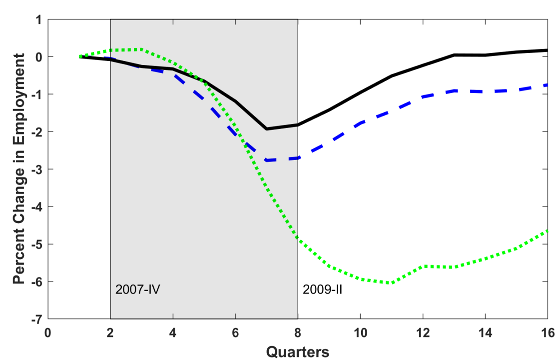
(F) 2001-I Recession Employment



(G) 2007-IV Recession Inputs



(H) 2007-IV Recession Employment



in that submarket is $f(\theta_t(a, w, b; \Omega))$. Let $J_t^a(w, b; \Omega)$ 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,

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

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

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

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:

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

such that firms take the aggregate law of motion as given (the equations are given by (1)) 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.

H.2.1 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.[40] For an employed agent (W) with credit access (C), their

[40]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,

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

Such that the law of motion for aggregates holds (the equations are given by (1)) and the budget constraint is satisfied:

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

H.2.2 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:

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

such that the universal default rule is given by,

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

and the bond price is given by,

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

H.2.3 Transition Experiment: On the Job Search

In the model with on-the-job (OJS), we set the probability of OJS to $\lambda = 1$. This is an *extreme* case of on-the-job search. Menzio and Shi [2011] use a smaller 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. To be consistent with the benchmark model, I also incorporate expense shocks into all of the OJS Bellman equations. However, for notational ease, they were omitted from the above equations.

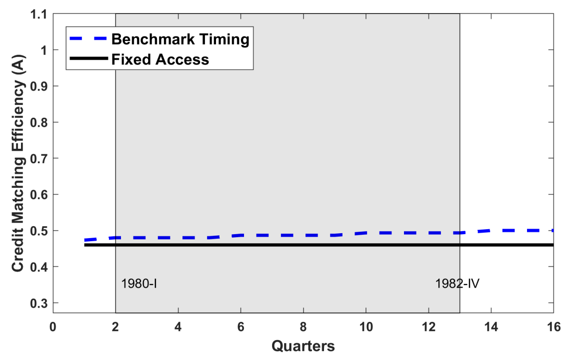
Table 16 illustrates the calibrated parameters for the model with OJS. Figure 15 illustrates employment fluctuations along the transition path with OJS. In general, the main quantitative results hold, and employment recoveries are still delayed with the credit expansions along the transition path. The correlation between u and v becomes twice as negative with OJS, dropping to -0.44978. The reason OJS lowers the correlation between u and v is simple: in the benchmark model, with fixed wages, firms hire during recessions because they can hire low-wage workers, so u and v tend to be positively correlated without OJS. With OJS, firms do not aggressively hire low-wage workers in recessions since those workers will immediately leave, and the firm will not recoup its vacancy cost. OJS can therefore generate a low correlation between u and v.

Table 16: On-the-job-search: Extension

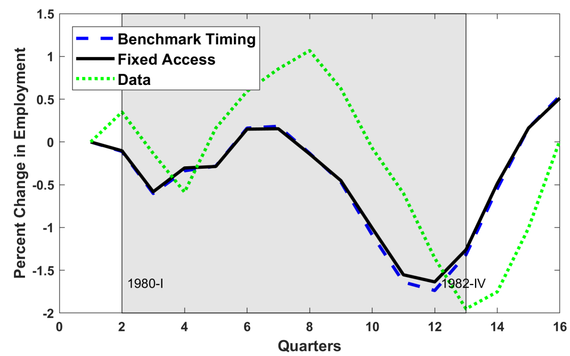
Parameter	Value	Description	Target	Model	Data	Source
κ_L	0.015198	Vacancy Posting Cost	Unemployment Rate	0.0582	0.0582	BLS (1948-2013)
κ_D	0.24202	Disutility of Default	Chargeoff Rate	0.0076	0.0106	Flow of Funds (1985-2007)
χ_C	0.2044	Utility cost of applying	Fraction of Unemployed Borrowing	0.3297	0.3310	SCF (2010)
η	0.60056	Flow Utility of Leisure	Autocorrelation of Unemployment	0.8986	0.9360	Shimer (2005)
A_{2010}	0.70578	Credit Matching Efficiency	Approval Rate	0.6674	0.6720	SCF Panel (2007-2009)
β	0.97318	Discount Factor	Gross Unempl. DTI	0.0579	0.0519	SCF (2010)

Figure 15: On-the-Job Search Transition Path: Employment Fluctuations

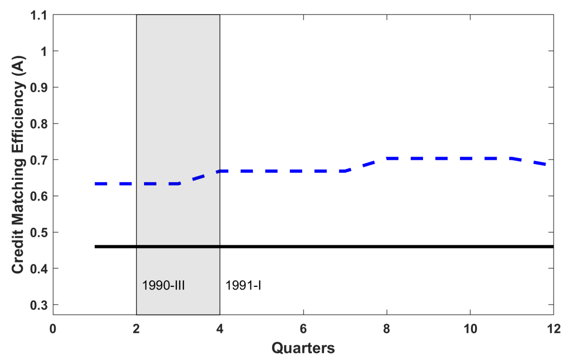
(A) 1980-I Recession Inputs



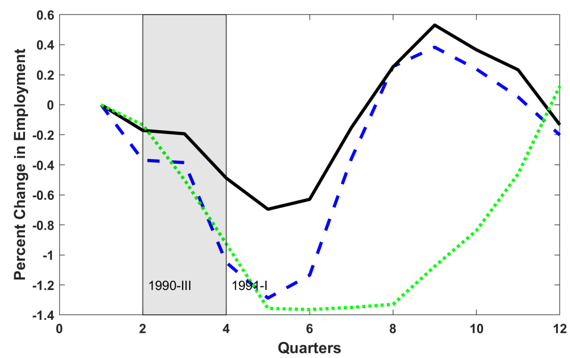
(B) 1980-I Recession Employment



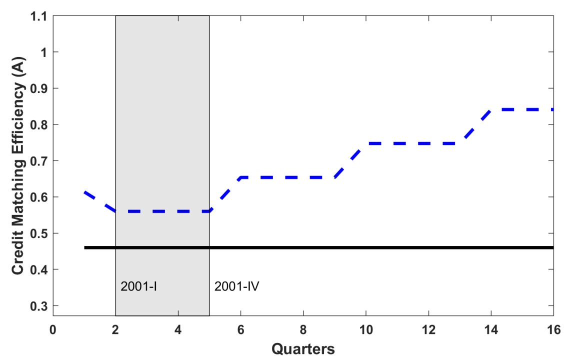
(C) 1990-III Recession Inputs



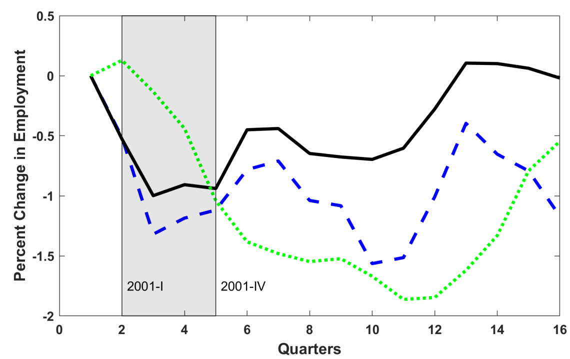
(D) 1990-III Recession Employment



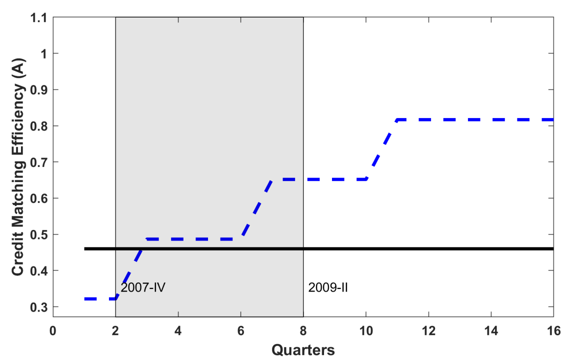
(E) 2001-I Recession Inputs



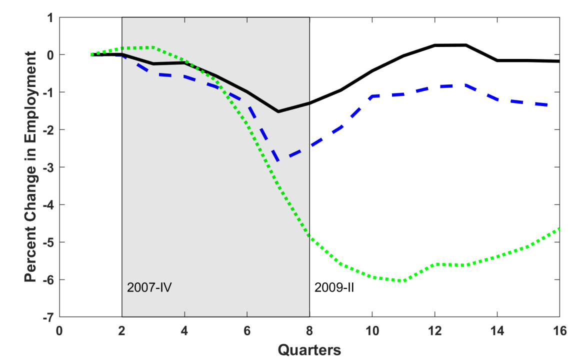
(F) 2001-I Recession Employment



(G) 2007-IV Recession Inputs



(H) 2007-IV Recession Employment



I Cyclicality of Lending Standards and Credit Technology Adoption

Appendix I.1 provides evidence on the procyclicality of lending standards. Appendix I.2 provides evidence on the procyclicality of credit technology adoption (as well as general technology adoption). Appendix I.3 describes the way in which the credit market was deregulated over the last 4 decades and how that has impacted availability of credit. Appendix I.4 discusses evidence related to subprime borrowing during the 2007-2009 crisis and subsequent recovery.

I.1 Cyclicality of Lending Standards from HMDA

One way of measuring the cyclical component of lending standards is to look at denial rates of mortgages in the Home Mortgage Disclosure Act (HMDA) data. The HMDA data records the denial rate of all types of mortgage loans, and provides demographic, interest rate, and income data from 1998 onwards. Figure 16 plots the composition adjusted denial rate on all mortgages, stratified by race, as tabulated by Li and Goodman [2014].[41] Figure 16 shows that the denial rate dropped in the pre-2005 period enormously for certain demographic groups, increased during the crisis, and then quickly returned to normal levels during the recovery.

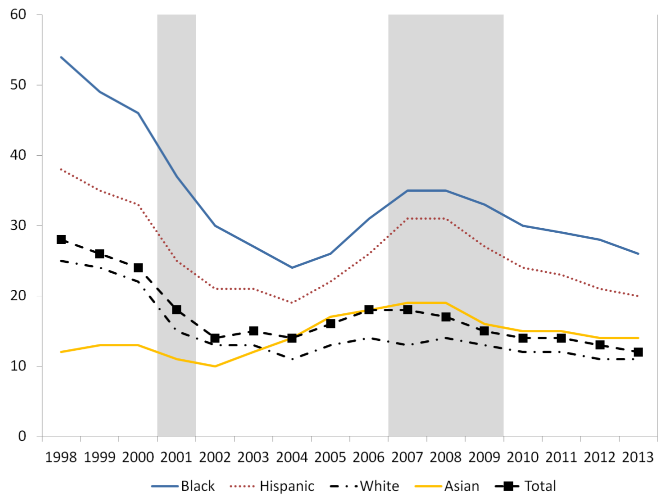
I.2 Procyclical Technology Adoption

In terms of general purpose technologies, recent work by Comin and Mestieri [2013] has illustrated that technology diffusion is greatly impacted by business cycles, and diffusion is strongly procyclical. Likewise, Alexopoulos [2011] details that technology diffusion tends to lead the business cycle with the correlation between the number of books published on computer technology today and GDP next year being .47.

With particular reference to credit technology adoption, Berger et al. [2011] provides data on the adoption of credit scoring technologies based on a random sample of 300 respondent community banks. The respondent banks outlined the year of credit scoring adoption. Figure 17 illustrates credit technology diffusion among those banks. While the earliest date of

[41] Li and Goodman [2014] restrict their sample to those with less than perfect credit. Since credit scores are ordinal, this is a constant percentage of households.

Figure 16: Mortgage Denial Rate, Adjusted for Composition (HMDA, 1998-2013, Source: Li and Goodman [2014])



adoption was truncated in the survey to 1994, the series is clearly procyclical. Why would credit scoring look like an increase in match efficiency? The though experiment is to put a bunch of unemployed households in a room with a bunch of bankers– prior to credit scoring, bankers had no way of telling who the lemons were from those who would borrow but ultimately repay (the most attractive type of customer). As a result, prior to credit scoring, there would be few matches that exited the room. With credit scoring, bankers can now isolate who the most attractive customers are and ultimately more matches exit the room.

In a separate article, Barren and Staten [2003] describe innovations to pricing. Barren and Staten [2003] provide direct evidence on the procyclical adoption of tiered-pricing by new-entrant credit card companies coming out of the 1990s recession:

> "Perhaps the most dramatic evidence of the impact of new entrants on credit card pricing occurred between 1990 and 1992... New entrants used externally-acquired demographic information, credit bureau data (as authorized by the Fair Credit Reporting Act), and data about the existing customers of their corporate affiliates to identify and target low-risk borrowers... Competitors knew no borders and reached customer mailboxes from thousands of miles away... In late 1991, American Express became the first major issuer to unveil a tiered pricing structure for its Optima product to slow customer defections... Shortly thereafter, Citibank announced a similar pricing structure for its Classic cardholders, who had been paying 19.8 percent."

Figure 18, replicated from Barren and Staten [2003], illustrates the effects of two-tier pricing coming out of the 1990-1991 recession on credit card interest rates (the data is from CardTrak and RAM research). The result of this 'technology diffusion' was a large decline in credit card rates as card companies adopted risk scoring. Grodzicki [2012] presents evidence consistent with the view that pricing strategies changed dramatically during the 1990s, resulting in a large credit boom.

Figure 17: Fraction of Community Banks Adopting Consumer Credit Scoring, Derived from Data Presented in Berger et al. [2011]

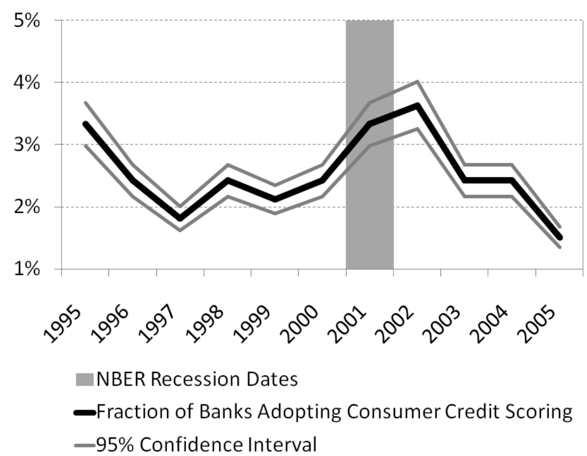


Figure 18: Credit Scoring Technology Diffusion, Barren and Staten [2003]

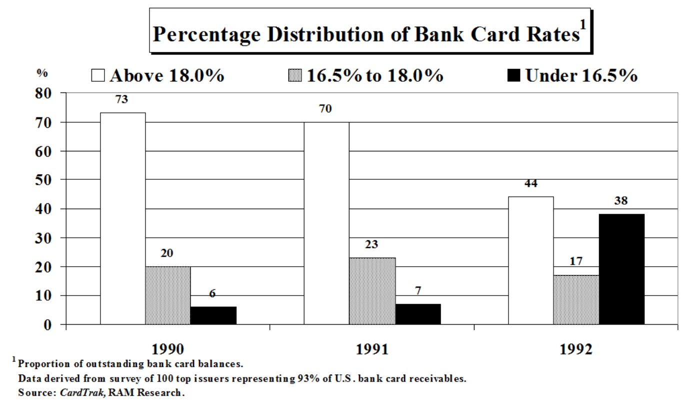


Figure 19, built with data kindly provided by Shiman [2001], illustrates the number of direct marketing customer lists. The ability to compile and diffuse customer lists grew rapidly coming out of the 1991 recession and is an integral part of the rise in credit card offers per capita show in Figure 20.

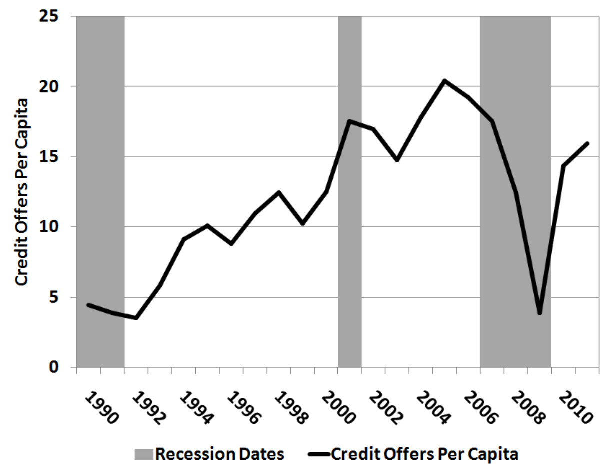
Figure 20 illustrates annual times series for credit card offers per capita, taken from Synovate/Ipsos and Mintel Comperemedia (Mintel Comperemedia recently acquired Synovate). What we see is that there is large growth in credit offers per capita both going into recessions as well as during recoveries. The procyclical nature of credit card offers is consistent with the technology adoption described by Barren and Staten [2003] and Berger et al. [2011].

I.3 Regulation

There have been many structural changes to consumer credit markets over the last 4 decades. In terms of regulations, there were many changes to credit markets that favored consumers and led to a boom in credit: Regulation Z (Truth in Lending,1968) standardized the credit

Figure 19: Number of Direct Marketing Customer Lists, Shiman [2001]

Figure 20: Credit Card Offers Per Capita (Source: Synovate and Mintel Comperemedia)



industry to increase transparency on credit terms; the Fair Credit Reporting Act of 1970 entitled consumers to receive free credit reports once a year to dispute information; the Bankruptcy Reform Act of 1978 strengthened Chapter 13 significantly; the Equal Credit Opportunity Act of 1974 banned redlining; and finally, the Fair Credit Billing Act of 1974 was a means for consumers to dispute credit charges.

As Berger et al. [1995] show, banking efficiency changed dramatically over the course of the 1980s. There were roughly 13,000 ATMs in 1979 and 109,00 ATMS by 1994; likewise, the cost of processing an electronic deposit fell by a factor of 8 from .09 cents to .01 cents per transaction. Mester [1997] also explains that prior to credit scoring, small business loans took 3 to 4 weeks to process. After the introduction of credit scoring, small business loans took a few mere hours to process. Credit scoring grew dramatically during the 1980s, culminating in Equifax going public in 1987.

Payday lending (see Melzer [2011] for more), also called a cash advance, was non-existent prior to the 1980s (the deceptive nature of this naming convention is that these loans are actually *not* contingent on employment). Stegman [2007] explains that "California went from zero payday lenders in 1996 to 2300 in 2004, with almost 450 new outlets opened in California in 2003 alone." A similar phenomenon occurred with HELOC loans (see Canner et al. [1998] for more).

I.4 Credit Expansion Coming out of the 2007 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 5). In the real world, where is this credit coming from? Even though there was a large decline in employed borrowing (which drives aggregate credit measures), Figure 5 (C) shows that there was roughly a 5 percentage point increase in the fraction of unemployed households who began revolving credit balances from 2007 to 2010. This is consistent with reports by both Equifax and Mintel Comperemedia which show a large subprime credit card expansion coming out of the 2009 recession.[42] Equifax reports that the subprime share of credit card originations rose from 20% in 2010 to nearly 33% in 2014 (pre-recession, subprime issuances were about 40% of credit card originations). Subprime credit limits increased by $9 billion in 2010 and $17 billion in 2014 (pre-recession, subprime credit card limits were increasing by $40 billion per annum).[43] Equifax also reports that while subprime credit card issuances fell from 2 million per annum in 2007 to .5 million per annum in 2009, by late 2010 and early 2011, subprime issuances were above 1 million per annum once again.[44] Moreover, although only a limited fraction of student loans have a revolving feature, the federal 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. As annual federal student loan issuances increased nearly two fold from $67 billion per annum in 2007 to $105 billion per annum by 2009 (NCES [2013]), this is one the largest expansions of credit among the non-employed in US history.

[42] See Davidson [2011], White [2012], and Andriotis and Sidel [2014].

[43] To put this in perspective, a year-long extension of the 99-week unemployment insurance program costs $30 billion. See 'Unemployment Insurance To Be Extended, $30 Billion Cost Won't Be Offset,' by Arthur Delaney and Sam Stein, Dec. 31, 2012.

[44] Appendix I shows that credit card offers per capita were back to 2004 levels by 2011.

I.5 FRB SLOOS Timing: Credit Matching Efficiency as a Residual

To better understand the nature of credit expansions, this section uses the Federal Reserve Board of Governor's (FRB) Senior Loan Officer Opinion Survey (SLOOS) and computes match efficiency based on the free entry condition in the credit market. The free entry condition is inverted to obtain match efficiency. Consider a simplified version of the free-entry condition where κ_C is the cost of sending a credit offer, A is the credit matching efficiency, u_C is the number of credit card applicants, v_C is the number of credit card offers sent, $M_C(u_C, v_C) = \frac{u_C \cdot v_C}{(u_C^{\zeta_C} + v_C^{\zeta_C})^{1/\zeta_C}}$ is the credit matching function, and Q is profit per credit card successfully issued:

$$\kappa_C = A \frac{M_C(u_C, v_C)}{v_C} Q$$

Rearranging and substituting $\frac{M_C(u_C,v_C)}{v_C} = (1 + \theta_C^{\zeta_C})^{-1/\zeta_C}$ where $\theta_C = v_C/u_C$,

$$A = \frac{\kappa_C (1 + \theta_C^{\zeta_C})^{1/\zeta_C}}{Q}$$

To directly estimate A, I must find data counterparts for κ_C, θ_C, and Q.

I proxy v_C using measure of credit supply from the Senior Loan Officers Opinion Survey (SLOOS). In particular, I use the "Net Percentage of Domestic Respondents Reporting Increased Willingness to Make Consumer Installment Loans." Since this series is a flow, I take the cumulative sum of this series which I will denote s_t (the minimum of this series is denoted $\underline{s}$, the maximum $\overline{s}$) and generate an index of credit supply

$$S_t = 1 + \frac{s_t - \underline{s}}{\overline{s} - \underline{s}}$$

I will refer to S_t as 'SLOOS Supply.'

To proxy for credit demand, u_C, I use the "Net Percentage of Domestic Respondents Reporting Stronger Demand for Consumer Loans" from the Senior Loan Officer Opinion Survey (available from 1990-II to 2011-I, quarterly). With no transformation to either series, I splice this with "Net Percentage of Domestic Banks Reporting Stronger Demand for Credit Card Loans" which is available from 2011-II onwards. Since this is a flow, I take the cumulative sum of this series which I will denote d_t (the minimum of this series is denoted

$\underline{d}$, the maximum $\overline{d}$) and generate an index of credit demand

$$D_t = 1 + \frac{d_t - \underline{d}}{\overline{d} - \underline{d}}$$

I will refer to D_t as 'SLOOS Demand.'

I proxy the cost of a credit credit offer, κ_C, using real direct mail advertising expenditures per piece of direct mail. The advertising expenditures are made available by Robert J. Coen from 1971-2012, annually, and the number of pieces of direct mail is taken from the USPS Household Diary Study over the same time period, annually.

Lastly, I must find a proxy for Q_c, which is the profit per credit card. I obtain real balances per credit card (in 2002\$) from Evans and Schmalensee [2005] which is available from 1970-2002, annually.[45] For the later years, I use the FRBNY Consumer Credit Panel to compute real balances per credit card from 1999-2013 (in 2002\$). For the period in which the two series overlap, the average ratio of the two series is .72. I scale the FRBNY balances per credit card by this constant fraction to obtain a spliced real balances per credit card series from 1970-2014 (in 2002\$). I proxy Q_c as the product of the real effective yield on credit cards times the average real balance held per credit card. The real effective yield is computed as the nominal interest rate on credit cards i_c, less inflation π, less chargeoffs d_c, plus swipe fees f_s. The swipe fee is important along two dimensions: first, it is a large component of profitability of credit card companies.[46] Second, for technical reasons, to prevent profits from becoming negative in the crisis, I must factor in swipe fees.

I obtain time series for i_c from the Federal Reserve Board of Governors, I use the CPI for π, and I use the chargeoff series on credit cards from the Federal Reserve Board of Governors for d_c. There exists no time series, to my knowledge, on swipe fees. In general, everytime a credit card is used ('swiped'), the merchant is charged a swipe fee ranging from .5% to 3% of the transaction value, depending on the issuer and the card, and so I set $f_s = .03$. Let b_c denote real balances per credit card. My proxy for lender profits is therefore $Q_c \propto [i_c - \pi - d_c + f_s] \times b_c$.

Table 17 includes the data and formulas used to construct the residual method path for credit matching efficiency, A_{resid}. Why does the residual method produce a large rise in

[45] Their series is derived from the Nilson Reports. I used PlotDigitalizer to infer the values of this series from Evans and Schmalensee [2005] with computer precision.

[46] In general, credit card issuers like Wells Fargo, are not directly paid the swipe fee. Visa, which owns the credit car network, is paid the swipe fee. The banks however own Visa – as Evans and Schmalensee [2005] explain, the Visa network is 'co-petitive,' i.e. the banks jointly own Visa and the banks only compete on issuing credit cards for the network. I will therefore count the swipe fees as indirect profits for the issuer.

matching efficiency during the 2007-2009 great recession recovery? With the chargeoff rate elevated to roughly 3x its historic norm, free entry implies that matching efficiency must increase enormously in order to rationalize the high credit supply and low credit demand. Of course, free entry is a heuristic approximation of reality, and therefore the residual method may generate spurious increases in matching efficiency when there are no such increases in the data. For that reason, the benchmark experiment indirectly infers credit matching efficiency from unemployed borrowers. This indirect inference approach provides the strongest discipline on the magnitude of the model's mechanism, which is proportional to the fraction who borrow, as well as the amount borrowed among the unemployed.

I index the credit matching efficiency series so that the residual timing and benchmark timing are the same in 2010, $A_{resid,2010} = A_{bench,2010}$. From 1991 to 2010, I index credit matching efficiency to the final column of Table 17. Let dm_t denote Column (L) of Table 17. The residual credit technology is $A_{resid,t} = A_{bench,2010} \cdot dm_t$ for $1991 \leq t \leq 2010$.

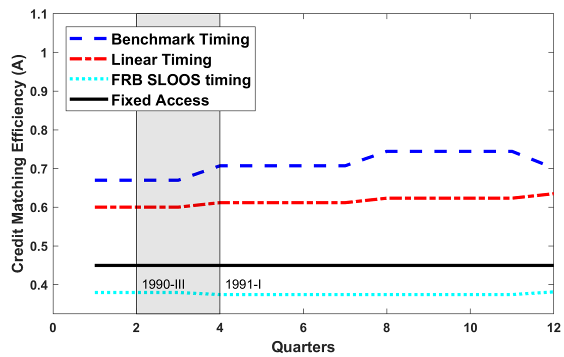
Figure 21 shows the impact of credit matching efficiency on employment when measured using the residual method. Panels (A) and (B) demonstrate that the residual method generates slightly higher employment during the 1990 recession. Panels (C) and (D) demonstrate that the residual method generates a similar employment path to the benchmark economy in the 2001 recession. Panels (E) and (F) demonstrate that the residual method generates a similar employment path to the benchmark economy in the 2007 recession. Overall the benchmark results are very similar to the residual method results.

Table 17: FRB SLOOS Measure of Credit Matching Efficiency

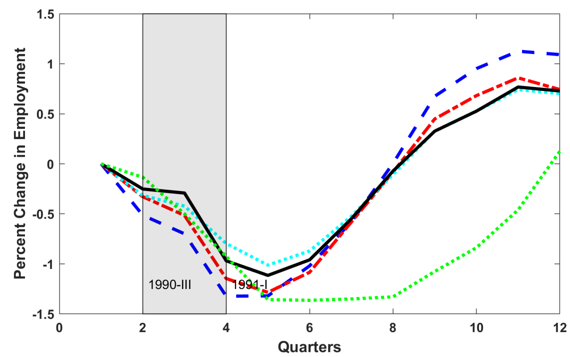
Year	Cumulative Credit Supply	Index of Credit Supply (between 1 and 2)	Cumulative Credit Demand	Index of Credit Demand (between 1 and 2)	Real Advertising Expenditure Per Direct Mail Piece (2002$)	Historical Credit Card Interest Rate	Charge-Off Rate	Inflation (CPI)	Nilson Report/FRBNY Spliced Average Balance per card, 2002$	Profit per annum using chargeoffs plus 3% spread	FRB SLOOS Measure of (A)	Normalized Measure of (A)
Column Label	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)	(K)	(L)
Source	FRB SLOOS		FRB SLOOS		Shiman (2005)	Flow of Funds	Flow of Funds	BLS	Nilson/Equifax			2010=1
Formula		1+[(A)-min(A)]/[max(A)-min(A)]		1+[(C)-min(C)]/[max(C)-min(C)]						(I)*[(F)-(G)/100-(H)+.03]	$\{[1+((B)/(D))^{.372}]^{(1/.372)}\}*(E)/(J)$	
1991	0.80	1.00	0.00	1.80	451.69	0.18	4.58	0.03	819.24	111.03	19.87	0.42
1992	22.40	1.03	-58.40	1.72	457.03	0.18	4.69	0.03	819.24	108.10	21.39	0.45
1993	92.90	1.14	-5.60	1.79	457.77	0.17	3.74	0.03	810.50	108.55	21.90	0.46
1994	191.60	1.29	80.10	1.91	462.12	0.16	3.10	0.03	845.48	109.68	22.49	0.47
1995	283.20	1.43	130.10	1.98	490.43	0.16	3.48	0.03	911.08	116.75	23.14	0.49
1996	319.60	1.49	144.60	2.00	501.05	0.16	4.48	0.03	981.05	105.17	26.59	0.56
1997	303.70	1.46	133.20	1.98	491.61	0.16	5.30	0.02	994.17	115.05	23.76	0.50
1998	322.00	1.49	107.70	1.95	491.77	0.16	5.22	0.02	959.18	112.92	24.64	0.52
1999	355.10	1.54	113.40	1.96	489.05	0.15	4.61	0.03	1011.66	106.20	26.42	0.55
2000	388.70	1.59	124.00	1.97	491.14	0.15	4.46	0.03	1055.39	106.07	26.89	0.56
2001	383.10	1.59	43.90	1.86	482.25	0.14	5.43	0.02	1029.15	107.13	26.82	0.56
2002	370.30	1.57	31.60	1.84	503.58	0.13	6.40	0.02	1024.78	74.68	40.11	0.84
2003	386.80	1.59	29.60	1.84	502.53	0.13	5.83	0.02	1069.62	87.58	34.43	0.72
2004	430.60	1.66	50.80	1.87	502.54	0.13	5.04	0.03	1090.42	85.79	35.58	0.75
2005	481.20	1.74	1.70	1.80	489.71	0.15	4.84	0.03	1078.28	100.28	30.90	0.65
2006	533.40	1.82	-57.70	1.72	514.71	0.15	3.55	0.03	1066.75	124.65	27.36	0.57
2007	559.30	1.85	-198.90	1.52	500.73	0.15	4.01	0.04	1089.53	104.27	34.24	0.72
2008	546.00	1.83	-307.60	1.37	485.45	0.14	5.52	0.00	1103.29	120.78	30.10	0.63
2009	426.20	1.65	-450.90	1.17	374.02	0.14	9.41	0.03	1233.42	64.20	44.87	0.94
2010	422.00	1.64	-547.50	1.03	442.88	0.14	9.34	0.02	1187.77	76.23	47.69	1.00
2011	499.00	1.76	-572.30	1.00	446.15	0.13	5.68	0.03	1087.79	80.66	48.04	1.01
2012	585.00	1.89	-552.70	1.03	430.23	0.13	4.08	0.02	1038.64	105.76	36.22	0.76
2013	654.10	2.00	-519.60	1.07	450.11	0.13	3.48	0.02	997.76	109.48	36.82	0.77

Figure 21: FRB SLOOS Timing: Employment Fluctuations

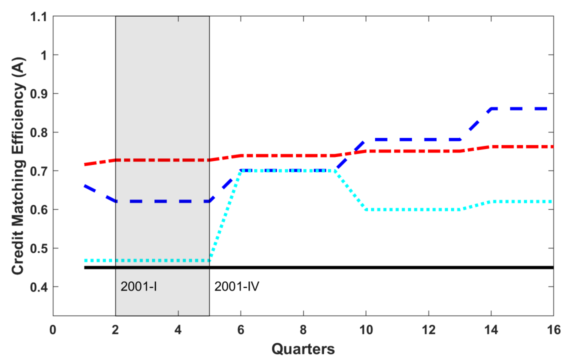
(A) 1990-III Recession Inputs



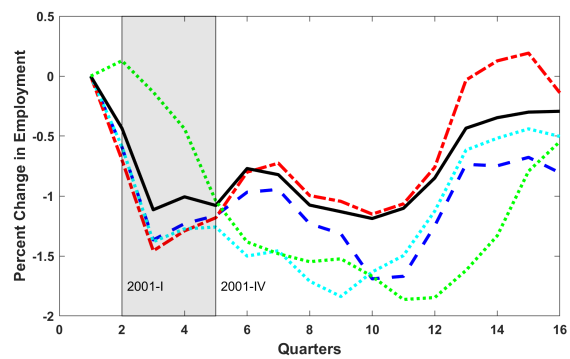
(B) 1990-III Recession Employment



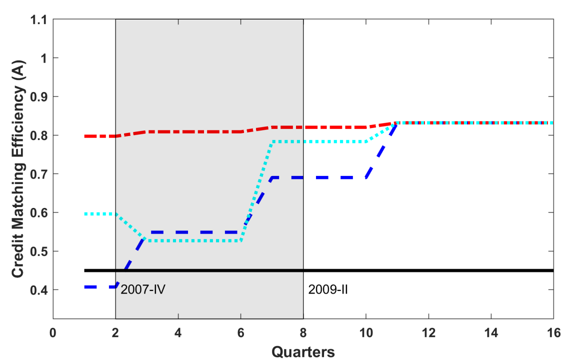
(C) 2001-I Recession Inputs



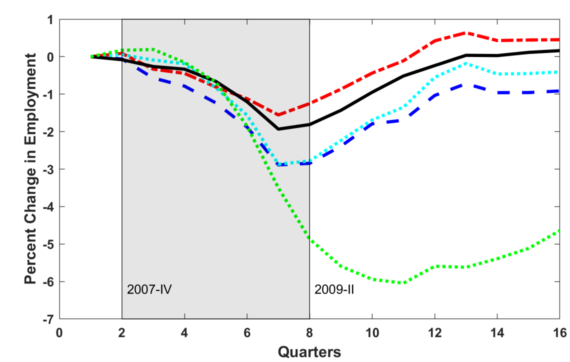
(D) 2001-I Recession Employment



(E) 2007-IV Recession Inputs



(F) 2007-IV Recession Employment



J Strength of Mechanism versus Existing Estimates

The mechanism in the model is very similar to unemployment insurance in the static sense: a credit limit increase is an increase in liquid resources available to a household just like an increase in unemployment insurance. The main difference between the two is in the dynamics: (1) loans must be repaid or defaulted upon (2) unemployment claimant rates have been very stable over the last 3 decades (Auray et al. [2012]) whereas credit access has grown enormously (see Section 1 in the main paper), (3) the line of credit can be drawn down before a household ever loses its jobs (in which case the household begins unemployment indebted and is forced to find a job faster than if it had never borrowed to begin with).

In terms of the search mechanism, Herkenhoff et al. [2015] use new administrative data from the Census LEHD merged by SSN to individual credit reports to study the impact of credit access on unemployment duration and replacement wages of displaced workers. They find that being able to replace 10% of prior annual income with revolving credit allows displaced workers to take between .33 and 2 weeks longer to find a job but their replacement wages are about .5% to 3.9% greater, conditional on finding a job, consistent with a reservation wage mechanism. They show that even if workers do not draw down the credit line, the *ability to borrow* affects every unemployed workers' search behavior. To put their results in context, one dollar of UI is roughly one-half to one-fourth as potent as one dollar of UI. Furthermore, Chetty [2008] has shown that access to liquid assets in the form of severance payments increases unemployment durations significantly.

To compare the model to these existing studies, I compute the duration and replacement wage elasticities in the model. To remove the impact of aggregate productivity fluctuations and transition dynamics, I compute the elasticity between steady states. I define the credit limit in the economy as the minimum observed net asset position in each steady state (e.g. $\underline{L}^{1977} = |\min_i\{b_i^{1977}\}|$ and $\underline{L}^{2010}$ is similarly defined). Likewise, I compute average credit approval rates (e.g. $\psi_{1977} = \frac{\sum_{i\in A} I(a_i^{1977}=C)}{|A|}$ where A is the set of applicants and $|A|$ denotes its cardinality, and ψ_{2010} is defined similarly). I compute income prior to layoff (e.g. $\bar{w}_{1977} = \frac{\sum_{i\in X} w_{i,-1}}{|X|}$ where X is the set of laid off individuals and $w_{i,-1}$ is their prior quarterly wage, and $\bar{w}_{2010}$ is defined similarly). The change in borrowing capacity to annual pre-layoff income is defined as $\Delta\frac{L}{Y} = \frac{\psi_{2010}\underline{L}^{2010}}{4\bar{w}_{2010}} - \frac{\psi_{1977}\underline{L}^{1977}}{4\bar{w}_{1977}}$. Define $\Delta Dur = Dur_{2010} - Dur_{1977}$ as the change in unemployment duration. Define $\Delta RR = RR_{2010} - RR_{1977}$ as the change in replacement rate, where the replacement rate is defined as the ratio of the wage 1 year after layoff to the wage 1 year before layoff, among job finders. We define the replacement rate semi-elasticity as $\frac{\Delta RR}{\Delta\frac{L}{Y}}$ and the duration semi-elasticity as $\frac{\Delta Dur}{\Delta\frac{L}{Y}}$. The model implied duration elasticity is

1.16, and the model implied replacement wage elasticity is .01. This implies agents take 1.39 weeks longer to find a job if they can replace 10% more of their prior annual income with credit, and agents find jobs that pay .1% greater.

Relative to the UI literature, Chetty [2008] finds that among households in the lowest quartile of wealth, after 1 quarter, a 5% increase in the replacement rate of UI leads to a 12% reduction in the quarterly job finding rate.[47] Chetty [2008] also reports results for the impact of receiving a severance payment on job finding hazards. The specific amount received in the severance payment is not available in Chetty [2008]'s data, however he provides a loose estimate that roughly 1 year of job-tenure translates into 1 week of severance pay.[48] Households were employed for roughly 7.5 years in Chetty [2008]'s sample, therefore when they are laid off they received roughly 7.5 weeks worth of prior wages. He finds that access to this amount of liquid assets lowers the quarterly job finding rate by approximately 8%.

In terms of the wage outcomes of households who have access to more liquid assets, the existing literature is largely supportive of wage effects. Ehrenberg and Oaxaca [1976] use the NLSY where they find that raising the replacement ratio by 10% increases "post unemployment" wages by 7%." Burgess and Kingston [1976] report significant wage gains associated with UI, using data from a random sample of UI claimants who participated in the Service to Claimants (STC) Project in 1969 and 1970. Feldstein and Poterba [1984] use a sample drawn from a special supplement to the May 1976 Current Population Survey to assess the impact of UI on *reservation wages*. Specifically, for job losers not on layoff, an increase in the replacement rate from 0.4 to 0.7 raises the reservation wage ratio by almost 13 percentage points. Blau and Robins [1990] find that a 10 percentage point increase in the replacement rate would increase wages by about 1%, which they consider a reasonably sized effect. Addison and Blackburn [2000] provide a nice summary of the existing studies and they themselves conduct an experiment in which they find slightly positive and significant effects of unemployment insurance on wage outcomes. Krueger and Mueller [2011] recently sampled 6,000 households from New Jersey and found limited effects of unemployment insurance on wage outcomes. This may reflect the fact that they only had about 600 workers for any 10-week window of unemployment spells (i.e. 600 workers were followed from weeks 20 to 30, etc.) and very high attrition rates (close to 40% of weekly follow surveys were not filled out). Hagedorn et al. [2013] find a strong impact of unemployment insurance on wages,

[47] This is a 5% increase for 26 weeks.

[48] Chetty [2008] writes, "Lee Hecht Harrison (2001) reports results from a survey of severance pay policies of human resource executives at 925 corporations in the U.S. in 2001... Using the percentages reported in this table for non-exempts (hourly workers) and coding the < 1 week category as 0.5 weeks, I compute that on average, individuals receive 1.35 weeks of severance pay per year of service."

exploiting cross-state variation in UI extensions. While Schmieder et al. [2016] find mixed evidence regarding unemployment insurance and wage outcomes in Germany, Nekoei and Weber [2017] find strong evidence in support of this paper's mechanism in Austria.

K Gross Debt vs. Net Debt and The Wealth Distribution

In the benchmark calibration, I target gross debt rather than negative net worth, and this warrants additional discussion. Others in the literature, including Livshits et al. [2010] follow a similar calibration strategy for several reasons, which are also applicable to the present paper: (i) asset exemptions matter (White [1998]) and roughly 15% of US households would benefit from discharging debts in the US, whereas targeting negative net worth would imply only 7% can discharge debts (ii) targeting negative net worth would produce estimates of a near-zero increase in borrowing during the 1990s, (iii) debt is understated in the SCF, and (iv) gross debt positions matter when targeting and interpreting chargeoff rates.

There are two more reasons, specific to the present paper, for targeting gross debt positions: (v) roughly 16.2% of unemployed individuals with positive net worth are rolling over debts from month to month. These individuals benefit from consumption smoothing via debt markets, even though they do not have negative net worth. Finally, (vi) there are many individuals who smooth consumption through default, even though they have positive net worth. While the SCF has limited bankruptcy and delinquency data, 11.8% of those with positive net worth enter delinquency in the prior year, and 21.8% of the unemployed with positive net worth enter delinquency in the prior year (this includes secured and unsecured debt payments).[49] Therefore, to capture the full extent to which individuals utilize credit markets to smooth consumption, I choose to target the fraction of unemployed individuals with positive gross credit balances.

[49] Default defined as 'Sometimes got behind or missed payments' (variable X3004) on a loan in prior year. Net worth defined as the sum of cash, checking, money market, CDs, mutual funds, stocks, and bonds minus credit card debt. Calculated using pooled, weighted, 1998-2013 SCF data, 11.8% of those with positive net worth got behind and missed payments (N=26,118). Conditional on being unemployed, 21.8% of those with positive net worth got behind and missed payments (N= 1,046).

K.1 Heterogeneous Discount Factors

To match the 90th percentile of the wealth distribution. I introduce discount factor heterogeneity. A mass μ of agents in both the growing-credit and fixed-credit economies is born with a discount factor of .9975 per quarter, corresponding to a 1% per annum discount rate. To solve the model, I assume that this mass of agents only saves $b' \geq 0$, and is therefore unresponsive to innovations in the credit market. This reduces the model's state space and allows me to expand the asset grid by a factor of 5 (I expand the upper bound of the asset grid from its previously non-binding value of 1.75 to 10), in order to allow for ultra-rich agents.[50] I assume there are 60,000 low-discount factor agents and 10,000 high-discount factor agents, and thus $\mu = 1/7 \approx 15\%$. Let U^H denote the bellman of an agent with a high discount rate.

$$U_t^H(z,b;\Omega) = \max_{b' \geq 0} u(c) + \eta$$
$$+ \beta \mathbb{E}_{\Omega'}\left[\max_{\tilde{w} \in \mathcal{W}} \; p_{t+1}(\tilde{w};\Omega')\Big(\widehat{W}_{t+1}^H(\tilde{w},b';\Omega')\Big) + \Big(1 - p_{t+1}(\tilde{w};\Omega')\Big)\Big(\widehat{U}_{t+1}^H(z,b';\Omega')\Big)\right] \qquad \forall t \leq T$$

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

subject to the budget constraint,

$$c + \frac{1}{1+r_f} b' \leq z + b,$$

and for each continuation Bellman equation $V \in \{W^H, U^H\}$, households incur expense shocks with probability p_x,

$$\widehat{V}(\tilde{w},b';\Omega') = p_x V(\tilde{w}, \max\{b' - x, 0\};\Omega') + (1 - p_x) V(\tilde{w}, b';\Omega')$$

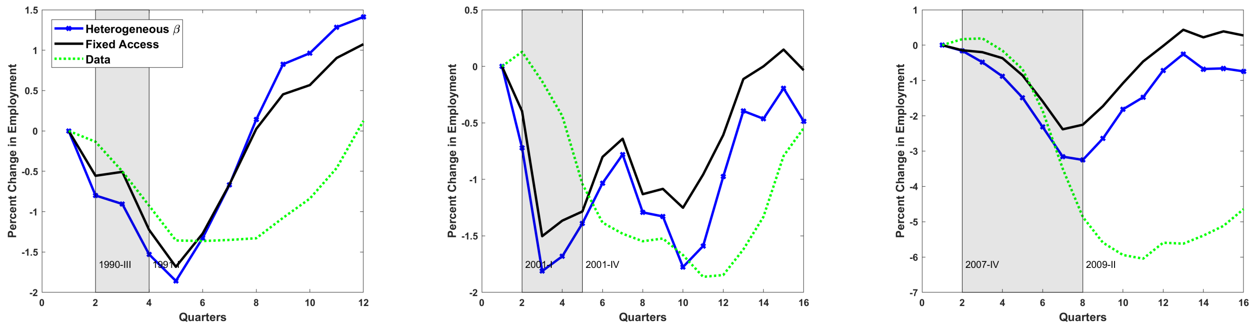
and take as given the law of motion for the aggregate state,

$$\begin{aligned} \Omega' &= (\mu', A', y'), \qquad \mu' = \Phi(\Omega, A', y') \\ y' &\sim F(y' \mid y), \qquad A' \sim G(A' \mid A). \end{aligned} \tag{5}$$

[50] A mass of approximately .8% of agents still reach the top of the expanded asset grid.

Figure 22: Transition Experiment: Employment Fluctuations with Heterogeneous β's

(A) 1990-III Recession **(B) 2001-I Recession** **(C) 2007-IV Recession**



L Testable Implications: Aggregate Trends

Figure 23 plots the fraction of households with net liquid assets to gross annual income less than 1% (LQTI<1%) from 1977-I to 2012-IV on the right hand axis (the solid line) versus the data (circles).[51] In the model there is a secular decline in liquid savings such that the fraction of households with LQTI<1% more than doubles from roughly 12% to 28%. In the data this statistic also more than doubles, increasing from approximately 16% to 38%. This statistic is designed to capture the fraction of individuals who would benefit from credit markets upon job loss. Other cutoffs of the LQTI distribution exhibit similarly stark increases.

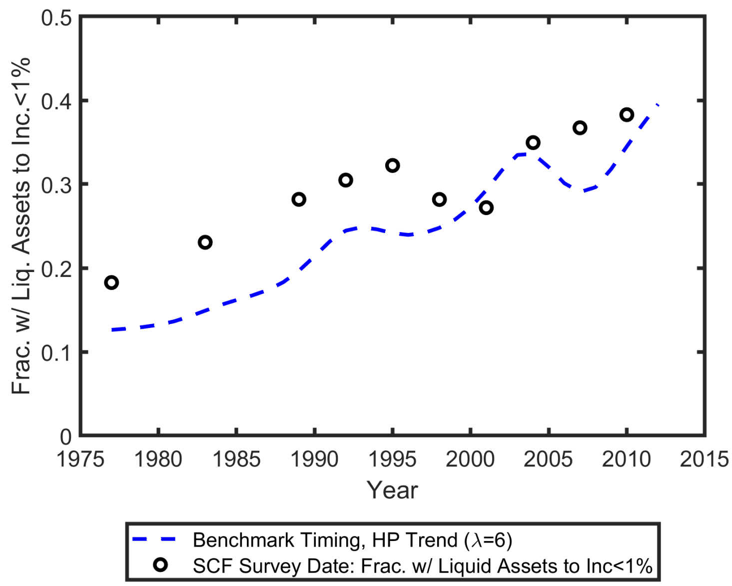
Figure 24 plots the model's annual trend in bankruptcies per agent in the model against the annual trend in bankruptcies per working age individual in the United States.[52] Since there is no distinction between default and bankruptcy in the model, I define bankruptcy in the model as a chargeoff of 30% or more of the value of the agent's debt; this corresponds to the amount that is discharged in the typical Chapter 13 filing (e.g. Li et al. [2007] reports a discharge rate of 33% in Ch 13 filings). The model generates a fourfold increase in bankruptcies per household (from .44% in 1977 to nearly 1.71% in 2012) caused by the growth in credit access, while in the data, bankruptcies per household increase nearly four fold (from .25% in 1977 to .97% in 2012). One important caveat is that the model does not include the 2005 bankruptcy reform; including this reform would potentially lower the bankruptcy rate to the levels observed in the data, however this is not the focus of the present analysis.

[51] 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.

[52] The bankruptcy data is from the Historical Statistics of the United States Millennial Edition for the years 1948 to 1979 and the American Bankruptcy Institute for the years 1980 to 2012.

Figure 25 plots the model's trend rise in unemployment duration. Over the 1977 to 2005 time period, the model produces a 1/2 week increase in unemployment duration, whereas in the data, unemployment duration increases by approximately 4.5 weeks. So growing credit access can account for approximately 11% of the rise in unemployment duration over this time period.[53]

Figure 23: Transition Experiment: Liquid Asset Holdings



[53]The model is unable to account for the rise in unemployment durations during the Great Recession since the extreme right tail of the unemployment duration distribution was likely driven by UI extensions (Hagedorn et al. [2013]), and the present paper does not incorporate UI extensions. In future work, I plan to explore the interaction between UI and credit.

Figure 24: Transition Experiment: Bankruptcy Rate

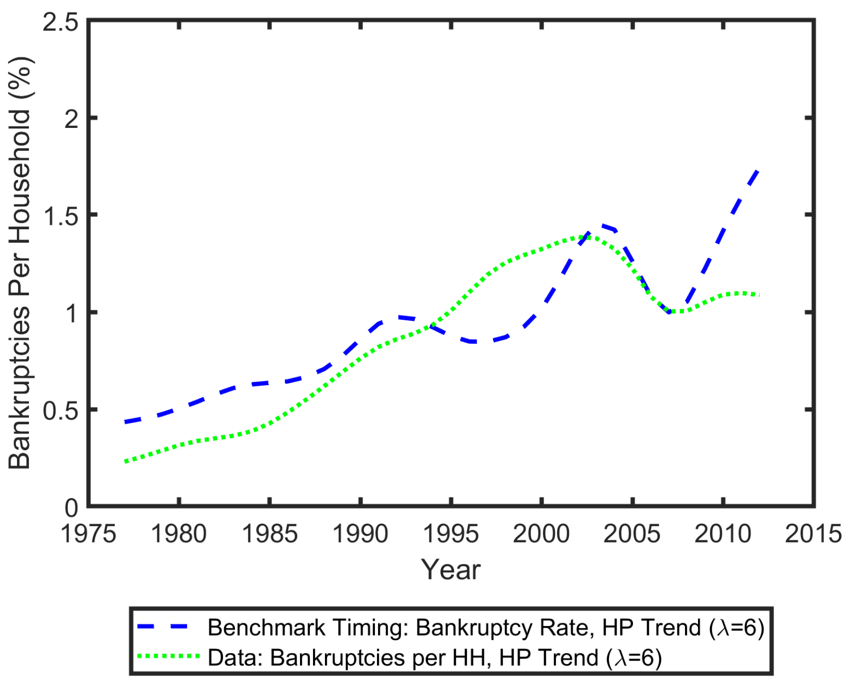
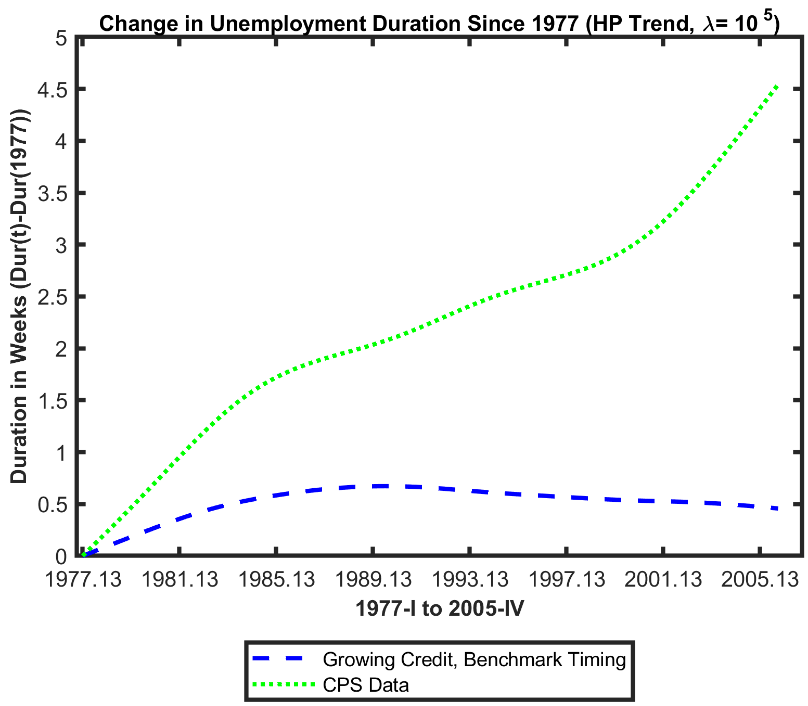


Figure 25: Transition Experiment: Unemployment Duration (1977-I to 2005-IV)



M Reaccess Rates

The model has an endogenous reaccess rate following bankruptcy. I compare this with the statistics in Jagtiani and Li [2015], who include summaries of credit reaccess rates among various bankruptcy filers. Table 18 demonstrates that the model produces similar reaccess rates to Ch 13 filers, but under predicts the reaccess rate when compared Ch 7 filers.

Table 18: Model Re-Access Rate

	Reaccess Rates
Model Prob, Obtain Credit Access 2Q After Default	2.67%
Data Prob. New Credit Card 2Q after filing, Ch. 13	3.34%
Data Prob. New Credit Card 2Q after filing, Ch. 7	12.42%

N Computation of Baseline Model

The model is solved in two steps. The first step is to use value function iteration over a discrete state space to recover the policy functions. The second step is to simulate the model using the recovered policy functions to obtain aggregate dynamics.

Firm Problem:

1. I begin by solving the firm's problem for the market tightness. I solve for $J_t(w; y)$ on the grid by working backward from $J_T(w; y) = y - w$. This involves no optimization.
2. I then invert the free entry condition $f^{-1}\Bigg(\kappa_L / J_t(w; y)\Bigg) = \theta_t(w; y)$ to obtain the market tightness at every wage, age, and aggregate productivity combination.

Household Problem:

1. I begin with guesses of zero for the continuation values for each of the household value functions.
2. **Period T:**
   (a) Work back from the last period of life, beginning with the default choice $D^*_T(\cdot)$ of the age T agent for every possible wage, asset, productivity, aggregate credit, credit access, and employment state. Optimal policy functions are determined using grid search. This alleviates any issues associated with non-convexities.
   (b) The asset choice is degenerate $b^*_T(\cdot) = 0$.
   (c) The bond price in that period is zero $q_T(\cdot) = 0$.
   (d) There is a zero contact rate between the household and lender since there is no borrowing.
   (e) I then step back and solve for the optimal wage policy function $w^*_T(\cdot)$.
3. **Period $t \in \{T-1, ..., 1\}$:**
   (a) Build the $q_t(\cdot)$ bond price based on next period's wage, asset, and default rules.
   (b) Solve for the asset policy function of the current period, and default decisions using $q_t(\cdot)$.
   (c) Determine, at each point in the state-space, if individuals apply for credit.

(d) Compute lender profits $Q_t(\cdot)$. Plug this into the free entry condition for lending to obtain the contact rate between lenders and households.

(e) Step back to determine the optimal wage.

(f) Repeat.

4. **Simulation:**

(a) Draw a matrix of random numbers $N \times T$ where N=60,000 and T=280. Simulate the economy using the above mentioned policy rules where every household begins unemployed with zero assets, no credit access, and the highest level of unemployment insurance.

(b) Drop the first 100 time periods, store aggregate variables, repeat R=10 times.

(c) Report averages over simulations.

O Alternative Initial Conditions

This section considers 3 different sets of initial conditions: (i) 'Benchmark': born unemployed with uniform draw of benefits, zero assets, no credit access, (ii) 'Uniform Assets and Benefits': born unemployed with uniform draw of benefits, *uniform draw of assets*, and no credit access, and (iii) 'Uniform Assets and Benefits, 10% Born with Access': born unemployed with uniform draw of benefits, *uniform draw of assets*, and *10% born with credit access*. I recalibrate parameters in each economy, and I recalibrate the full transition path of credit match efficiency. Panels (A) through (C) of Figure 26 illustrate the credit matching efficiency paths in both economies, as well as the data targets. Panels (A) through (D) of Figure 27 illustrate the main result in both economies; the trough of employment is exacerbated, and in the 2001 and 2007 recession, the business-cycle expansion of credit matching efficiency coming out of the recession results in a slower employment recovery.

Relative welfare gains of newborns along the transition path are presented in Table 19. The welfare gain is the fraction of lifetime consumption a newborn would give up to be born the economy with expanding credit access versus the economy with fixed credit access. We see that welfare gains diminish for both the 'Uniform Assets and Benefits' economy and 'Uniform Assets and Benefits, 10% Born with Access' economy. The welfare gains are 7% and 12% smaller, respectively. When more agents are born with credit access, the welfare gain from switching economies is lower.

Figure 26: Transition Experiment: Calibration Targets and Credit Matching Efficiency Path

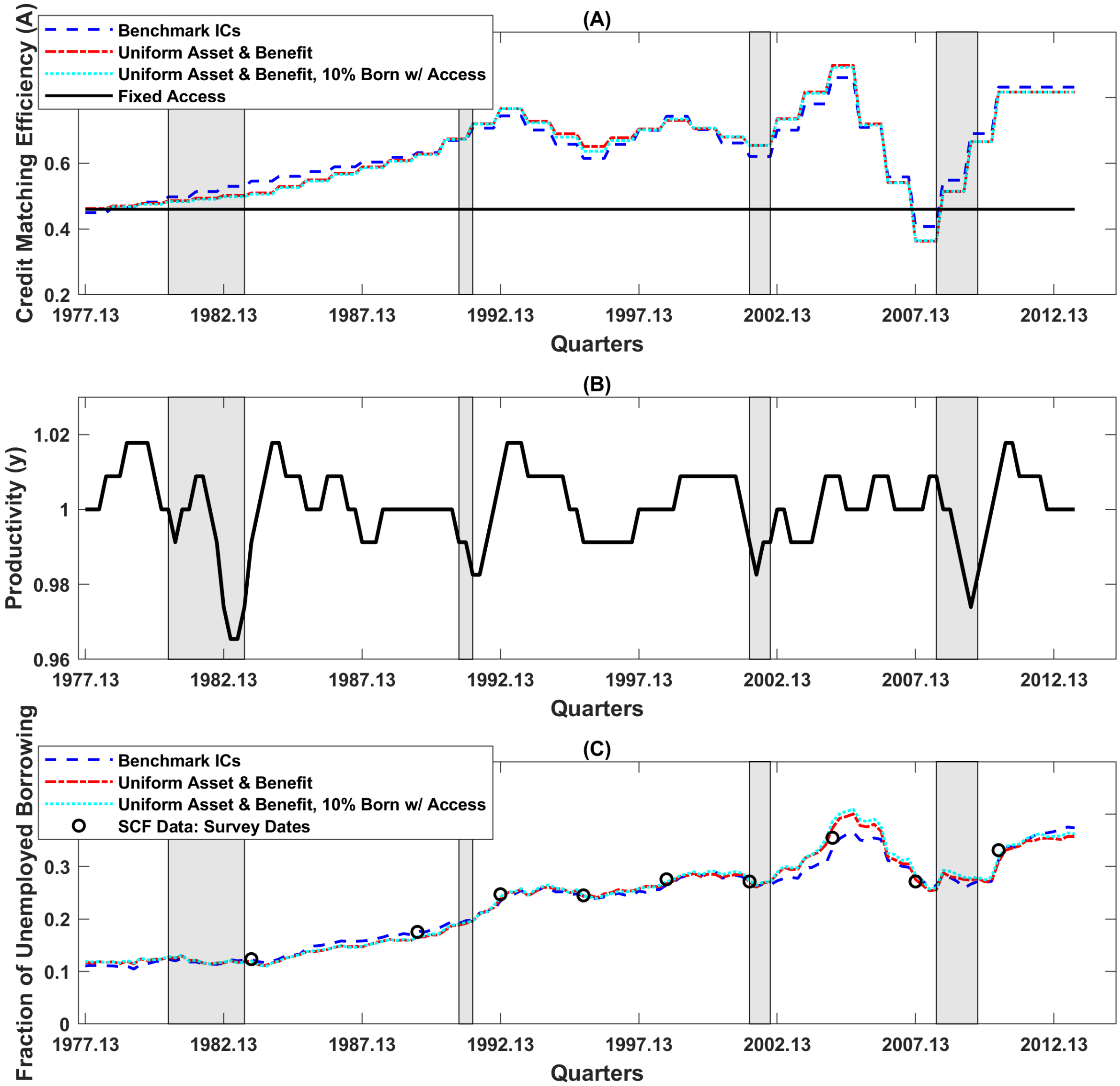


Figure 27: Transition Experiment: Employment Fluctuations

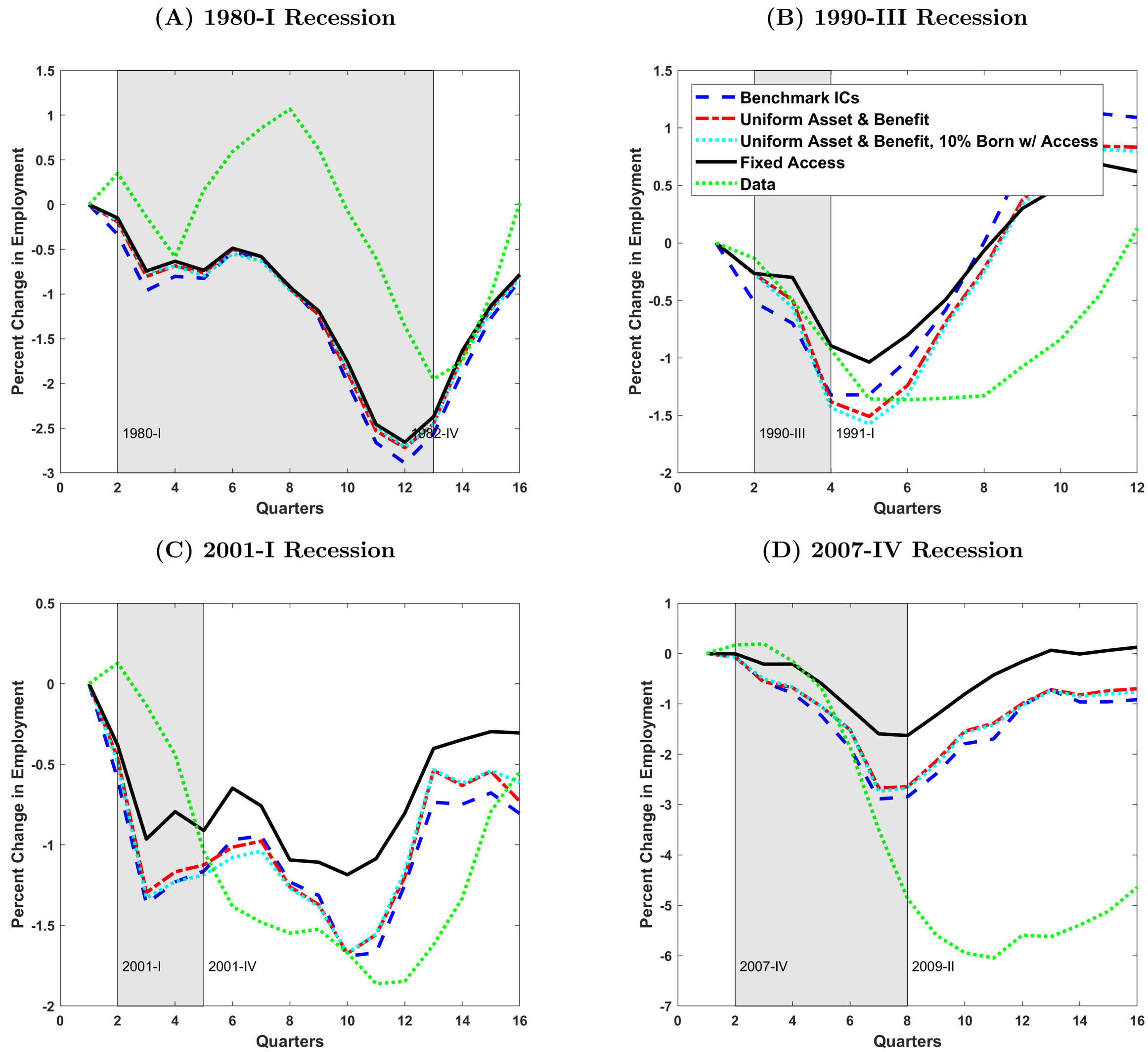


Table 19: Welfare gains along transition path, initial 1977-1982 cohorts

	Benchmark	Uniform Assets and Benefits	Uniform Assets and Benefits, 10% Born with Access
Welfare gain of newborns of moving from fixed 1970s credit access to expanding 2010 credit access (relative to benchmark)	1.00	0.93	0.88

P Credit Volatility in the 1980s

This section assesses the role of credit volatility in the 1980s for the model's employment predictions. The result shown below is that a 150% reduction in credit access in the 1980s has very little impact on the economy because there are simply so few borrowers. Since most households are not expecting to use credit in the 1980s, the fraction of non-borrowing individuals who change job search behavior in response to extremely volatile credit shocks is also small. The net effect is very similar employment dynamics in the 1980s even with large percentage deviations in matching efficiency.

There are no good proxies, to my knowledge, for credit match efficiency in the 1980s. I therefore turn to log deviations of the Senior Loan Officer Opinion Survey (SLOOS) to inform credit dynamics prior to 1989 (when the SCF was only conducted every 6 years). To map the SLOOS to the model, I must take a stance on what 'willingness to lend' means in the model. I compute log deviations of the time series, plus a constant to avoid negative values, $S_t = log(SLOOSWillingness_t + 100)$. While the choice of constant is arbitrarily set to 100, the chosen constant produces enormous volatility of credit in the 1980s; larger values of the constant imply dampened responses, and the results shown below persist. Figure 28 plots the log deviations of the transformed SLOOS, with the value -1.5 corresponding to a 150% negative deviation in willingness to lend. Let $\hat{S}_t$ denote deviations from trend. I use the value of A_{1977} and compute its value going forward as $A_{SLOOS,t} = max\{A_{1977}(1 + \hat{S}_t - \hat{S}_{1977}), .01\}$, where the max operator ensures that the matching efficiency cannot reach negative values. I then feed in $A_{SLOOS,t}$, and compute the employment response.

Figure 29 uses deviations of the senior loan officer opinion survey from trend ($A_{SLOOS,t}$) to inform the matching efficiency in the 1980s recession. Panel (A) plots the path of credit, and Panel (B) plots the path of employment. The employment fluctuations in the 1980s are mostly unaffected by the large swings in $A_{SLOOS,t}$. There are two main reasons for this result: (i) the stock of borrowers is roughly half that of the 2000s, thus relatively few borrowers face rollover risk, and (ii) the flow into borrowing is extremely small, and therefore the chance of obtaining credit is already low so additional downward fluctuations in credit matching efficiency have a muted impact on employment and saving decisions. Since most households are not expecting to use credit in the 1980s, the fraction of non-borrowing individuals who change job search behavior is also small. The net effect is very similar employment dynamics in the 1980s even with large percentage deviations in matching efficiency.

Figure 28: Deviations from trend, $S_t = log(SLOOSWillingness_t + 100)$

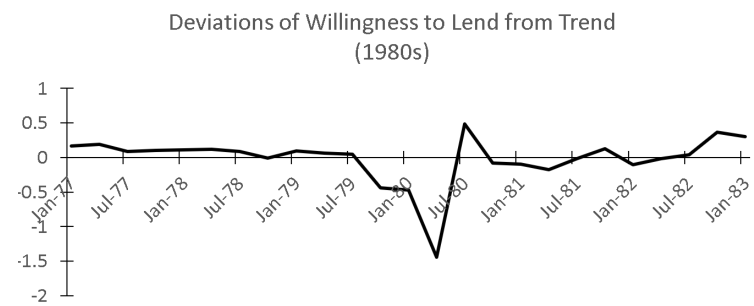
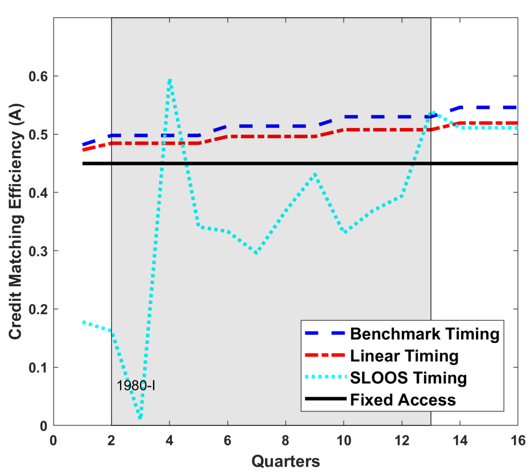


Figure 29: Transition Experiment: Employment Fluctuations

(A) 1980-I Recession Matching Eff.



(B) 1980-I Recession Employment