How Credit Constraints Impact Job Finding Rates, Sorting & Aggregate Output*

Kyle Herkenhoff Gordon Phillips Ethan Cohen-Cole

January 20, 2019

Abstract

How do consumer credit markets affect the allocation of workers to firms? To answer this question, we integrate risk aversion and borrowing into a model with worker and firm heterogeneity. We use the model to estimate the impact of credit limits on job search behavior, and then we validate our model predictions using a new panel dataset linking consumer credit to individual job outcomes. We then assess the effects of credit expansion between 1964 and 2004 on sorting and welfare. Credit expansions let low human capital workers, who are typically constrained, find more capital intensive jobs. Consequently, sorting declines ('bad' workers get 'good' jobs). However, output, productivity and welfare improve.

Keywords: credit access, job search, sorting

JEL Codes: D14, E21, E24, J64

*Herkenhoff: University of Minnesota. Phillips: Dartmouth, University of Maryland, & NBER. Cohen-Cole: Vega Economics. We are grateful for comments from numerous seminar participants at Bonn, Central Bank of Chile, Census, CESifo, Columbia, ES-Bocconi, FGV, Harvard, Iowa, Johns Hopkins, Michigan, Miami, Minneapolis Fed, NBER SI-Macro Perspectives, NBER-Corporate Finance, Northwestern, Notre Dame, NYU, MIT, Philadelphia Fed, Queens, Richmond Fed, Rochester, SAM, SED, SOLE/MEA, Toronto, USC, and Virginia. We thank Brian Littenberg and the Census for their hospitality and ongoing support. We thank Ming Xu for excellent research assistance. Herkenhoff and Phillips thank the National Science Foundation (Award No. 1824422) and the Washington Center for Equitable Growth for funding. Cohen-Cole and Phillips thank the NSF (Award No. 0965328) for funding. Any opinions and conclusions expressed herein are those of the author(s) and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed. This research uses data from the Census Bureau's Longitudinal Employer Household Dynamics Program, which was partially supported by the following National Science Foundation Grants SES-9978093, SES-0339191 and ITR-0427889; National Institute on Aging Grant AG018854; and grants from the Alfred P. Sloan Foundation.

As the technology to screen, issue, and monitor credit products has improved over the last 5 decades, access to credit by low-income and unemployed individuals has increased from 13% in 1977 to 45% in 2010 (e.g. Herkenhoff [2013], Livshits, MacGee, and Tertilt [2016], and Drozd and Serrano-Padial [2017]). The average job loser can replace 29% of their prior annual income using revolving credit and over 50% using all types of credit, making consumer credit a potentially important private source of self-insurance. While the impact of public safety-net programs on labor outcomes is well explored (*inter alia* Katz and Meyer [1990], Ljungqvist and Sargent [1998], Acemoglu and Shimer [1998], Chetty [2008], Mitman and Rabinovich [2012], and Hagedorn, Karahan, Manovskii, and Mitman [2013]), little is known about the role that private markets, such as consumer credit, play in the search decisions of workers who lose their jobs, and even less is known about how this interaction affects the macroeconomy.[1] Unlike welfare or unemployment insurance, consumer credit must be repaid or defaulted upon; these dynamic costs of self-insuring with credit alter the set of jobs for which individuals will search, thus making credit an imperfect substitute for unemployment insurance. This paper provides the first attempt at measuring how access to credit markets affects the job finding rate and the types of jobs unemployed workers obtain, as well as measuring what our estimates imply for aggregate outcomes such as labor productivity and output.

Our theoretical contribution is to develop a general equilibrium labor sorting model with consumer credit, integrating models of two-sided heterogeneity (e.g. Shimer and Smith [2000]) with defaultable debt (e.g. Chatterjee, Corbae, Nakajima, and Ríos-Rull [2007]). We use the model to structurally estimate the impact of credit market development from 1964 to 2004 on job search behavior and the aggregate economy. Our empirical contribution is to test the model's predictions against micro data in which we link consumer credit access to job finding rates, re-employment earnings, and firm characteristics.

To study the way credit markets affect the allocation of workers to firms, we relax the standard assumption of risk-neutrality in labor sorting models (e.g. Shimer and Smith [2000]). In our model, heterogeneous credit-constrained workers accumulate human capital while working. When unemployed, they direct their search, as in Menzio and Shi [2010,

[1] The nascent but growing theoretic literature that links credit and search decisions has focused on two mechanisms, the self-insurance role of credit (e.g. Athreya and Simpson [2006], Herkenhoff [2013], Athreya et al. [2014]) and labor demand effects of credit (e.g. Bethune et al. [2013], Donaldson et al. [2014]). The equally sparse empirical literature on unemployment and borrowing is limited due to data constraints and finds mixed results (Hurst and Stafford [2004], Sullivan [2008], Bethune [2015] among others) but recent inroads are being made with new account level data (Baker and Yannelis [2015], Gelman, Kariv, Shapiro, Silverman, and Tadelis [2015], Ganong and Noel [2015], Braxton, Herkenhoff, and Phillips [2018] among others). These papers do not study the affect of credit access on job search.

2011], for jobs among heterogeneous firms.[2] Firms differ with respect to capital and produce output by combining the human capital of workers with their own physical capital (for simplicity we refer to firm capital as physical capital, but this may also be thought of as intellectual capital). We allow firms to endogenously choose their level of capital. We assume supermodularity, meaning that firms with greater amounts of physical capital produce more with workers who have greater amounts of human capital. We therefore measure sorting in the model as the raw correlation coefficient between worker human capital and firm physical capital.[3] The ability of unemployed households to save or borrow, and thus self-insure against income loss, affects which worker matches with which firm and therefore determines the paths of output and labor productivity.

We estimate the model and then compute how credit limits affect non-employment durations and re-employment earnings as well as the types of jobs workers obtain. In terms of firm characteristics, we primarily focus on firm productivity proxied by the firm's total pay per employee, henceforth *wage-per-worker*.[4] We find an elasticity of non-employment duration with respect to unused credit of .15. This implies that if an agent can borrow 10% more of their prior annual earnings, they take .17 weeks longer to find a job. We define the earnings replacement rate to be the ratio of annual labor earnings one year after layoff to one year before layoff. We estimate an elasticity of the earnings replacement rate with respect to unused credit, among those who find a job, of .054. This implies that if an agent can borrow 10% more of their prior annual earnings, their earnings replacement rate is .54% greater. Lastly, we find that agents who have better access to credit markets are more likely to find jobs above the 50th and 75th percentiles of the firm wage-per-worker distribution. However, credit access has limited effects at the high-end of the wage-per-worker distribution: credit does not help agents find jobs above the 90th percentile of the firm wage-per-worker distribution.

We test the predictions of the model using a new employee level database that links credit to employment histories. We build a new panel dataset that links TransUnion credit

[2]Related theoretical work includes sorting models with frictions (inter alia Eeckhout and Kircher [2011], Hagedorn et al. [2012], Bagger and Lentz [2014], Bonhomme et al. [2014]), frictionless assignment models with borrowing constraints (Fernandez and Gali [1999], Legros and Newman [2002], and Strauss [2013]), and occupational choice under credit constraints (inter alia Neumuller [2014], and Dinlersoz et al. [2015]).

[3]This measure is highly correlated with the Spearman Rank correlation coefficient. We also report the Spearman Rank correlation coefficient for completeness.

[4]Wage-per-worker is the total firm payroll divided by the number of employees. We will also call this 'wage bill-per-worker' or the firm 'wage'.

reports to the Longitudinal Employer-Household Dynamics (LEHD) database. We show that individuals who have greater access to credit markets take longer to find jobs and, conditional on finding a job, they earn more and work at more productive firms as proxied by the firm's wage-per-worker. We show that these relationships hold in the raw data as well as when we use a worker's account age as an instrument, similar to Gross and Souleles [2001]. Our range of estimates imply that being able to replace 10% more of prior annual labor earnings with personal revolving credit allows displaced workers to take .33 to .53 weeks longer to find a job, and, among those who find a job, they have a .61% to 1.34% greater annual earnings replacement rate. Moreover, individuals with greater access to credit find jobs at more productive firms. Second, in the LEHD database, we establish that for a large fraction of displaced workers, earnings losses are purely transitory and so theory predicts that these individuals should borrow. We confirm this in our linked LEHD-TransUnion data by showing that close to 1/3 of the displaced workers in our sample borrow, and we also show that roughly 25% of workers who lose their jobs report borrowing to smooth consumption in the RAND American Life Panel.

Given the model's success at generating micro behavior consistent with the TransUnion-LEHD data, our final contribution is to aggregate across agents and use the model as a laboratory to examine how credit access affects labor sorting, productivity, and welfare along the transition path from 1964 to 2004, as credit markets developed. Relative to existing search models such as Herkenhoff [2013] and Bethune [2015], the allocation of workers to firms endogenously determines productivity, output and welfare. Our theory allows us to provide the first estimates, to our knowledge, of the way improvements in household access to capital markets have affected aggregate sorting and productivity. Our initial steady state is the 'no-credit' 1964 steady state (in 1964 BankAmericard and other precursors to VISA and Mastercard were at their inception or simply did not yet exist), and our final steady state is in 2004, which exhibits significant credit access. We find that as credit expands along the transition path, workers are able to sort into higher capital jobs, and firms invest in creating those jobs. As a result, welfare increases by 2.6% between the 1964 and 2004 steady state, output increases by .1% and labor productivity (output per worker) increases by .1%.

In terms of worker allocations, looser debt limits actually depress standard measures of sorting along the transition path. There are three forces driving this result: (i) when credit limits expand, low human capital workers become less credit constrained, allowing them to search for harder-to-find high-capital jobs, and (ii) firms invest more in capital intensive jobs, and (iii) high human capital workers are relatively wealthy and thus unaffected by the credit constraints, and thus they continue to find high-capital jobs. The end result is that with more generous credit limits, low human capital workers sort into high capital jobs, whereas high human capital workers' sorting patterns remain unchanged. Therefore standard measures of sorting decline (i.e. the economy moves closer to an allocation with low human capital workers being paired with high physical capital jobs), even though our production function is supermodular. This negative correlation between sorting and welfare, which is a reversal of the behavior of standard models in the literature under supermodular production functions (e.g. Becker [1973]), is due to risk aversion and firm investment. Other models such as Anderson and Smith [2010] and Herkenhoff et al. [2018] generate a similar reversal in models with linear utility and dynamic types. However, allowing for saving and investment is standard in most quantitative macroeconomic models. In this regard, the model we develop brings models of two-sided heterogeneity closer to quantitative macro models (e.g., Guerrieri and Lorenzoni [2011]).

Our findings have implications for the provision of public insurance. Both of our quantitative and empirical estimates suggest that at the micro level, \$1 of consumer credit is approximately half as potent as \$1 of unemployment insurance for non-employment duration and wage outcomes (see Nakajima [2012b] for a summary of the range of estimates in the literature). In other words, consumer credit has similar properties to public safety-net programs, when measured by labor market outcomes. Moreover, our findings suggest that consumer credit has a large impact on welfare, with relatively moderate aggregate side-effects on the employment rate. Whether or not these aggregate labor market effects of credit are larger or smaller than the aggregate effects of an unemployment insurance expansion is a point of contention as there is little consensus in the literature (e.g. Hagedorn et al. [2013] and Chodorow-Reich and Karabarbounis [2013] summarize both sides of the debate).

Relative to existing studies, our paper makes both theoretical and empirical contributions. Theoretically, we develop the first labor sorting model with consumer credit. We build on existing labor sorting models such as Marimon and Zilibotti [1999], Shimer and Smith [2000], Shi [2001], Shimer [2001], Barlevy [2002], Lise and Robin [2013], Eeckhout and Sepahsalari [2014], and Bagger and Lentz [2014] by generating interactions between heterogeneous credit histories and the allocation of workers to firms. We build on existing work that studies the aggregate implications of tighter debt limits, e.g. Guerrieri and Lorenzoni

[2011], in Bewley-Huggett-Aiyagari frameworks. We integrate productive heterogeneity of both workers and firms which allows us to study the way credit distorts worker allocations and thus aggregate productivity. We also build on the influential work of Barlevy [2002] and Lise and Robin [2013] who consider sorting over the business cycle with risk neutrality, and we complement the contemporaneous and innovative work by Eeckhout and Sepahsalari [2014] who characterize the impact of assets on sorting patterns. The main differences between Eeckhout and Sepahsalari [2014] and our paper are that (i) we allow for debt and (ii) workers have heterogeneous productivity. These two features allow credit markets to affect sorting.

Empirically, we build the first dataset to merge individual credit reports with administrative employment records and measure the impact of consumer credit access on job finding rates, re-employment earnings, and the types of jobs displaced workers take. Our findings complement the large empirical literature on employment effects of public programs, such as unemployment insurance (e.g. Chetty [2008], Hagedorn et al. [2013], and Chodorow-Reich and Karabarbounis [2013]), by measuring the degree of self-insurance provided by private credit markets. Our paper also complements recent efforts to measure sullying and cleaning effects over the business cycle using matched employer-employee data, e.g. Crane et al. [2017] for the U.S. and Nakamura et al. [2019] for Canada.

Our work also complements influential earlier work that integrates assets into labor search models by Lentz and Tranaes [2001], Krusell, Mukoyama, and Şahin [2010], Karahan and Rhee [2011], Nakajima [2012a], Lise [2012], Herkenhoff [2013], Chaumont and Shi [2017], Griffy [2017] and Ji [2018]. We depart from this existing class of models by allowing for sorting and credit. The two-sided heterogeneity generates a concept of 'the right worker for the right job.' Therefore this framework allows us to provide the first estimates of how consumer credit affects the allocation of workers to jobs. Moreover, our framework is tractable enough that it can be used by future researchers to study a variety of questions related to misallocation and credit access, including credit access among firms.

The paper proceeds as follows. Section 1 describes the environment. Section 2 details the model calibration strategy. Section 3 computes the model implied elasticities of labor market outcomes with respect to credit access. Section 4 tests the model in the TransUnion-LEHD panel. Section 5 summarizes the steady state findings. Section 6 computes the aggregate implications of expanding credit access between 1964 and 2004, and lastly, Section 7 concludes.

1 Model

In order to answer the question of how consumer credit constraints impact the allocation of workers to firms, we require three features. First, we require risk aversion and borrowing. Second, we must drop the neoclassical assumptions of a large-family with full intra-household insurance. We do this by incorporating shocks to idiosyncratic human capital. Third, we need some concept of 'good' and 'bad' jobs, which we generate by modeling idiosyncratic firm investment. To capture these features, we incorporate consumer credit, e.g. Chatterjee, Corbae, Nakajima, and Ríos-Rull [2007], into a general equilibrium labor sorting model, e.g. Shimer and Smith [2000]. By incorporating standard Bewley-Huggett-Aiyagari features into the sorting literature, we are bringing frameworks with two-sided heterogeneity closer to quantitative-macro models and allowing the growing sorting literature to address broader ranges of questions.

1.1 Households

Time is discrete and runs forever. There are three types of agents in this economy. A unit measure of risk averse finitely-lived households, a continuum of risk neutral entrepreneurs that run the endogenously chosen measure of operating firms, and a unit measure of risk neutral lenders.

As in Menzio et al. [2012], there are $T \geq 2$ overlapping generations of risk averse households that face both idiosyncratic and aggregate risk. The aggregate risk is important for our counterfactuals; it allows us to alter aggregate debt limits in good and bad times in order to study how credit impacts the allocation of workers to firms. Each household lives T periods deterministically and discounts the future at a constant rate $\beta \in (0, 1)$. Let t denote age and τ denote birth cohort. Every period households first participate in an asset market where they make asset accumulation, borrowing, and bankruptcy decisions. After the asset market closes, households enter the labor market where they direct their search for jobs. Let $c_{t,\tau+t}$ and $D_{t,\tau+t}$ respectively denote the consumption and default decisions of an age t agent at date $\tau + t$. Let χ denote the utility penalty of default. The objective of a household is to maximize the expected lifetime flow utility from non-durable consumption less any default penalties,

$$\mathbb{E}_\tau\left[\sum_{t=1}^{T}\beta^t u(c_{t,\tau+t}) - \chi D_{t,\tau+t}\right]$$

From this point on, we focus on a recursive representation. Agents' continuation values still depend on their age t.

Households are heterogeneous along several dimensions. Households are either employed or unemployed, where employed value functions are denoted W and unemployed value functions are denoted U. Let $e \in \{W, U\}$ denote employment status. Let $b \in \mathcal{B} \equiv [\underline{b}, \bar{b}] \subset \mathbb{R}$ denote the net asset position of the household, where $b > 0$ denotes that the household is saving, and $b < 0$ indicates that the household is borrowing. Let $h \in \mathcal{H} \equiv [\underline{h}, \bar{h}] \subset \mathbb{R}_+$ denote the human capital of the worker. Workers also differ with respect to the capital $k \in \mathcal{K} \equiv [\underline{k}, \bar{k}] \subset \mathbb{R}_+$ of the firm with which they are matched, and with respect to their credit access status $a \in \{G, B\}$ where $a = G$ denotes good standing, and $a = B$ denotes bad standing. Let $\mathbb{N}_T = \{1, 2, \ldots, T\}$ denote the set of ages.

The aggregate state of the economy includes two components: (i) the borrowing limit $\underline{b} \subset \mathbb{R}_-$, and (ii) the distribution of agents across states $\mu : \big\{W, U\big\} \times \big\{G, B\big\} \times \mathcal{B} \times \mathcal{H} \times \mathcal{K} \times \mathbb{N}_T \to [0, 1]$. Let $\Omega = (\underline{b}, \mu) \in \mathbb{R}_- \times M$ summarize the aggregate state of the economy where M is the set of distributions over the state of the economy. Let $\mu' = \Phi(\Omega, \underline{b}')$ be the law of motion for the distribution, and the borrowing limit follows a Markov process. It is important to note that even though there is an exogenously imposed borrowing limit $\underline{b}$, debt will be individually priced as in Chatterjee et al. [2007], and many workers will have 'effective borrowing limits' where the bond price reaches zero well before $\underline{b}$.

Let $M(u, v)$ denote the matching function, and define the labor market tightness to be the ratio of vacancies to unemployment. Since there is directed search, there will be a separate labor market tightness for each submarket. In each submarket, there is a job finding rate for households, $p(\cdot)$, that is a function of the labor market tightness $\theta_t(h, k; \Omega)$, such that $p(\theta_t(h, k; \Omega)) = \frac{M(u_t(h,k;\Omega), v_t(h,k;\Omega))}{u_t(h,k;\Omega)}$. On the other side of the market, the hiring rate for firms $p_f(\cdot)$ is also a function of the labor market tightness and is given by $p_f(\theta_t(h, k; \Omega)) = \frac{M(u_t(h,k;\Omega), v_t(h,k;\Omega))}{v_t(h,k;\Omega)}$. When households enter the labor market, they choose which capital intensity submarket, k, to search in.[5] Once matched with a firm, a worker produces $f(h, k) : \mathcal{H} \times \mathcal{K} \to \mathbb{R}_+$ and keeps a share α of this production.

[5]This is the only dimension along which households optimize their search since their own human capital h and age t are predetermined states.

At the beginning of every period, households receive expense shocks and then make default decisions. The only trigger for default in the baseline model is job loss, but only about 1/3 of defaults are job loss related (Herkenhoff [2013]). To disconnect employment status and default decisions, with probability p_x an agent's net assets are reduced by x. These expense shocks are designed to capture unmodeled out-of-pocket expenditures associated with divorce, health, or spousal unemployment (e.g. Livshits et al. [2007]). In the present formulation, the default punishment is similar to Ch. 7 bankruptcy in the United States. A household in bankruptcy has a value function scripted by B and cannot save or borrow. With probability λ, a previously bankrupt agent regains access to asset markets. If a household is in good standing (i.e. they have regained access to asset markets), its value function is scripted with a G, and the household can freely save and borrow. We denote the price of a loan of size b' by $q_{e,t}(b', h, k; \Omega)$, expressed as a discount on the face value, which is a function of an agent's employment status $e \in \{W, U\}$, age, human capital, and firm capital as well as the aggregate state. We discuss the bond price in more detail in Section 1.2.

Lastly, to suppress an additional state variable, we allow unemployment benefits $z(k)$ to be a function of the worker's prior wage, but only through its dependence on k.[6] The problem of an age t unemployed household in good standing is given below:

$$\begin{aligned}
U_t^G(b, h, k; \Omega) = \max_{b' \geq \underline{b}} u(c) + \beta \mathbb{E}\Big[\max_{\tilde{k}} \, & p(\theta_{t+1}(h', \tilde{k}; \Omega'))[(1-p_x)W_{t+1}(b', h', \tilde{k}; \Omega') \\
& \qquad + p_x W_{t+1}(b' - x, h', \tilde{k}; \Omega')] \\
& + \big(1 - p(\theta_{t+1}(h', \tilde{k}; \Omega'))\big)[(1-p_x)U_{t+1}(b', h', k; \Omega') \\
& \qquad + p_x U_{t+1}(b' - x, h', k; \Omega')]\Big], \quad t \leq T
\end{aligned}$$

$$U_{T+1}^G(b, h, k; \Omega) = 0$$

Such that

$$c + q_{U,t}(b', h, k; \Omega)b' \leq z(k) + b$$

We assume that human capital abides by the following law of motion (note that the process is indexed by employment status U):

$$h' = H(h, U)$$

[6] Shocks to k during unemployment could proxy expiration of unemployment benefits.

And the shock processes and aggregate law of motion are taken as given:

$$\underline{b}' \sim F(\underline{b}' \mid \underline{b}), \quad \mu' = \Phi(\Omega, \underline{b}'), \quad \Omega' = (\underline{b}', \mu') \tag{1}$$

For households who default, they are excluded from both saving and borrowing. Following Livshits et al. [2007], if a household has an expense shock while bankrupt, the debt is discharged and the household incurs the utility penalty of default again. The continuation value of a bankrupt household is given below:

$$\begin{aligned}
U_t^B(0,h,k;\Omega) = u(c) + \lambda\beta\mathbb{E}\Big[\max_{\tilde{k}} p(\theta_{t+1}(h',\tilde{k};\Omega'))[(1-p_x)W_{t+1}(0,h',\tilde{k};\Omega') \\
+ p_x W_{t+1}(-x,h',\tilde{k};\Omega')] \\
+ \big(1 - p(\theta_{t+1}(h',\tilde{k};\Omega'))\big)[(1-p_x)U_{t+1}(0,h',k;\Omega') \\
+ p_x U_{t+1}(-x,h',k;\Omega')]\Big] \\
+ (1-\lambda)\beta\mathbb{E}\Big[\max_{\tilde{k}} p(\theta_{t+1}(h',\tilde{k};\Omega'))[(1-p_x)W_{t+1}^B(0,h',\tilde{k};\Omega') \\
+ p_x(W_{t+1}^B(0,h',\tilde{k};\Omega') - \chi)] \\
+ \big(1 - p(\theta_{t+1}(h',\tilde{k};\Omega'))\big)[(1-p_x)U_{t+1}^B(0,h',k;\Omega') \\
+ p_x(U_{t+1}^B(0,h',k;\Omega') - \chi)]\Big], \quad t \le T
\end{aligned}$$

$$U_{T+1}^B(b,h,k;\Omega) = 0$$

Such that

$$c \le z(k)$$

and the law of motion for human capital and aggregates are taken as given. For households in good standing, at the start of every period, they must make a default decision:

$$U_t(b,h,k;\Omega) = \max\Big\{U_t^G(b,h,k;\Omega), U_t^B(0,h,k;\Omega) - \chi\Big\}$$

Let $D_{U,t}(b,h,k;\Omega)$ denote the unemployed household's default decision. Due to the finite life cycle, a utility penalty of default, χ, is necessary to support credit in equilibrium.

A similar problem holds for the employed. The value functions are denoted with a W for employed households, and at the end of every period, employed households face layoff risk δ. If they are laid off, since the period we will ultimately use is 1 quarter, we must allow the workers to search immediately for a new job.[7] We relegate the employed value functions to Online Appendix C.

1.2 Lenders

There is a continuum of potential lenders who are risk neutral and can obtain funds, without constraint, at the risk free rate r_f. Lenders may lend to households or firms. Recall $e \in \{W, U\}$ denotes employment status. The price of debt for households must therefore satisfy the inequality below:

$$q_{e,t}(b', h, k; \Omega) \leq \frac{\mathbb{E}\Big[1 - [(1-p_x)D_{e',t+1}(b', h', k'; \Omega') + p_x D_{e',t+1}(b'-x, h', k'; \Omega')]\Big]}{1 + r_f} \tag{2}$$

Under free entry, the price of debt must yield exactly the risk free rate, r_f, and this equation holds with equality.

The price of debt for firms follows a similar form. For the sake of brevity, and the necessity for additional notation, this bond price will be shown below in the firm section. Since lenders earn zero profit for each contract in equilibrium, lenders are indifferent between lending to a firm or a household.

1.3 Firms

There is a continuum of risk neutral entrepreneurs that operate constant returns to scale production functions. The entrepreneurs invest in capital $k \in \mathcal{K} \subset \mathbb{R}_+$ and post vacancies to attract workers in the frictional labor market. We assume capital is denominated in units of the final consumption good.

When deciding whether or not to post a vacancy, the firm solves the following problem. It chooses capital $k \in \mathcal{K}$ and what types of workers, indexed by human capital and age $(h, t) \in \mathcal{H} \times \mathbb{N}_T$, to hire. Entering entrepreneurs are subject to a financing constraint.[8] New entrants must borrow the money, $b_f < 0$, to finance the initial capital investment. In the event that the worker is hired, the firm commits to repay b_f. In the event that no worker

[7] This allows the model to match labor flows in the data.

[8] Firms are not subject to the aggregate borrowing constraint, although this is straightforward to relax.

can be found, the firm defaults.

Let $J_t(h,k;\Omega)$ be the profit stream of a firm that has k units of physical capital and is matched with an age t worker with human capital h. Let $q_{f,t}(b,k,h;\Omega)$ denote the bond price faced by the firm. Then the problem a firm solves when attempting to recruit a worker is given below (recall b is negative if borrowing),

$$\kappa \leq \max_{k,h,t} p_f(\theta_t(h,k;\Omega))[J_t(h,k;\Omega)+b_f] + (1-p_f(\theta_t(h,k;\Omega)))\cdot 0 \tag{3}$$

such that

$$-k \geq q_{f,t}(b_f,k,h;\Omega)b_f \tag{4}$$

With free entry in the lending market, the price of debt must be given by (note that k is implicitly related to b_f in the equation above),

$$q_{f,t}(b_f,k,h;\Omega) = \frac{p_f(\theta_t(h,k;\Omega))}{1+r_f} \tag{5}$$

Using the fact that Equation (3) holds with equality under free entry and that Equation (4) must also hold with equality, the market tightness in each submarket that is entered with positive probability and is given by,

$$\theta_t(h,k;\Omega) = p_f^{-1}\left(\frac{\kappa+(1+r_f)k}{J_t(h,k;\Omega)}\right) \tag{6}$$

For tractability, we assume that workers and firms split output according to a constant piece-rate α. We assume the firm keeps a share $1-\alpha$ of its production, and workers receive the remaining share α of production. The value function for the firm is given by,

$$J_t(h,k;\Omega) = (1-\alpha)f(h,k) + \beta\mathbb{E}\big[(1-\delta)J_{t+1}(h',k;\Omega')\big], \quad \forall t \leq T$$

$$J_{T+1}(h,k;\Omega) = 0$$

Three assumptions are implicit in this value function, (i) zero liquidation value of capital, (ii) static capital, and (iii) no on-the-job search. In Online Appendix E we allow capital to have a nonzero liquidation value. In Online Appendix E we also allow firms to dynamically invest in capital. We do not explicitly model on-the-job search due to tractability issues (it would require firms knowing workers' asset policy functions – see Herkenhoff [2013] for a model with one sided heterogeneity, credit, and OJS), but by allowing firms to invest in capital, we mitigate workers' incentives to switch jobs. In fact, with frictionless capital adjustment, firms set capital to the surplus maximizing value and workers have no incentive to leave the firm.

1.4 Equilibrium: Definition and Existence

Let $\mathbf{x}$ summarize the state vector of a household. An equilibrium in this economy is a set of household policy functions for saving and borrowing $(\{b'_{e,t}(\mathbf{x})\}_{t=1}^{T})$, bankruptcy $(\{D_{e,t}(\mathbf{x})\}_{t=1}^{T})$, a capital search choice $\{k_t(\mathbf{x})\}_{t=1}^{T}$, a debt price $(\{q_{e,t}(\mathbf{x})\}_{t=1}^{T})$ for both the employed $(e = W)$ and unemployed $(e = U)$, a debt price for firms $(\{q_{f,t}(\mathbf{x})\}_{t=1}^{T})$, a market tightness function $\theta_t(h, k; \Omega)$, a process for aggregate shocks $(\underline{b})$, and an aggregate law of motion $\Phi(\Omega, \underline{b}')$ such that

i. Given the law of motion for aggregates, the bond price, and market tightness function, households' decision rules are optimal.

ii. Given the law of motion for aggregates and the bond price, the free entry condition in the labor market (6) holds.

iii. Given household policy functions, the labor market tightness function, and the law of motion for aggregates, the free entry conditions for lenders making loans to households (2) and firms (5) both hold.

iv. The aggregate law of motion is consistent with household policy functions.

Even though we have two sided-heterogeneity, we are able to use the tools developed in Shi [2009] and Menzio and Shi [2011] to solve for a Block Recursive Equilibrium in which policy functions and prices do not depend on the aggregate distribution μ (even though it fluctuates over time and can be recovered by simulation). However, policy functions still depend on the borrowing limit, $\underline{b}$.

In Online Appendix D, we prove that a Block Recursive Equilibrium exists in this economy, and thus to solve the model economy, we only need to solve the first 'block' of the equilibrium i.-iii. ignoring iv., and then we can simulate to recover the dynamics of μ.

2 Calibration

The parameters are calibrated so that the model's steady state is consistent with 2004 averages. Steady state means that the aggregate borrowing limit ($\underline{b}$) is constant.[9] Due to the computationally demanding nature of the model, we take as many standard parameters from the literature as possible, and then we jointly estimate the remaining non-standard parameters to match key moments.

The period is one quarter. We set the annualized risk free rate to 4%. We use constant relative risk aversion preferences $u(c) = \frac{c^{1-\sigma}-1}{1-\sigma}$, and we set the risk aversion parameter to $\sigma = 2$. The life span is set to $T = 120$ quarters (30 years), and newly born agents are born unemployed, with zero assets, in good credit standing, and with the lowest human capital. The household share of production, α, is set to $\frac{2}{3}$, and the production function is Cobb-Douglas, $f(h,k) = h^a k^{(1-a)}$ with parameter $a = \frac{2}{3}$. The human capital processes, $H(h,U)$ and $H(h,W)$, are governed by two parameters $p_{-\Delta}$ and $p_{+\Delta}$.

$$H(h,U) = h' = \begin{cases} h - \Delta & \text{w/ pr. } p_{-\Delta} \text{ if unemployed} \\ h & \text{w/ pr. } 1 - p_{-\Delta} \text{ if unemployed} \end{cases}$$

$$H(h,W) = h' = \begin{cases} h + \Delta & \text{w/ pr. } p_{+\Delta} \text{ if employed} \\ h & \text{w/ pr. } 1 - p_{+\Delta} \text{ if employed} \end{cases}$$

In the calibration below, the grid for human capital, $h \in [.5, .6, .7, .8, .9, 1]$, as well as the step size, $\Delta = .1$, between grid points are taken as given. We use lifecycle wage growth and long-term consumption losses following layoff to estimate $p_{+\Delta}$ and $p_{-\Delta}$, as detailed below.

For the labor market matching function, we 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 [2012]. Following Silva and Toledo [2009], we set the vacancy posting cost to κ=.036.

[9] A large number of agents (N=80,000) is then simulated for a large number of periods (T=280 quarters, discarding the first 100 quarters). Averages are reported over the remaining 180 quarters across $R = 5$ repetitions. Online Appendix F describes the solution algorithm in detail.

In the credit market, the bankruptcy re-access parameter is set to $\lambda = .036$. This parameter generates the statutory 7 year exclusion period following bankruptcy. Following Herkenhoff [2013] who uses the PSID to infer the probability of an expense shock[10], we set the probability of an expense shock to 2.2% per quarter. The severity of the expense shock, x, is estimated to be 28% of 1 quarter's wage. Since the wage is endogenous, we must jointly calibrate x.

The eight unassigned parameters including the utility penalty χ, the layoff rate δ, the human capital appreciation rate $p_{+\Delta}$, the human capital depreciation rate $p_{-\Delta}$, the transfer to the unemployed z, the expense shock x, the discount factor β, and the borrowing limit $\underline{b}$ are jointly estimated to match eight moments, respectively: the bankruptcy rate, the unemployment rate, the life cycle wage profile, the 2-year consumption loss upon layoff, the 1-year consumption loss upon layoff, the change in debt to income ratio conditional on receiving an expense shock, the fraction of unemployed revolving unsecured debt balances, and the median unsecured credit utilization rate.

The default penalty $\chi = .088$ is set to target the quarterly bankruptcy rate per capita of .2% in 2004 (American Bankruptcy Institute, bankruptcies per capita). The layoff rate $\delta = .071$ is set to target a 5.5% unemployment rate in 2004 (Bureau of Labor Studies).

The human capital appreciation rate $p_{+\Delta} = .055$ is set to target the ratio between the average wages of 24 to 26 and 52 to 54 year olds of 1.509 (Current Population Survey, pooled 2000-2016 data).[11] The human capital depreciation rate $p_{-\Delta} = .147$ is set to target the 2-year consumption loss upon layoff (Saporta-Eksten [2013]). Our estimate for the human capital depreciation rate implies that once every year-and-a-half, unemployed agents in the model expect to fall one rung on the human capital ladder. This generates 10% to 20% earnings losses per full year of unemployment, depending on the initial human capital.

The transfer to the unemployed is set to a constant $z(k) = .148 \ \forall k$ in order to target the 1-year consumption loss upon layoff (Browning and Crossley [2001]). This value of z yields an average UI replacement rate of approximately 30% for the lowest human capital workers, but implies significantly lower UI replacement rates of 15% for higher human capital workers, which is closer to Chodorow-Reich and Karabarbounis [2013]'s findings.

[10] The expense shocks include (1) spousal unemployment (2) recent divorce, (3) disability, or a (4) medical expense shock equal to 5% or more of annual income.

[11] Among prime aged individuals, 24 to 26 year olds earn the lowest observed wage and 52 to 54 year olds earn the highest observed wage.

The severity of the expense shock $x = .175$ is estimated to match the 28% increase in debt to income ratios observed after receiving an expense shock (Herkenhoff [2013]). The household discount factor $\beta = .971$, which implies a discount rate of 12.3% per annum, is calibrated to match the fact that 34.8% of unemployed households are revolving credit balances in 2004 (Survey of Consumer Finances). Lastly, we set the borrowing limit $\underline{b} = -.491$ in order to match the median unused unsecured credit utilization rate in 2004 (Survey of Consumer Finances, measured as credit card limit minus balance, divided by credit limit).

Table 1 summarizes the parameters, and Table 2 summarizes the model's fit relative to the targeted moments. The key targeted moments that control the sensitivity of agents to credit are the consumption drop upon layoff, which is most directly controlled by z (UI), and the long term consumption loss, which is controlled by $p_{-\Delta}$ (the human capital depreciation rate). The model matches those targeted moments quite well.

Table 1: Summary of Model Parameters.

	Non-estimated	
Variable	Value	Description
r_f	4%	Annualized Risk Free Rate
κ	0.036	Firm Entry Cost
ζ	1.6	Matching Function Elasticity
σ	2	Risk Aversion
α	0.66	Worker Share of Production
a	0.66	Cobb-Douglas Labor Share
λ	0.036	Bankruptcy Re-Access
p_x	0.022	Expense Shock Probability

	Jointly-Estimated	
Variable	Value	Description
χ	0.088	Bankruptcy Utility Penalty
δ	0.071	Quarterly Layoff Rate
$p_{+\Delta}$	0.055	Appreciation Rate of Human Cap.
$p_{-\Delta}$	0.147	Depreciation Rate of Human Cap.
z	0.148	Transfer to the Unemployed
x	0.175	Expense Shock Severity
β	0.971	Discount Factor
$\underline{b}$	-0.491	Aggregate Debt Limit

Table 2: Model Calibration, 2004 Steady State

	Model	**Target**	**Variable**	**Value**	**Source**
Bankruptcy Rate	0.002	0.002	χ	0.088	ABI 2004
Unemployment Tate	0.055	0.055	δ	0.071	BLS 2004
Lifecycle W(52-54)/W(24-26)	1.509	1.500	$p_{+\Delta}$	0.055	CPS 2000-2016
Cons Drop 2 Yrs After Layoff	0.944	0.920	$p_{-\Delta}$	0.147	Saporta-Eksten 2013
Cons Drop 1 Yr After Layoff	0.878	0.840	z	0.148	Browning Crossley 2001
Expense Shock to Income	0.240	0.280	x	0.175	Herkenhoff 2013
Fraction Unempl. Borrowing	0.348	0.355	β	0.971	SCF 2004
Median Credit Card Utilization	0.275	0.267	$\underline{b}$	-0.491	SCF 2004

Notes. 2004 steady state computed with using N=80,000 agents simulated for T=280 quarters, discarding the first 100 quarters. Averages are reported over the remaining 180 quarters across $R = 5$ *repetitions. Online Appendix F describes the solution algorithm in detail.*

3 Calculating Model Elasticities

In this section, we use the model generated policy functions to estimate the impact of changes in credit limits on unemployment duration, replacement earnings as well as proxies for firm productivity.

Since the debt pricing schedule does not have an explicit credit limit, we define the credit limit to be the maximum of either the level of debt where the bond interest rate becomes infinite (we denote the corresponding level of debt $b_\infty(\cdot)$) or the exogenous debt limit $\underline{b}$. Therefore, we define the credit limit for an agent with state vector $\mathbf{x}$ as $L(\mathbf{x}) = \min\{-b_\infty(\mathbf{x}), -\underline{b}\}$. Let the aggregate debt limit take two values $\underline{b} \in \{\underline{b}_H, \underline{b}_L\}$. We isolate newly laid off agents (let I_δ denote this set of agents, and let N_δ denote its cardinality), and then we compute each agent's optimal search decision under loose ($\underline{b} = \underline{b}_L$) and tight exogenous debt limits ($\underline{b} = \underline{b}_H > \underline{b}_L$), ceteris paribus. For only this portion of the paper, agents believe the transition matrix between aggregate borrowing limit states is the identity matrix,

$$P_{\underline{b}} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

This transition matrix implies that conditional on being in a given aggregate state, agents believe that the state will persist. Thus, the changes in debt limits are unanticipated and perceived to be permanent. We define the two aggregate borrowing limits to be $\underline{b}_H$=-.1 (tight) and $\underline{b}_L$=-.491 (loose).[12] We calculate the duration and replacement earnings elasticities using 80,000 agents simulated for 280 periods (discarding the first 100 periods).

What makes this calculation feasible is that the policy function of each agent is contingent on the realization of Ω which includes the exogenous debt limit $\underline{b}$. At each decision node, the policy function includes the search decision of the agent with loose and tight debt limits. What makes this experimental design valid is the block recursive nature of the model; the menu of job choices faced by the household is not a function of $\underline{b}$. This allows us to determine the impact of changing debt limits, holding all else constant, including the set of jobs from which households can choose.[13]

We compute the change in unemployment duration, weighted by the distribution of job losers after moving from an exogenous limit $\underline{b} = \underline{b}_L$ to $\underline{b} = \underline{b}_H$ as follows,[14]

$$\Delta Dur_t = \sum_{i \in I_\delta} \frac{Dur(b_{i,t}, h_{i,t}, k_{i,t}; \underline{b}_H) - Dur(b_{i,t}, h_{i,t}, k_{i,t}; \underline{b}_L)}{N_\delta}$$

Define $\frac{\Delta(L_t+b_t)}{Y_{t-1}}$ as the change in the unused credit to income ratio that the agent faces if the exogenous debt limit is tightened.[15] The model implied duration elasticity is therefore given by,

$$\epsilon_{dur} = \frac{\Delta Dur_t}{\left(\frac{\Delta(L_t+b_t)}{Y_{t-1}}\right)} = 0.1496$$

In other words, if an agent's unused credit to income ratio increased by 10%, then agents would take .17 weeks (=.1496*.1*12) longer to find a job.

Next, we calculate the elasticity of replacement earnings with respect to credit, including households who do not find a job and thus have a replacement rate of zero. Let $e_i \in \{W, U\}$ denote employment status and let $\mathbb{I}$ be the indicator function. Then define $R_t(\underline{b})$ as the

[12] The elasticities are largely insensitive to the choice of $\underline{b}_H$.

[13] This is formally shown in the existence proof. $J_T(h,k) = f(h,k)$ does not depend on $\underline{b}$, and working back, neither does $J_t(h,k)$ for arbitrary t. Therefore, using the free entry condition, $\theta_t(h,k) = p_f^{-1}\big([\kappa + (1+r_f)k]/J_t(h,k)\big)$. So the market tightness does not depend on $\underline{b}$, thus the set of jobs (open submarkets) that agents may choose from does not depend on $\underline{b}$.

[14] The expected duration is based on the 1-quarter ahead implied job finding rate, based on the search policy function. In quarters, for large M, the expected duration is given by, $Dur(b_t, h_t, k_t; \underline{b}_H) = \sum_{m=1}^{M} mp(\theta_t(h_t, k^*(b_t, h_t, k_t; \underline{b}_H); \underline{b}_H)) * (1 - p(\theta_t(h_t, k^*(b_t, h_t, k_t; \underline{b}_H); \underline{b}_H)))^{(m-1)}$.

[15] Let Y_{t-1} denote earnings prior to layoff. Define $\frac{\Delta(L_t+b_t)}{Y_{t-1}} = \frac{1}{N_\delta}\sum_{i \in I_\delta} \frac{(L(h_{i,t}, k_{i,t}; \underline{b}_H) + b_{i,t} * \mathbb{I}(b_{i,t}<0)) - (L(h_{i,t}, k_{i,t}; \underline{b}_L) + b_{i,t} * \mathbb{I}(b_{i,t}<0)))}{4\alpha f(y_{i,t-1}, h_{i,t-1}, k_{i,t-1})}$

earnings replacement rate, $R_t(\underline{b}) = \frac{1}{N_\delta}\sum_{i\in I_\delta} \frac{\mathbb{I}(e_i=W)*4\alpha f(h_{i,t},k^*(b_{i,t},h_{i,t},k_{i,t};\underline{b}))+0*\mathbb{I}(e_i=U)}{4\alpha f(y_{i,t-1},h_{i,t-1},k_{i,t-1})}$.[16] The model implied replacement earnings elasticity is therefore given by,

$$\epsilon_{Rep} = \frac{R_t(\underline{b}_H) - R_t(\underline{b}_L)}{\left(\frac{\Delta(L_t+b_t)}{Y_{t-1}}\right)} = -0.014$$

The model replacement rate (inclusive of 0s) produces a small, slightly negative, earnings replacement rate elasticity of -.014. To understand why this is the case, we can decompose earnings losses into two offsetting components: (i) access to additional credit depresses job finding rates which tends to depress replacement earnings, and (ii) access to additional credit increases the capital intensity of submarkets searched by agents which tends to raise replacement earnings. We can compute each of these components separately.

Define the job finding rate for agents as $JF_t(\underline{b}) = \frac{1}{N_\delta}\sum_{i\in I_\delta} p(\theta_t(h_{i,t}, k^*(b_{i,t}, h_{i,t}, k_{i,t}; \underline{b}); \underline{b}))$. Then the model implied job finding elasticity is given by,

$$\epsilon_{JF} = \frac{JF_t(\underline{b}_H) - JF_t(\underline{b}_L)}{\left(\frac{\Delta(L_t+b_t)}{Y_{t-1}}\right)} = -0.044$$

This implies that when debt limits expand by 10% of prior annual income, job finding rates fall by .44% as workers can better self-insure while searching more thoroughly for jobs. This increased search tends to decrease the replacement earnings of agents, since unemployed workers have an earnings replacement rate of zero.

Turning to the second component of replacement earnings, define the capital intensity rate of submarkets in which agents search as $K_t(\underline{b}) = \frac{1}{N_\delta}\sum_{i\in I_\delta} k^*(b_{i,t}, h_{i,t}, k_{i,t}; \underline{b})$. Then the model implied capital intensity elasticity is given by,

$$\epsilon_K = \frac{K_t(\underline{b}_H) - K_t(\underline{b}_L)}{\left(\frac{\Delta(L+b)}{Y_{t-1}}\right)} = 0.249$$

In other words, being able to replace 10% more of prior income with credit allows agents in the model to search in submarkets with 2.5% greater physical (or intellectual) capital intensity. This increased search in markets with more capital intensity tends to increase the replacement earnings of agents. The combination of the two effects, namely the negative influence of job finding rates and positive influence of capital intensity on replacement earnings, yields the

[16] Anticipating the empirical section, we annualize quarterly earnings.

near-zero replacement earnings elasticity observed in the model.

Next, we calculate the elasticity of replacement earnings with respect to credit among job finders. By isolating job finders, we implicitly drop zeros from the replacement rate calculation. Let $I_e(\underline{b})$ denote the set of job finders at the end of period t. Let $N_{\delta,e}$ denote the cardinality of $I_\delta \cap I_e(\underline{b})$, which is the set of laid off households who find a job at the end of period t. Define replacement earnings among this set of households as $R_{t,e}(\underline{b}) = \frac{1}{N_{\delta,e}} \sum_{i \in I_\delta \cap I_e(\underline{b}_L)} \frac{4\alpha f(h_{i,t}, k^*(b_{i,t}, h_{i,t}, k_{i,t}; \underline{b}))}{4\alpha f(y_{i,t-1}, h_{i,t-1}, k_{i,t-1})}$. Lastly, define $\frac{\Delta(L_{t,e}+b_{t,e})}{Y_{t-1,e}}$ to be the change in credit limits to income of those who find a job at the end of period t under borrowing limit $\underline{b}_L$.[17] The model implied replacement earnings elasticity, among the employed, is therefore given by,

$$\epsilon_{Rep,e} = \frac{R_{t,e}(\underline{b}_H) - R_{t,e}(\underline{b}_L)}{\left(\frac{\Delta(L_{t,e}+b_{t,e})}{Y_{t-1,e}}\right)} = 0.054$$

This implies that in the model, among job finders, being able to replace 10% more of prior income with credit results in a .54% greater earnings replacement rate.

Lastly, we compute the impact of credit access on the types of jobs workers take, in particular, the firm's productivity. We proxy firm productivity in the model (and in the data), using deciles of the wage-per-worker distribution. Since the production function exhibits constant returns to scale, the delineation of a firm in the model is ambiguous. We group all workers employed at a job with capital k and we call that a firm. Within each of these firms, we compute the wage-per-worker. We then compute the 50th percentile, 75th percentile, and 90th percentile of the firm wage-per-worker distribution. Let $\mathbb{I}_{50}(b_{i,t}, h_{i,t}, k_{i,t}; \underline{b})$ be an indicator if a worker finds a job in the 50th percentile or better of the firm wage per worker distribution ($\mathbb{I}_{75}(\cdot)$ and $\mathbb{I}_{90}(\cdot)$ are defined analogously). Similar to the replacement rate, we condition on those who find a job. Let the fraction of job finders at the 50th percentile of the wage-per-worker distribution or above be given by $f_{50}(\underline{b}) = \frac{1}{N_{\delta,e}} \sum_{i \in I_\delta \cap I_e(\underline{b})} \mathbb{I}_{50}(b_{i,t}, h_{i,t}, k_{i,t}; \underline{b})$. We define the elasticity of firm productivity with respect to the credit limit using the following formula:

$$\epsilon_{50,e} = \frac{f_{50}(\underline{b}_H) - f_{50}(\underline{b}_L)}{\left(\frac{\Delta(L_{t,e}+b_{t,e})}{Y_{t-1,e}}\right)} = .102$$

This estimate implies that if a worker has 10% greater unused credit to income prior to job

[17] $\frac{\Delta(L_{t,e}+b_{t,e})}{Y_{t-1,e}} = \frac{1}{N_{\delta,e}} \sum_{i \in I_\delta \cap I_e(\underline{b}_L)} \frac{(L(h_{i,t}, k_{i,t}; \underline{b}_H) + b_{i,t} * \mathbb{I}(b_{i,t}<0)) - (L(h_{i,t}, k_{i,t}; \underline{b}_L) + b_{i,t} * \mathbb{I}(b_{i,t}<0)))}{4\alpha f(y_{i,t-1}, h_{i,t-1}, k_{i,t-1})}$. The results are insensitive to our choice of denominator, and are very similar using $\frac{\Delta(L_t+b_t)}{Y_{t-1}}$.

loss, conditional on finding a job they are 1% more likely to work at a firm at, or above, the 50th percentile of the wage-per-worker distribution.

We conduct similar calculations for the other percentiles of the wage-per-worker distribution:

$$\epsilon_{75,e} = \frac{f_{75}(\underline{b}_H) - f_{75}(\underline{b}_L)}{\left(\frac{\Delta(L_{t,e}+b_{t,e})}{Y_{t-1,e}}\right)} = 0.104, \qquad \epsilon_{90,e} = \frac{f_{90}(\underline{b}_H) - f_{90}(\underline{b}_L)}{\left(\frac{\Delta(L_{t,e}+b_{t,e})}{Y_{t-1,e}}\right)} = 0.034$$

These estimates imply that if a worker has 10% greater unused credit to income prior to job loss, conditional on finding a job they are 1% more likely to work at a firm at, or above, the 75th percentile; likewise, they are .3% more likely to work at a firm at, or above, the 90th percentile. In the model, credit helps workers find jobs in the top half of the wage-per-worker distribution, but credit has a much more muted impact on job finding rates at the high end of the wage-per-worker distribution (90th percentile and above).

Are these mechanisms borne out in the data? To our knowledge, there are no existing studies documenting the way consumer credit limits impact unemployment durations, subsequent wage outcomes, or the characteristics of the firms where these households ultimately take jobs. While this mechanism is at the heart of the unemployment insurance literature, there is limited evidence linking access to private liquid assets and job search decisions. Relative to the UI literature, there are two main reasons that consumer credit differs from unemployment insurance: (1) consumer credit must be repaid, rolled over, or defaulted upon; these intertemporal costs alter the set of admissible jobs for consumers and make consumer credit an imperfect substitute for liquid assets, (2) in dynamic models such as ours, consumer credit can be drawn down before job loss (e.g. using a severance payment analogy, this would be like entering job loss with a negative severance payment); as a result, increasing credit access may worsen job finding outcomes if individuals borrow while employed, and then lose their jobs with large existing debts, severely distorting their labor market outcomes (i.e. individuals already have their 'backs against the wall' upon job loss). This second effect generates defaults, which is a pervasive feature of consumer credit markets (*inter alia* Gerardi et al. [2017]) that limits the scope and substitutability between credit and other forms of public insurance.

To fill this gap in the empirical literature, we construct a new database that links TransUnion credit reports to LEHD employment records. We then test the predictions of the model, and we show that the model and reduced form estimates are quite close.

4 Empirical Tests of the Model: Data and Definitions

Our main data source is a panel of 4 million TransUnion credit reports which are linked by a social security number, then anonymized, to the Longitudinal Employment and Household Dynamics (LEHD) database. All consumer credit information is taken from TransUnion at an annual frequency from 2001 to 2008. The TransUnion data includes information on the balance, limit, and status (delinquent, current, etc.) of different classes of accounts held by individuals. The different types of accounts include unsecured credit as well as secured credit on mortgages.

The LEHD database is a quarterly matched employer-employee dataset that covers 95% of U.S. private sector jobs. The LEHD includes data on earnings, worker demographic characteristics, firm size, firm age, and average wages. Our main sample of earnings records includes individuals with credit reports between 2001 and 2008 from the 11 states for which we have LEHD data: California, Illinois, Indiana, Maryland, Nevada, New Jersey, Oregon, Rhode Island, Texas, Virginia, and Washington. Since job dismissal and reason of dismissal are not recorded in the LEHD, we follow Jacobson et al. [1993] and focus on mass layoffs.[18]

We then define several labor market variables of interest. First, we define non-employment duration to be the number of quarters it takes an individual to find a job following a mass displacement.[19] Non-employment duration therefore takes values ranging from 0 (indicating immediate job finding) to 9 (all spells longer than 9 quarters of non-employment are assigned a value of 9).[20]

Second, we define replacement earnings as the ratio of annual earnings 1 year after layoff over annual pre-displacement earnings. Suppose a worker is displaced in year t, then we define the replacement earnings ratio to be the ratio of annual earnings in the year after layoff, in year $t+1$, to the pre-displacement annual earnings, in year $t-1$. To avoid

[18] Online Appendix A includes details on the identification of mass layoffs.

[19] We follow Abowd et al. [2009] (Appendix A, Definitions of Fundamental LEHD Concepts) to construct our measures of job accessions and employment at end-of-quarter. See Online Appendix A for more discussion.

[20] Very few workers in our sample of displaced workers remain non-employed for longer than 4 quarters. Changing the censored value to 8 or 10 has no impact on the results.

confounding the duration of non-employment with replacement earnings, when we measure replacement earnings, we condition on individuals who have a full year of earnings in year $t+1$. We consider longer-term measures of replacement earnings (e.g. in year $t+2$) in Online Appendix B.

We focus on revolving credit from TransUnion because it can be drawn down on short notice following job loss and paid-off slowly over time without any additional loan-applications or income-checks. Our main measure of credit access is therefore an individual's unused credit limit across all types of revolving debt (excluding mortgage related revolving debt) over annual earnings, measured prior to displacement.[21] We call this ratio the '*unused revolving credit to income ratio.*'[22] The main components of revolving credit include bank revolving (bank credit cards), retail revolving (retail credit cards), and finance revolving credit (other personal finance loans with a revolving feature). In Online Appendix A.5 we use alternate measures of credit access prior to layoff including (i) credit scores, (ii) unused revolving credit inclusive of HELOCs, and (iii) total secured and unsecured unused credit.

4.1 Sample Descriptions and Summary Statistics

Main Sample: Our main sample includes all prime-age displaced workers who had at least 1 year of tenure at the time of displacement. These are standard restrictions used in the literature (e.g. Davis and Von Wachter [2011], Huckfeldt [2014], and Jarosch [2014]), to mitigate any issues associated with seasonal employment or weak labor-force attachment. Under these criteria we end up with a sample of 81,000 individuals (rounded to the nearest thousand given Census disclosure requirements). Given the way we identify displacements, and our use of lagged credit prior to displacement as the main independent variable, this sample covers the years 2002-2006.[23]

Table 3 includes key summary statistics. All variables are deflated by the CPI, and the top 1% (and bottom 1% if the variable is not bound below) of continuous variables are winsorized. Columns (1) and (2) of Table 3 summarize the entire sample of displaced

[21] The reason that our main measure of credit access excludes mortgage related credit is because we want to isolate the impact of credit access on employment, independent of housing wealth. To control for the component of housing wealth that can be drawn down upon job loss, we include directly HELOC limits and home equity proxies as controls in our empirical analysis.

[22] Online Appendix A includes details on the construction of this ratio.

[23] Census requires sample numbers to be rounded off to the nearest hundred to ensure no individual data is disclosed or can be inferred. We round to the nearest thousand to allow for quicker disclosure of results.

individuals. Column (1) shows that they were on average 38.8 years old, took 2.43 quarters to find a job, and had an earnings replacement rate of 81%. They could replace roughly 29% of their prior annual earnings with unsecured revolving credit, 51% of their prior annual earnings across all types of credit, and the average age of their oldest account is 11.58 years.[24] Column (2) shows the same sample conditional on the individual finding a job in the proceeding year (at t+1). On average, their earnings replacement rate is 1.14 (meaning their earnings at their new job are 14% higher than their pre-displacement earnings), their lagged prior income is slightly higher, and they could replace about 27% of their prior earnings with unsecured credit. This conditional replacement rate is very high relative to the typical mean replacement rate reported in the displaced worker literature; however, this conditional replacement rate simply reflects the fact that the earnings loss distribution is highly skewed with many individuals having a zero replacement rate. We plot this distribution of earnings losses in Figure 4, and in Section 4.5, we argue that for many displaced individuals, their earnings losses are purely transitory, and we should therefore expect these individuals to borrow if they have limited liquid assets.

Table 3: Summary Statistics for Main Sample

	(1) Entire Sample	**(2)** Employed, t+1
Age	38.8	38.5
Tenure	3.6	3.7
Imputed Education	13.2	13.3
Lagged Annual Earnings	$ 44,317	$ 46,772
Lagged Unused Revolving Credit to Income	0.29	0.27
Lagged Unused Total Credit to Income	0.51	0.47
Duration of Non-Employment (In Quarters)	2.43	0.78
Replacement Rate (Annual Earnings Year t+1/Annual Earnings Year t-1)	0.81	1.14
Lagged Months Since Oldest Account Opened	139	140
Observations (Rounded to 000s)	81000	36000

Notes. Sample selection criteria in Section 4.1. Lagged refers to (t-1), the year before displacement.

To illustrate composition corrected correlations between access to credit, unemployment durations, and replacement rates, we run regressions of unemployment durations and replacement rates on quintiles of unused credit to income, controlling for basic demographics such as age, sex, and education, as well as regional and firm characteristics. In par-

[24]The distribution of available credit is skewed. In the SCF, *unused credit card limits* to annual *family* income among the unemployed peaks at 38% in 1998, and among the employed it peaks at 33% in 2007.

Figure 1: Non-Employment Duration by Unused Revolving Credit to Income Decile

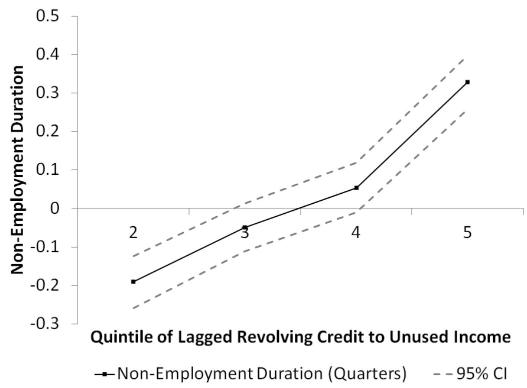
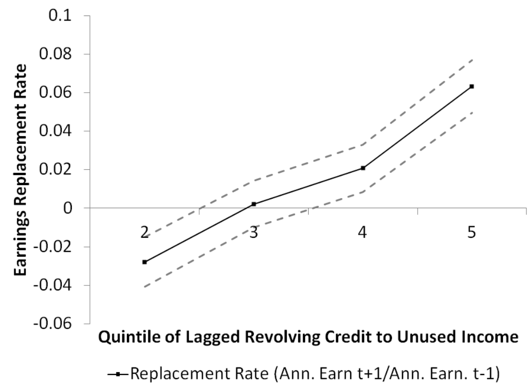


Figure 2: Replacement Earnings 1 Year After Layoff by Unused Revolving Credit to Income Decile, Among Job Finders



ticular, Figure 1 plots the coefficients, β_j, from a regression of duration on unused revolving credit to income quintiles prior to layoff for the full sample of displaced workers ($dur_{i,t} = \sum_j \beta_j \mathbb{I}_{i,t}(j) + \Gamma X_{i,t} + \epsilon_{i,t}$ where $\mathbb{I}_{i,t}(j)$ is a dummy if individual i is in quintile j of the unused credit to income distribution). Relative to the second quintile of credit access, those in the fifth quintile take approximately .5 quarters longer to find a job. Figure 2 plots the coefficients, β_j, from a regression of earnings replacement rates on unused revolving credit to income quintiles prior to layoff for the sample of displaced workers who are employed at t+1 ($reprate_i = \sum_j \beta_j \mathbb{I}_{i,t}(j) + \Gamma X_{i,t} + \epsilon_{i,t}$). Relative to the second quintile of credit access, those in the fifth quintile have a 10% higher replacement rate. Both figures reveal a generally monotone increasing relationship between unused credit prior to layoff and both durations and earnings replacement rates, with a pronounced rise in the last quintile of unused credit. The empirical analysis that follows is designed to draw causal inference about the relationships seen in Figures 1 and 2, and express the relationship as an elasticity that can be mapped to models.

4.2 OLS

Table 4 includes OLS regressions of labor market outcomes on access to unused credit prior to layoff. In every specification, our vector of controls ($X_{i,t}$) includes quadratics in age and tenure as well as sex, race and education dummies, lagged annual income, cumulative lagged earnings (to proxy for assets), 1-digit SIC industry dummies, lagged characteristics of the previous employer including the size, age, and wage per worker, a dummy for the presence of auto loans, an equity proxy (the highest mortgage balance observed less the current balance), HELOC limits (to proxy for available housing wealth upon layoff), as well as year dummies, the MSA unemployment rate, and MSA income per capita.

Let t denote the year of layoff and let i denote the individual. Let $l_{i,t-1}$ be the unused credit limit to annual earnings ratio measured prior to layoff, in year $t-1$ (the *unused revolving credit to income ratio*). Let $D_{i,t}$ denote duration of non-employment. We estimate specifications of the following form:

$$D_{i,t} = \gamma l_{i,t-1} + \beta X_{i,t} + \epsilon_{i,t} \tag{7}$$

The dependent variable in Column (1) is non-employment duration measured in quarters. The point estimate in Column (1) implies that an individual who can replace 10% more of annual pre-displacement earnings with credit takes .33 (=.279*.1*12) weeks longer to find a job. Column (2) of Table 4 illustrates the impact of unused credit on replacement rates of annual earnings, including replacement rates equal to zero for those who do not find a job. The point estimate in Column (2) suggests that the impact of additional credit access on replacement earnings is statistically indistinguishable from zero. There are two competing forces generating this result: (i) durations increase with more credit access, depressing replacement earnings, (ii) of those who find a job, those who have more credit access find higher wages, increasing replacement earnings.

To avoid confounding annual replacement earnings with durations, in Column (3) of Table 4, we isolate the set of households who have positive earnings in each quarter during the year after layoff. Column (3) reveals that conditional on finding a job, those with greater credit access find higher wage jobs. The point estimate implies that if an individual can replace 10% more of their prior annual earnings with credit, their replacement rate is .61% higher. This exercise warrants additional discussion; Column (3) conditions on an outcome, employment, and selection may generate differences between job-finders and non-finders. In Section 5.1, we compute the same wage elasticity using model simulated data and we correct for selection on unobserved worker types (i.e. human capital is assumed to be unobserved to the econometrician but is present in the model). With and without selection, we show that a reservation wage strategy simultaneously explains the zero effect of credit on replacement rates among the broader population while simultaneously producing positive and significant

Table 4: Credit and Labor Market Outcomes: Baseline OLS.

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	——All Displaced——		————Job Finders 1 Yr. After Layoff————			
Dependent Variable:	Duration	Rep. Rate (0s)	Rep. Rate	Prod.>p50	Prod.>p75	Prod.>p90
Unused Revolving Credit to Income Ratio	0.279***	0.00286	0.0605***	-0.00259	0.00140	0.0123***
	(0.0207)	(0.00418)	(0.00477)	(0.00381)	(0.00437)	(0.00304)
Controls (Demographic, Regional, Lagged Earnings, HELOC Limits, Equity Proxy)	Y	Y	Y	Y	Y	Y
R2	0.052	0.0857	0.229	0.126	0.175	0.175
Round N	81000	81000	36000	36000	36000	36000

*Notes. Robust Std. errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Columns 1 and 2 use all displacements, Columns 3 through 6 condition on those employed in the year after layoff. Dependent variables: Col. 1 is duration of non-employment in quarters; Col. 2 and 3 are annual earnings t+1 over annual earnings t-1; Col. 4, 5, and 6 are dummies for whether the worker works at a firm the X percentile or higher of the wage per worker distribution. Independent Variables: Unused Revolving Credit to Income measured 1 year prior to layoff. Demographic controls include quadratic in age & tenure, race, sex and education dummies as well as year & auto loan dummies. Industry controls include 1-digit SIC dummies and size, age, and wage per worker of prior firm. MSA controls include real per capita GDP and the MSA unemployment rate. Lagged earnings controls include prior real annual earnings and cumulative real annual earnings to proxy for assets. Equity proxy is highest observed mortgage balance less current mortgage balance. HELOC limits include combined home equity limits.*

effects of credit on the wages of job finders.[25]

Columns (4), (5), and (6) demonstrate the relationship between credit access and productivity. We show that among individuals who find a job in the year after displacement, those with greater credit access are more likely to work at more productive firms. Our main dependent variables are indicator functions for whether the worker finds a job at a firm which is ranked above the 50th, 75th, or 90th percentile of the wage-per-worker distribution in the year after job loss.[26] This is our proxy for productivity.

While Columns (4) and (5) yield insignificant point estimates, Column (6) of Table 4 implies that if an individual can replace 10% more of their prior annual earnings with credit, their odds of working at a firm in the 90th percentile of the wage-per-worker distribution or greater increases by .12%. Thus credit is positively correlated with workers sorting into more productive jobs.

In Online Appendix A.4, we compute OLS regressions of unemployment duration on credit access in the SCF, and we show that the inclusion of liquid wealth and other illiquid assets has little impact on the correlation between credit and unemployment duration. While we include proxies for liquid assets (cumulative lagged earnings) and illiquid assets (HELOCs,

[25]In Online Appendix B, we explore earnings replacement rates at longer horizons.

[26]What we call firms in the text are State Employment Identification Numbers (SEINs) in the LEHD. SEINs aggregate all plants within a state. Wage-per-worker is calculated as the aggregate wage bill divided by total employees.

Auto Loans, and an Equity Proxy) in all of our benchmark regressions on Census data, we interpret our SCF results as suggestive evidence that including more complete, direct measures of the household wealth portfolio will have little impact on our point estimates.

Online Appendix B.1 merges our sample with Schedule C tax records to adjust the non-employment spells for self-employment. Online Appendix B.1 also uses the earnings gap method to infer partial quarters of non-employment. Under either of these definitions of non-employment duration, we find that the main results hold.

4.3 Gross and Souleles Instrument

While the structural estimates are immune to concerns regarding endogeneity, we augment our reduced form OLS analysis with an instrumental variables approach. We use the identification strategy of Gross and Souleles [2002] who exploit the fact that credit card limits increase automatically as a function of the length of time an account has been open. This identification strategy generates individual level variation in credit access.

As Gross and Souleles [2002] discuss, the general mechanism is that credit issuers revise account limits based on arbitrary time intervals. The subsequent limit revision is a function of credit scores, and credit scores, by construction, positively weight account ages. Account ages are one of the few characteristics credit scoring companies publicly discuss as a positive contributor to the credit score. We exploit these time-contingent changes in credit access by using the age of the oldest account as an instrument for credit limits.

The Equal Credit Opportunity Act of 1974 made it illegal for credit scoring companies to condition on age, as well as most other demographic characteristics, and thus credit scoring companies used the age of the oldest account as a proxy for physical age. Therefore, the main challenge to exogeneity for this instrument is that account ages are related to physical ages. Unlike credit scoring companies, however, we observe physical age. Our identifying assumption is that conditional on physical age as well as a host of other individual characteristics, variation in credit access due to differences in account ages is random and simply an artifact of the credit scoring formula.

More formally, let t denote the year of layoff and let i denote the individual. The first-stage regression is to predict the unused credit limit ratio prior to layoff ($l_{i,t-1}$) as a function

Table 5: Credit and Labor Market Outcomes: Instrument Variable, Age of Oldest Account ('Gross and Souleles Instrument,' GS-IV).

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	——All Displaced——		————Job Finders 1 Yr. After Layoff————			
Dependent Variable:	Duration	Rep. Rate (0s)	Rep. Rate	Prod.>p50	Prod.>p75	Prod.>p90
Unused Revolving Credit to Income Ratio	0.442***	0.0592***	0.134***	0.121***	0.159***	0.0806***
	(0.0929)	(0.0159)	(0.0183)	(0.0177)	(0.0230)	(0.0169)
Controls (Demographic, Regional, Lagged Earnings, HELOC Limits, Equity Proxy)	Y	Y	Y	Y	Y	Y
R2, 1st Stage	0.0433	0.0433	0.0396	0.0396	0.0396	0.0396
Angirst Pischke FStat Pval	0	0	0	0	0	0
Round N	81000	81000	36000	36000	36000	36000

*Notes. Robust Std. errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Instrumental variable for unused credit to income is age of oldest account. See Table 4 for samples and controls.*

of the age of the oldest account, $s_{i,t}$, and a vector of controls $X_{i,t}$, including physical age.

$$l_{i,t-1} = \pi s_{i,t} + BX_{i,t} + u_{i,t} \tag{8}$$

These first-stage estimates of π and B are used to isolate the exogenous component of the unused credit limit ratio, $\hat{l}_{i,t-1}$. The second stage regression is then used to estimate how this exogenous variation in credit impacts employment outcomes such as duration, $D_{i,t}$:

$$D_{i,t} = \gamma \hat{l}_{i,t-1} + \beta X_{i,t} + \epsilon_{i,t} \tag{9}$$

Table 5 includes our point estimates when we adopt this instrumental variable approach. The coefficient in Column (1) means that individuals who can replace 10% more of their pre-displacement earnings with credit take .53 (=.442*.1*12) weeks longer to find a job. Column (2) implies that individuals who can replace 10% more of their pre-displacement earnings with credit earn .592% more, including those who do not successfully find a job. Among job finders, however, the impact of credit on replacement rates is stronger. Column (3)'s point estimate implies that being able to replace 10% more of prior annual earnings with credit increases replacement rates by 1.34%, conditional on being employed throughout the year after layoff. Columns (4), (5), and (6) demonstrate that those who can replace 10% more of prior annual earnings with credit are 1.2%, 1.6%, and .8% more likely to find jobs at firms above the 50th, 75th, and 90th percentile of the wage-per-worker distribution, respectively. In contrast to the OLS result, once credit is properly instrumented, access to credit allows individuals to disproportionately find jobs in the top half or top quartile of the wage distribution, but credit has roughly a 200% weaker impact on the ability of individuals to find jobs in the top decile of the productivity distribution.

4.4 Borrowing by Displaced Workers

One important point is that regardless of realized borrowing, the *potential* to borrow affects job search decisions regardless if the credit line is actually drawn down. Workers know that if their buffer stock of liquid assets is depleted, they can borrow, and this affects their job search decisions even if they never borrow. Existing work by Sullivan [2008] using the PSID and SIPP has shown that about 20% of workers borrow during unemployment, and it is precisely low wealth workers who borrow during unemployment (see also Collins et al. [2015] who have updated Sullivan [2008] through the great recession). This does not imply that only 20% of workers change job search decisions; all of those with low liquid assets, which includes the majority of job losers according to Gruber [2001], who foresee any necessity to borrow, will alter job search decisions.

As more direct evidence of borrowing by the unemployed, we also include Table 6, which is based on direct questions in the RAND American Life Panel (ALP) about borrowing in response to job loss. Table 6 reveals that roughly one-quarter of job losers borrow to replace income, and roughly one-third of job losers skip their obligated monthly payments and become delinquent (we will refer to this as default) to smooth consumption. This evidence supports the mechanism that unconstrained unemployed individuals borrow, whereas among job losers who are indebted or have other obligated payments, they become delinquent to smooth consumption. The ability to default separates credit from unemployment insurance or other safety-net programs, and this evidence reveals that it is used frequently by job losers.

To understand why some existing empirical studies have found a mean impact of job loss on borrowing to be close to zero, Figure 3, which is a smoothed density, plots the change in revolving balance among displaced workers in the year of layoff relative to one year before layoff. The graph reveals significant heterogeneity in borrowing responses among displaced workers. This is the finding of a recent paper by Braxton, Herkenhoff, and Phillips [2018] who show that many workers borrow, consistent with Sullivan [2008] and Table 6, whereas many workers deleverage through default, also consistent with Sullivan [2008]'s regression

Table 6: Borrowing by Unemployed (Source: RAND ALP 2009-2015)

	In response to job loss, percent who...		
	Borrow	**Default**	**N**
2009	23.4%	30.8%	107
2010	23.1%	37.8%	320
2011	23.7%	33.5%	266
2012	22.7%	30.1%	229
2013	30.5%	40.6%	315
2014	29.0%	42.0%	200
2015	23.5%	33.7%	243

Notes. Sample include those who answer 'Yes' to question 'Did your family income go down as a result of... losing a job?' We 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.' We combine responses 'fell behind on rent' and 'skipped or postponed paying some other bills' as a non-mortgage 'default.'

results. As a result, the net amount borrowed among displaced workers is close to zero (e.g. Baker and Yannelis [2015], Gelman et al. [2015], Bethune [2015], and Ganong and Noel [2015]). However, this masks the fact that deleveragers are smoothing consumption using credit markets by defaulting on prior obligations, and those increasing their leverage are also smoothing consumption using credit markets but in a more 'traditional' way as argued in Braxton, Herkenhoff, and Phillips [2018]. The small mean amount borrowed by the unemployed obfuscates the large and economically significant heterogeneity in the way displaced workers use credit markets to smooth consumption. We refer readers to Braxton, Herkenhoff, and Phillips [2018] for more analysis of borrowing patterns by the unemployed.

Figure 3: Change in Real Revolving Debt between Year of Layoff Minus 1 Year Before Layoff

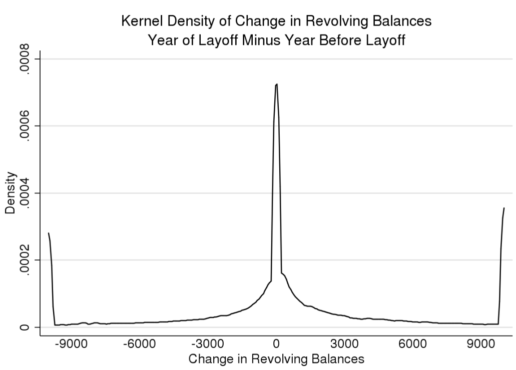
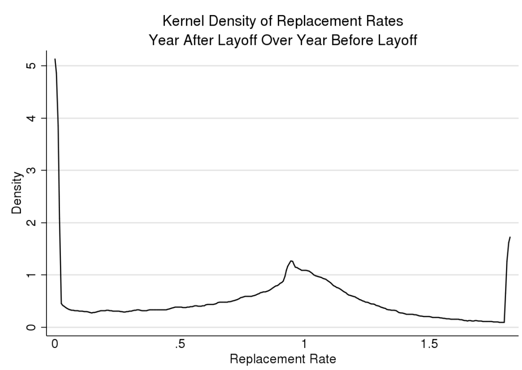


Figure 4: Replacement Rate Distribution (Annual Earnings t+1/ Annual Earnings t-1)



For our sample, Table 7 illustrates regression results for the relationship between non-employment duration and borrowing, controlling for as many characteristics of workers as possible. The coefficient in Column (1) implies that for every additional quarter of non-employment, workers borrow on average \$84, which is a relatively small average amount. However, as discussed above, this regression confounds the offsetting impact of borrowing (which increases balances) and default (which tends to reduce balances). The result is a small average impact even though both mechanisms provide consumption smoothing to job losers via credit markets. Column (2) shows that for every additional quarter of non-employment, workers are .14% more likely to enter collection on their debts (i.e. they have defaulted and their delinquent accounts have been sold to a collection agency).

Table 7: Borrowing by Unemployed: OLS, All Displacement.

Dependent Variable:	**(1)** Change in Revolving Debt (Year of Layoff minus 1 Year Before)	**(2)** Odds of Entering Collections at t+1
Duration of Unemployment	84.83***	0.00149***
	(23.37)	(0.000507)
Controls	Y	Y
R-squared	0.030	0.083
Round N	81000	81000

*Notes. Robust Std. errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Sample includes all displacements. Col. 1 dependent variable is Change in Real Revolving Debt 1 Year After Layoff Minus 1 Year Before Layoff. Col. 2 dependent variable is odds of entering collections. Same control definitions as Table 4.*

4.5 Permanent vs. Transitory Earnings Losses

Our empirics are consistent with the large earnings losses incurred after layoff (e.g. Davis and Von Wachter [2011], Huckfeldt [2014], and Jarosch [2014]). However, as Braxton et al. [2018] show, a very large fraction of unemployed individuals will find new jobs which pay as much, or more, than their previous job. Figure 4 plots the *distribution* of earnings replacement rates for displaced workers in our sample. Theory would predict that those individuals with earnings replacement rates above 1 should borrow (e.g. Sullivan [2008] and Braxton et al. [2018]), since job loss is a transitory shock for them. On the other hand, there is a large mass of workers with replacement rates equal to zero. For those who have more permanent losses, ex-post, the ability to default is an important consumption smoothing mechanism (e.g. Gerardi et al. [2017]). Both of these mechanisms play an important role in reconciling our model with the data, and these mechanisms distinguish credit from unemployment insurance.

5 Model vs. Data

Table 8 summarizes the elasticities obtained from the structural estimation as well as from the reduced form analysis. All three estimates of labor market elasticities provide useful benchmarks for subsequent analysis.[27] The exclusion restriction cannot be tested, and the IV estimates are inherently local whereas the structural estimates are global. While one set of estimates may or may not be preferred to another, there are several patterns in the data that are consistent across the three sets of estimates, and we view this as suggestive evidence that the model's mechanisms are borne out in the data. The model and data exhibit strong resemblance along several dimensions in Table 8: (1) more credit access implies longer unemployment durations, (2) including both those who successfully and unsuccessfully find jobs, credit does not necessarily result in better job outcomes one year after layoff, (3) conditional on finding a job, workers with more credit find higher wage jobs, and (4) and conditional on finding a job, workers with more credit are more likely to work at more productive firms (measured in terms of wage-per-worker).

Table 8: Model Elasticities Versus Data Elasticities

	(1) Model	(2) OLS	(3) GS-IV
Duration	0.150	0.279***	0.442***
Replacement Rate (with 0s)	-0.014	0.00286	0.0592***
Replacement Rate, Job Finders (without 0s)	0.054	0.0605***	0.134***
Productivity>p50, Job finders	0.102	-0.00259	0.121***
Productivity>p75, Job finders	0.104	0.00140	0.159***
Productivity>p90, Job finders	0.040	0.0123***	0.0806***

*Notes. Col. 1 Model estimates from Section 3. For data estimates, *** p<0.01, ** p<0.05, * p<0.1. Col. 2 estimates from Table 4. Col. 3 estimates from Table 5.*

5.1 Selection Correction

By conditioning on finding a job when computing wage replacement rates, both the model estimates and reduced from estimates include selection effects. In this section, we use the fact that we can condition on the variables that are generating the selection effect in the model, and thus provide a selection correction factor for both the model and reduced form

[27] Since this paper was written, several papers have already benchmarked their estimates against ours, for example innovative work by Ji [2018] benchmarks his structural elasticities to ours.

estimates. In particular, a worker's human capital is observed in the model but not observed in the data. Therefore, it is possible to compute the replacement wage elasticity (or any of the other conditional estimates), among job finders stratified by human capital and then reweight the human-capital-specific estimates according to the unconditional distribution of human capital. The resulting estimate is free from human capital (worker quality) induced selection. We implement this procedure in Table 9. First we compute the replacement wage elasticity among job finders stratified by human capital in year of layoff (date t):

$$\epsilon_{Rep,e}(h) = \frac{R_{t,e}(\underline{b}_H, h) - R_{t,e}(\underline{b}_L, h)}{\left(\frac{\Delta(L_{t,e}(h)+b_{t,e}(h))}{Y_{t-1,e}(h)}\right)}$$

These estimates are reported in row 1 of Table 9. We see that high human capital agents have the least gains from an additional dollar of credit – this is because high human capital agents have sufficient liquid assets that they behave approximately unconstrained. We then weight each of the replacement elasticities by the unconditional job loser human capital distribution, $f_\delta(h)$. The selection corrected replacement elasticity is:

$$\epsilon_{Rep,e}^{selection\ corrected} = \sum_h f_p(h)\epsilon_{Rep,e}(h) = .059$$

This is reported in row 2 of Table 9. Comparing this to the raw estimate of the replacement rate elasticity yields the selection correction factor (row 4 of Table 9):

$$\textbf{Selection Correction Factor} = \frac{\epsilon_{Rep,e}^{selection\ corrected}}{\epsilon_{Rep,e}} = \frac{.059}{.054} = 1.08$$

Because high human capital agents generate more surplus, they find jobs faster than low human capital agents. Therefore, the set of job finders is disproportionately high human capital workers, and thus our replacement rate elasticities place too much weight on low values of the replacement rate elasticity. Our selection correction exercise implies that our conditional elasticities should be multiplied by a factor of 1.08 to obtain the population elasticity.

Table 9: Model Replacement Rates Among Job Finders, Controlling for Selection

	Human Capital					
	$h = .5$	$h = .6$	$h = .7$	$h = .8$	$h = .9$	$h = 1$
Replacement Elasticity for Job Finders, Fixed h	0.088	0.059	0.058	0.064	0.049	0.028
Weighted Replacement Elasticity for Job Finders, Fixed h (Selection Corrected Elasticity)	0.059					
Replacement Elasticity for Job Finders (Raw)	0.054					
Selection Correction Factor (=.059/.054)	1.08					

Notes. Model estimates derived from simulating 80,000 agents in 2004 steady state for T=280 (discarding the first 100 periods) and computing job finding behavior under counterfactually looser limits, conditional on a fixed level of human capital. The second row weights the point estimates by the ergodic distribution of human capital. The third and fourth rows compute the ratio of the selection corrected estimate to the raw estimate.

5.2 Comparison to Unemployment Insurance Estimates

Since credit must either be repaid, rolled over, or defaulted upon, these intertemporal costs of borrowing should make credit an imperfect substitute for unemployment insurance. This is indeed the case, and our estimates imply that $1 of additional unused credit limit is about half as potent for unemployment durations as $1 of unemployment benefit. Being able to replace 5% of annual earnings on a credit card is equivalent to a 10% increase in UI replacement rates for the typical 6-month duration of unemployment benefits. In the empirical UI literature, the impact of a 10% increase in the UI replacement rate for 6 months is to increase unemployment durations by .3 to 2 weeks with the modal estimate lying between .5 and 1 for the US (see Nakajima [2012b] and Card et al. [2015] for a summary of recent empirical and quantitative elasticities). Our three sets of estimates imply an equivalent elasticity with respect to credit of .09 to .26 weeks.

Where there is overlap, our results are qualitatively in line with US estimates in the UI literature. Studies that have considered the impact of unemployment benefits on re-employment earnings have found positive and significant but mixed-magnitude effects in US data (see Addison and Blackburn [2000] for a summary), whereas European studies have found both positive (e.g. Nekoei and Weber [2015]) and insignificant effects. In contrast to unemployment insurance, consumer credit must be repaid or defaulted upon, altering the set of admissible jobs for which individuals will search. This paper provides the first attempt at measuring how self-insurance provided by private credit markets alters job search and acceptance decisions. Moreover, since we use matched employer-employee data, we are able to measure how credit access affects they types of firm characteristics that individuals pursue. Our results indicate that credit access incentivizes individuals to search longer for higher paying jobs at more productive firms.

6 Aggregate Implications

Based on the model's success at replicating key non-targeted micro moments, we now aggregate across individual agents to explore how credit access affects the macroeconomy. In this section, we compute the transition path for our model economy as credit limits expand from 1964 to 2004. In particular, we study the way changes in borrowing limits affect the path of labor market sorting which, in turn, endogenously determines productivity and output from 1964 to 2004.

Due to lack of data, we calibrate the initial 1964 steady state by relying on the narrative of Evans and Schmalensee [2005]. As Evans and Schmalensee [2005] document through various primary sources, the general purpose credit card industry was in its very infancy in the late 1950s and early 1960s. Many of the local banks and companies that would one day comprise Visa and Mastercard were just being founded, or did not exist, in 1964. For instance, the path-breaking BankAmericard program (the precursor to Visa) began in Fresno, California in 1958. It did not begin to expand outside of California until 1965, and then only after a series of mergers and other developments did BankAmericard become Visa in 1976. We therefore approximate the U.S. in 1964 under the assumption that $\underline{b}_{1964} = 0$.

In order to calibrate the final 2004 steady state, we use the estimated debt limit $\underline{b}_{2004} = -.491$. Throughout most of the simulated transition path, public information on credit card debt limits is not available; the Survey of consumer finances does not begin collecting credit limit information until 1989. We therefore assume that the debt limit expands linearly, once per decade (for computational feasibility), between 1964 and 2004. We therefore have 5 aggregate debt limits, $\underline{b} \in [\underline{b}_{1964}, \underline{b}_{1974}, \underline{b}_{1984}, \underline{b}_{1994}, \underline{b}_{2004}]$. Table 10 illustrates the corresponding values of the debt limit along the transition path.

Table 11 compares the path for the exogenous borrowing limit $\underline{b}$ relative to the Survey of Consumer Finances. The linear credit limit expansion implies a 50% increase in borrowing limits from 1994 to 2004, whereas this number is 58% in the Survey of Consumer Finances. Agents understand that debt limits follow a Markov chain. They rationally anticipate that credit limits will expand once every ten years, and upon reaching the final 2004 steady state,

Table 10: Debt limits along transition path

Year	1964	1974	1984	1994	2004
Variable	$\underline{b}_{1964}$	$\underline{b}_{1974}$	$\underline{b}_{1984}$	$\underline{b}_{1994}$	$\underline{b}_{2004}$
Value	0	-0.1228	-0.2455	-0.3683	-0.4911

Table 11: Model Borrowing Limits vs. Data Borrowing Limits

	Survey of Consumer Finances			**Model**
	Limits (84-94=1)	Limits ($)	SCF Surveys	Limits (84-94=1)
1964 to 1974	-	-	-	0.00
1974 to 1984	-	-	-	0.50
1984 to 1994	1.00	9,227	‘89, ‘92	1.00
1994 to 2004	1.58	14,539	‘95, ‘98, ‘01, ‘04	1.50

Notes. Survey of Consumer Finances weighted with individual weights and then averaged across survey dates within decade. Limits refers to bankcard limits.

there are no further credit expansions. Agents therefore believe that the transition matrix governing the debt limits is,

$$P_{\underline{b}} = \begin{bmatrix} .975 & 0.025 & 0 & 0 & 0 \\ 0 & .975 & 0.025 & 0 & 0 \\ 0 & 0 & .975 & 0.025 & 0 \\ 0 & 0 & 0 & .975 & 0.025 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}_{5\times 5} \qquad (10)$$

6.1 Transition Path Results

This section includes the results of the transition path experiment between 1964 and 2004.[28] Agents believe the Markov chain for the aggregate borrowing limit path is governed by the transition matrix (10) with corresponding values for $\underline{b}$ listed in Table 10. The realizations of the Markov chain are such that credit expands in 1974, 1984, 1994, and 2004 as shown in Figure 5.

[28] While the model is simulated at a quarterly frequency, figures are aggregated to decades for ease of exposition.

Figure 5: Exogenous Borrowing Limit $\underline{b}$

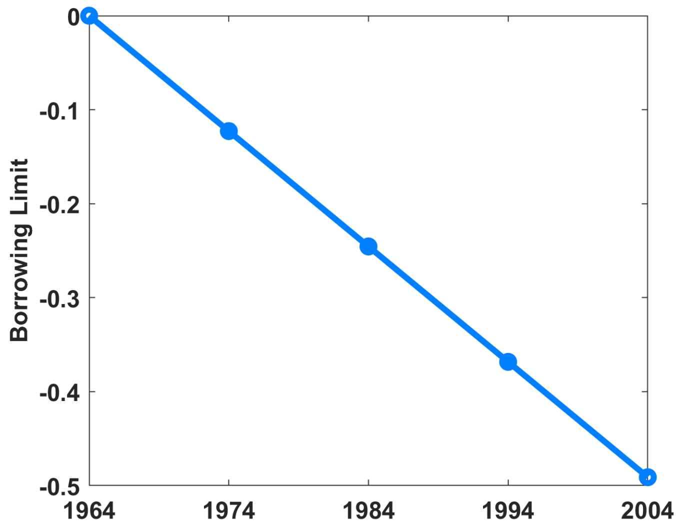


Figure 6: Output, Employment & Productivity

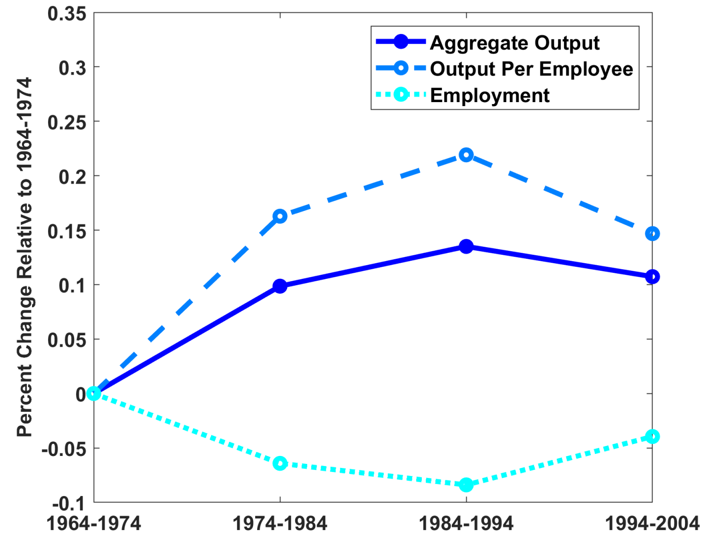


Figure 7: Sorting and Capital

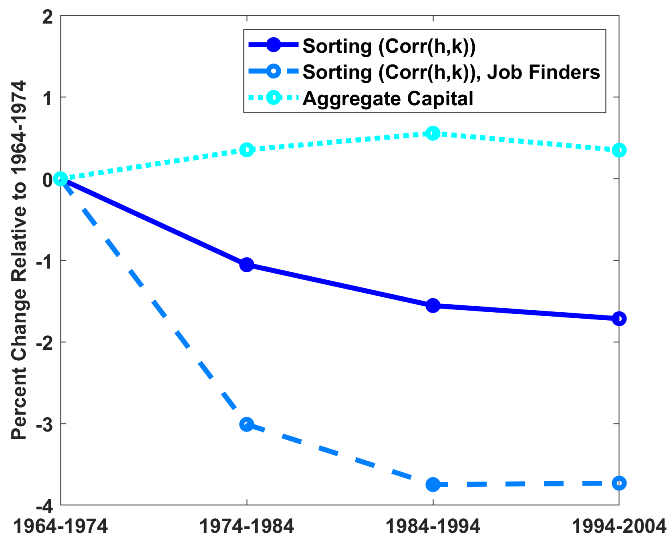


Figure 8: Sorting Patterns, 1964 versus 2004

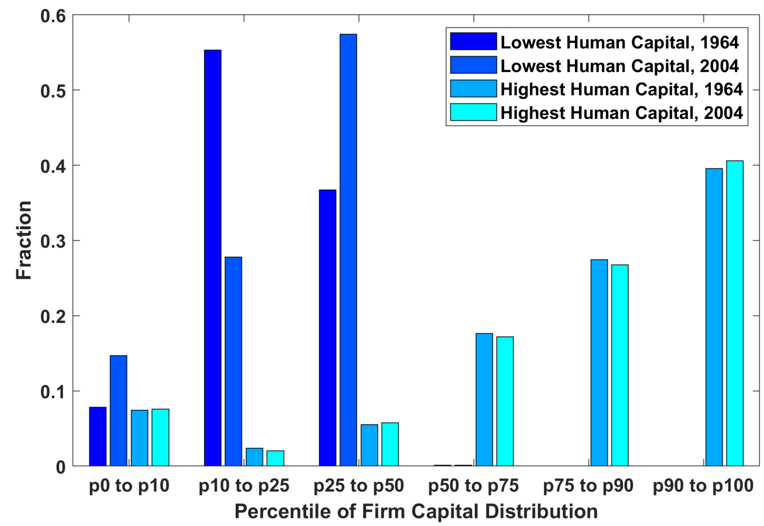


Figure 6 plots output, output per employee (labor productivity), and employment relative to 1964 levels. When debt limits loosen, employment tends to decrease slightly. Because of the presence of two-sided heterogeneity, labor productivity is endogenous along the transition path. The mechanism is that with looser credit limits (e.g. 1994 to 2004), unemployed households borrow to smooth consumption while searching for more capital-intensive jobs. When debt limits are tight (e.g. 1964 to 1974), constrained agents with low liquid assets must take low-capital-intensity jobs that are relatively quick to find.

In terms of production, the impact of tighter debt limits on aggregate output is theoretically ambiguous: households find jobs more slowly, but the jobs workers find are more productive. As credit expands from 1964 to 2004, even though fewer individuals are employed (relative employment falls by .1% in the credit economy), agents find jobs with greater capital intensity and so output increases and output per worker increases. Because households become less constrained and take jobs in which there is more capital per unit of labor, Figure 6 shows that measured labor productivity, defined as output over employment, increases when debt limits are loosened. Relative labor productivity increases by .15% along the transition path (peaking at .22% between 1984 and 1994) and aggregate output increases by .11% along the transition (peaking at .14% between 1984 and 1994).[29]

The mechanism at the heart of the output gain involves a reallocation of workers from low capital firms to high capital firms. To understand this reallocation in greater detail, we now turn to measures of sorting. Figure 7 plots the percentage change in the correlation between human capital, h, and firm capital, k, from 1964 to 2004 for all individuals in the economy as well as new job finders. Figure 7 shows that in the economy in which debt limits are looser, sorting *declines*. The mechanism behind this sorting deterioration is that in the economy in which debt limits loosen, unemployed agents with low-human-capital can borrow to smooth consumption while thoroughly searching for jobs. Therefore, they take jobs that are more-capital-intensive, but less abundant. On average, since low human capital workers are less productive (recall the assumption of supermodularity), looser debt limits allow these 'low quality' workers to take 'high quality' jobs. As such, standard measures of sorting decline, even as output increases. What drives the increase in output is the increased capital investment of entrepreneurs. As Figure 7 shows, the aggregate capital

[29]The non-monotonicity in the time series is generated by the slow-moving nature of savings in the model; as agents begin to dissave, access to liquid assets begins to partially return to pre-expansion levels. In the short-run (right after an expansion) and before agents dissave, access to liquid assets is high and agents take disproportionately longer to find jobs.

stock held by entrepreneurs increases as credit limits expand. This is entirely driven by new entrepreneurial entrants posting more vacancies in submarkets with more capital, and unconstrained households searching for jobs in those submarkets.

Figure 8 demonstrates the micro mechanism generating reduced sorting. Low human capital workers are able to find more productive jobs (jobs in greater percentiles of the firm capital distribution, between p25 and p50) as credit limits expand from 1964 to 2004. However, high human capital workers are largely unaffected by the loosening of constraints. As credit constraints loosen, they are marginally more likely to search for jobs in the highest deciles of the firm capital distribution, but the changes in their search patterns are nearly indiscernible as limits expand from 1964 to 2004. This is true not only in terms of capital percentiles, but also in terms of capital levels.

Lastly, we compute the welfare gains from the credit expansion. Let c_t and D_t denote consumption and default decisions under tight debt limits in the 1964 steady state. Let c_t^b and D_t^b denote consumption and default decisions under loose debt limits in the 2004 steady state. We compute the welfare gain from loosening credit limits as follows:

$$\Delta_W = \left[\frac{\sum_{t=1}^{T} \beta^t [\frac{(c_t^b)^{1-\sigma}}{1-\sigma} - \chi D_t^b] + \sum_{t=0}^{T} \beta^t \chi D_t}{\sum_{t=0}^{T} \beta^t [\frac{(c_t)^{1-\sigma}}{1-\sigma}]} \right]^{1/(1-\sigma)} - 1$$

We find that newborns would be willing to give up 2.60% of their lifetime consumption in order to be born under 2004 credit market conditions instead of 1964 credit market conditions. There are positive welfare gains among newborns along each point of the transition path as well.

Our quantitative and empirical results yield several policy implications. When measured by labor market outcomes, private credit markets act as a relatively effective safety-net; however, in aggregate, even large amounts of credit generate mild 'moral hazard' effects (employment falls by .1%) while actually significantly improving the allocation of labor to firms (raising labor productivity, persistently, by 1/6th of a percentage point) and providing large welfare gains to households (2.6% of lifetime consumption). Our results suggest that as access to private credit markets among low-income US households expands, as it has from 1964 to 2004, the fiscal benefits of relying more heavily on privately provided forms of self-insurance may be significant, with no negative (and perhaps even positive) effects on productivity. The relatively muted response of aggregates to significant credit expansions is not necessarily a null result, but, in fact, and very promising result for public finance. Concurrent work by Braxton et al. [2018] exploits these insights in a public finance setting.

Lastly, allowing firms to invest and workers to save are standard assumptions in most neoclassical business cycle models but are often difficult to incorporate in search models. The fact that these two assumptions are sufficient to generate a negative covariance between standard measures of sorting and welfare, even with supermodular production, raises questions about the quantitative relevance of welfare implications derived in sorting models with linear utility and fixed distributions of firm types.

6.2 Robustness: Capital Investment and Liquidation Value

We conduct two robustness exercises in Online Appendix E. First, we allow for the entrepreneurs to invest in capital over time, mitigating concerns about both quits and on-the-job-search. With costless adjustments to entrepreneur capital, there would never be a reason to quit or change jobs. We find that our main results are largely unchanged, but the ability to invest in capital marginally amplifies the productivity, output, and sorting responses along the transition path. Second, we allow for a liquidation value of firm capital, and again, the main predictions of the model still hold.

7 Conclusions

We examine how consumer credit markets affect the allocation of workers to firms by integrating risk aversion and borrowing into a model with worker and firm heterogeneity. We use the model to estimate the impact of credit limits on job search behavior, and then we examine our model predictions in a new panel dataset linking consumer credit to individual job outcomes.

We find that displaced workers who are able to replace more of their annual income with revolving credit, take longer to find a job and once employed obtain earnings replacement rates that are higher. Furthermore, displaced individuals with greater credit access tend to find jobs at more productive firms. Relative to existing public safety-net programs, consumer credit provides a relatively strong degree of self-insurance when measured by labor market outcomes.

Our theoretical contribution is to develop a model which has credit in addition to 'good' and 'bad' jobs. Our model combines the labor sorting framework of Shimer and Smith [2000] with the consumer credit literature, e.g. Chatterjee et al. [2007]. The model allows us to use public moments to provide a structural estimate of how responsive consumers are to changes in credit access. The model yields estimates of .15 and .054, respectively, for the elasticity of unemployment durations with respect to credit and the elasticity of income replacement rates with respect to credit. Both the structural and reduced form estimates imply that $1 of consumer credit is approximately half as potent as $1 of unemployment insurance in terms of non-employment duration and wage outcomes.

We aggregate across individuals to assess the macroeconomic implications of using credit for self-insurance. Relative to existing search and matching models, productivity is endogenously determined by the allocation of workers to firms. Productivity is therefore a function of the degree of self-insurance available to agents. As credit limits expand from 1964 to 2004 output and labor productivity increase by .11 and .15 percentage points, respectively, whereas employment declines. This reflects the self-insurance mechanism: tighter debt limits force constrained, low-human-capital households to cut their job search shorter, taking relatively unproductive jobs that are more abundant. Looser limits benefit low human capital workers and allow them to find jobs at more productive firms. Mechanically, standard measures of sorting deteriorate since low-human capital workers are allocated to high-capital jobs as credit limits loosen from 1964 to 2004.

Our empirical and quantitative findings have implications for the optimal provision of unemployment insurance (Marimon and Zilibotti [1999], Acemoglu and Shimer [1998], Shimer and Werning [2005]). First, when measured by labor market outcomes, private credit markets act as a relatively effective safety-net. Second, even in the presence of strong individual effects of credit on labor market outcomes, the aggregate impact of large credit market expansions are quite moderate. The widespread access to private credit markets among low-income US households means that the fiscal benefits of relying more heavily on privately provided forms of self-insurance may be quite large. However, credit is strongly countercyclical. This raises valid concerns that substituting out of public insurance into private insurance may result in welfare losses, particularly during episodes in which insurance is needed most, and so the optimal mix of public and private insurance will, in all likeness, not be degenerate.

We view this paper as contributing to the growing research agenda that uses new micro data and theory to understand how household access to capital markets affects worker employment, including choice of occupation (self-employment or formal-employment etc.). Our subsequent work continues to advance this research agenda, focusing on (1) quantifying the optimal mix of public and private insurance (Braxton et al. [2018]), and (2) quantifying the impact of household consumer credit constraints on the decision to start a business (Herkenhoff et al. [2016]).

References

John M Abowd, Bryce E Stephens, Lars Vilhuber, Fredrik Andersson, Kevin L McKinney, Marc Roemer, and Simon Woodcock. The lehd infrastructure files and the creation of the quarterly workforce indicators. In *Producer Dynamics: New Evidence from Micro Data*, pages 149–230. University of Chicago Press, 2009.

Daron Acemoglu and Robert Shimer. Efficient unemployment insurance. Technical report, National Bureau of Economic Research, 1998.

John T Addison and McKinley L Blackburn. The effects of unemployment insurance on postunemployment earnings. *Labour Economics*, 7(1):21–53, 2000.

Axel Anderson and Lones Smith. Dynamic matching and evolving reputations. *The Review of Economic Studies*, 77(1):3–29, 2010.

Kartik Athreya, Juan M Sánchez, Xuan S Tam, and Eric R Young. Labor market upheaval, default regulations, and consumer debt. *Federal Reserve Bank of St. Louis Working Paper Series*, (2014-002), 2014.

K.B. Athreya and N.B. Simpson. Unsecured debt with public insurance: From bad to worse. *Journal of Monetary economics*, 53(4):797–825, 2006.

Jesper Bagger and Rasmus Lentz. An empirical model of wage dispersion with sorting. *The Review of Economic Studies*, 2014.

Scott R Baker and Constantine Yannelis. Income changes and consumption: Evidence from the 2013 federal government shutdown. *Available at SSRN 2575461*, 2015.

Gadi Barlevy. The sullying effect of recessions. *The Review of Economic Studies*, 69(1):65–96, 2002.

Gary S Becker. A theory of marriage: Part i. *The Journal of Political Economy*, pages 813–846, 1973.

Zach Bethune. Consumer credit, unemployment, and aggregate labor market dynamics. Technical report, Working Paper, 2015.

Zach Bethune, Guillaume Rocheteau, and Peter Rupert. Aggregate unemployment and household unsecured debt. 2013.

Stéphane Bonhomme, Thibaut Lamadon, and Elena Manresa. A distributional framework for matched employer employee data. 2014.

J. Carter Braxton, Kyle F Herkenhoff, and Gordon Phillips. Can the unemployed borrow? implications for public insurance. *Manuscript*, 2018.

Martin Browning and Thomas F Crossley. Unemployment insurance benefit levels and consumption changes. *Journal of Public Economics*, 80(1):1–23, 2001.

David Card, Andrew Johnston, Pauline Leung, Alexandre Mas, and Zhuan Pei. The effect of unemployment benefits on the duration of unemployment insurance receipt: New evidence from a regression kink design in missouri, 2003-2013. Technical report, National Bureau of Economic Research, 2015.

S. Chatterjee, D. Corbae, M. Nakajima, and J.V. Ríos-Rull. A quantitative theory of unsecured consumer credit with risk of default. *Econometrica*, 75(6):1525–1589, 2007.

Gaston Rene Chaumont and Shouyong Shi. Wealth accumulation, on the job search and inequality. 2017.

R. Chetty. Moral hazard vs. liquidity and optimal unemployment insurance. Technical report, National Bureau of Economic Research, 2008.

Gabriel Chodorow-Reich and Loukas Karabarbounis. The cyclicality of the opportunity cost of employment. Technical report, National Bureau of Economic Research, 2013.

J Michael Collins, Kathryn Edwards, and Maximilian Schmeiser. The role of credit cards for unemployed households in the great recession. *Manuscript*, 2015.

Leland Crane, Henry Hyatt, and Seth Murray. Cyclical labor market sorting. Technical report, Mimeo, 2017.

Steven Davis and Till Von Wachter. Recessions and the costs of job loss. 2011.

Emin Dinlersoz, Henry R Hyatt, and Hubert P Janicki. Who works for whom? worker sorting in a model of entrepreneurship with heterogeneous labor markets. *US Census Bureau Center for Economic Studies Paper No. CES-WP-15-08*, 2015.

Jason Roderick Donaldson, Giorgia Piacentino, and Anjan Thakor. Bank capital, bank credit, and unemployment. 2014.

Lukasz A Drozd and Ricardo Serrano-Padial. Modeling the revolving revolution: The debt collection channel. *American Economic Review*, 107(3):897–930, 2017.

Jan Eeckhout and Philipp Kircher. Identifying sorting—in theory. *The Review of Economic Studies*, page rdq034, 2011.

Jan Eeckhout and Alireza Sepahsalari. Unemployment risk and the distribution of assets. Technical report, Manuscript, 2014.

David S Evans and Richard Schmalensee. *Paying with plastic: the digital revolution in buying and borrowing*. MIT Press, 2005.

Raquel Fernandez and Jordi Gali. To each according to…? markets, tournaments, and the matching problem with borrowing constraints. *The Review of Economic Studies*, 66(4):799–824, 1999.

Peter Ganong and Pascal Noel. How does unemployment affect consumer spending? Technical report, Working paper, 2015.

Michael Gelman, Shachar Kariv, Matthew D Shapiro, Dan Silverman, and Steven Tadelis. How individuals smooth spending: Evidence from the 2013 government shutdown using account data. Technical report, National Bureau of Economic Research, 2015.

Kristopher Gerardi, Kyle F Herkenhoff, Lee E Ohanian, and Paul S Willen. Can't pay or won't pay? unemployment, negative equity, and strategic default. *The Review of Financial Studies*, 31 (3):1098–1131, 2017.

Ben Griffy. Borrowing constraints, search, and life-cycle inequality. *Manuscript*, 2017.

David B Gross and Nicholas S Souleles. Do liquidity constraints and interest rates matter for consumer behavior? evidence from credit card data. Technical report, National bureau of economic research, 2001.

David B Gross and Nicholas S Souleles. Do liquidity constraints and interest rates matter for consumer behavior? evidence from credit card data*. *The Quarterly journal of economics*, 117 (1):149–185, 2002.

Jonathan Gruber. The wealth of the unemployed. *Industrial and Labor Relations Review*, pages 79–94, 2001.

Veronica Guerrieri and Guido Lorenzoni. Credit crises, precautionary savings, and the liquidity trap. Technical report, National Bureau of Economic Research, 2011.

Marcus Hagedorn, Tzuo Hann Law, and Iourii Manovskii. Identifying equilibrium models of labor market sorting. Technical report, National Bureau of Economic Research, 2012.

Marcus Hagedorn, Fatih Karahan, Iourii Manovskii, and Kurt Mitman. Unemployment benefits and unemployment in the great recession: the role of macro effects. *Economics working paper, University of Pennsylvania*, 2013.

K.F. Herkenhoff. The impact of consumer credit access on unemployment. *Manuscript*, 2013.

Kyle Herkenhoff, Jeremy Lise, Guido Menzio, and Gordon M Phillips. Production and learning in teams. Technical report, National Bureau of Economic Research, 2018.

Kyle F Herkenhoff, Gordon Phillips, and Ethan Cohen-Cole. The impact of consumer credit access on employment, earnings and entrepreneurship. *Manuscript*, 2016.

Christopher Huckfeldt. The scarring effect of recessions: A quantitative analysis. *New York University*, 2014.

E. Hurst and F. Stafford. Home is where the equity is: mortgage refinancing and household consumption. *Journal of Money, Credit and Banking*, pages 985–1014, 2004.

Louis S Jacobson, Robert J LaLonde, and Daniel G Sullivan. Earnings losses of displaced workers. *The American Economic Review*, pages 685–709, 1993.

Gregor Jarosch. Searching for job security and the consequences of job loss. 2014.

Yan Ji. Job search under debt: Aggregate implications of student loans. *Manuscript*, 2018.

F. Karahan and S. Rhee. Housing and the labor market: The role of migration on aggregate unemployment. *University of Pennsylvania, mimeo*, 2011.

Lawrence F Katz and Bruce D Meyer. Unemployment insurance, recall expectations, and unemployment outcomes. *The Quarterly Journal of Economics*, 105(4):973–1002, 1990.

Per Krusell, Toshihiko Mukoyama, and Ayşegül Şahin. Labour-market matching with precautionary savings and aggregate fluctuations. *The Review of Economic Studies*, 77(4):1477–1507, 2010.

Patrick Legros and Andrew F Newman. Monotone matching in perfect and imperfect worlds. *The Review of Economic Studies*, 69(4):925–942, 2002.

Rasmus Lentz and Torben Tranaes. Job search and savings: Wealth effects and duration dependence. 2001.

Jeremy Lise. On-the-job search and precautionary savings. *The Review of Economic Studies*, page rds042, 2012.

Jeremy Lise and Jean-Marc Robin. The macro-dynamics of sorting between workers and firms. 2013.

Igor Livshits, James MacGee, and Michele Tertilt. Accounting for the rise in consumer bankruptcies. Technical report, National Bureau of Economic Research, 2007.

Igor Livshits, James C MacGee, and Michele Tertilt. The democratization of credit and the rise in consumer bankruptcies. *The Review of Economic Studies*, 83(4):1673–1710, 2016.

L. Ljungqvist and T.J. Sargent. The european unemployment dilemma. *Journal of Political Economy*, 106(3):514–550, 1998.

Ramon Marimon and Fabrizio Zilibotti. Unemployment vs. mismatch of talents: reconsidering unemployment benefits. *The Economic Journal*, 109(455):266–291, 1999.

G. Menzio and S. Shi. Block recursive equilibria for stochastic models of search on the job. *Journal of Economic Theory*, 145(4):1453–1494, 2010.

G. Menzio and S. Shi. Efficient search on the job and the business cycle. *Journal of Political Economy*, 119(3):468–510, 2011.

Guido Menzio, Irina A Telyukova, and Ludo Visschers. Directed search over the life cycle. Technical report, National Bureau of Economic Research, 2012.

Kurt Mitman and Stanislav Rabinovich. Do changes in unemployment insurance explain the emergence of jobless recoveries? 2012.

Makoto Nakajima. Business cycles in the equilibrium model of labor market search and self-insurance*. *International Economic Review*, 53(2):399–432, 2012a.

Makoto Nakajima. A quantitative analysis of unemployment benefit extensions. *Journal of Monetary Economics*, 59(7):686–702, 2012b.

Alice Nakamura, Emi Nakamura, Kyle Phong, and Jón Steinsson. New evidence on the cyclicality of employer-to-employer flows from canada. *American Economic Review Papers and Proceedings*, 2019.

Arash Nekoei and Andrea Weber. Does extending unemployment benefits improve job quality? 2015.

Seth Neumuller. Inter-industry wage differentials revisited: Wage volatility and the option value of mobility. *Available at SSRN 2143814*, 2014.

Itay Saporta-Eksten. Job loss, consumption and unemployment insurance. 2013.

Edouard Schaal. Uncertainty, productivity and unemployment in the great recession. *Federal Reserve Bank of Minneapolis, mimeo*, 2012.

Shouyong Shi. Frictional assignment. i. efficiency. *Journal of Economic Theory*, 98(2):232–260, 2001.

Shouyong Shi. Directed search for equilibrium wage–tenure contracts. *Econometrica*, 77(2):561–584, 2009.

Robert Shimer. The assignment of workers to jobs in an economy with coordination frictions. Technical report, National Bureau of Economic Research, 2001.

Robert Shimer and Lones Smith. Assortative matching and search. *Econometrica*, 68(2):343–369, 2000.

Robert Shimer and Iván Werning. Liquidity and insurance for the unemployed. Technical report, National Bureau of Economic Research, 2005.

José Ignacio Silva and Manuel Toledo. Labor turnover costs and the cyclical behavior of vacancies and unemployment. *Macroeconomic Dynamics*, 13(S1):76–96, 2009.

David Strauss. Financial development and sorting reversals-a theory of structural change. 2013.

J.X. Sullivan. Borrowing during unemployment. *Journal of Human Resources*, 43(2):383–412, 2008.

Online Appendix, Not For Publication

"How Credit Constraints Impact Job Finding Rates, Sorting & Aggregate Output"

Herkenhoff, Phillips, and Cohen-Cole

January 20, 2019

Table of Contents

A Data Appendix

Employer reports are based on the ES-202 which is collected as part of the Covered Employment and Wages (CEW) program (run by BLS). One report per establishment per quarter is filed. On this form, wages subject to statutory payroll taxes are reported.

The employment records are associated with a firm's State Employment Identification Number (SEIN). This is an identifier based on an employer within a given state, and it is, in general, not an identifier of the establishment of the worker. Minnesota is the only state to collect establishment identifiers, and in all other states, an imputation based on place-of-work is used to generate establishment level identifiers. In general, workers are included in the dataset if they earn at least one dollar from any employer.

The Quarterly Census of Employment and Wages (QCEW) contains firm level data which is collected in each state. This dataset includes information on industry, ownership, and worksite.

The demographic data in the LEHD comes from the 2000 census as well as social security records, and tax returns. These are linked by social security number with the unemployment insurance data. In the LEHD, social security numbers are not present, rather there is a scrambled version called a Protected Identification Key (PIK).

The main demographic information database is the Person Characteristic File (PCF). Information on sex, date of birth, place of birth, citizenship, and race are included here.

A.1 Employment and Duration Definitions

Our main concept of employment is end of quarter employment, as in Abowd et al. [2009]. For example, to be counted as employed at the end of quarter 1 at employer X, the worker in question must have had positive earnings at employer X in quarter 1 and quarter 2. Our earnings threshold is $500 in each quarter, and we find no significant impact on our results for greater earnings thresholds. If a mass displacement occurs at employer X in quarter 2 (i.e. 30% of their employees leave or they close, see the following section), and the worker separates from employer X (meaning the worker is not end of quarter employed at employer X in quarter 2), then we count the worker as mass displaced. If the worker becomes end of quarter employed at employer Y in quarter 2, then the non-employment duration spell is marked as a zero. If the worker is end of quarter employed at employer Y in quarter 3, then the duration is 1 quarter, and so on. We truncate durations at 9 quarters. In Section B.1, we adjust these spells for partial quarters of non-employment duration using the earnings gap method, and we also adjust for self-employment. We have also used other measures of employment, and we find no significant impact on our results.

A.2 Identifying Mass Layoffs

To identify mass layoffs, we combine data from the Longitudinal Business Dynamics (LBD) database on establishment exits with the LEHD. In each state, employers are assigned a State Employment Identification Number (SEIN) in the LEHD database. This is our unit of analysis for mass layoffs. We define a mass layoff to occur when an SEIN with at least 25 employees reduces its employment by 30% or more within a quarter and continues operations, or exits in the LEHD with a contemporaneous plant exit in the LBD. In California, we do not have LBD establishment exit information, however. To ensure that the there was actually a mass layoff, we then verify that fewer than 80% of laid-off workers move to any other single SEIN using the Successor Predecessor File (SPF). This allows us to remove mergers, firm name-changes, and spin-offs from our sample.

A.3 TransUnion Variables

The unused revolving credit limit ratio is defined as,

$$\frac{\text{(Total Revolving Credit Limit - HELOC credit limit) - (Total Revolving Balance - HELOC balance)}}{\text{Lagged Annual Earnings}}$$

'Total Revolving Credit Limit' corresponds to the TransUnion variable 'Revolving High Credit/Credit Limit.' 'Revolving High Credit/Credit Limit' is constructed as the sum of the 'High Credit/Credit Limit' across all types of revolving debt. The 'High Credit/Credit Limit' is defined as the actual credit limit if such a limit is recorded or the highest historical balance if no credit limit is recorded. 'HELOC credit limit' is the sum across all available HELOC credit limits, and 'HELOC balance' is the sum across all available HELOC balances.

A.4 Correlation of Unemployment Durations and Credit Limits in the SCF, Controlling for Assets

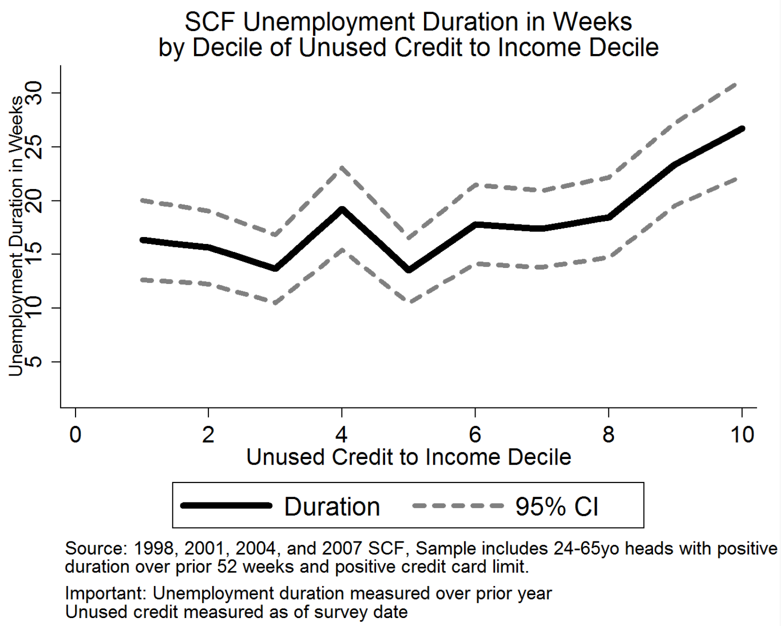
In the SCF between 1998 and 2007 (which includes the 1998, 2001, 2004, and 2007 surveys), we can compute the raw correlation between unused credit limits and unemployment durations, controlling for a host of assets, including home values. Figure 9 plots the raw correlation between unemployment duration and credit limits in the SCF, and it reveals a similar pattern to the LEHD/TransUnion dataset. Table A1 provides a more formal analysis, including controls for the entire portfolio of a household's assets. Table A1 demonstrates a strong correlation between unused credit card limits and unemployment durations, subject to time aggregation bias (the unused credit limit is measured as of the survey date whereas unemployment duration is measured over the last year). The 'Unused Unsecured Limit to Income' refers to unused credit card limits (as of the survey date) over annual gross family income (over the prior year). Unemployment duration measures weeks spent unemployed over the past 12 months prior to the survey. It is measured in weeks, and does not distinguish individual unemployment spells.

Column 1 of Table A1 shows that simple regressions of unemployment duration on unused credit card limits reveal a strong positive correlation, even after controlling for income and liquid assets. Columns 2 and 3 impose age restrictions and add basic demographic controls, but the positive and significant relationship persists. Column 4 adds in all available categories of illiquid assets, and finally Column 5 restricts the dataset to mortgagors (as is the case in the LEHD/TransUnion sample considered in the text). The strong positive and significant relationship between unused credit limits and unemployment durations persists. An unused credit limit worth 10% of prior annual family income is associated with 1 week longer unemployment spells, somewhat larger than the IV estimate in the LEHD/TransUnion sample considered in the text.

A.5 Alternate Measures of Personal Financial Constraints: Total Credit, Revolving Credit Including HELOCs, and Credit Scores

In Table A2, we use alternate endogenous regressors: (i) unused revolving credit to income, including HELOCs (ii) total unused credit, including all types of secured (including HELOCs

Figure 9: **Survey of Consumer Finances:** Correlation of Unemployment Durations (in Weeks) on Unused Credit (Source: 1998-2007 SCF)



and mortgage debt) and unsecured debt (we define 'total unused credit to income' as the total credit limit less the amount currently borrowed over annual earnings, where the ratio is measured 1 year prior to layoff)[30], and (iii) credit scores (this corresponds to TransUnion's bankruptcy model, and ranges from 0 to 1000, with higher scores indicating less credit risk).

Table A2 instruments the alternate endogenous regressors with the Gross and Souleles instrument. Columns (1) and (2) of Table A2 illustrate that revolving unused credit, inclusive of HELOCs, has a similar effect on duration and replacement rates (conditional on being employed at $t+1$), respectively, as the baseline definition in the text, Table 5, (which excludes HELOCs). Likewise, Columns (3) and (4) of Table A2 illustrate that total unused credit has a similar effect on duration and replacement rates. Columns (5) and (6) of Table A2 are more difficult to interpret, since the units are in terms of the TU bankruptcy model ('credit score'), but in general, if an individual has a higher score prior to layoff, they take longer to find a job, and they find higher replacement rates, conditional on finding a job.

[30]The Total Credit Limit is formally the TransUnion variable "Total High Credit/Credit Limit" which is sum of actual credit limits across all types of debt, or if the credit limit is not stated, it is the highest observed prior balance. This measure of credit includes secured credit lines like home equity lines of credit and installment credit, as well as auto loans, and other personal finance loans.

Table A1: **Survey of Consumer Finances:** OLS Regressions of Unemployment Durations (in Weeks) on Unused Credit, Controlling for Assets (Source: 1998-2007 SCF)

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	Dep. Var. is SCF Unemployment Duration in Weeks					
Unused Unsecured Limit to Income	12.334***	10.430***	8.733***	9.338***	8.155***	7.854***
	(5.85)	(4.87)	(4.02)	(4.31)	(3.75)	(2.66)
Year Dummies	N	Y	Y	Y	Y	Y
Demographics and Income	N	Y	Y	Y	Y	Y
Liquid Assets to Inc (Checking/Savings plus Stocks and Bonds)	N	N	**Y**	N	**Y**	**Y**
Illiquid Assets to Inc (Homes, Vehicles, etc.)	N	N	N	**Y**	**Y**	**Y**
Mortgagors Only	N	N	N	N	N	**Y**
Observations	764	764	764	759	759	421
R-squared	0.052	0.130	0.144	0.137	0.148	0.157

Notes: SCF 24 to 65yo Heads of Household with Positive Unemployment Spell over Prior 12 months and Positive Limit. Restrict to Mortgagors in Col 6. Demographics include quadratic in age, dummies for education, and dummies for race and Income refers to gross annual family income. Liquid Assets include cash, checking, money market funds, CDS, corporate bonds, government saving bonds, stocks, and mutual funds less credit card debt. Unused Credit Limit to Income refers to total credit card limits less credit card balances. Illiquid Assets includes Homes, Vehicles, Retirement, Annuities, Life Insurance at self-reported market values.

Table A2: Alternate Measures of Access to Credit. IV estimates using the Gross and Souleles Instrument. (Source: 2002-2006 LEHD/TransUnion)

	(1) Duration	(2) Rep Rate (Among Employed t+1)	(3) Duration	(4) Rep Rate (Among Employed t+1)	(5) Duration	(6) Rep Rate (Among Employed t+1)
Unused Revolving Credit to Income Ratio (Incl. HELOCS)	0.447***	0.139***				
	(0.0939)	(0.0189)				
Total Unused Credit to Income Ratio			0.318***	0.100***		
			(0.0667)	(0.0135)		
Credit Score					0.00401***	0.00130***
					(0.000874)	(0.000237)
Controls	Y	Y	Y	Y	Y	Y
R2 (1st Stage for IVs)	0.0440	0.0392	0.0517	0.0464	0.00288	0.00194
Angirst Pischke FStat Pval	0	0	0	0	0	0
Pval Weak Id Null Weak	0	0	0	0	0	0
Round N	81000	36000	81000	36000	81000	36000

B Replacement Earnings 2 Years After Layoff

Consider the set of households who find a job 1 year after layoff. In the main text, we focus on the impact of credit on the wages of job finders 1 year after layoff. To assess the impact of consumer credit access on longer term wage outcomes, Table A3 analyzes wages 2 years after layoff for this same sample. Column (1) reveals that under OLS, replacement earnings are .66% higher, 2 years after layoff, for households who can replace 10% more of their lost income with unused credit. Column (2) replicates this analysis using the Gross and Souleles instrument, and again, we find a significant positive impact of credit on long-term earnings.

Table A3: Dependent Variable is Replacement Rate, Measured 2 Years After Layoff Relative to 1 Year Before Layoff. Sample Restricted to Job Finders 1 Year After Layoff. (Source: 2002-2006 LEHD/TransUnion)

	(1)	(2)
	—— Dep. Var. is Rep. Rate at t+2 ——	
	OLS	IV-GS
Unused Revolving Credit to Income Ratio	0.0660***	0.139***
	(0.00536)	(0.0211)
Controls	Y	Y
R2 (1st Stage for IVs)	0.201	0.0396
Round N	36000	36000

Notes. Same as Table 4.

B.1 Self-Employment and the Earnings Gap Method

Table A4 redoes the main analysis in two different ways. Column (1) repeats the original duration regression from Table 5. Column (2) is a regression of duration on unused credit where the self-employed with more than 5k in annual Schedule C earnings are counted as employed. Column (3) infers the length of unemployment duration using the earnings gap method. Using quarterly earnings prior to layoff as the base (E_{q-1}), then those who find a job within the first quarter of layoff will have spent $1 - E_q/E_{q-1}$ fraction of the quarter unemployed. Table A4 illustrates that the main results are robust to these alternate definitions.

Table A4: Column (1) is duration of non-employment, counting the self-employed who earn more than 5k in a year as employed, and Column (2) is duration of non-employment with partial duration values inferred using the earnings gap method. (Source: LEHD / TransUnion)

	(1) Duration (Baseline)	(2) Duration (Self-Employment)	(3) Duration (Earnings Gap Method)
Unused Revolving Credit to Income Ratio	0.442*** (0.0929)	0.450*** (0.0914)	0.444*** (0.0923)
Demographic, Industry, MSA, & Lagged Earnings Controls	Y	Y	Y
HELOC Limits and Equity Proxy	Y	Y	Y
R2 (1st Stage for IVs)	0.0433	0.0433	0.0433
Angirst Pischke FStat Pval	0	0	0
Round N	81000	81000	81000

*Notes. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Revolving Unused Credit to Income measured 1 year prior to layoff. Demographic controls include quadratic in age & tenure, race, sex and education dummies as well as year & auto loan dummies. Industry controls include 1-digit SIC dummies. MSA controls include real per capita GDP and the MSA unemployment rate. Lagged earnings controls include lagged real annual earnings.*

C Employed Value Functions

For employed households, value functions are denoted with a W, and at the end of every period, employed households face layoff risk δ. If they are laid off, since the period is 1 quarter, we must allow the workers to search immediately for a new job.[31]

$$
\begin{aligned}
W_t^G(b,h,k;\Omega) = \max_{b'\geq \underline{b}} u(c) + \beta\mathbb{E}\Big[&(1-\delta)[p_x W_{t+1}(b'-x,h',k;\Omega') + (1-p_x)W_{t+1}(b',h',k;\Omega')] \\
&+\delta\Big\{\max_{\tilde{k}} p(\theta_{t+1}(h',\tilde{k};\Omega'))[p_x W_{t+1}(b'-x,h',\tilde{k};\Omega') + (1-p_x)W_{t+1}(b',h',\tilde{k};\Omega')] \\
&\quad + \big(1-p(\theta_{t+1}(h',\tilde{k};\Omega'))\big)[p_x U_{t+1}(b'-x,h',k;\Omega') + (1-p_x)U_{t+1}(b',h',k;\Omega')]\Big\}\Big], \quad t\leq T
\end{aligned}
$$

$$W_{T+1}^G(b,h,k;\Omega) = 0$$

Such that the aggregate laws of motion are given by equation (1), human capital evolves according to the law of motion: $h' = H(h,W)$, and the budget constraint holds,

$$c + q_{W,t}(b',h,k;\Omega)b' \leq \alpha f(h,k) + b$$

The value functions for employed borrowers who default as well as the discrete default decision are formulated in an identical fashion to that of the unemployed.

$$
\begin{aligned}
W_t^B(0,h,k;\Omega) = u(c) + \lambda\beta\mathbb{E}\Bigg[&(1-\delta)[p_x W_{t+1}(-x,h',k;\Omega') + (1-p_x)W_{t+1}(0,h',k;\Omega')] \\
&+\delta\Big\{\max_{\tilde{k}} p(\theta_{t+1}(h',\tilde{k};\Omega'))[p_x W_{t+1}(-x,h',\tilde{k};\Omega') + (1-p_x)W_{t+1}(0,h',\tilde{k};\Omega')] \\
&\quad + \big(1-p(\theta_{t+1}(h',\tilde{k};\Omega'))\big)[p_x U_{t+1}(-x,h',k;\Omega') + (1-p_x)U_{t+1}(0,h',k;\Omega')]\Big\}\Bigg] \\
&+ (1-\lambda)\beta\mathbb{E}\Bigg[(1-\delta)[p_x(W_{t+1}^B(-x,h',k;\Omega') - \chi) + (1-p_x)W_{t+1}^B(0,h',k;\Omega')] \\
&+\delta\Big\{\max_{\tilde{k}} p(\theta_{t+1}(h',\tilde{k};\Omega'))[p_x(W_{t+1}^B(-x,h',\tilde{k};\Omega') - \chi) + (1-p_x)W_{t+1}^B(0,h',\tilde{k};\Omega')] \\
&\quad + \big(1-p(\theta_{t+1}(h',\tilde{k};\Omega'))\big)[p_x(U_{t+1}^B(-x,h',k;\Omega') - \chi) + (1-p_x)U_{t+1}^B(0,h',k;\Omega')]\Big\}\Bigg] \\
&, \quad t\leq T
\end{aligned}
$$

[31] This allows the model to match labor flows in the data.

$$W^B_{T+1}(b,h,k;\Omega) = 0$$

Such that the aggregate laws of motion are given by equation (1), human capital evolves such that $h' = H(h, W)$ and the budget constraint is given by,

$$c \leq \alpha f(h,k)$$

For employed households in good standing, at the start of every period, they must make the following default decision,

$$W_t(b,h,k;\Omega) = \max\left\{W^G_t(b,h,k;\Omega), W^B_t(0,h,k;\Omega) - \chi\right\}$$

Let $D_{W,t}(b,h,k;\Omega)$ denote the employed household's default decision.

D Characterizing Existence

In this section, we characterize existence of a block recursive equilibrium for the model economy. The proofs use a similar methodology to Menzio et al. [2012], extended to an environment with two-sided heterogeneity. To simplify notation, we assume there are no expense shocks for the proofs. We begin with Proposition D.1 which is the existence result for a Block Recursive Equilibrium.

Proposition D.1. *Assume that the utility function meets standard conditions ($u' > 0, u'' < 0, \lim_{c\to 0} u'(c) = \infty, \lim_{c\to\infty} u'(c) = 0$, and u is invertible), the matching function is invertible and constant returns to scale, and there is a bounded support (which can be non-binding) for the choice set of debt $b \in \mathbb{B} \subseteq [\underline{b}, \overline{b}]$ and the capital of firms $k \in \mathcal{K} \subseteq [\underline{k}, \overline{k}]$, then a Block Recursive Equilibrium exists.*

Proof. The proof will follow backward induction. Let $t = T$, and consider an unemployed household for the sake of brevity (an identical argument follows for employed households). Since the household's continuation value is zero from $T + 1$ onward, the household dynamic programming problem trivially does not depend on the aggregate distribution μ across states in the last period of life,

$$\begin{aligned} U_T^G(b,h,k;\Omega) &= u(z(k)+b,1)+\beta\cdot 0 \\ &= U_T^G(b,h,k;\underline{b}) \end{aligned}$$

$$\begin{aligned} W_T^G(b,h,k;\Omega) &= u(\alpha f(h,k)+b,1)+\beta\cdot 0 \\ &= W_T^G(b,h,k;\underline{b}) \end{aligned}$$

In this last period of life, the saving and borrowing policy function $b'_{e,T}(b,h,k;\underline{b})$ is trivially zero (for both employed $e=W$ and unemployed agents $e=U$). Likewise, for households in bad standing in the last period of life, the value of unemployment (and nearly identical conditions hold for the employed, and so are omitted) is given by,

$$U_t^B(b,h,k;\underline{b}) = u(z(k),1)+\beta\cdot 0$$

Stepping back to the default decision, U_T will also not depend on the aggregate distribution μ,

$$U_T(b,h,k;\underline{b}) = \max\left\{U_T^G(b,h,k;\underline{b}), U_T^B(0,h,k;\underline{b})-\chi\right\}$$

Let $D_{U,T}(b,h,k;\underline{b})$ denote the policy function of the household. Since there is a utility penalty χ of defaulting, debt can be supported in equilibrium, and $D_{U,T}$ will not be trivially zero.

Now stepping back to the labor search problem, the firm's value function will be independent of μ as well (and, as we will use in the text, it is also independent of the aggregate shock itself, $\underline{b}$),

$$\begin{aligned} J_T(h,k;\Omega) &= (1-\alpha)f(h,k)+\beta\cdot 0 \\ &= J_T(h,k) \end{aligned}$$

And the labor market tightness will also be independent of μ (and, similar to the firm problem, it is also independent of the aggregate shock itself, $\underline{b}$),

$$\theta_T(h,k;\Omega) = p_f^{-1}\left(\frac{\kappa+(1+r_f)k}{J_T(h,k)}\right)$$
$$= \theta_T(h,k)$$

The household at age $T-1$ (note that the primes below simply note that age $T-1$ risk over $\underline{b}$ has already been realized and human capital has already evolved to h') must therefore make the following labor market search choice over k, the capital of firms,

$$\max_{k\in\mathcal{K}} \; p(\theta_T(h',k))W_T(b',h',k;\underline{b}') + \big(1-p(\theta_T(h',k))\big)U_T(b',h',k;\underline{b}') \tag{11}$$

So long as k lies in a bounded interval, the extreme value theorem guarantees at least one solution to this problem. It is possible for certain classes of utility functions, as shown in an earlier version of this draft, to establish uniqueness.

Given the household policy functions for labor search $k'_{T-1}(h',k;\underline{b}')$ and default $D'_{e,T}(h',k;\underline{b}')$, the bond price $q_{U,T-1}(b',h,k;\Omega)$ is given by,

$$q_{U,T-1}(b',h,k;\Omega) = \frac{\mathbb{E}\Big[1-D_{e',T}(b',h',k';\underline{b}')\Big]}{1+r_f}$$
$$= q_{U,T-1}(b',h,k;\underline{b})$$

Clearly the bond price does not depend on the aggregate distribution μ.

Stepping back from $t = T-1,\ldots,1$, and repeating the above procedure completes the proof.

□

A simple corollary follows in which one can establish the existence of an equilibrium with debt.

Corollary D.2. *Under the hypotheses of Proposition D.1, so long as $\chi > 0$ and $\mathcal{B}$ contains a neighborhood of debt around 0, a Block Recursive Equilibrium with credit exists.*

Proof. Because of the inada conditions, for every positive $\chi \in \mathbb{R}_+$, there exists a sufficiently small debt in an ϵ-neighborhood around zero, $b \in N_\epsilon(0)$, such that the household strictly prefers repayment in the last period of life. The households repayment choice is given by,

$$\max\left\{U_T^G(b,h,k;\underline{b}), U_T^B(0,h,k;\underline{b}) - \chi\right\}$$

This holds with equality at the cutoff debt b^*,

$$U_T^G(b^*,h,k;\underline{b}) = U_T^B(0,h,k;\underline{b}) - \chi$$

Substituting,

$$u(z(k)+b^*,1) = u(z(k),1) - \chi$$

The minimum supportable debt is given by,

$$b^* = u^{-1}(u(z(k),1) - \chi, 1) - z(k) < 0$$

□

E Model Robustness: Capital Investment and Liquidation

E.1 Model with Firm Investment

To ease notation, assume there are no expense shocks. Now assume that Firms can invest in capital, depending on the worker's type. The problem of an unemployed household is unchanged. The value functions for employed borrowers who default as well as the discrete default decision are formulated in an identical fashion to that of the unemployed, except workers must now forecast the investment decision of the firm.

Timing assumption: New capital is not operable immediately.

The Bellman equation for a household in bad standing is given below (good standing is extremely similar):

$$
\begin{aligned}
W_t^B(b,h,k;\Omega) = u(c) + \lambda\beta\mathbb{E}\Big[&(1-\delta)W_{t+1}(0,h',k';\Omega') \\
&+ \delta\Big\{\max_{\tilde{k}} p(\theta_{t+1}(h',\tilde{k};\Omega'))W_{t+1}(0,h',\tilde{k};\Omega') \\
&\qquad + \big(1-p(\theta_{t+1}(h',\tilde{k};\Omega'))\big)U_{t+1}(0,h',k;\Omega')\Big\}\Big] \\
&+ (1-\lambda)\beta\mathbb{E}\Big[(1-\delta)W_{t+1}^B(0,h',k';\Omega') \\
&+ \delta\Big\{\max_{\tilde{k}} p(\theta_{t+1}(h',\tilde{k};\Omega'))W_{t+1}^B(0,h',\tilde{k};\Omega') \\
&\qquad + \big(1-p(\theta_{t+1}(h',\tilde{k};\Omega'))\big)U_{t+1}^B(0,h',k;\Omega')\Big\}\Big], \quad t \leq T
\end{aligned}
$$

$$
W_{T+1}^B(b,h,k;\Omega) = 0
$$

Such that the aggregate laws of motion are given by equation (1), human capital evolves such that $h' = H(h,W)$ and the budget constraint is given by,

$$
c \leq \alpha f(h,k)
$$

And, additionally

$$
k' = k_t^{*'}(h,k;\Omega)
$$

This final condition $k' = k_t^{*'}(h,k;\Omega)$ means that households have rational expectations over what the entrepreneurs' optimal investment decisions are.

E.2 Lenders

Lenders' bond prices are updated to reflect changes in capital, since it may affect the wage of the worker and hence their repayment probability.

E.3 Entrepreneurs

We now allow entrepreneurs to invest in capital subject to an adjustment cost $\Gamma(k' - k)$. Therefore the value function for the firm is given by,

$$J_t(h, k; \Omega) = \max_{k'} (1 - \alpha) f(h, k) - i - \Gamma(k' - k) + \beta \mathbb{E}\big[(1 - \delta) J_{t+1}(h', k'; \Omega')\big]$$

Subject to a unit investment cost (i.e. the MRT of output and capital is 1, excluding the adjustment cost),

$$i = k' - k$$

$$J_{T+1}(h, k; \Omega) = 0$$

In the results below, we choose a quadratic adjustment cost $\Gamma(x) = x^2$. Figure 10 illustrates that the movements in productivity, output, and employment are larger once we allow for firm investment. Figure 11 illustrates that sorting (the correlation between human capital and capital) continues to decline and investment in capital continues to increase under the quadratic adjustment cost assumption.

Figure 10: Capital Investment: Employment, Output and Productivity

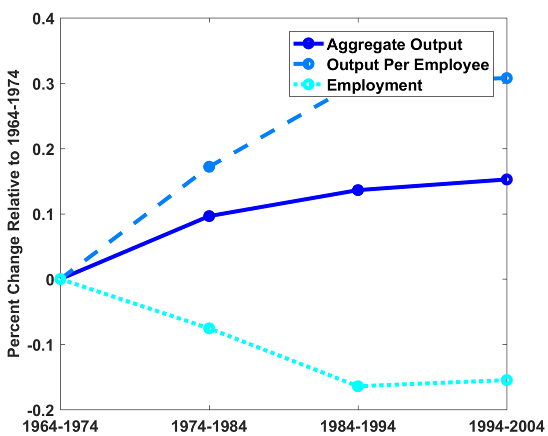
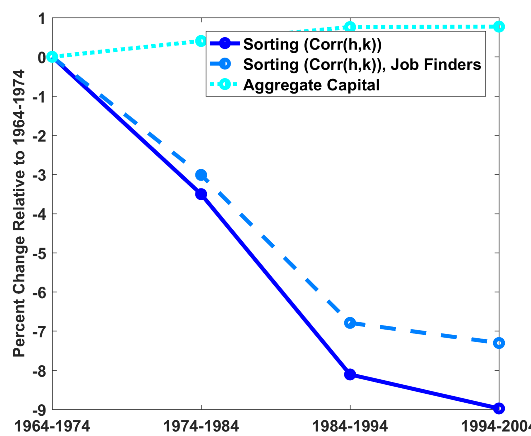


Figure 11: Capital Investment: Sorting and Capital



E.4 Liquidation

We also allow for the baseline model to have a liquidation value of capital, χ_f. The continuation value of the firm becomes,

$$J_t(h,k;\Omega) = (1-\alpha)f(h,k) + \beta\mathbb{E}\big[(1-\delta)J_{t+1}(h',k;\Omega') + \delta\chi_f k\big]$$

In the results below, we choose $\chi_f = .5$ which is relatively low, but it allows us to preserve the calibration, approximately. For larger values of χ_f, the same aggregate patterns emerge, except we must significantly expand the capital grid to a point that it becomes computationally infeasible. Figures 12 and 13 illustrate the model's main results with liquidation values. Employment and sorting fall as debt limits loosen, while output, productivity and aggregate capital rise as debt limits loosen. This is consistent with the benchmark results in the text.

Figure 12: Liquidation Value: Employment, Output and Productivity

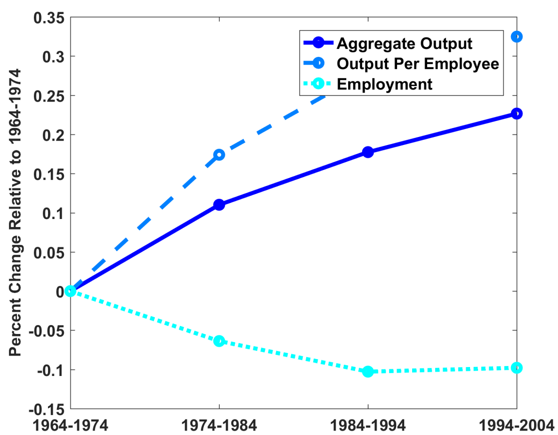
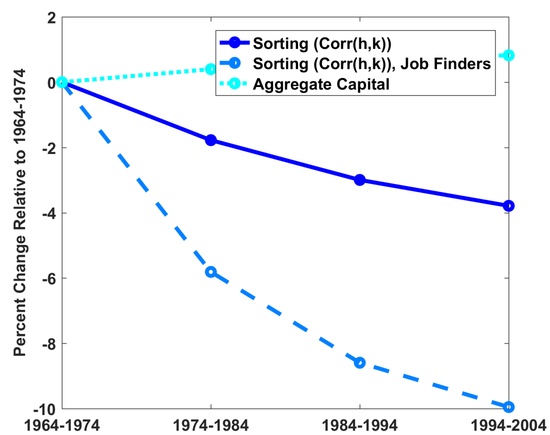


Figure 13: Liquidation Value: Sorting and Capital



F Solution Algorithm

We solve the model using value function iteration on a discrete grid. Capital lies in the interval [0.05,6.14] with 179 grid points including the ends of the grid. We evenly space 36 grid points from .05 to 1.8, where agents do not often search, and we evenly space 143 grid points from 1.85 to 6.14, where agents search most commonly. Bonds lie on the grid [-.4911]∪[-.49,3.35] with 110 evenly spaced grid points between -.49 and 3.35, including zero. The human capital grid is 6 evenly spaced grid points including the end of the grid over [.5,1]. The aggregate bond limit follows the Markov chain discussed in the text.

Starting at $t = T$ and working backwards, the solution method is given below:

i. Recover $J_t(h, k; \Omega)$ using value function iteration.

ii. Recover $\theta_t(h, k; \Omega)$, the market tightness, by free entry, $\theta_t(h, k; \Omega) = p_f^{-1}\left(\frac{\kappa+(1+r_f)k}{J_t(h,k;\Omega)}\right)$

iii. Solve the household default decision to recover $D_{e,t}(b, h, k; \Omega)$.

iv. Solve the household maximization problem over the grid of k's to recover $k_t(b, h, k; \Omega)$ using the market tightness and the implied job finding rates in step ii.

v. Use realized search behavior and default outcomes to recover the bond price $q_{e,t}(b, h, k; \Omega)$ (in the last period of life, this is simply zero).

vi. Solve the household maximization problem over the grid of b's to recover $b'_{e,t}(b, h, k; \Omega)$, taking the bond price from step v as given.

vii. Repeat i to vi until t=1.

viii. Use policy functions from the household problem to simulate 80,000 households for 280 periods, 5 times, burning the first 100 periods. We report averages over the 5 simulations.