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

Kyle Herkenhoff    Gordon Phillips    Ethan Cohen-Cole

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**Abstract**

How do consumer credit markets affect the allocation of workers to firms, output, and labor productivity? We address this question in two steps. First, we use new microdata to estimate empirical elasticities of job search patterns to credit. Second, we estimate our novel theory of sorting under risk aversion to match these elasticities, and then we conduct aggregate counterfactuals. Empirically, we show that an increase in credit limits worth 10% of prior annual earnings allows individuals to take 0.33 weeks longer to find a job. Conditional on finding a job, they earn 1.85% more and work at higher paying firms. We also find that young and high-utilization individuals are more responsive to credit. Theoretically, we integrate risk aversion and borrowing into a model with worker and firm heterogeneity. We estimate the model to match our new empirical elasticities, and we then measure how the credit expansion from 1964 to 2004 affected sorting and output. Sorting improves as credit expands since constrained workers – in particular constrained, young, high human capital workers – find more capital-intensive jobs.

Keywords: credit access, job search, sorting

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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 (Livshits, MacGee, and Tertilt [2016], Drozd and Serrano-Padial [2017], and Herkenhoff [2019]). The average worker losing their job can replace 29% of their prior annual income using revolving 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 (see, among others, Katz and Meyer [1990], Ljungqvist and Sargent [1998], Acemoglu and Shimer [1999], 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 search, thus making credit an imperfect substitute for unemployment insurance.

Using novel micro data, this paper provides the first attempt to measure the elasticities of unemployment durations, wage replacement rates, and average firm wages to credit access. We then use these empirical elasticities to estimate a theoretical model that integrates consumption-savings decisions into a model of two-sided worker and firm heterogeneity. We then use the estimated model to ask *how access to consumer credit affects the allocation of workers to firms* and *what this implies for aggregate outcomes such as labor productivity, output, and employment dynamics.*

Empirically, we use a new employee level database that links credit to employment histories. We build a new panel dataset that links TransUnion credit 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, earn more and work at more productive firms, as proxied by the firm's wage-per-worker. We

[1] The nascent but growing theoretical literature that links credit and search decisions has focused on two mechanisms, the self-insurance role of credit (e.g., Athreya and Simpson [2006], Athreya, Sánchez, Tam, and Young [2015], Herkenhoff [2019]) and labor demand effects of credit (e.g., Bethune, Rocheteau, and Rupert [2015], Donaldson, Piacentino, and Thakor [2019]). The equally sparse empirical literature on unemployment and borrowing is limited because of data constraints and finds mixed results (Hurst and Stafford [2004], Sullivan [2008], Bethune [2015], among others), but recent inroads have been made with new account level data (Baker and Yannelis [2017], Gelman, Kariv, Shapiro, Silverman, and Tadelis [2020], Ganong and Noel [2019], Braxton, Herkenhoff, and Phillips [2020], among others). These papers do not study the effect of credit access on job search. Very recent work on secured credit by He and le Maire [2021] finds similar labor market responses (lower employment, greater earnings) in response to the greater availability of home equity loans in Denmark in the 1990s, and Gopalan, Hamilton, Kalda, and Sovich [2021] find significant labor market lock-in from negative equity.

show that these relationships hold in an ordinary least squares analysis. They also hold when we use a worker's account age as an instrument, as in Gross and Souleles [2002], and also when we use housing supply elasticities as an instrument, as in Saiz [2010]. Our preferred estimates are based on the account age instrument. These estimates imply that being able to replace 10% more of prior annual labor earnings with personal revolving credit allows displaced workers to take 0.33 weeks longer to find a job, and, the annual earnings replacement rate of those who find a job (excluding replacement rates of 0) is 1.85% greater.[2]

We find that individuals with greater access to credit find better jobs at firms in the higher percentiles of the firm wage-per-worker distribution.[3] Those who can replace 10% more of prior annual earnings with credit are 0.9%, 1.5%, 0.5%, and 0.0% more likely to find jobs at firms above the 50th, 75th, 90th, and 99th percentile of the wage-per-worker distribution, respectively. Thus, credit has the largest impact on job finding rates at the lower quartiles of the wage-per-worker distribution and the least impact in the top decile.

We then investigate the role of worker heterogeneity. We find that younger individuals (less than 40 years of age) have duration and replacement rate elasticities that are 20% and 30% more responsive to changes in credit access than older individuals (greater than 40 years of age), respectively. Likewise, high-utilization individuals (who have above-average revolving credit balance to limit) exhibit duration and replacement rate elasticities roughly 4 times larger than those of low-utilization individuals (who have below-average revolving credit balance to limit). These stark differences in responsiveness across age and borrowing capacity serve to discipline the model's mechanisms.

We establish in the full LEHD database that for a large fraction of displaced workers, earnings losses are purely transitory, and thus the 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, which closely matches the 25% of displaced workers who report borrowing to smooth consumption in the RAND American Life Panel.

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

[2] The annual earnings replacement rate is the ratio of annual earnings between the year after layoff over the year before layoff.

[3] 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".

[2000]) with models of defaultable debt (e.g., Chatterjee, Corbae, Nakajima, and Ríos-Rull [2007]). 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 [2017]). We use the model and the moments from our empirical analysis to structurally estimate the impact of credit market development between 1964 and 2004 on job search behavior and the aggregate economy.

In our model, heterogeneous credit-constrained workers accumulate human capital while working. When unemployed, they direct their search for jobs among heterogeneous firms, as in Menzio and Shi [2010, 2011].[4] 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 (like that in Shimer and Smith [2000]).

Firms use differing amounts of capital and produce output by combining the human capital of workers with their physical capital (which may also be thought of as intellectual capital or sweat equity). 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.[5] 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 to be consistent with (1) our empirical estimates of how credit limits affect non-employment durations, re-employment earnings, and the types of jobs workers obtain, and (2) the differentials in duration and wage-per-worker elasticities by age and credit utilization. Our model is over-identified: 10 model parameters are estimated to match 14 regression moments and 9 aggregate moments. Despite such extensive over-identification, the model does well at matching both targeted and non-targeted moments. Among targeted moments, the model reproduces a duration elasticity of 0.28, measured in quarters[6] – ver-

[4] Related theoretical work includes sorting models with frictions (inter alia Eeckhout and Kircher [2011], Hagedorn, Law, and Manovskii [2017], Bagger and Lentz [2019], Bonhomme, Lamadon, and Manresa [2019]), 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, Hyatt, and Janicki [2019]).

[5] This measure is highly correlated with the Spearman rank correlation coefficient in our setting.

[6] A duration elasticity of 0.28 implies that an individual with 10% greater unused credit takes 0.33 [$= 0.28 \times 0.10 \times 12$] weeks longer to find a job, consistent with the estimates reported throughout the text.

sus 0.28 in the data – a replacement rate elasticity of 0.06, conditional on finding a job[7] – versus 0.18 in the data – and elasticities of job finding rates above the 50th percentile, 75th percentile, 90th percentile, and 99th percentiles of 0.08, 0.19, 0.17, and 0.00, respectively – versus 0.01, 0.15, 0.05 , and 0.00 in the data.[8] Notably, among non-targeted moments, the model reproduces replacement rate elasticities among high- and low-utilization displaced workers. As in the data, constrained (above average utilization) individuals are much more sensitive to credit. Their replacement rate elasticity is 0.53 in the data and 0.34 in the model, both of which are more than 4 times greater than the low-utilization elasticities of 0.11 and 0.06 in the data and model, respectively.

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, output, and productivity along the transition path from 1964 to 2004, as credit markets developed. [9] 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.

The impact of credit access on sorting is theoretically ambiguous. Credit access allows constrained individuals to find higher capital intensity jobs. If constrained individuals primarily have low human capital, then sorting can deteriorate as low human capital individuals borrow to finance job search for high capital intensity jobs. On the other hand, it is also the case that constrained individuals with high human capital aggressively borrow against future wage income to finance job search. We find that looser debt limits improve standard measures of sorting along the transition path from 1964 to 2004. These improvements in sorting generate productivity and output gains, but greater self-insurance mildly depresses

[7]A replacement rate elasticity of 0.06 implies that an individual with 10% greater unused credit earns 0.6% [$= 0.06 \times 0.10 \times 100$] more, conditional on finding a job.

[8]A job finding elasticity at the 50th percentile of the wage-per-worker distribution of 0.08 implies that an individual with 10% greater unused credit is 0.8% [$= 0.08 \times 0.10 \times 100$] more likely to work at a firm in the 50th percentile of the wage per worker distribution, conditional on finding a job.

[9]Relative to existing search models such as Herkenhoff [2019] and Bethune [2015], the allocation of workers to firms in our model endogenously determines productivity, output and welfare.

employment.

To understand why credit improves sorting, we examine heterogeneity in responsiveness to credit by human capital, age and credit constraints. Across the spectrum of human capital, all workers search for higher capital jobs as credit expands. Low human capital workers search for higher capital jobs, depressing sorting. High human capital workers search for higher capital jobs, improving sorting. However, in terms of magnitudes, constrained high human capital workers are the most sensitive to credit. These constrained high human capital workers tend to be in the early stages of their lifecycle. Among the set of young constrained individuals, capital intensity elasticities of the highest human capital workers are roughly 10 times greater than those of the lowest human capital workers. The net effect is that the behavior of constrained, high human capital workers dominates aggregate measures of sorting, and thus sorting improves as "high quality" workers find "high quality" jobs.

Our findings have implications for the provision of public insurance. Both 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 relatively moderate side-effects on the employment rate.[10] Whether 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, Karahan, Manovskii, and Mitman [2013], Hagedorn, Manovskii, and Mitman [2015] and Chodorow-Reich and Karabarbounis [2016] summarize both sides of the debate).

**Literature.** Relative to existing studies, our paper makes both theoretical and empirical contributions. Empirically, we build the first dataset to merge individual credit reports with administrative employee 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 empirical literature on employment effects of public programs such as unemployment insurance[11] by measuring the degree of self-insurance provided by private

[10] Note that these statements are true across many demographic splits individuals in the data.

[11] See Chetty [2008], Hagedorn et al. [2013], and Chodorow-Reich, Coglianese, and Karabarbounis [2019].

credit. Our paper also complements recent work that measures sorting over the business cycle using matched employer-employee data, for example, Crane, Hyatt, and Murray [2022] for the U.S. and Nakamura, Nakamura, Phong, and Steinsson [2019] for Canada.

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], Barlevy [2002], Lise and Robin [2017], Bagger and Lentz [2019], and Eeckhout and Sepahsalari [2022], 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 in Bewley-Huggett-Aiyagari frameworks, for example, Guerrieri and Lorenzoni [2017]. We integrate productive heterogeneity of both workers and firms. Doing so 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 [2017], who consider sorting over the business cycle with risk neutrality, and we complement contemporaneous work by Eeckhout and Sepahsalari [2022], who characterize the impact of assets on sorting patterns. The main differences between these papers 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.

Our work also complements earlier influential work that integrates assets into labor search models by Lentz and Tranaes [2001], Krusell, Mukoyama, and Şahin [2010], Nakajima [2012a], Lise [2013], Karahan and Rhee [2019], Herkenhoff [2019], Chaumont and Shi [2022], Griffy [2021] and Ji [2021]. We depart from this existing class of models by allowing for sorting and credit. The most related model is Herkenhoff [2019], however the theory in Herkenhoff [2019] has no firm heterogeneity, and thus there are no productivity consequences of job search since all jobs produced the same amount, Herkenhoff [2019] also abstracts from productive attributes of workers, and due to the lack of firm and worker attributes in production, there is *no notion of sorting* in Herkenhoff [2019]. 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.

Lastly, our work relates to theories of sorting under risk (e.g., Chade and Eeckhout [2016] and Chade and Lindenlaub [2022]) and with firm investment (e.g., Acemoglu and

Shimer [1999]).[12] Of particular note is influential work by Acemoglu and Shimer [1999]. It characterizes sorting when workers have assets, but in their setting, workers do not differ in productive attributes, and in their forward looking model, they solve a "one-shot" (i.e., born unemployed, find a job and then no further separations) CARA version in which assets do not affect job search behavior. More recent work by Chade and Lindenlaub [2022] considers a two stage game in which workers initially make investments in their human capital and then match to heterogeneous firms. We complement this work by considering the dynamic consumption-saving problem of households in a setting with firm heterogeneity, investment, and human capital differences.

The paper proceeds as follows. Section 1 discusses conceptually how credit can impact job finding and re-employment earnings and describes our sample and linked credit data to employee administrative job record. Section 2 provides estimates of how credit impacts job finding and re-employment earnings for our displaced workers. In this section, we also show how our results vary with worker characteristics such as age and prior access to credit. Section 3 presents our theoretical model. Section 4 details the model calibration strategy. Section 5 computes the model implied elasticities of labor market outcomes with respect to credit access. Section 6 computes the aggregate implications of expanding credit access between 1964 and 2004, and Section 7 concludes.

# 1 Empirical Analysis of Credit and Job Finding

We begin by discussing the conceptual framework and data, and then we present our empirical approach and results in the next section.

Unsecured credit allows unemployed households to augment today's liquid asset position by borrowing against future income. In McCall models of search, such as those studied by Athreya and Simpson [2006] and Chetty [2008], access to liquid assets allows households to search more thoroughly for higher wage jobs. While this mechanism is at the heart of the unemployment insurance literature, there is limited evidence linking access to liquid assets and job search decisions. In an influential paper, Chetty [2008] shows that workers who receive unemployment benefits take longer to find jobs, with the effect being strongest among low wealth households. He also shows that unemployed households who receive severance

[12] See the summary by Chade, Eeckhout, and Smith [2017] for a summary of the sorting literature.

payments take significantly longer to find jobs.

Unlike unemployment insurance or other liquid assets, consumer credit has two distinct properties. First, 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. Second, in dynamic models such as ours, consumer credit can be drawn down before job loss (using the severance payment analogy, this is equivalent to 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, distorting their labor market outcomes (i.e., individuals already have their "backs against the wall" upon job loss).

To our knowledge, there are no existing studies documenting the way consumer credit limits impact non-employment durations, subsequent wage outcomes, or the characteristics of the firms where these households ultimately take jobs. To fill this gap in the empirical literature, we test two hypotheses:

**Hypothesis 1:** Ceteris paribus, greater credit access increases non-employment durations.

**Hypothesis 2:** Ceteris paribus, greater credit access increases re-employment earnings.

It is important to note that because durations increase with greater credit access, the theoretical prediction of credit access on earnings (including zeros) is ambiguous since those who have more credit are taking longer to find jobs and so they are more likely to have zero earnings. However, we test whether unemployed workers with greater credit access find higher wage jobs, *conditional* on finding a job.

## 1.1 Data: Personal Credit and Employee Outcomes

Our main data source is a panel of 4 million TransUnion credit reports which are linked by a social security number to the Longitudinal Employment and Household Dynamics (LEHD) database, then anonymized.[13] All consumer credit information is taken from TransUnion at an annual frequency from 2001 to 2008. The TransUnion data include information on the balance, limit, and status (delinquent, current, etc.) of different classes of accounts held

[13]We over-sampled bankrupt individuals, so when we compute population estimates, we reweight the sample to match yearly aggregate bankruptcy, delinquency, and foreclosure rates in the 13 states for which we have data.

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. It 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 database, we follow Jacobson, LaLonde, and Sullivan [1993] and focus on mass layoffs.[14]

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.[15] 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).[16] With slight abuse of convention, we use 'non-employment duration' and 'unemployment duration' interchangeably.

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, $t+1$, to the pre-displacement annual earnings in year $t-1$. To avoid 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 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 over annual earnings, measured before displace-

[14] Appendix A includes details on the identification of mass layoffs. Mass displacements are more likely to occur in recessions, and so we take care to include time fixed effects in all specifications; however, without longer panel data, it is difficult to assess how different our elasticities are across booms and busts.

[15] We follow Abowd, Stephens, Vilhuber, Andersson, McKinney, Roemer, and Woodcock [2009] (Appendix A, Definitions of Fundamental LEHD Concepts) to construct our measures of job accessions and employment at end-of-quarter. See Appendix A for more discussion.

[16] 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.

ment. We call this ratio the *unused revolving credit to income ratio*.[17] The main components of revolving credit include bank revolving credit (bank credit cards), retail revolving credit (retail credit cards), finance revolving credit (other personal finance loans with a revolving feature), and revolving home equity lines of credit (HELOCs).

## 1.2 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 and earned at least $5,000 in the year before displacement. These are standard restrictions used in the literature (e.g., Davis and Von Wachter [2011], Jarosch [2014], Braxton and Taska [2020], Huckfeldt [2022]) to mitigate any issues associated with seasonal employment or weak labor-force attachment. Under these criteria, we end up with a sample of 217,000 individuals (rounded to the nearest thousand given Census disclosure requirements). Given the way we identify displacements and our use of lagged credit before displacement as the main independent variable, this sample covers the years 2002-2006.[18]

Table 1 includes key summary statistics. All variables are deflated by the CPI with 2008 as the base year, 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 1 summarize the entire sample of displaced individuals. Column (1) shows that they were on average 38.4 years old, took 2.1 quarters to find a job, and had an earnings replacement rate of 90%. They could replace roughly 30% of their prior annual earnings with unsecured revolving credit. Column (1) also shows that the average age of their oldest account is 8.83 years (105.9 months).[19] Column (2) shows the same sample conditional on the individual finding a job in the subsequent year (at $t + 1$). On average, their earnings replacement rate is 1.20 (meaning their earnings at their new job is 20% 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;

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

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

[19] 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.

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. In Section 2.5, we argue that many displaced individuals' earnings losses are purely transitory, and we should therefore expect these individuals to borrow if they have limited liquid assets.

Table 1: Summary Statistics for Main Sample

| | **(1)** Entire Sample | **(2)** Employed, $t+1$ |
|---|---|---|
| Age | 38.4 | 38.4 |
| Tenure | 3.5 | 3.6 |
| Imputed Education | 13.1 | 13.2 |
| Lagged Annual Earnings | \$42,250 | \$45,200 |
| Lagged Unused Revolving Credit to Income | 29.1% | 27.1% |
| Duration of Non-Employment (In Quarters) | 2.1 | 0.7 |
| Replacement Rate (Annual Earnings Year t+1/Annual Earnings Year t-1) | 0.9 | 1.2 |
| Lagged Months Since Oldest Bankcard Opened | 105.9 | 107.9 |
| Observations (Rounded to 000s) | 217000 | 98000 |

*Notes. Sample selection criteria in Section 1.2. Lagged refers to period 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 particular, Figure 1 plots the coefficients, $\beta_j$, from a regression of duration on unused revolving credit to income quintiles before 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 those in the second quintile of credit access, those in the fifth quintile take approximately 0.4 quarters longer to find a job. Figure 2 plots the coefficients, $\beta_j$, from a regression of earnings replacement rates on unused revolving credit to income quintiles before 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 8% higher replacement rates. Both figures reveal an increasing relationship between unused credit before 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

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

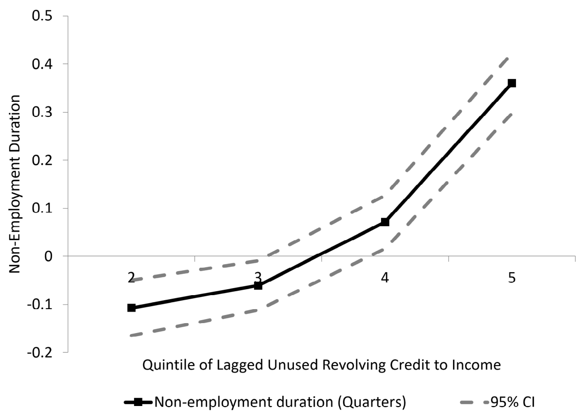
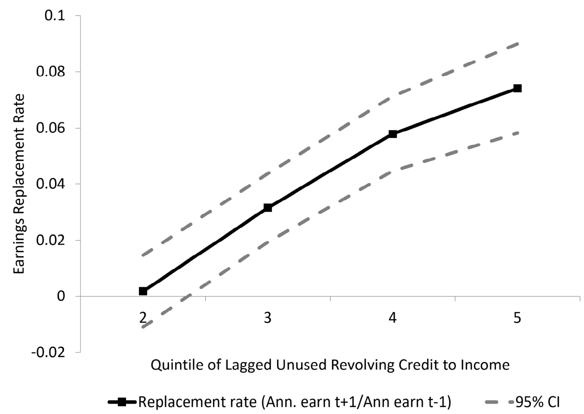



Figure 2: Replacement Earnings 1 Year After Layoff by Unused Revolving Credit to Income Decile, Among Job Finders




and 2, and express the relationship as an elasticity that can be mapped to models.

# 2 Empirical Results: Credit and Labor Market Outcomes

In this section, we use both ordinary least squares (OLS) and instrumental variable (IV) approaches to measure correlations and elasticities of unemployment duration, wage replacement rates, and firm characteristics with respect to credit access. We first provide OLS estimates in Section 2.1, and then we turn to the age of the oldest credit account as an instrument for credit access in Section 2.2. In Appendix B.2, we use the Saiz [2010] housing supply elasticities as an alternate instrument, and we show that the age of the oldest account passes J-tests across a variety of specifications. We then explore the heterogeneity of our results and estimate how age and credit utilization impact these estimates.

## 2.1 OLS results

We begin with our OLS specifications. 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 before 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:

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

The coefficient of interest is the semi-elasticity $\gamma$, which can be interpreted as follows: a 10% increase in limits to income $\Delta l = 0.10$ (expressed as a fraction) is associated with an increase in non-employment duration of $\gamma \times \Delta l = \gamma \times 0.10$ quarters. When interpreting magnitudes, we multiply the quarterly number by 12 in order to express the elasticity in weeks.

In every specification, our vector of controls ($X_{i,t}$) includes a quadratic in tenure, a full set of age, year, sex, race, 1-digit SIC industry and education dummies, lagged annual income, cumulative lagged earnings (to proxy for assets), lagged characteristics of the previous employer including the size, age, and wage per worker, a dummy for the presence of a mortgage, a dummy for the presence of an auto loan, an equity proxy (the highest mortgage balance observed less the current balance), and the state unemployment rate.

Table 2 reports our OLS results. 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 0.3 (=0.254*0.1*12) weeks longer to find a job. Column (2) of Table 2 illustrates the impact of unused credit on replacement rates of annual earnings, inclusive of zeros (i.e., this specification includes job finders whose replacement rate is non-zero and non-job finders whose replacement rate is zero). The elasticity of replacement rates with respect to unused credit is 0.038, implying that an individual who can replace 10% more of annual pre-displacement earnings with credit has a replacement rate that is 0.38% higher. There are two competing forces generating this relatively small replacement rate result. First, durations increase with more credit access, depressing replacement earnings. Second, 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 2, we isolate the set of households that 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 1.13% higher.[20] This

[20] In Appendix B, we explore earnings replacement rates at 2-year horizons.

exercise warrants additional discussion; Column (3) conditions on an outcome, employment, and selection may generate differences between job-finders and non-finders. In Appendix B.7, 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). We find very little scope for selection, even in a model in which human capital is unobserved and the primary driver of heterogeneity in job finding rates.

Columns (4), (5), (6), and (7) measure the relationship between credit access and average firm wages. 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 firms that are higher in the wage-per-worker distribution. Our main dependent variables are indicator functions for whether the worker finds a job at a firm that is ranked above the 50th, 75th, 90th, or 99th percentile of the wage-per-worker distribution in the year after job loss.[21] In our theoretical framework, and in conceptual discussions of our results, we treat this as our proxy for firm productivity.

While Column (4) yields insignificant point estimates, Columns (5) through (7) of Table 2 imply that if an individual can replace 10% more of their prior annual earnings with credit, their odds of working at a firm ranked at (or above) the 75th, 90th, and 99th percentile of the wage-per-worker distribution increases by 0.078%, 0.145%, and 0.015%, respectively. Thus, credit is positively correlated with workers sorting into higher paying, more productive employers, but the effects are weaker at the top percentile of the wage-per-worker distribution.

In Appendix A.4, we compute OLS regressions of unemployment duration on credit access in the Survey of Consumer Finances, 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, 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.

Appendix B.1 merges our sample with Schedule C tax records to adjust the non-employment spells for self-employment. Appendix B.1 also uses the earnings gap method to infer partial

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

Table 2: Credit and Labor Market Outcomes: Baseline OLS.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| **Sample:** | All Displaced | | Job Finders 1 Yr. After Layoff | | | | |
| **Dependent Variable:** | Duration | Rep. Rate (0s) | Rep. Rate | $\overline{w}_{firm}$ >p50 | $\overline{w}_{firm}$ >p75 | $\overline{w}_{firm}$ >p90 | $\overline{w}_{firm}$ >p99 |
| Unused Revolving Credit to Income Ratio | 0.254*** | 0.0328*** | 0.113*** | -0.00258 | 0.00767** | 0.0145*** | 0.00153** |
| | (0.0169) | (0.00569) | (0.00993) | (0.00344) | (0.00354) | (0.00219) | (0.000733) |
| Controls (Demographic, Industry, Regional, Lagged Earnings, Equity Proxy) | Y | Y | Y | Y | Y | Y | Y |
| R2 | 0.049 | 0.081 | 0.182 | 0.141 | 0.195 | 0.201 | 0.027 |
| Round N | 217000 | 217000 | 98000 | 98000 | 98000 | 98000 | 98000 |

*Notes. Standard errors clustered at individual level, *** 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 where the year of layoff is t; Col. 4, 5, and 6 are dummies for whether the worker works at a firm in the $X^{th}$ percentile or higher of the wage per worker distribution at $t+1$ (denoted $\overline{w}_{firm}$ >pX). Independent Variables: Unused Revolving Credit to Income measured 1 year before layoff at $t-1$. Demographic controls include a quadratic in tenure and dummies for age, race, sex and education as well as year, mortgage, and auto loan dummies. Industry controls include 1-digit SIC dummies and size, age, and wage per worker of prior firm. Regional controls include the state 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.*

quarters of non-employment. Under either of these definitions of non-employment duration, we find that the main results hold.

## 2.2 IV results: Gross and Souleles Instrument

To more closely map our empirics to our structural framework, we attempt to remove various forms of endogeneity (that are not present in our structural setting) by augmenting 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 timing thresholds. 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 use 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 as good as 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 before layoff ($l_{i,t-1}$) as a function of the age of the oldest account, $s_{i,t}$, and a vector of controls $X_{i,t}$, including physical age:

$$l_{i,t-1} = \pi s_{i,t} + BX_{i,t} + u_{i,t}. \tag{2}$$

These first-stage estimates of $\pi$ and $B$ are used to isolate the exogenous component of the unused credit limit ratio, $\hat{l}_{i,t-1}$. Crucially, our set of controls $X_{i,t}$ includes a full set of age dummies, as well as all of the other controls used in the OLS specifications. We include the first stage regression results in Appendix B.3.

The second stage regression is then used to estimate how this exogenous variation in credit impacts employment outcomes such as duration, $D_{i,t}$:

$$D_{i,t} = \gamma \hat{l}_{i,t-1} + \beta X_{i,t} + \epsilon_{i,t} \tag{3}$$

The coefficient of interest is $\gamma$, which is a semi-elasticity. As in the OLS specification, if unused limits to income increase by 10% , $\Delta l = 0.10$ (expressed as a fraction), durations increase by $\gamma \Delta l = \gamma \times 0.10$ quarters.

Table 3 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 0.33 (=0.277*0.1*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 1.1% more, including those who do not successfully find a job.

When we condition on job finders in order to remove the mechanically dampening effect of greater unemployment durations, we find that 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 1.85%, conditional on being employed throughout the year after layoff.

Table 3: Credit and Labor Market Outcomes: Instrumental Variable, Age of Oldest Bankcard Account ("Gross and Souleles Instrument," GS-IV).

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| **Sample:** | All Displaced | | Job Finders 1 Yr. After Layoff | | | | |
| **Dependent Variable:** | Duration | Rep. Rate (0s) | Rep. Rate | $\overline{w}_{firm}$ >p50 | $\overline{w}_{firm}$ >p75 | $\overline{w}_{firm}$ >p90 | $\overline{w}_{firm}$ >p99 |
| Unused Revolving Credit to Income Ratio | 0.277*** | 0.111*** | 0.185*** | 0.0950*** | 0.149*** | 0.0527*** | -0.00189 |
| | (0.0629) | (0.0127) | (0.0176) | (0.0125) | (0.0154) | (0.0108) | (0.00322) |
| Controls (Demographic, Industry, Regional, Lagged Earnings, Equity Proxy) | Y | Y | Y | Y | Y | Y | Y |
| R2, 1st Stage | 0.0596 | 0.0596 | 0.0614 | 0.0614 | 0.0614 | 0.0614 | 0.0614 |
| Angirst Pischke FStat Pval | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Round N | 217000 | 217000 | 98000 | 98000 | 98000 | 98000 | 98000 |

*Notes. Standard errors clustered at individual level, *** p<0.01, ** p<0.05, * p<0.1. Instrumental variable for unused credit to income is age of oldest bankcard account. See Table 2 for samples and controls.*

Columns (4), (5), (6) and (7) demonstrate that those who can replace 10% more of prior annual earnings with credit are 0.9%, 1.5%, and 0.5% more likely to find jobs at firms above the 50th, 75th, 90th, and 99th percentiles of the wage-per-worker distribution, respectively. In contrast to the OLS results, once credit is properly instrumented, access to credit allows individuals to find jobs disproportionately 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.

### 2.2.1 Robustness

We conduct three robustness exercises: (1) adding controls for historic default patterns to proxy for borrower quality, (2) using an alternate housing supply elasticity instrument based on Saiz [2010], and (3) exploiting the presence of two instruments (account age and housing supply elasticity) to conduct overidentification tests (J-tests).

**Borrower quality.** One potential concern is that shorter account ages reflect lower borrower quality (even conditional on controls for age) and that borrower quality is related to labor market outcomes through channels other than the age of the oldest account. The rich panel dimension of our data allows us to address this concern by including a saturated set of controls for prior default behavior in our IV specifications. These controls include the presence of bankruptcy, foreclosure and delinquency flags, the aggregate amount on which the individual has defaulted, and months since the most recent delinquency. The results in Table 4 show that our main credit elasticities are extremely robust to explicitly controlling for past negative credit events for individual workers. Thus, observable proxies for borrower quality do not substantively alter our results.

Table 4: Controlling for Default Histories: Instrumental Variable, Age of Oldest Bankcard Account ('Gross and Souleles Instrument,' GS-IV).

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| **Sample:** | All Displaced | | Job Finders 1 Yr. After Layoff | | | | |
| **Dependent Variable:** | Duration | Rep. Rate (0s) | Rep. Rate | $\overline{w}_{firm}$ >p50 | $\overline{w}_{firm}$ >p75 | $\overline{w}_{firm}$ >p90 | $\overline{w}_{firm}$ >p99 |
| Unused Revolving Credit to Income Ratio | 0.277*** | 0.111*** | 0.187*** | 0.0977*** | 0.151*** | 0.0528*** | -0.00200 |
| | (0.0645) | (0.0130) | (0.0181) | (0.0129) | (0.0159) | (0.0112) | (0.00332) |
| Lagged 90+ Days Late Delinquency | -0.00641 | 0.00548 | 0.00884 | 0.0130*** | 0.0183*** | 0.00194 | -0.000682 |
| | (0.0237) | (0.00544) | (0.00699) | (0.00477) | (0.00560) | (0.00381) | (0.00111) |
| Lagged Foreclosure Flag | -0.0280 | 0.0407 | 0.0567* | 0.00167 | 0.0440 | -0.00853 | -0.00150 |
| | (0.123) | (0.0251) | (0.0295) | (0.0224) | (0.0281) | (0.0183) | (0.00497) |
| Lagged Bankruptcy Flag | -0.0496 | 0.00932 | 0.0125 | 0.0476*** | 0.0480*** | -0.000503 | 0.00164 |
| | (0.0413) | (0.00844) | (0.0102) | (0.00776) | (0.00940) | (0.00642) | (0.00197) |
| Aggregate Amount of Derogatory Public Flags on Record in File History | 2.05e-07 | 1.98e-08 | 2.73e-08 | 3.23e-08** | 6.86e-08*** | -6.11e-09 | -5.90e-11 |
| | (3.92e-07) | (3.74e-08) | (3.07e-08) | (1.29e-08) | (1.31e-08) | (8.98e-09) | (2.08e-09) |
| Month Since Most Recent Delinquency | -0.000103 | -8.59e-06 | -0.000244* | -9.61e-05 | 4.40e-05 | 4.40e-05 | 9.80e-06 |
| | (0.000560) | (0.000123) | (0.000147) | (0.000103) | (0.000128) | (9.33e-05) | (2.83e-05) |
| Controls (Demographic, Industry, Regional, Lagged Earnings, Equity Proxy) | Y | Y | Y | Y | Y | Y | Y |
| R2, 1st Stage | 0.0584 | 0.0584 | 0.0597 | 0.0597 | 0.0597 | 0.0597 | 0.0597 |
| Angirst Pischke FStat Pval | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Round N | 217000 | 217000 | 98000 | 98000 | 98000 | 98000 | 98000 |

*Notes. Standard errors clustered at individual level, *** p<0.01, ** p<0.05, * p<0.1. Instrumental variable for unused credit to income is age of oldest bankcard account. See Table 2 for samples and controls.*

**Housing supply elasticity instrument.** In Appendix B.2, as a second robustness exercise, we use the Saiz [2010] housing supply elasticity as an instrument for credit access. We find qualitatively similar results to our preferred estimates based on Gross and Souleles [2002]. Our point estimates imply that an individual who can replace 10% more of their pre-displacement earnings with credit takes 2.22 (=1.85*.1*12) weeks longer to find a job and has a 1.67% greater replacement rate, conditional on being employed throughout the year after layoff. Those who can replace 10% more of prior annual earnings with credit are 0.94% (insig.), 1.6% (insig.), and 0.15% (insig.), and 0.62% (sig.) more likely to find jobs at firms above the 50th, 75th, 90th, and 99th percentile of the wage-per-worker distribution, respectively. While our results using regional variation in housing supply elasticities to instrument credit are significantly less precise, the qualitative job finding patterns are quite similar across the instruments. Next, we exploit the presence of two instruments to conduct over-identification tests.

**Overidentification results.** In appendix B.4, we conduct over-identification tests using both the Saiz [2010] and Gross and Souleles [2002] instruments. While there is no true test for exogeneity, we provide the closest possible test of whether the instruments are exogenous using Hansen's J-test. A simplified intuition for these tests is that they estimate the IV specification using one instrument and then check if the resulting second-stage residuals are correlated with the excluded instrument. Under the null that the instruments are valid, the resulting residuals and the excluded instrument should be insignificantly correlated.

First, simultaneously using the Saiz [2010] and Gross and Souleles [2002] instruments yields similar duration, replacement rate, and firm wage-per-worker elasticities as our benchmark results based on Gross and Souleles [2002] alone.

Second, the instruments pass the J-test at standard statistical levels. We *cannot* reject the null that the instruments are valid at the 1%, 5%, or 10% significant levels. The lack of rejection of any of the specifications at the 10% level is fairly strong evidence that there is little correlation between each instrument and its counterpart's residuals, suggesting exogeneity. What makes these tests more convincing is that the geographic variation in the Saiz [2010] instrument is conceptually and mechanically very different from the individual specific variation in the account ages.

## 2.3 Heterogeneous Responses of Workers

In this section, we explore heterogeneous responses of workers to credit, based on age and credit utilization. Age maps directly to our life-cycle model and reflects differences in accumulated human capital as well as credit constraints. Credit utilization also maps directly to debt positions in the model and largely reflects credit constraints. In subsequent sections, we show that our model has strong predictions that younger and credit constrained individuals are more sensitive to credit.

### 2.3.1 Relative Importance of Credit by Age

We first explore the responses of younger individuals versus those of older ones. Table 5 runs the same IV specifications given by equations (2) and (3), except it now includes interactions between unused revolving credit and an indicator of whether the individual's age is above 40 years old. We implement a full interaction with controls and the constant by running two separate regressions: one for those above the age of 40, and one for those below the age of 40.[22]

The point estimates in Table 5 imply that the effect of credit on the duration and replacement rate of income are larger for younger workers. Our point estimates imply that an individual less than 40 years old who can replace 10% more of their pre-displacement earnings with credit takes 0.38 (=0.314*.1*12) weeks longer to find a job versus 0.31 (=0.255*.1*12) for older individuals. With 10% more unused credit, younger individuals have a 3.29% greater replacement rate, conditional on being employed throughout the year after layoff, versus 0.99% for older individuals. Among younger individuals, we find stronger sorting patterns along all wage-per-worker percentiles.

We formally test the equality of these coefficients in the last row of Table 5. While the duration elasticities cannot be distinguished at conventional levels of significance, the greater replacement elasticity and wage-per-worker elasticities at the 75th, 90th, and 99th percentiles are significantly different between older and younger individuals at the 5% level.

Table 5: Less than or equal to 40/greater than 40: Age of Oldest Account IV

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Sample:** | All Displaced | Job Finders 1 Yr. After Layoff | | | | |
| **Dependent Variable:** | Duration | Rep. Rate | $\overline{w}_{firm}$ >p50 | $\overline{w}_{firm}$ >p75 | $\overline{w}_{firm}$ >p90 | $\overline{w}_{firm}$ >p99 |
| Less than 40 × Unused Revolving Credit to Income Ratio | 0.314*** | 0.329*** | 0.116*** | 0.221*** | 0.136*** | 0.0128* |
| | (0.118) | (0.0405) | (0.0256) | (0.0314) | (0.0222) | (0.00720) |
| Greater than 40 × Unused Revolving Credit to Income Ratio | 0.255*** | 0.0990*** | 0.0807*** | 0.117*** | 0.0234* | -0.00693** |
| | (0.0745) | (0.0187) | (0.0142) | (0.0177) | (0.0125) | (0.00350) |
| Pval H0: Equal Coefficients | 0.671 | 2.38e-07 | 0.233 | 0.00369 | 1.03e-05 | 0.0138 |
| Combined Round N | 217000 | 98000 | 98000 | 98000 | 98000 | 98000 |

*Notes. Standard errors clustered at individual level, *** p<0.01, ** p<0.05, * p<0.1. Instrumental variable for unused credit to income is age of oldest bankcard account. See Table 2 for samples and controls.*

[22]The instrument is interacted in a parallel fashion, and Appendix B.5 includes the OLS version of these results.

### 2.3.2 Relative Importance of Credit by Utilization

Next, we explore our prediction that credit is more important for workers who are more credit constrained. To proxy for credit constraints, we split the sample by above versus below average revolving credit utilization. The assumption is that individuals with above average utilization are more constrained, as they have used more of their credit in the past. Similar to the age regressions, Table 6 implements a full interaction between utilization rates, unused credit, controls and the constant by running two separate regressions: one for those with above average utilization, and one for those with below average utilization.[23]

Table 6 shows that the duration and replacement rate elasticities are respectively 3 and 5 times larger for high-utilization displaced workers relative to low-utilization ones. The last row of Table 6 shows that these elasticities are statistically distinguishable from one another at the 5% level. The sorting patterns across the firm wage-per-worker distribution are also significantly stronger for high-utilization individuals. This cross-sectional heterogeneity in utilization rates plays an important role in understanding the aggregate consequences of changes in the supply of credit.

Table 6: Above/below avg utilization: Age of Oldest Account IV

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Sample:** | All Displaced | Job Finders 1 Yr. After Layoff | | | | |
| **Dependent Variable:** | Duration | Rep. Rate | $\overline{w}_{firm}$ >p50 | $\overline{w}_{firm}$ >p75 | $\overline{w}_{firm}$ >p90 | $\overline{w}_{firm}$ >p99 |
| Below avg. utilization × Unused Revolving Credit to Income Ratio | 0.200*** | 0.111*** | 0.0759*** | 0.122*** | 0.0411*** | -0.00113 |
| | (0.0758) | (0.0185) | (0.0143) | (0.0174) | (0.0121) | (0.00322) |
| Above avg. utilization × Unused Revolving Credit to Income Ratio | 0.595*** | 0.527*** | 0.226*** | 0.334*** | 0.129*** | -0.00269 |
| | (0.187) | (0.0609) | (0.0401) | (0.0507) | (0.0355) | (0.0113) |
| Pval H0: Equal Coefficients | 0.0493 | 6.03e-11 | 0.000433 | 7.36e-05 | 0.0194 | 0.894 |
| Combined Round N | 217000 | 98000 | 98000 | 98000 | 98000 | 98000 |

*Notes. Standard errors clustered at individual level, *** p<0.01, ** p<0.05, * p<0.1. Instrumental variable for unused credit to income is age of oldest bankcard account. See Table 2 for samples and controls.*

## 2.4 Borrowing by Displaced Workers

One important point is that regardless of realized borrowing, the *potential* to borrow affects job search decisions regardless of whether the credit line is actually drawn down. Workers

[23] Appendix B.6 reports the corresponding OLS results.

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 do so (see also Collins, Edwards, and Schmeiser [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 who foresee any necessity to borrow, which includes the majority of displaced workers (see Gruber [2001], among others), will alter job search decisions.

As more direct evidence of borrowing by the unemployed, we also include Table 7, which is based on direct questions in the RAND American Life Panel (ALP) about borrowing in response to job loss. Table 7 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 to smooth consumption (we will refer to this as default). This evidence supports the mechanism that unconstrained unemployed individuals borrow, whereas unemployed workers who are indebted or have other obligated payments 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 unemployed workers.

Table 7: 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 includes 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 6. Increased debt 7. None of the above.' We combine responses 'fell behind on rent' and 'skipped or postponed paying some other bills' as a non-mortgage 'default.'*

To understand why some existing empirical studies have found a mean impact close to zero of job loss on borrowing, in Figure 3, which is a smoothed density, we plot 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 [2020], who show that many workers borrow, consistent with Sullivan [2008] and Table 7, whereas many workers deleverage through default, also consistent with Sullivan [2008]'s regression results. As a result, the net amount borrowed among displaced workers is close to zero (Baker and Yannelis [2017], Gelman et al. [2020], Bethune [2015], and Ganong and Noel [2019]). 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 [2020]. 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 [2020] 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

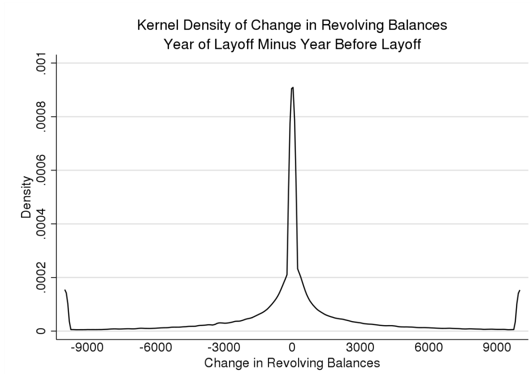
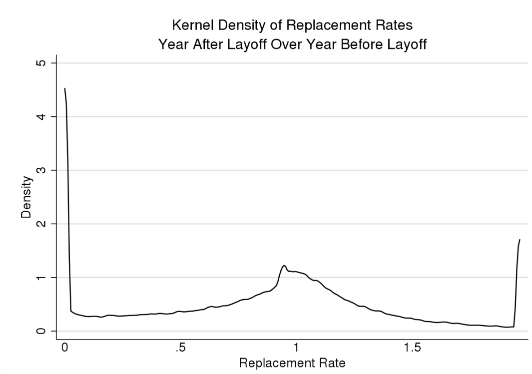



Figure 4: Replacement Rate Distribution (Annual Earnings t+1/ Annual Earnings t-1)




For our sample, Table 8 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 \$30, 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 displaced workers via credit markets. Column (2) shows that for every additional quarter of non-employment, workers are 0.23% 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 8: 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 | 30.03** | 0.00232*** |
| | (13.02) | (0.000470) |
| Controls (Demographic, Industry, Regional, Lagged Earnings and Balances, Equity Proxy) | Y | Y |
| R2 | 0.149 | 0.118 |
| Round N | 217000 | 217000 |

*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. Demographic controls include a quadratic in tenure and dummies for age, race, sex and education as well as year, mortgage, and auto loan dummies. Industry controls include 1-digit SIC dummies and size, age, and wage per worker of prior firm. Regional controls include the state unemployment rate. Lagged earnings and balances controls include prior real annual earnings and cumulative real annual earnings to proxy for assets as well as lagged revolving credit balance to control for mean reversion in borrowing. Equity proxy is highest observed mortgage balance less current mortgage balance.*

### 2.5 Permanent vs. Transitory Earnings Losses

Our empirics are consistent with the large earnings losses incurred after layoff (Davis and Von Wachter [2011], Jarosch [2014], and Huckfeldt [2022]). However, as Braxton et al. [2020] show, a very large fraction of unemployed individuals will find new jobs that 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 (see, e.g., Sullivan [2008] and Braxton et al. [2020]), 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 (Gerardi, Herkenhoff, Ohanian, and Willen [2017]). Both of these mechanisms play an important role in reconciling our model with the data, and these mechanisms distinguish credit from unemployment insurance.

## 3 Model

Given the local nature of our IV estimates, we develop a structural model in order to measure the aggregate effects of credit access on unemployment duration and earnings replacement rate elasticities, as well as worker sorting patterns. To address the question of how consumer credit constraints impact the allocation of workers to firms, we require three model features. First, we require risk aversion and borrowing. Second, we must drop the neoclassical assumption of a large family with full intra-household insurance. We do this by incorporating shocks to idiosyncratic human capital and assuming complete markets. 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, as in Chatterjee, Corbae, Nakajima, and Ríos-Rull [2007], into a general equilibrium labor sorting model, like that of 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.

## 3.1 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 who run the endogenously chosen measure of operating firms, and a unit measure of risk neutral lenders.

As in Menzio, Telyukova, and Visschers [2016], there are $T \geq 2$ overlapping generations of risk averse households that face both idiosyncratic and aggregate risk. The aggregate risk is important for our counterfactuals; it allows us to alter aggregate debt limits 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 $\tau$ 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 $\chi$ 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. 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 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. Workers differ 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 $\mu : \{W, U\} \times \{G, B\} \times \mathcal{B} \times \mathcal{H} \times \mathcal{K} \times \mathbb{N}_T \rightarrow [0, 1]$. 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. 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 heterogeneous "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 their desired capital level $k$. Once matched with a firm, a worker produces $f(h, k) : \mathcal{H} \times \mathcal{K} \rightarrow \mathbb{R}_+$ and keeps a fixed share $\alpha$ of this production. Therefore, the worker's wage payment is $\alpha f(h, k)$.[24] In Appendix F, we show that our main results hold when we allow workers to jointly optimize over the piece-rate/capital tuple $(\alpha, k)$. One important conceptual benefit of the endogenous choice of the piece-rate is that it disconnects wage gains from output gains. However, this joint optimization poses significant computation challenges and significantly reduces the tractability of the model.[25]

[24] This is a similar assumption to the one in Kaplan and Menzio [2016], and is only made for tractability purposes.

[25] The curse of dimensionality forces us to use sparser grids on key dimensions of the model and prevents us from running transition path experiments (which require a $t$-fold increase in the state space) because of

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 [2019]). To disconnect employment status and default decisions, we assume that 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 (Livshits, MacGee, and Tertilt [2010]). If the agent defaults, they incur a utility penalty of default and are excluded from credit markets, as with Ch. 7 bankruptcy in the United States. A household in bankruptcy has a value function scripted by $B$ and can only save. With probability $\lambda$, a previously bankrupt agent regains access to asset markets. Bankrupt agents are still subject to expense shocks, and if the expense shock would force them into a region in which they would have to borrow, they re-default and incur the utility penalty of default again.[26]

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 $q_{W,t}(b', h, k; \Omega)$ if employed or $q_{U,t}(b', h; \Omega)$ if unemployed. The bond price is 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, firm capital (if employed), and piece rate (if employed) as well as the aggregate state. We discuss the bond price in more detail in Section 3.2.

We assume that home production is constant and given by $z$. The problem of an age $t$ unemployed household in good standing is given below:

$$U_t^G(b, h; \Omega) = \max_{b' \geq \underline{b}} u(c) + \beta \mathbb{E}\Big[ \max_{\tilde{k}} p(\theta_{t+1}(h', \tilde{k}; \Omega')) \widehat{W}_{t+1}^G(b', h', \tilde{k}; \Omega') + \big(1 - p(\theta_{t+1}(h', \tilde{k}; \Omega'))\big) \widehat{U}_{t+1}^G(b', h'; \Omega') \Big], \quad t \leq T$$

$$\widehat{U}_{T+1}^G(b, h; \Omega) = 0$$

such that

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

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

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

memory issues.

[26] Among those with credit access, we additionally assume that expense shocks that would move the agent below the fixed debt limit $\underline{b}$ move the agent exactly to $\underline{b}$.

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

$$\underline{b}' \sim F(\underline{b}' \mid \underline{b}), \quad \mu' = \Phi(\Omega, \underline{b}'), \quad \Omega' = (\underline{b}', \mu'). \tag{4}$$

Households that default are excluded from borrowing. The continuation value of a bankrupt household is given below:

$$\begin{aligned} U_t^B(b,h;\Omega) = &\max_{b' \geq 0} u(c) + \lambda\beta\mathbb{E}\Big[\max_{\tilde{k}} p(\theta_{t+1}(h',\tilde{k};\Omega'))\widehat{W}_{t+1}^G(b',h',\tilde{k};\Omega') + \big(1 - p(\theta_{t+1}(h',\tilde{k};\Omega'))\big)\widehat{U}_{t+1}^G(b',h';\Omega')\Big] \\ &+ (1-\lambda)\beta\mathbb{E}\Big[\max_{\tilde{k}} p(\theta_{t+1}(h',\tilde{k};\Omega'))\widehat{W}_{t+1}^B(b',h',\tilde{k};\Omega') + \big(1 - p(\theta_{t+1}(h',\tilde{k};\Omega'))\big)\widehat{U}_{t+1}^B(b',h';\Omega')\Big], \quad t \leq T \end{aligned}$$

$$\widehat{U}_{T+1}^B(b,h;\Omega) = 0$$

such that

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

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:

$$\widehat{U}_t^G(b,h;\Omega) = (1-p_x)\max\Big\{U_t^G(b,h;\Omega), U_t^B(0,h;\Omega) - \chi\Big\} + p_x \max\Big\{U_t^G(b-x,h;\Omega), U_t^B(0,h;\Omega) - \chi\Big\}.$$

Since expense shocks continue to be incurred in bad standing, households must be given the option to re-default:[27]

$$\widehat{U}_t^B(b,h;\Omega) = (1-p_x)\max\Big\{U_t^B(b,h;\Omega), U_t^B(0,h;\Omega) - \chi\Big\} + p_x \max\Big\{U_t^B(b-x,h;\Omega), U_t^B(0,h;\Omega) - \chi\Big\}.$$

For unemployed households in good standing, let $D_{U,t}(b,h;\Omega)$ denote their default decision. Because of the finite life cycle, a utility penalty of default, $\chi$, 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 $\delta$. If they are laid off, since the period length we ultimately use in the calibration is 1 quarter, we must allow the workers to search immediately for a new job.[28] We present the employed value functions in Appendix C.

[27] Without the option to re-default, positive consumption can be infeasible.

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

### 3.2 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:

$$q_{e,t}(b', h, k; \Omega) \leq \frac{\mathbb{E}\Big[1 - [(1 - p_x)D_{e',t+1}(b', h', k'; \Omega') + p_x D_{e',t+1}(b' - x, h', k'; \Omega')]\Big]}{1 + r_f}. \quad (5)$$

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 section on firms. Since lenders earn zero profit for each contract in equilibrium, lenders are indifferent between lending to a firm or a household.

### 3.3 Firms

There is a continuum of risk neutral entrepreneurs who operate constant returns to scale production functions. The entrepreneurs invest in capital and post vacancies at cost $\kappa$ to attract workers in the frictional labor market. We assume capital is denominated in units of the final consumption good.

Vacancies are posted in specific submarkets which specify a level of capital, $k \in \mathcal{K}$, as well as the human capital and age, $(h, t) \in \mathcal{H} \times \mathbb{N}_T$, of admissible workers. Entering entrepreneurs are subject to a financing constraint.[29] 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 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 $q_{f,t}(b_f, k, h; \Omega)$ denote the bond price faced by the firm. For a given vacancy submarket $(h, k, t)$, firms choose their level of

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

borrowing $b_f$ to solve

$$\max_{b_f} p_f(\theta_t(h,k;\Omega))[J_t(h,k;\Omega)+b_f]+(1-p_f(\theta_t(h,k;\Omega)))\cdot 0 \tag{6}$$

such that

$$-k \geq q_{f,t}(b_f,k,h;\Omega)b_f. \tag{7}$$

With free entry in the lending market, the price of debt must be given by

$$q_{f,t}(b_f,k,h;\Omega)=\frac{p_f(\theta_t(h,k;\Omega))}{1+r_f}. \tag{8}$$

Optimal financing by firms also implies that equation (7) must also hold with equality. Combining this with the debt price (8) yields an expression for $b_f$,

$$b_f=(1+r_f)\cdot\frac{-k}{p_f(\theta_t(h,k;\Omega))}.$$

We assume there is free entry among entrepreneurs. Therefore, at the optimal choice of $b_f$, equation (6) must equal the vacancy posting cost $\kappa$ in all operating submarkets. Combining the optimal choice of debt with free entry yields

$$\kappa=p_f(\theta_t(h,k;\Omega))\left[J_t(h,k;\Omega)-(1+r_f)\cdot\frac{k}{p_f(\theta_t(h,k;\Omega))}\right].$$

Therefore, the market tightness in each submarket entered with positive probability is given by

$$\theta_t(h,k;\Omega)=p_f^{-1}\left(\frac{\kappa+(1+r_f)k}{J_t(h,k;\Omega)}\right). \tag{9}$$

For tractability, we assume that workers and firms split output according to a constant piece-rate $\alpha$. We assume the firm keeps a share $1-\alpha$ of its production, and workers receive the remaining share $\alpha$ of production (see Appendix F for a relaxation of this assumption). 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 Appendix E, we allow capital to have a nonzero liquidation value. In Appendix E, we also allow firms to dynamically invest in capital. We do not explicitly model on-the-job search owing to tractability issues (it would require firms knowing workers' asset and default policy functions – see Herkenhoff [2019] 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. With frictionless capital adjustment, firms set capital to maximize the net present value of output less costs, mitigating any incentive for the worker to leave the firm. Since we find very similar results for our main counterfactuals when we allow for non-zero liquidation values and capital investment, our benchmark model abstracts from these features for tractability.

## 3.4 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 (9) 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 (5) and firms (8) 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 $\mu$ (even though it fluctuates over time and can be recovered by simulation). However, policy functions still depend on the borrowing limit, $\underline{b}$.

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

# 4 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.[30] Because of 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 an exponential draw of initial human capital. We denote the distribution of initial human capital by $F(h) = e^{-\xi h}$, where $\xi$ is estimated to match the p90-p10 wage differential among 24-year-olds in the CPS. The household share of production, $\alpha$, is set to $\frac{2}{3}$, and the production function is Cobb-Douglas, $f(h,k) = h^{1-a}k^{a}$. We estimate the curvature of the production function with respect to capital, $a$, to match our empirical elasticities of wages and firm characteristics with respect to borrowing limits. Lower values of $a$ imply greater decreasing returns to capital and thus less responsiveness of wages and sorting to changes in credit access. The human capital

[30] A large number of agents (N=200,000) is then simulated for a large number of periods (T=250 quarters, discarding the first 100 quarters). Averages are reported over the remaining 150 quarters across $R = 3$ repetitions. Appendix G describes the solution algorithm in detail. To estimate the regression analysis, we take the final cross-section of the simulated model at $T = 350$, and we repeatedly lay off all individuals (since layoff is exogenous, the set of laid off households is representative) 100 times. We stack these representative layoffs into a panel that we use for computing the model-implied elasticities.

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, $h \in [0.50, 0.75, 1.00, 1.25, 1.50]$, as well as the step size, $\Delta = 0.25$, 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:

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

The matching elasticity parameter is $\zeta = 1.6$, as estimated in Schaal [2017]. Following Silva and Toledo [2009], we set the vacancy posting cost to 3.6% of one quarter's wages, and so $\kappa = 0.036 \times \alpha f(h,k)$.

In the credit market, the bankruptcy re-access parameter is set to $\lambda = 0.025$. This parameter generates the statutory 10 year exclusion period following Chapter 13 bankruptcy. Following Herkenhoff [2019], who uses the PSID to infer the probability of an expense shock, we set the probability of an expense shock to 2.2% per quarter.[31] The severity of the expense shock, $x$, is estimated to be 28% of one quarter's wage. Since the wage is endogenous, we must jointly calibrate $x$.

The 9 unassigned parameters including the utility penalty $\chi$, the layoff rate $\delta$, 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 $\beta$, the borrowing limit $\underline{b}$, the production function curvature $a$, and the exponential parameter governing newborn human capital $\xi$ are jointly estimated to match the following *over-identified* set of 23 moments,

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

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, the median unsecured credit utilization rate, the responsiveness of labor market outcomes to credit access (including the duration, replacement rate, and wage-per-worker elasticities), the heterogeneous age/utilization duration and wage-per-worker elasticities, and the p90-p10 wage ratio of 24-year-olds.

The default penalty $\chi = 0.62$ is set to target the quarterly bankruptcy rate per capita of 0.21% in 2004 (American Bankruptcy Institute, bankruptcies per capita). The layoff rate $\delta = 0.08$ is set to target a 5.5% unemployment rate in 2004 (Bureau of Labor Studies).

The human capital appreciation rate $p_{+\Delta} = 0.02$ is set to target the ratio between the average wages of 24 to 26 and 52 to 54 year olds of 1.48 (Current Population Survey, 2004). The human capital depreciation rate $p_{-\Delta} = 0.03$ is set to target the 2-year consumption loss upon layoff (Stephens Jr [2004]). Our estimate for the human capital depreciation rate implies that once every 33 quarters, unemployed agents in the model expect to fall one rung on the human capital ladder. In simulations, conditional on receiving a human capital depreciation shock, earnings fall on average by 31% for low human capital workers and 18% for high human capital workers.

The transfer to the unemployed is set to $z = 0.15\ \forall k$ in order to target the 1-year consumption loss upon layoff (Stephens Jr [2004]). This value of $z$ yields an average UI replacement rate of approximately 37% for the lowest human capital workers, but implies significantly lower UI replacement rates of 13% for higher human capital workers, which is closer to Chodorow-Reich and Karabarbounis [2016]'s calculations.

The severity of the expense shock $x = 0.15$ is estimated to match the 28% increase in debt to income ratios observed after receiving an expense shock (Herkenhoff [2019]). The household discount factor $\beta = 0.98$, which implies a discount rate of 10% per annum, is calibrated to match the fact that in 2004, 35.5% of unemployed households have revolving credit balances (Survey of Consumer Finances). Lastly, we set the borrowing limit $\underline{b} = -0.66$ 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). The model also does well at matching the mean unused unsecured credit utilization rate in 2004; the model generates mean utilization of 19.5%, versus 25.4% in the data.

The newborn exponential parameter $\xi = 3.60$ generates an old-young wage ratio of 1.94, versus 3.03 in the data, moderately understating the wage dispersion observed in the data. Both directed search and the ability to self-insure limit the model's ability to generate the high level of wage dispersion observed in the data.

Lastly, the loading on capital in the production function $a = 0.20$ is set to match the regression elasticities observed in the data. The model does well at matching the duration, replacement rate, and firm wage-per-worker elasticities. Moreover, the model is able to match the relative patterns and ranking of these elasticities across old (greater than 40 years old) and young job losers, as well as high utilization (above average utilization) and low utilization job losers. The next section provides details on the method used to compute the model implied elasticities.

Table 9 summarizes the parameters, and Table 10 summarizes the model's fit relative to the targeted moments.

Table 9: Summary of Model Parameters.

| | **Non-estimated** | |
|---|---|---|
| Variable | Value | Description |
| $r_f$ | 4% | Annualized Risk Free Rate |
| $\kappa$ | 0.036 | Firm Entry Cost |
| $\zeta$ | 1.6 | Matching Function Elasticity |
| $\sigma$ | 2 | Risk Aversion |
| $\alpha$ | 0.66 | Worker Share of Production |
| $\lambda$ | 0.025 | Bankruptcy Re-Access |
| $p_x$ | 0.022 | Expense Shock Probability |

| | **Jointly-Estimated** | |
|---|---|---|
| Variable | Value | Description |
| $\chi$ | 0.62 | Default penalty |
| $\beta$ | 0.98 | Discount factor |
| $x$ | 0.15 | Expense shock magnitude |
| $\underline{b}$ | -0.66 | Aggregate borrowing limit |
| $\delta$ | 0.08 | Layoff rate |
| $z$ | 0.15 | Benefit |
| $p_{-\Delta}$ | 0.03 | Prob HC loss unempl |
| $p_{+\Delta}$ | 0.02 | Prob HC gain empl |
| $\xi$ | 3.60 | Newborn HC exponential param |
| $a$ | 0.80 | Production function loading on labor |

Table 10: Model Calibration, 2004 Steady State

| Parameter | Description | Value | Moment and Source | Model | Data |
|---|---|---|---|---|---|
| $\chi$ | Default penalty | 0.62 | Bankruptcy rate per capita (ABS, 2004) | 0.21 | 0.21 |
| $\beta$ | Discount factor | 0.98 | Fraction unemployed borrowing (SCF, 2004) | 0.38 | 0.35 |
| $x$ | Expense shock magnitude | 0.15 | Herkenhoff [2019] | 0.28 | 0.28 |
| $\underline{b}$ | Aggregate borrowing limit | -0.66 | Unused limit to income, median (SCF, 2004) | 0.12 | 0.15 |
| $\delta$ | Layoff rate | 0.08 | Unemployment rate (BLS, 2004) | 0.05 | 0.06 |
| $z$ | Benefit | 0.15 | 1-year consumption loss (Stephens Jr [2004]) | -0.16 | -0.19 |
| $p_{-\Delta}$ | Prob HC loss unempl | 0.03 | 2-year consumption loss (Stephens Jr [2004]) | -0.04 | -0.16 |
| $p_{+\Delta}$ | Prob HC gain empl | 0.02 | Old (52-54) to young (24-26) wage ratio, (CPS, 2004) | 1.39 | 1.48 |
| $\xi$ | Newborn HC exponential param | 3.60 | Young (24-26) p90-p10 wage ratio, (CPS, 2004) | 1.94 | 3.03 |
| $a$ | Production function loading on capital | 0.20 | Duration elasticity (LEHD-TU) | 0.28 | 0.28 |
| | | | Replacement rate elasticity among EUE (LEHD-TU) | 0.06 | 0.18 |
| | | | $\overline{w}_{firm} > p50$ elasticity among EUE (LEHD-TU) | 0.08 | 0.10 |
| | | | $\overline{w}_{firm} > p75$ elasticity among EUE (LEHD-TU) | 0.19 | 0.15 |
| | | | $\overline{w}_{firm} > p90$ elasticity among EUE (LEHD-TU | 0.17 | 0.05 |
| | | | $\overline{w}_{firm} > p99$ elasticity among EUE (LEHD-TU | 0.00 | -0.00 |
| | | | $<$ 40 years old, Duration elasticity (LEHD-TU) | 0.32 | 0.31 |
| | | | $<$ 40 years old, $\overline{w}_{firm} > p75$ elasticity among EUE (LEHD-TU) | 0.21 | 0.22 |
| | | | $>$ 40 years old, Duration elasticity (LEHD-TU) | 0.25 | 0.26 |
| | | | $>$ 40 years old, $\overline{w}_{firm} > p75$ elasticity among EUE (LEHD-TU) | 0.17 | 0.12 |
| | | | $<$median utilization, Duration elasticity (LEHD-TU) | 0.28 | 0.20 |
| | | | $<$median utilization, $\overline{w}_{firm} > p75$ elasticity among EUE (LEHD-TU) | 0.19 | 0.12 |
| | | | $>$median utilization, Duration elasticity(LEHD-TU) | 1.09 | 0.59 |
| | | | $>$median utilization, $\overline{w}_{firm} > p75$ elasticity among EUE (LEHD-TU) | 0.67 | 0.33 |

*Notes. 2004 steady state computed by simulating N=200,000 agents for T=250 quarters, discarding the first 100 quarters. Averages are reported over the remaining 150 quarters across $R = 3$ repetitions. Appendix G describes the solution algorithm in detail. To estimate the regression analysis, we take the final cross-section of the simulated model at $T = 350$, and we repeatedly lay off all individuals (since layoff is exogenous, the set of laid off households is representative) 100 times. We stack these representative layoffs into a panel that we use for computing the model-implied elasticities. Section 5 of the text provides greater detail.*

# 5 Model Elasticities

In this section, we provide our method for computing the model's implied elasticities of unemployment duration, replacement earnings as well as proxies for firm productivity. Table 11 compares the elasticities obtained from the structural estimation as well as from the various reduced form analyses (OLS, GS-IV based on Gross and Souleles [2002] and *targeted in our estimation*, and Saiz-IV based on Saiz [2010]).

## 5.1 Methodology for computing elasticities

We exploit the block recursive structure of the model to compute job finding behavior under counterfactually tighter debt limits. We proceed in three steps: (1) we define the counterfactual debt limit, (2) we define agents' beliefs over those debt limits, and (3) we discuss implementation and prove that the *menu* of job finding rates is independent of the counterfactual debt limit.

**(1) Counterfactual debt limit.** Let the aggregate debt limit take two values $\underline{b} \in \{\underline{b}_{tight}, \underline{b}_{loose}\}$. We define the two aggregate borrowing limits $\underline{b} \in \{\underline{b}_{tight}, \underline{b}_{loose}\}$ to be consistent with our empirics in Section 1. The loose debt limit is the 2004 steady state debt limit, $\underline{b}_{loose} = -0.66$. The tight debt limit is scaled to reflect the inter-quintile range (1st quintile minus 5th quintile) of debt limits observed in the data, $\underline{b}_{tight} = -0.13$ $(=\frac{0.287}{1.45}\underline{b}_{loose})$.[32]

Since the debt pricing schedule does not have an explicit credit limit, we define an individual's 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 $L(\mathbf{x}) = \min\{-b_\infty(\mathbf{x}), -\underline{b}\}$. Since individuals face different endogenous costs of borrowing, changes in the aggregate debt limits yield idiosyncratic variation in the degree to which

[32] In the data, among the sample of individuals represented in Figure 2, the lagged revolving credit to income ratio averages 28.7% within the 1st quintile, 31.3% within the 2nd quintile, 34.2% within the 3rd quintile, 52.1% within the 4th quintile, and 145% within the 5th quintile. We use the inter-quintile range (1st quintile minus 5th quintile) to discipline our estimated elasticities. Thus, we set $\underline{b}_{tight} = \frac{.287}{1.45}\underline{b}_{loose}$. The non-linearities of the model imply that smaller differences in $\underline{b}_{tight}$ and $\underline{b}_{loose}$ imply moderately smaller elasticities. However, we obtain similar parameter estimates if the model is re-calibrated under the assumption that the tight debt limit is scaled to reflect the 2nd quintile minus the 4th quintile (instead of 1st quintile minus 5th quintile in the main text).

individual borrowing limits expand or tighten.

**(2) Beliefs over counterfactual debt limit.** For only this portion of the paper, agents believe the transition matrix between aggregate borrowing limit states $\underline{b} \in \{\underline{b}_{tight}, \underline{b}_{loose}\}$ 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, changes in debt limits are unanticipated and perceived to be permanent.

**(3) Implementation and independence of $\theta(\cdot)$ from $\underline{b}$.** We isolate newly laid off agents (let $I_\delta$ denote this set of agents, and let $N_\delta$ denote its cardinality), and then we compute each agent's optimal search decision under loose and tight exogenous debt limits, *ceteris paribus*.

To compute model implied elasticities, we simulate $N = 200,000$ agents under the assumption of 2004 levels of credit access ($\underline{b}_{loose}$). We then isolate the final cross-section in the terminal period $T = 350$, corresponding to the ergodic distribution. We lay off all $N = 200,000$ individuals and simulate two future earnings paths assuming (1) borrowing limits remain loose at 2004 levels, $\underline{b} = \underline{b}_{loose}$, and (2) borrowing limits unexpectedly tighten in the period of layoff, $\underline{b} = \underline{b}_{tight}$.[33] We repeat this exercise 100 times. We report the results of pooled elasticities based on the 100 simulations.

What makes this calculation feasible is that the policy function of each agent is contingent on the realization of $\Omega$, which includes both exogenous debt limits $\underline{b} \in \{\underline{b}_{tight}, \underline{b}_{loose}\}$. At each stage of the agent's problem, 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.[34]

[33] Since layoff is exogenous, the set of laid off households is representative.

[34] This is formally shown in the existence proof in Appendix D, proposition D.1: $J_T(h,k) = (1-\alpha)f(h,k)$ 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 $\underline{b}$.

## 5.2 Model implied elasticities

We apply our method to compute the elasticity of unemployment durations, wage replacement rates, and average firm wages to unused credit.

**Duration elasticity.** For each individual $i \in I_\delta$ , let $D_i(\underline{b}_{loose})$ and $D_i(\underline{b}_{tight})$ denote expected unemployment duration in quarters under loose and tight borrowing limits, respectively.[35] Let $ULTI_i(\underline{b}_{loose})$ and $ULTI_i(\underline{b}_{tight})$ denote the ratio of unused limit to prior annual income (ULTI) at the start of the period in which they are laid off. The model implied duration elasticity is therefore given by

$$\epsilon_{Dur} = \frac{1}{N_\delta} \sum_{i \in I_\delta} \frac{D_i(\underline{b}_{loose}) - D_i(\underline{b}_{tight})}{ULTI_i(\underline{b}_{loose}) - ULTI_i(\underline{b}_{tight})} = 0.28.$$

This estimate implies that if an agent's unused credit to income ratio increased by 10%, then they take 0.33 weeks ($= 0.28 \times 0.1 \times 12$) longer to find a job, on average. This elasticity is targeted in our estimation, and the model produces an estimate very similar to the data estimate of 0.277 (Column (3) of Table 11).

**Replacement rate elasticity (including 0s).** Next, we calculate the elasticity of replacement earnings with respect to credit, including households that do not find a job and thus have a replacement rate of zero. Let $R_i^0(\underline{b}_{loose})$ and $R_i^0(\underline{b}_{tight})$ denote expected replacement rate (earnings at $t+1$ divided by earnings at $t$), in which we allow earnings at $t+1$ to be zero if the agent does not find a job. The model implied replacement rate elasticity (inclusive of zeros) is given by

$$\epsilon_{Rep} = \frac{1}{N_\delta} \sum_{i \in I_\delta} \frac{R_i^0(\underline{b}_{loose}) - R_i^0(\underline{b}_{tight})}{ULTI_i(\underline{b}_{loose}) - ULTI_i(\underline{b}_{tight})} = -0.09.$$

The model replacement rate (inclusive of 0s) produces a negative earnings replacement rate elasticity of $-0.09$, meaning that a 10% higher unused credit to income ratio is associated with an expected wage that is 0.9% lower. The corresponding OLS estimate is 0.033, the GS-IV estimate is 0.111, and the Saiz-IV estimate is -0.195 (all of which are significant at

[35] We define the expected duration to be the inverse of the job finding rate.

the 5% level). This elasticity is non-targeted in our estimation, and the model produces an estimate closest to the Saiz instrument used in Appendix B.2.

We can use our theory to decompose this negative expected earnings elasticity 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.

Let the job finding rate for agents be given by $JF_i(\underline{b}_{loose})$ and $JF_i(\underline{b}_{tight})$. Then the model implied job finding elasticity is given by

$$\epsilon_{JF} = \frac{1}{N_\delta} \sum_{i \in I_\delta} \frac{JF_i(\underline{b}_{loose}) - JF_i(\underline{b}_{tight})}{ULTI_i(\underline{b}_{loose}) - ULTI_i(\underline{b}_{tight})} = -0.13.$$

This implies that when debt limits expand by 10% of prior annual income, job finding rates fall by 1.3%, 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, let the capital intensity rate of submarkets in which agents search be $k_i(\underline{b}_{loose})$ and $k_i(\underline{b}_{tight})$. Then, the model implied capital intensity elasticity is given by

$$\epsilon_K = \frac{1}{N_\delta} \sum_{i \in I_\delta} \frac{k_i(\underline{b}_{loose}) - k_i(\underline{b}_{tight})}{ULTI_i(\underline{b}_{loose}) - ULTI_i(\underline{b}_{tight})} = 0.63.$$

In other words, being able to replace 10% more of prior income with credit allows agents in the model to search in submarkets with 6.3% greater physical (or intellectual) capital intensity. A greater propensity to search in markets with more capital 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 negative replacement earnings elasticity (inclusive of 0s) observed in the model.

**Replacement rate elasticity (excluding 0s).** 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 $I^e_\delta$ denote the set of laid off individuals who find a job in the period after layoff (i.e., they complete an EUE spell). Let

$N_\delta^e$ denote the cardinality of $I_\delta^e$. The model implied replacement earnings elasticity among those who complete an EUE spell is given by

$$\epsilon_{Rep,e} = \frac{1}{N_\delta^e} \sum_{i \in I_\delta^e} \frac{R_i(\underline{b}_{loose}) - R_i(\underline{b}_{tight})}{ULTI_i(\underline{b}_{loose}) - ULTI_i(\underline{b}_{tight})} = 0.059.$$

This implies that in the model, among job finders, being able to replace 10% more of prior income with credit results in a 0.59% greater earnings replacement rate. The comparable estimate in the data is 1.8% (Column (3) of Table 11), implying that the model moderately understates the wage gains attributable to credit.

**Firm wage-per-worker elasticity (excluding 0s).** Lastly, we compute the impact of credit access on the types of jobs workers take. We proxy firm productivity in the model (and in the data), using percentiles of the wage-per-worker distribution.[36] 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 label that a firm. Within each of these firms, we compute the wage-per-worker. We then compute the 50th percentile, 75th percentile, 90th percentile, and 99th percentile of the firm wage-per-worker distribution.

Let the probability that agent $i$ finds a job above the Xth percentile of the firm wage-per-worker distribution be given by $\overline{w}_i^X(\underline{b}_{loose})$ and $\overline{w}_i^X(\underline{b}_{tight})$. As with the replacement rate, we condition on those who find a job. Then, the model implied elasticity of finding a job at the Xth percentile of the firm wage-per-worker distribution is given by

$$\epsilon_{\overline{w},e}^X = \frac{1}{N_\delta^e} \sum_{i \in I_\delta^e} \frac{\overline{w}_i^X(\underline{b}_{loose}) - \overline{w}_i^X(\underline{b}_{tight})}{ULTI_i(\underline{b}_{loose}) - ULTI_i(\underline{b}_{tight})}.$$

The model yields elasticities of finding a job above the 50th percentile, 75th percentile, 90th percentile, and 99th percentiles of 0.08, 0.19, 0.17, and 0.00, respectively. The corresponding estimates in the data are 0.01, 0.15, 0.05 , and 0.00 (Column (3) of Table 11). In the model, the 75th percentile estimate implies that if a worker has 10% greater unused credit to income before job loss, conditional on finding a job, they are 1.9% more likely to work at a firm at, or above, the 75th percentile of the wage-per-worker distribution. Credit helps

[36]These percentiles are held constant and based on the 2004 steady state with loose limits.

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 extremely high end of the wage-per-worker distribution (99th percentile and above).

Table 11: Model Elasticities versus Data Elasticities (Column (3) targeted)

| | **(1)** **Model** | **(2)** **OLS** | **(3)** **GS-IV** *(Targeted)* | **(4)** **Saiz-IV** |
|---|---|---|---|---|
| Duration | 0.285 | 0.254*** | 0.277*** | 1.850*** |
| Replacement rate, among EUE (without 0s) | 0.059 | 0.113*** | 0.185*** | 0.167*** |
| $\overline{w}_{firm} > p50$ elasticity among EUE | 0.076 | -0.00258 | 0.0950*** | 0.0944 |
| $\overline{w}_{firm} > p75$ elasticity among EUE | 0.191 | 0.00767** | 0.149*** | 0.158 |
| $\overline{w}_{firm} > p90$ elasticity among EUE | 0.171 | 0.0145*** | 0.0527*** | 0.0152 |
| $\overline{w}_{firm} > p99$ elasticity among EUE | 0.00027 | 0.00153** | -0.00189 | 0.0615*** |

*Notes. Col. 1 Model estimates from Section 5. For data estimates, *** p<0.01, ** p<0.05, * p<0.1. Col. 2 estimates from Table 2. Col. 3 estimates from Table 3. Col. 4 estimates from Table 19.*

**Age and utilization heterogeneity.** Table 12 summarizes the model's ability to reproduce duration and replacement rate elasticities by age and credit utilization. There is an exact mapping between age in the model and data, and so we compute identical model implied elasticities by conditioning on those below/above 40 years old. The model matches the old-to-young ratio of unemployment duration elasticities by construction, but it also does quite well at matching the non-targeted old-to-young ratio of replacement rate elasticities. Younger workers in the model have less accumulated human capital, but they are also the most constrained. Their replacement rate elasticities are 30% higher than those of older workers, a finding that is non-targeted and borne out in the data.

Likewise, the model reproduces non-targeted replacement rate elasticities among high- and low-utilization job losers. As in the data, constrained (above average utilization) individuals are much more sensitive to credit. Their replacement rate elasticity is 0.527 in the data and 0.344 in the model, both of which are more than 4 times greater than the corresponding low-utilization elasticities of 0.108 and 0.056 in the data and model, respectively.

Heterogeneity by age and utilization also provides insight into the model's mechanisms. Both young and constrained agents are the most sensitive to credit and alter their job search choices the most. The sensitivity of young individuals' capital intensity is 30% greater than that of older individuals. The sensitivity of constrained individuals' capital intensity choice is 5 times greater than unconstrained individuals. The disproportionate sensitivity of young and constrained individuals governs the evolution of sorting patterns and thus aggregate output in the transition experiment (Section 6).

Table 12: Model vs. Data, Age and Utilization Splits

| Elasticity (rows) | OLS | GS-IV | Model | OLS | GS-IV | Model | OLS | GS-IV | Model |
|---|---|---|---|---|---|---|---|---|---|
| | **Less than 40** | | | **Greater than 40** | | | **Old-Young Ratio** | | |
| Duration (targeted) | 0.257*** | 0.314*** | 0.320 | 0.258*** | 0.255*** | 0.250 | 1.004 | 0.812 | 0.783 |
| Rep. Rate, no 0s (non-targeted) | 0.177*** | 0.329*** | 0.070 | 0.0844*** | 0.0990*** | 0.047 | 0.477 | 0.301 | 0.667 |
| Capital Intensity (non-targeted) | – | – | 0.770 | – | – | 0.542 | – | – | 0.704 |
| | **Below Avg. Utilization** | | | **Above Avg. Utilization** | | | **High-Low Utilization Ratio** | | |
| Duration (targeted) | 0.200*** | 0.225*** | 0.278 | 0.453*** | 0.595*** | 1.095 | 2.265 | 2.644 | 3.934 |
| Rep. Rate, no 0s (non-targeted) | 0.111*** | 0.108*** | 0.056 | 0.235*** | 0.527*** | 0.344 | 2.117 | 4.880 | 6.119 |
| Capital Intensity (non-targeted) | – | – | 0.634 | – | – | 3.337 | – | – | 5.264 |

*Notes. Col. 1 Model estimates from Section 5. For data estimates, *** p<0.01, ** p<0.05, * p<0.1. Age splits from Table 5, and utilization splits from Table 6.*

## 5.3 Comparison with Unemployment Insurance Estimates

Since credit must 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 preferred estimates imply that an additional \$1 of unused credit is about half as potent for unemployment durations as \$1 of unemployment benefits. 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 0.3 to 2.0 weeks, with the modal estimate lying between 0.5 and 1.0 for the US (see Nakajima [2012b] and Card, Johnston, Leung, Mas, and Pei [2015] for a summary of recent empirical and quantitative elasticities). Our three sets of estimates imply an equivalent elasticity with respect to credit of 0.15 weeks (OLS), 0.16 weeks (GS-IV, our preferred estimates) and 1.1 weeks (Saiz-IV).

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 [2017]) 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 the 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

Following the model's success at replicating key micro moments, we now aggregate across individual agents to explore how consumer 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.

**1964 steady state.** Owing to a 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 infancy in the late 1950s and early 1960s. In 1964, many of the local banks and companies that would one day comprise Visa and Mastercard were just being founded or did not exist. 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 $\underline{b}_{1964} = 0$.

**2004 steady state.** In order to calibrate the final 2004 steady state, we use the estimated debt limit $\underline{b}_{2004} = -0.66$. Throughout most of the simulated transition path, public information on credit card debt limits is not available; the Survey of Consumer Finances did 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 13 illustrates the corresponding values of the debt limit along the transition path.

Table 13: 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 | -0.1661 | -0.3321 | -0.4982 | -0.6643 |

Table 14 compares the path for the exogenous borrowing limit $\underline{b}$ relative to the path in 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.

Table 14: Model Borrowing Limits vs. Data Borrowing Limits

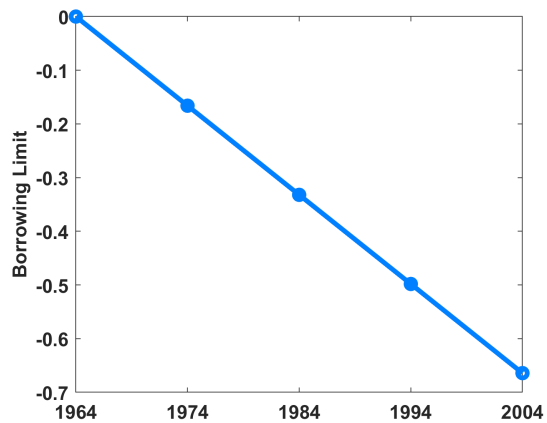
| | **Survey of Consumer Finances** | | | **Model** |
|---|---|---|---|---|
| | Limits (84-94=1) | Limits ($) | SCF Surveys | Limits (84-94=1) |
| 1964 to 1974 | - | - | - | 0.00 |
| 1974 to 1984 | - | - | - | 0.50 |
| 1984 to 1994 | 1.00 | 9,227 | ‘89, ‘92 | 1.00 |
| 1994 to 2004 | 1.58 | 14,539 | ‘95,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

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

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

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




## 6.1 Transition Path Results

In this section, we report the results of the transition path experiment between 1964 and 2004.[37] Agents rationally 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 13. The realizations of the Markov chain are such that credit expands at the start of each decade, consistent with agents' beliefs.[38] Figure 5 plots the path for limits.

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

[38]$\underline{b} = 0$ in 1964, and then expands linearly thereafter in 1970, 1980, 1990, and 2000.

Figure 6: Output, Employment & Productivity

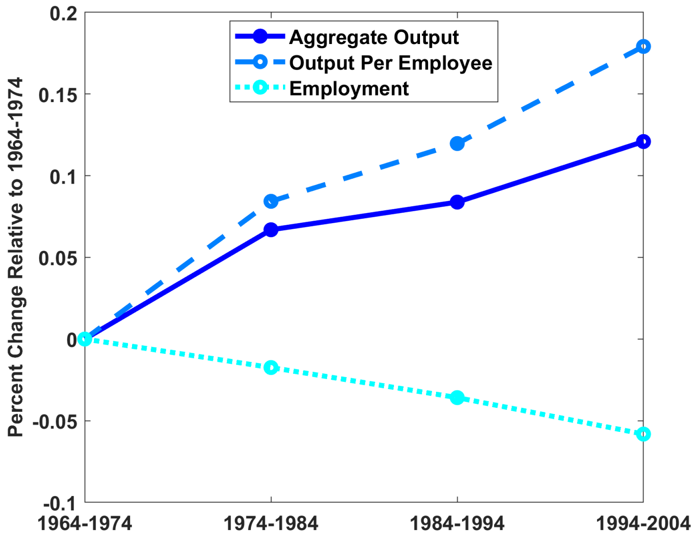



Figure 7: Sorting and Capital

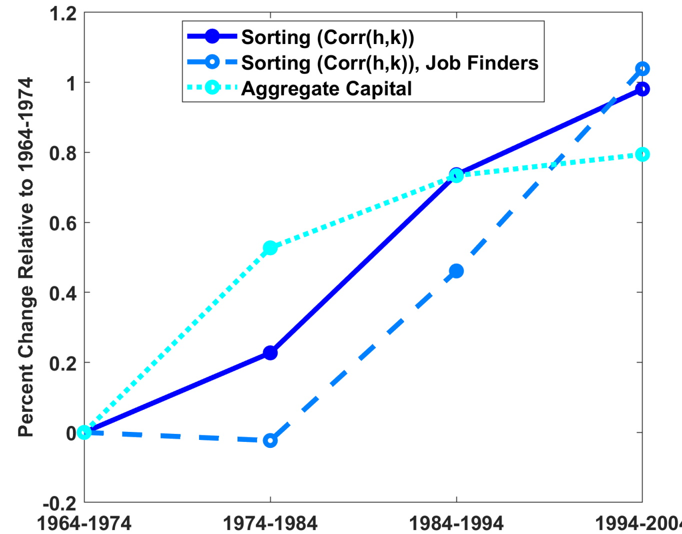



Figure 8: Capital $k$ by Human Capital $h$

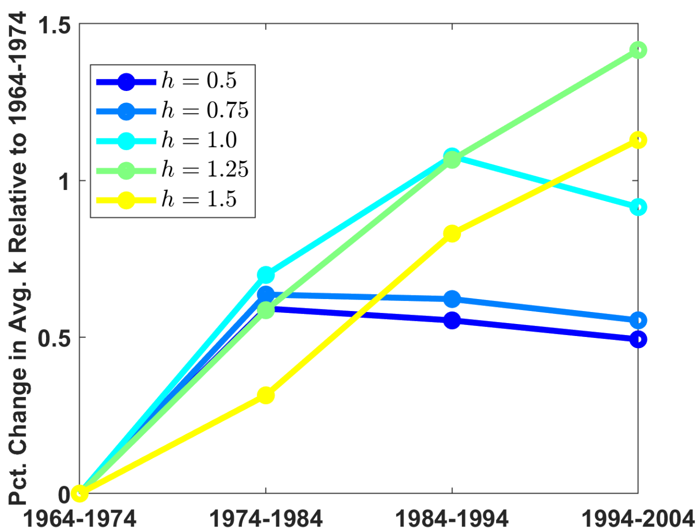



Figure 9: Capital $k$ and Constraints

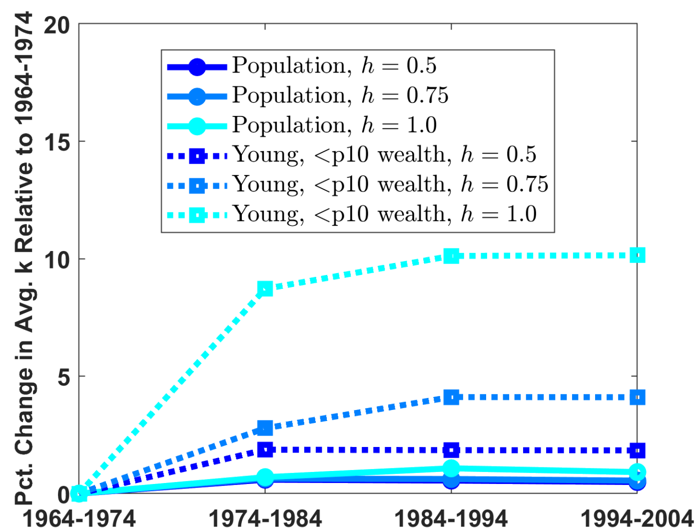


Figure 6 plots output, output per employee (labor productivity), and employment relative to 1964 levels. In terms of production, the impact of tighter debt limits on aggregate output is theoretically ambiguous: households find jobs more slowly, but the jobs workers find are more productive. As credit expands from 1964 to 2004, fewer individuals are employed, as they become less constrained and take longer to find jobs (employment falls by 0.05% by 2004). On the other hand, as credit constraints loosen, agents find jobs with greater capital intensity, and so output and output per worker increase. 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, endogenously increases when debt limits are loosened. Labor productivity increases by 0.18% along the transition path, and aggregate output increases by 0.13% along the transition.

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. Similar to output, the impact of credit access on sorting is also theoretically ambiguous. Credit access allows constrained individuals to find higher capital intensity jobs. If constrained individuals primarily have low human capital, then sorting can deteriorate as low human capital individuals borrow to finance job search for high capital intensity jobs. On the other hand, it is also the case that constrained individuals with high human capital can more aggressively borrow against future wage income to finance job search. If constrained individuals primarily have high human capital, then sorting can improve as high human capital individuals borrow to finance their search for high capital intensity jobs.

Figure 7 shows that in the economy in which debt limits are looser, sorting improves. As we discuss below, both constrained high- and low- human capital workers take longer to search for higher capital jobs. Ultimately, however, constrained high human capital workers are the most responsive to credit expansions. Looser debt limits allow these constrained "high quality" workers to take "high quality" jobs. Thus, standard measures of sorting improve. What drives the increase in output is the increased capital investment of entrepreneurs. As Figure 7 shows, the aggregate capital stock held by entrepreneurs increases as credit limits expand. This is driven entirely by new entrepreneurial entrants posting more vacancies in submarkets with more capital and constrained households searching for jobs in those submarkets.

Figures 8 and 9 demonstrate the micro mechanism generating the improvement in sorting. Low human capital workers are able to find more productive jobs (jobs in greater percentiles of the firm capital distribution) as credit limits expand from 1964 to 2004 – this puts downward pressure on sorting as "low quality" workers finder "higher quality" jobs. However, high human capital workers respond more to increased credit access, increasing the average capital intensity of their jobs by greater than 1% from 1964 to 2004 (versus 0.5% for the lowest human capital workers). That "high quality" workers obtain "high quality" jobs puts upward pressure on sorting.

Why do high human capital workers respond to increases in credit? A non-trivial fraction of high-human capital workers have little wealth. Figure 9 shows that relative to the overall population, constrained agents at the middle rung of the human capital distribution ($h = 1.0$) are significantly more responsive to credit expansions than workers on lower rungs of the human capital distribution are. To better understand this, in Table 15 we report the human capital distribution among newborns, the population, and the lowest wealth decile.[39] Roughly 17% of constrained individuals (bottom wealth decile) are high human capital workers (i.e., $h = 1.0$ and above). They are primarily young, and they have very high capital intensity elasticities. Row 4 of Table 15 shows that the capital intensity elasticity among those in the lowest wealth decile ranges from 0.33 for the lowest human capital workers to 3.76 for those with the highest human capital. These heterogeneous effects of credit are in line with our empirics (summarized in Table 12), showing that both young and constrained individuals are most responsive to credit access.

A second force that contributes to low human capital workers being less sensitive to increases in aggregate credit limits is that low human capital workers do not benefit one-for-one with aggregate credit limit expansions; instead, low human capital workers are often times endogenously constrained at lower levels of credit access by the convex profile of interest rates inherent in defaultable debt models (Chatterjee et al. [2007]). The bottom row of Table 15 reports borrowing limits in levels in 2004, measured along the transition path. The initial credit expansion from $\underline{b}_{1964} = 0$ to $\underline{b}_{1974} = -0.166$ between 1964 and 1974 allows all agents across the human capital distribution to borrow more. Subsequent credit expansions from 1974 onwards predominately allow higher human capital agents to borrow more, since lower human capital agents are constrained endogenously by infinite interest rates at much tighter

[39] All distributions are pooled along the transition path.

Table 15: Human capital distribution and sensitivity to credit among population and constrained agents

| | Human Capital | | | | |
|---|---|---|---|---|---|
| | $h = 0.50$ | $h = 0.75$ | $h = 1.0$ | $h = 1.25$ | $h = 1.5$ |
| Newborn $h$ distribution | 60% | 24% | 10% | 4% | 2% |
| Population $h$ distribution | 27% | 28% | 21% | 13% | 11% |
| Lowest wealth decile, $h$ distribution | 61% | 21% | 9% | 5% | 3% |
| Lowest wealth decile, Capital Intensity Elasticity | 0.33 | 0.71 | 1.49 | 2.66 | 3.76 |
| Average credit limit in 2004 (transition path) | 0.10 | 0.17 | 0.26 | 0.34 | 0.41 |

*Notes. First row model estimates computed following identical procedure to Section 5, 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.*

borrowing limits (e.g., in Table 15, the average borrowing limit as defined in Section 6 for the lowest human capital borrowers is -0.10). Therefore, endogenous borrowing constraints bound the potential effect of credit on the sorting patterns of low human capital workers. This also contributes to improvements in sorting post-1974 as expansions in the borrowing limit primarily allow constrained high human capital workers to find better jobs.

**Policy implications.** 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 0.05%) while actually significantly improving the allocation of labor to firms (raising labor productivity persistently by 1/8th of a percentage point). Our results suggest that as access to private credit markets among low-income US households expands, as it did 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, a very promising result for public finance. Concurrent work by Braxton et al. [2020] examines these insights.

# 7 Conclusions

We develop a novel database linking consumer credit reports to employment histories in order to measure the elasticities of non-employment durations, wage replacement rates, and average firm wages to consumer credit. We then use these empirical elasticities to estimate a theoretical model that integrates consumption-savings decisions into a model of two-sided worker and firm heterogeneity. The model then shows how access to consumer credit affects the allocation of workers to firms and the impact on aggregate outcomes such as labor productivity, output, and employment dynamics.

We show that individuals who have greater access to credit markets take longer to find jobs and, conditional on finding a job, earn more and work at more productive firms, as proxied by the firm's wage-per-worker. We show that these relationships hold in ordinary least squares analysis as well as when we instrument credit using age-of-oldest account and housing supply elasticities. We find that displaced workers with greater access to credit find jobs at firms in higher percentiles of the firm wage-per-worker distribution, and we find that these elasticities are more pronounced among younger individuals and workers with high credit utilization.

We use these elasticities to estimate a novel general equilibrium labor sorting model with consumer credit, integrating models of two-sided heterogeneity (Shimer and Smith [2000]) with defaultable debt (Chatterjee, Corbae, Nakajima, and Ríos-Rull [2007]). The model does well at reproducing pooled as well as age- and utilization-dependent duration and replacement rate elasticities.

We then use the estimated model to analyze the impact of credit market development from 1964 to 2004 on job search behavior and the aggregate economy. We find that greater access to credit generates improvements in sorting as well as productivity and output. The mechanism underlying greater sorting is that constrained, high human capital workers search more intensively for higher capital jobs when their credit constraints are loosened; thus, as credit expands, these "high quality" workers find "high quality" jobs.

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, and so on). Our work continues to advance this research agenda, focusing on (1) quantifying the optimal mix of public and private insurance (Braxton et al. [2020]), and (2) quantifying the impact of household consumer credit constraints on the decision to start a business (Herkenhoff, Phillips, and Cohen-Cole [2021]).

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# Online Appendix

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

Herkenhoff, Phillips, and Cohen-Cole

April 25, 2023

# 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 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., 20% 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

We define a mass layoff to occur when an SEIN with at least 20 employees reduces its employment by 20% or more within a quarter. To ensure that 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,

$$\frac{\text{Total Revolving Credit Limit - Total Revolving Balance}}{\text{Lagged Annual Earnings}}$$

'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.

## 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 10 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 16 provides a more formal analysis, including controls for the entire portfolio of a household's assets. Table 16 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 before the survey. It is measured in weeks, and does not distinguish individual unemployment spells.

Column 1 of Table 16 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.

Figure 10: **Survey of Consumer Finances:** Correlation of Unemployment Durations (in Weeks) on Unused Credit (Source: 1998-2007 SCF)

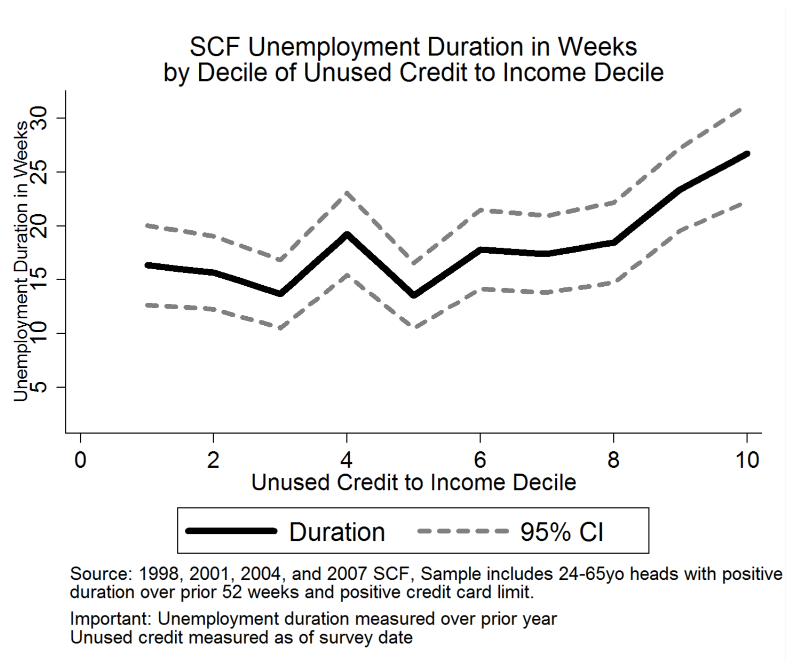


Table 16: **Survey of Consumer Finances:** OLS Regressions of Unemployment Durations (in Weeks) on Unused Credit, Controlling for Assets (Source: 1998-2007 SCF)

| | **(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.*

# 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 17 analyzes wages 2 years after layoff for this same sample. Column (1) reveals that under OLS, replacement earnings are 1.19% 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. The IV analysis implies that replacement earnings are 1.92% higher, 2 years after layoff, for households who can replace 10% more of their lost income with unused credit.

## B.1 Self-Employment and the Earnings Gap Method

Table 18 redoes the main analysis in two different ways. Column (1) repeats the original duration regression from Table 3. Column (2) is a regression of duration on unused credit

Table 17: 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 | 0.119*** | 0.192*** |
| | (0.0106) | (0.0194) |
| Controls (Demographic, Industry, Regional, Lagged Earnings, Equity Proxy) | Y | Y |
| R2 (1st stage for IV) | 0.168 | 0.0614 |
| Round N | 98000 | 98000 |

*Notes. See Table 2.*

where the self-employed with more than \$1k 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 before 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 18 illustrates that the main results are robust to these alternate definitions.

Table 18: 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 | 0.277*** | 0.256*** | 0.268*** |
| | (0.0629) | (0.0618) | (0.0624) |
| Controls (Demographic, Industry, Regional, Lagged Earnings, Equity Proxy) | Y | Y | Y |
| R2, 1st Stage | 0.0596 | 0.0596 | 0.0596 |
| Angirst Pischke FStat Pval | 0 | 0 | 0 |
| Round N | 217000 | 217000 | 217000 |

*Notes. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. See Table 2 for samples, controls, and notes.*

## B.2 Saiz Instrument: Housing Supply Elasticity

As a second robustness exercise, we use the Saiz [2010] housing supply elasticity as an instrument for credit access. This mirrors the approach used by Mian and Sufi [2011] and Mian and Sufi [2014] who apply this instrument to understand how housing net worth affects labor markets. There are two reasons why house prices determine access to revolving credit: (i) workers have more access to capital and are less likely to default, increasing the propensity of lenders to extend any type of credit, and (ii) lenders expect workers to consume more, and therefore offer more credit cards since they profit from transaction volume (not just balances). In the first-stage regression shown in Appendix B.3, from a purely statistical point of view, we show that the Saiz [2010] geographic constraint instrument is a strong predictor of the unused credit limit ratio of individual workers for the 38 MSAs present in our sample. In the second stage regression, the predicted unused credit limit ratios from the first stage are used to measure the impact of credit on non-employment durations and annual earnings replacement rates.

The two main challenges to exogeneity of the Saiz [2010] instrument are (i) aggregate demand conditions, and (ii) housing wealth. First, we address aggregate demand conditions. While Mian and Sufi [2014] argue that there is no correlation between the supply elasticity and aggregate conditions except through leverage, if there is a correlation, it should bias our results toward zero. Suppose MSAs with low supply elasticities have quickly rising house prices and have better labor markets, then credit should expand and non-employment durations should be shorter in those MSAs. As we will show below, our IV estimates imply the opposite relationship. We additionally control for the MSA unemployment rate and MSA real gross domestic product per capita to proxy for aggregate demand conditions.

To mitigate concerns about housing wealth, we include an equity proxy (the highest mortgage balance ever observed less the current balance) and HELOC limits (home equity lines of credit) in all specifications. We argue that HELOCs isolate the amount of home equity that can be used as an ATM immediately following a job loss. In other words, the HELOC credit limit just before a job loss is a good proxy for access to liquid housing assets during the non-employment spell. Furthermore, we do not see workers disproportionately take out new mortgages (which would indicate potential cash-out refinancing) or pay off mortgages (indicating a sale) during or after layoff.

Table 19 shows the point estimates from our second stage regression using the Saiz

Table 19: Credit and Labor Market Outcomes: Instrumental Variable, Housing Supply Elasticity ('Saiz Instrument,' S-IV).

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| **Sample:** | ——All Displaced—— | | ——————Job Finders 1 Yr. After Layoff—————— | | | | |
| **Dependent Variable:** | Duration | Rep. Rate (0s) | Rep. Rate | $\overline{w}_{firm}$ >p50 | $\overline{w}_{firm}$ >p75 | $\overline{w}_{firm}$ >p90 | $\overline{w}_{firm}$ >p99 |
| Unused Revolving Credit to Income Ratio | 1.850*** | -0.195** | 0.167*** | 0.0944 | 0.158 | 0.0152 | 0.0615*** |
| | (0.556) | (0.0771) | (0.0379) | (0.198) | (0.272) | (0.161) | (0.0184) |
| Controls (Demographic, Industry, MSA, Lagged Earnings, Equity Proxy, HELOC Limit) | Y | Y | Y | Y | Y | Y | Y |
| R2, 1st Stage | 0.00765 | 0.00765 | 0.00545 | 0.00545 | 0.00545 | 0.00545 | 0.00545 |
| Angirst Pischke FStat Pval | 0.0286 | 0.0286 | 0.0639 | 0.0639 | 0.0639 | 0.0639 | 0.0639 |
| Round N | 53000 | 53000 | 25000 | 25000 | 25000 | 25000 | 25000 |

*Notes. Standard errors clustered at state level, *** p<0.01, ** p<0.05, * p<0.1. Instrumental variable is housing supply elasticity. Demographic controls include a quadratic in tenure and dummies for age, race, sex and education as well as year, mortgage, and auto loan dummies. Industry controls include 1-digit SIC dummies and size, age, and wage per worker of prior firm. Regional controls include the MSA unemployment rate and MSA total per capita real gross domestic product. 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 Limit is the total limit on open home equity lines of credit.*

housing supply elasticity instrument. Among all displaced, the coefficient in Column (1) means that individuals who can replace 10% more of their pre-displacement earnings with credit take 2.22 (=1.85*0.1*12) weeks longer to find a job. The estimate in Column (2) for the ability of credit to replace income is negative for job finding for all displaced. However, this column includes those individuals who do not find a job in the next 8 quarters. Among job finders, the impact of credit on replacement rates is positive and significant. Column (3)'s point estimate implies that being able to replace 10% more of prior annual earnings with credit increases replacement rates by 1.67%, conditional on being employed throughout the year after layoff - similar in magnitude as that reported in the previous estimates with the age of the oldest account instrument. Columns (4) through (7) demonstrate that those who can replace 10% more of prior annual earnings with credit are .9%, 1.6%, and .6% more likely to find jobs at firms above the 50th, 75th, and 99th percentile of the wage-per-worker distribution, respectively.

## B.3 First Stage Regressions

This section shows the first stage regressions for both Table 3 and Table 19. In the next section, we also show the results of the over-identification tests for the two instrumental variables: the age of the oldest account and the housing supply elasticity.

Table 20: First stage regressions

| **Sample:** | (1) GS-All | (2) GS-Job Finders | (3) Saiz-All | (4) Saiz-Job Finders | (5) Over ID-All | (6) Over ID-Job Finders |
|---|---|---|---|---|---|---|
| **Dependent Variable:** | Unused Revolving Credit to Income Ratio | | | | | |
| Lagged Age of Oldest Bankcard | 0.00261*** | 0.00243*** | | | 0.00294*** | 0.00274*** |
| | (4.82e-05) | (6.65e-05) | | | (0.000109) | (0.000146) |
| Lagged Housing Supply Elasticity | | | -0.0840*** | -0.0612*** | -0.0756*** | -0.0544*** |
| | | | (0.00716) | (0.00917) | (0.00692) | (0.00887) |
| Round N | 217000 | 98000 | 53000 | 25000 | 53000 | 25000 |

*Notes. Standard errors clustered at state level, *** p<0.01, ** p<0.05, * p<0.1. Instrumental variables for unused credit to income are (1) age of oldest bankcard account, and (2) housing supply elasticity. See table 21 for a description of controls.*

## B.4 Over-identification tests

In this section, we conduct over-identification tests using both the Saiz [2010] and Gross and Souleles [2002] instruments. Table 21 shows that using both the Saiz [2010] and Gross and Souleles [2002] instruments in our IV specifications yields similar duration, replacement rate, and firm wage-per-worker elasticities as our benchmark results based on Gross and Souleles [2002] alone. The duration elasticity is 0.51 (versus 0.28 using Gross and Souleles [2002] alone), the replacement rate elasticity is 0.13 (versus 0.19 using Gross and Souleles [2002] alone), and the job elasticity at the 75th percentile of the wage-per-worker distribution is 0.13 (versus 0.15 using Gross and Souleles [2002] alone).

The row entitled "Pval J-test, H0: Valid Instrument" in Table 21 reports the P-values from Hansen's J-test using the both the Saiz [2010] and Gross and Souleles [2002] instruments. Informally, the J-test relies on the intuition that each instrumental variable should be orthogonal to residuals obtained solely from the other instrument. The null hypothesis is that the instruments are valid, thus small p-values indicate rejection of the null, large p-values indicate inability to reject the null. The instruments pass the J-test at standard statistical levels. We *cannot* reject the null that the instruments are valid at the 1%, 5%, or 10% significant levels. The lack of rejection of any of the specifications at the 10% level is fairly strong evidence that there is little correlation between each instrument and its counterpart's residuals, suggesting exogeneity. What makes these tests more convincing is that the geographic variation in the Saiz [2010] instrument is conceptually and mechanically very different from the individual specific variation in the account ages.

Table 21: Over-identification Tests: Instrument Variables, Age of Oldest Bankcard Account and Housing Supply Elasticity.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| **Sample:** | All Displaced | | | Job Finders 1 Yr. After Layoff | | | | |
| **Dependent Variable:** | Duration | Duration (Self-Employed) | Duration (Earnings Gap) | Rep. Rate | $\overline{w}_{firm}$ >p50 | $\overline{w}_{firm}$ >p75 | $\overline{w}_{firm}$ >p90 | $\overline{w}_{firm}$ >p99 |
| Unused Revolving Credit to Income Ratio | 0.511*** | 0.488*** | 0.506*** | 0.133*** | 0.0716*** | 0.126*** | 0.0531*** | 0.00761 |
| | (0.0824) | (0.0783) | (0.0802) | (0.0255) | (0.0202) | (0.0410) | (0.0186) | (0.00669) |
| Controls (Demographic, Industry, MSA, Lagged Earnings, Equity Proxy, HELOC Limit) | Y | Y | Y | Y | Y | Y | Y | Y |
| Pval J-test, H0: Valid Instrument | 0.166 | 0.180 | 0.165 | 0.253 | 0.907 | 0.897 | 0.781 | 0.163 |
| R2, 1st Stage | 0.003 | 0.003 | 0.003 | 0.021 | -0.036 | -0.051 | -0.005 | -0.000 |
| Angirst Pischke FStat Pval | 2.84e-10 | 2.84e-10 | 2.84e-10 | 3.98e-10 | 3.98e-10 | 3.98e-10 | 3.98e-10 | 3.98e-10 |
| Round N | 53000 | 53000 | 53000 | 25000 | 25000 | 25000 | 25000 | 25000 |

*Notes. Standard errors clustered at state level, *** p<0.01, ** p<0.05, * p<0.1. Instrumental variables for unused credit to income are (1) age of oldest bankcard account, and (2) housing supply elasticity. See table 21 for a description of controls.*

## B.5 OLS: Age and Utilization Heterogeneity

The OLS estimates in Table 22 correspond to the IV estimates of Table 5. Both sets of point estimates suggest greater replacement rates and more sensitive sorting patterns among younger workers.

Table 22: Less than or equal to 40/greater than 40: OLS

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Sample:** | All Displaced | Job Finders 1 Yr. After Layoff | | | | |
| **Dependent Variable:** | Duration | Rep. Rate | $\overline{w}_{firm}$ >p50 | $\overline{w}_{firm}$ >p75 | $\overline{w}_{firm}$ >p90 | $\overline{w}_{firm}$ >p99 |
| Less than 40 × Unused Revolving Credit to Income Ratio | 0.257*** | 0.177*** | -0.00777 | 0.0111* | 0.0196*** | 0.00257** |
| | (0.0279) | (0.0199) | (0.00586) | (0.00607) | (0.00385) | (0.00123) |
| Greater than 40 × Unused Revolving Credit to Income Ratio | 0.258*** | 0.0844*** | -0.000370 | 0.00474 | 0.0110*** | 0.000942 |
| | (0.0212) | (0.0109) | (0.00425) | (0.00433) | (0.00264) | (0.000903) |
| Pval H0: Equal Coefficients | 0.965 | 4.28e-05 | 0.307 | 0.393 | 0.0639 | 0.288 |
| Combined Round N | 217000 | 98000 | 98000 | 98000 | 98000 | 98000 |

*Notes. Standard errors clustered at individual level, *** p<0.01, ** p<0.05, * p<0.1. See Table 2 for samples and controls.*

## B.6 OLS Utilization Heterogeneity

The OLS results presented in Table 23 correspond to the IV regression in Table 6 in the main text. Both tables show that the impact of unused credit is greater for individuals with high credit utilization, consistent with credit being more important for job finding when workers are likely to be more constrained.

Table 23: Above/below avg utilization: OLS

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Sample:** | All Displaced | Job Finders 1 Yr. After Layoff | | | | |
| **Dependent Variable:** | Duration | Rep. Rate | $\overline{w}_{firm}$ >p50 | $\overline{w}_{firm}$ >p75 | $\overline{w}_{firm}$ >p90 | $\overline{w}_{firm}$ >p99 |
| Below avg. utilization × Unused Revolving Credit to Income Ratio | 0.225*** | 0.108*** | -0.00319 | 0.00720* | 0.0137*** | 0.00160** |
| | (0.0202) | (0.0108) | (0.00414) | (0.00425) | (0.00256) | (0.000810) |
| Above avg. utilization × Unused Revolving Credit to Income Ratio | 0.453*** | 0.235*** | 0.00325 | 0.0164** | 0.0290*** | 0.00384* |
| | (0.0410) | (0.0322) | (0.00800) | (0.00834) | (0.00585) | (0.00209) |
| Pval H0: Equal Coefficients | 5.93e-07 | 0.000175 | 0.475 | 0.323 | 0.0163 | 0.316 |
| Combined Round N | 217000 | 98000 | 98000 | 98000 | 98000 | 98000 |

*Notes. Standard errors clustered at individual level, *** p<0.01, ** p<0.05, * p<0.1. See Table 2 for samples and controls.*

## B.7 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 unobserved variable (human capital) that is generating the selection effect in the model, and thus provide a selection correction factor for both the model and reduced form 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 rate 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 find very little scope for selection effects.

We implement this procedure in Table 24. First we compute the replacement rate elasticity among job finders stratified by the human capital with which they enter layoff, denoted $\epsilon_{Rep,e}(h)$. We report the model's human capital specific replacement elasticities in row 1 of Table 24. We see that low human capital agents have the greatest replacement rate gains from an additional dollar of credit – but the effects are highly non-linear. Newborn high-human capital individuals are constrained and alter their job search significantly in response to greater credit access as well. In row 2 of Table 24, we weight each of the replacement elasticities by the unconditional human capital distribution, $f_{pop}(h)$. The selection corrected replacement elasticity is:

$$\epsilon_{Rep,e}^{selection\ corrected} = \sum_h f_{pop}(h)\epsilon_{Rep,e}(h) = .0593$$

This is reported in row 2 of Table 24. Comparing this to the raw estimate of the replacement rate elasticity yields the selection correction factor (row 4 of Table 24):

$$\textbf{Selection Correction Factor} = \frac{\epsilon_{Rep,e}^{selection\ corrected}}{\epsilon_{Rep,e}} = \frac{.0593}{.0587} = 1.0103$$

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 1.01 to obtain the population elasticity. This selection correction factor is both economically and statistically small.

Table 24: Model Replacement Rates Among Job Finders, Controlling for Selection

| | **Human Capital** | | | | |
|---|---|---|---|---|---|
| | $h = 0.50$ | $h = 0.75$ | $h = 1.0$ | $h = 1.25$ | $h = 1.5$ |
| Replacement Elasticity for Job Finders, Fixed $h$ | 0.0629 | 0.0565 | 0.0562 | 0.0631 | 0.0585 |
| *Weighted* Replacement Elasticity for Job Finders, Fixed $h$ (Selection Corrected Elasticity) | 0.0593 | | | | |
| Replacement Elasticity for Job Finders (Raw) | 0.0587 | | | | |
| Selection Correction Factor (=.059/.054) | 1.0103 | | | | |

*Notes. First row model estimates computed following identical procedure to Section 5, 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.*

# C Employed Value Functions

In this section, we describe the continuation values for employed households in our benchmark model. Employed value functions are denoted with a $W$, and at the end of every period, employed households face layoff risk $\delta$. If they are laid off, since the period is 1 quarter, we must allow the workers to search immediately for a new job.[40]

$$W_t^G(b,h,k;\Omega) = \max_{b' \geq \underline{b}} u(c) + \beta \mathbb{E}\Bigg[(1-\delta)\widehat{W}_{t+1}^G(b',h',k;\Omega')$$
$$+\delta\Big\{\max_{\tilde{k}} p(\theta_{t+1}(h',\tilde{k};\Omega'))\widehat{W}_{t+1}^G(b',h',\tilde{k};\Omega') + \big(1-p(\theta_{t+1}(h',\tilde{k};\Omega'))\big)\widehat{U}_{t+1}^G(b',h';\Omega')\Big\}\Bigg], \quad t \leq T$$

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

such that the aggregate laws of motion are given by equation (4), human capital evolves according to the law of motion ($h' = H(h,W)$), and the budget constraint holds,

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

For those in bad standing, the continuation value of an employed worker is given by,

$$W_t^B(b,h,k;\Omega) = \max_{b' \geq 0} u(c) + \lambda\beta \mathbb{E}\Bigg[(1-\delta)\widehat{W}_{t+1}^G(b',h',k;\Omega')$$
$$+\delta\Big\{\max_{\tilde{k}} p(\theta_{t+1}(h',\tilde{k};\Omega'))\widehat{W}_{t+1}^G(b',h',\tilde{k};\Omega') + \big(1-p(\theta_{t+1}(h',\tilde{k};\Omega'))\big)\widehat{U}_{t+1}^G(b',h';\Omega')\Big\}\Bigg]$$
$$+ (1-\lambda)\beta\mathbb{E}\Bigg[(1-\delta)\widehat{W}_{t+1}^B(b',h',k;\Omega')$$
$$+\delta\Big\{\max_{\tilde{k}} p(\theta_{t+1}(h',\tilde{k};\Omega'))\widehat{W}_{t+1}^B(b',h',\tilde{k};\Omega') + \big(1-p(\theta_{t+1}(h',\tilde{k};\Omega'))\big)\widehat{U}_{t+1}^B(b',h';\Omega')\Big\}\Bigg], \quad t \leq T$$

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

such that the aggregate laws of motion are given by equation (4), human capital evolves

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

according to the law of motion ($h' = H(h, W)$), and the budget constraint holds,

$$c + \frac{1}{1 + r_f} b' \leq \alpha f(h, k) + b.$$

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

$$\widehat{W}_t^G(b, h, k; \Omega) = (1-p_x) \max\left\{W_t^G(b, h, k; \Omega), W_t^B(0, h, k; \Omega) - \chi\right\} + p_x \max\left\{W_t^G(b-x, h, k; \Omega), W_t^B(0, h, k; \Omega) - \chi\right\}.$$

Since expense shocks continue to be incurred in bad standing, households must be given the option to re-default. Therefore, those in bad standing make the following default decision:

$$\widehat{W}_t^B(b, h, k; \Omega) = (1-p_x) \max\left\{W_t^B(b, h, k; \Omega), W_t^B(0, h, k; \Omega) - \chi\right\} + p_x \max\left\{W_t^B(b-x, h, k; \Omega), W_t^B(0, h, k; \Omega) - \chi\right\}.$$

# 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. [2016], 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 and continuous), the production function is continuous and also meets standard inada conditions, the matching function is invertible, continuous 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 $\mu$ across states in the last period of life,

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

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

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,

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

Stepping back to the default decision, $U_T$ will also not depend on the aggregate distribution $\mu$,

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

Let $D_{U,T}(b,h,k;\underline{b})$ denote the policy function of the household. Since there is a utility penalty $\chi$ 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 $\mu$ 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 $\mu$ (and, similar to the firm problem, it is also independent of the aggregate shock itself, $\underline{b}$),

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

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 and the objective is continuous, the extreme value theorem guarantees at least one solution to this problem under the assumption $f$ and $u$ are continuous (as maintained in the hypothesis). 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,

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

Clearly the bond price does not depend on the aggregate distribution $\mu$.

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 $\epsilon$-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,

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

The minimum supportable debt is given by,

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

□

# E Model Robustness

## E.1 Model with Firm Investment

In this section, we allow firms to invest in capital after a match is formed. 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):

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

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

such that the aggregate laws of motion are given by equation (4), human capital evolves such that $h' = H(h,W)$ and the budget constraint is given by,

$$
c + \frac{1}{1+r_f}b' \leq \alpha f(h,k) + b
$$

and the law of motion of firm capital is given by

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

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 at price $p_k$ after entry, subject to an adjustment cost $\Gamma(k'-k)$. Therefore the value function for the firm is given by,

$$J_t(h,k;\Omega) = \max_{k'} (1-\alpha) f(h,k) - p_k(k'-k) - \Gamma(k'-k) + \beta \mathbb{E}\big[(1-\delta) J_{t+1}(h',k';\Omega')\big]$$
$$J_{T+1}(h,k;\Omega) = 0$$

In the results below, we choose a quadratic adjustment cost $\Gamma(x) = \overline{\Gamma} x^2$. We first consider the case where the MRT of output and capital is 1.0, excluding the adjustment cost, thus $p_k = 1$, and we assume $\overline{\Gamma} = 1$. Figure 11 illustrates that sorting increases by 1% and investment in capital continues to increase by 0.8% under these assumptions. We then consider the other extreme in which 16% of firms are investing every year (similar to the 18% investment spike rate per annum reported by Cooper and Haltiwanger [2006]) by assuming the price of capital and adjustment costs are four times lower, thus $p_k = 0.25$ and $\overline{\Gamma} = 0.25$. Figure 12 illustrates that sorting continues to increase by 1% and investment continue to increase by 0.7%. Such a drastic change in capital investment requires a recalibration, but we note that such a recalibration is infeasible – allowing for endogenous investment requires a significant expansion of capital grids, significantly reducing the speed of the model solution. We leave this endeavor to future work.

Figure 11: Capital Investment MRT 1.0: Sorting and Capital

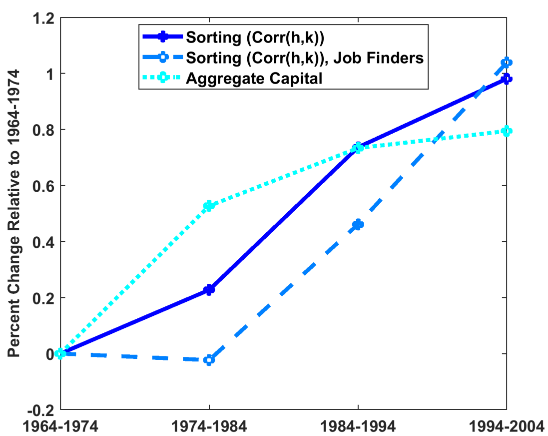
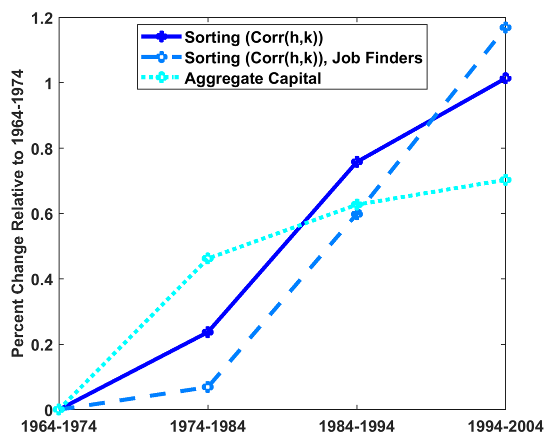



Figure 12: Capital Investment MRT 0.25: Sorting and Capital



## E.4 Liquidation

We also allow for the baseline model to have a liquidation value of capital, $\chi_f$. 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 consider $\chi_f \in \{0.1, 0.85\}$. We first consider a low liquidation value, $\chi_f = 0.1$, as a proxy for lost sweat equity capital and other intangible capital that may not be patented or inherently transferrable. Figure 13 plots the results for $\chi_f = 0.1$, showing that sorting increases by 1%, which is very similar to the baseline model. We also consider a much larger liquidation value, $\chi_f = 0.85$ based on bankruptcy cost estimates (e.g., Branch [2002]). Figure 14 plots the results for $\chi_f = 0.85$, showing that sorting increases by 3% versus 1% in the baseline model. For larger values of $\chi_f$, the same aggregate patterns emerge, except we must significantly expand the capital grid to a point that it becomes computationally infeasible.

Figure 13: 10% Liquidation Value: Sorting and Capital

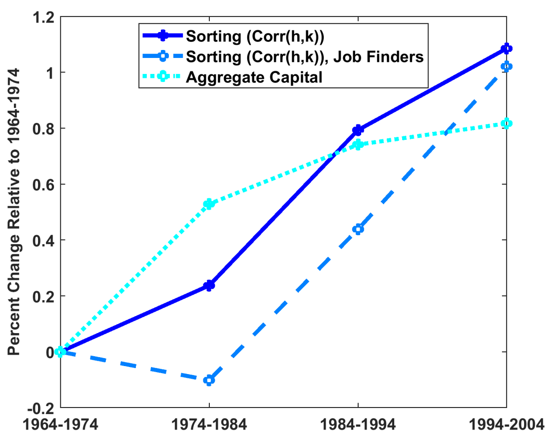
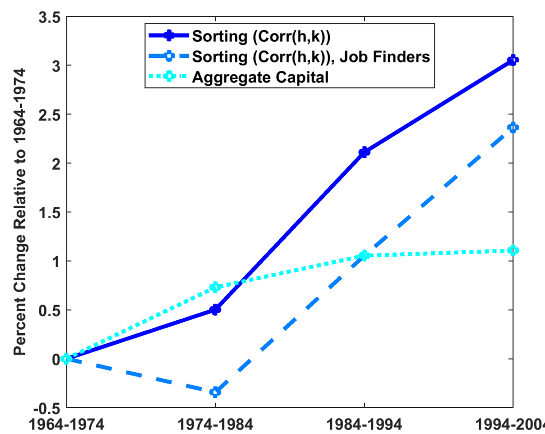



Figure 14: 85% Liquidation Value: Sorting and Capital




## E.5 Initial Assets

In this section, we endow newborn individuals with median net liquid asset positions (based on 24-year-olds in the 2004 SCF) and we show that our main results are robust. Table

25 illustrates two measures of liquid asset to income ratios among 24-year-olds in the 2004 SCF. The first definition is the standard gross liquid asset position, including cash, checking, savings, CDs, money market funds, stocks, and bonds; the second is the net liquid asset position which subtracts credit card balances from the gross liquid asset position. Table 25 clearly shows that most young individuals have extremely little net liquid assets, with the median individual being able to replace roughly 2% of their annual income with their net liquid assets. Likewise, the 75th percentile can replace roughly 12.0% of annual income with their net quit asset position. There is a very thin, but fat tail of liquid assets, skewing the mean liquid asset to income ratio to 29.6%.

Our benchmark economy assume that individuals enter with zero net worth. In this section, we assume that all newborn agents are endowed with assets worth approximately 3% of average income (approximating the p50 net liquid asset position in the data); all other parameters are held fixed. Figure 15 shows that our main results regarding both sorting and aggregate capital are quite similar.

Table 25: Liquid asset to income ratios, 24 years old (Source: 2004 SCF)

| | 24 year olds, 2004 SCF<br>Liquid assets to income | Net liquid assets to income |
|---|---|---|
| p25 | 0.009 | 0.000 |
| p50 | 0.053 | 0.020 |
| p75 | 0.140 | 0.120 |
| Mean | 0.296 | 0.267 |
| Observations | 48 | 48 |

## E.6 Discount at risk free rate

In this section, we discount firm profits at the risk-free rate $r_f$. Figure 16 illustrates the resulting sorting patterns along the transition path. They are nearly identical to our baseline economy in which firms use the household's rate of time preferences.

Figure 15: Newborn assets $b_0 = 0.125$: Sorting and Capital

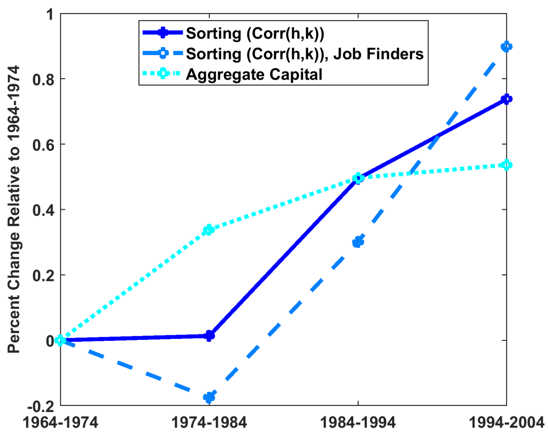
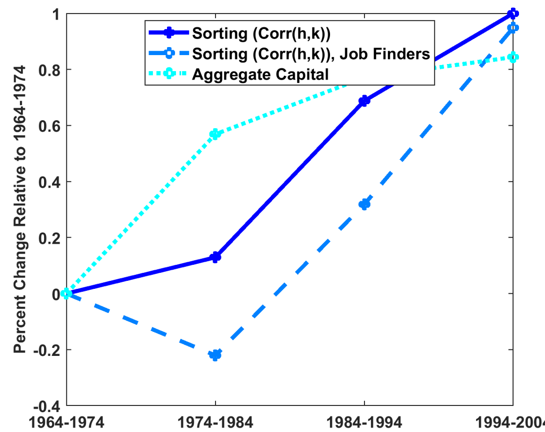



Figure 16: Firms Discount at $r_f$: Sorting and Capital




# F Employed Value Functions: Endogenous Piece-Rate

In this section, we allow for the piece-rate paid to households to be endogenously chosen by households. Submarkets are now indexed by $\alpha$, in addition to age, human capital, and the capital intensity of the firm. For employed households, value functions are denoted with a $W$, and at the end of every period, employed households face layoff risk $\delta$. If they are laid off, since the period is 1 quarter, we must allow the workers to search immediately for a new job:

$$W_t^G(b,h,k,\alpha;\Omega) = \max_{b'\geq \underline{b}} u(c) + \beta \mathbb{E}\Bigg[(1-\delta)\widehat{W}_{t+1}^G(b',h',k,\alpha;\Omega')$$

$$+\delta\Bigg\{\max_{\tilde{k},\tilde{\alpha}} p(\theta_{t+1}(h',\tilde{k},\tilde{\alpha};\Omega'))\widehat{W}_{t+1}^G(b',h',\tilde{k},\tilde{\alpha};\Omega') + \big(1-p(\theta_{t+1}(h',\tilde{k},\tilde{\alpha};\Omega'))\big)\widehat{U}_{t+1}^G(b',h';\Omega')\Bigg\}\Bigg], \quad t \leq T$$

$$\widehat{W}_{T+1}^G(b,h,k,\alpha;\Omega) = 0$$

Such that the aggregate laws of motion are given by equation (4), human capital evolves according to the law of motion ($h' = H(h,W)$), and the budget constraint holds,

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

For those in bad standing, the continuation value of an employed worker is given by,

$$
\begin{aligned}
W_t^B(b,h,k,\alpha;\Omega) &= \max_{b'\geq 0} u(c) + \lambda\beta\mathbb{E}\Bigg[(1-\delta)\widehat{W}_{t+1}^G(b',h',k,\alpha;\Omega') \\
+\delta\Bigg\{ \max_{\tilde{k},\tilde{\alpha}} p(\theta_{t+1}(h',\tilde{k},\tilde{\alpha};\Omega'))\widehat{W}_{t+1}^G(b',h',\tilde{k},\tilde{\alpha};\Omega') &+ \big(1-p(\theta_{t+1}(h',\tilde{k},\tilde{\alpha};\Omega'))\big)\widehat{U}_{t+1}^G(b',h';\Omega')\Bigg\}\Bigg] \\
&+ (1-\lambda)\beta\mathbb{E}\Bigg[(1-\delta)\widehat{W}_{t+1}^B(b',h',k,\alpha;\Omega') \\
+\delta\Bigg\{ \max_{\tilde{k},\tilde{\alpha}} p(\theta_{t+1}(h',\tilde{k},\tilde{\alpha};\Omega'))\widehat{W}_{t+1}^B(b',h',\tilde{k},\tilde{\alpha};\Omega') &+ \big(1-p(\theta_{t+1}(h',\tilde{k},\tilde{\alpha};\Omega'))\big)\widehat{U}_{t+1}^B(b',h';\Omega')\Bigg\}\Bigg], \quad t\leq T
\end{aligned}
$$

$$\widehat{W}_{T+1}^B(b,h,k,\alpha;\Omega) = 0$$

Such that the aggregate laws of motion are given by equation (4), human capital evolves according to the law of motion ($h' = H(h,W)$), and the budget constraint holds,

$$c + \frac{1}{1+r_f}b' \leq \alpha f(h,k) + b$$

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

$$\widehat{W}_t^G(b,h,\alpha;\Omega) = (1-p_x)\max\Big\{W_t^G(b,h,\alpha;\Omega), W_t^B(0,h,\alpha;\Omega)-\chi\Big\} + p_x\max\Big\{W_t^G(b-x,h,\alpha;\Omega), W_t^B(0,h,\alpha;\Omega)-\chi\Big\}$$

Since expense shocks continue to be incurred in bad standing, households must be given the option to re-default. Therefore, those in bad standing make the following default decision:

$$\widehat{W}_t^B(b,h,\alpha;\Omega) = (1-p_x)\max\Big\{W_t^B(b,h,\alpha;\Omega), W_t^B(0,h,\alpha;\Omega)-\chi\Big\} + p_x\max\Big\{W_t^B(b-x,h,\alpha;\Omega), W_t^B(0,h,\alpha;\Omega)-\chi\Big\}$$

The model with the endogenous wage choice runs an order of magnitude slower than our benchmark economy. Nonetheless, we calibrate the economy in a very similar fashion. Table 27 describes the model's calibration. We follow an identical approach to Section 4. The model performs similarly along almost all dimensions to the fixed piece-rate benchmark model. The model matches the duration, replacement rate, and wage-per-worker elasticities. The key parameter governing these moments, $a$ (curvature on capital in the production function), takes a value of 0.26 versus 0.20 in our benchmark calibration. Thus, even the parameter estimates are nearly identical between our two calibrations.

Table 26: Endogenous piece-rate: Sorting, output, and output per worker with 2004 credit access vs. 1964 no credit access

| **Description** | **%Δ 2004 vs. 1964** |
|---|---|
| Percent change in sorting, credit vs. non-credit economy | 0.98% |
| Percent change in output, credit vs. non-credit economy | 0.22 % |
| Percent change in output per worker, credit vs. non-credit economy | 0.34 % |

It is important to note that the model with the endogenous piece-rate uses significantly more memory than our original code (where the scaling is nearly proportional to the number of grid points on the piece-rate grid) in steady state. Due to these memory constraints, we are unable to compute the transition path with sufficiently fine grids. We therefore assess the robustness of our main results by comparing output, output-per-worker, and sorting in economies with our calibrated 2004 levels of credit versus a counterfactual economy without credit. Table 26 reports the results. Sorting improves by nearly 1%, very similar to our benchmark transition path results with a fixed piece-rate (e.g., the estimates numbers can be compared to Section 6, Figures 6 and 7). Output and output-per-worker improve by 0.2% and 0.3%, respectively. We view these results as suggesting that modeling endogenous piece-rates does little to our main quantitative results. For both tractability analytically and computationally, the main text and our benchmark estimates are based on the exogenous piece-rate economy.

Table 27: Endogenous Piece-Rate Model Calibration, 2004 Steady State

| Parameter | Description | Value | Moment and Source | Model | Data |
|---|---|---|---|---|---|
| $\chi$ | Default penalty | 0.85 | Bankruptcy rate per capita (ABS, 2004) | 0.17 | 0.21 |
| $\beta$ | Discount factor | 0.97 | Fraction unemployed borrowing (SCF, 2004) | 0.42 | 0.35 |
| $x$ | Expense shock magnitude | 0.15 | Herkenhoff [2019] | 0.27 | 0.28 |
| $\underline{b}$ | Aggregate borrowing limit | -0.79 | Unused limit to income, median (SCF, 2004) | 0.16 | 0.15 |
| $\delta$ | Layoff rate | 0.08 | Unemployment rate (BLS, 2004) | 0.05 | 0.06 |
| $z$ | Benefit | 0.15 | 1-year consumption loss (Stephens Jr [2004]) | -0.17 | -0.19 |
| $p_{-\Delta}$ | Prob HC loss unempl | 0.04 | 2-year consumption loss (Stephens Jr [2004]) | -0.05 | -0.16 |
| $p_{+\Delta}$ | Prob HC gain empl | 0.02 | Old (52-54) to young (24-26) wage ratio, (CPS, 2004) | 1.41 | 1.48 |
| $\xi$ | Newborn HC exponential param | 3.66 | Young (24-26) p90-p10 wage ratio, (CPS, 2004) | 1.95 | 3.03 |
| $a$ | Production function loading on capital | 0.26 | Duration elasticity (LEHD-TU) | 0.30 | 0.28 |
| | | | Replacement rate elasticity among EUE (LEHD-TU) | 0.07 | 0.18 |
| | | | $\overline{w}_{firm} > p50$ elasticity among EUE (LEHD-TU) | 0.09 | 0.10 |
| | | | $\overline{w}_{firm} > p75$ elasticity among EUE (LEHD-TU) | 0.32 | 0.15 |
| | | | $\overline{w}_{firm} > p90$ elasticity among EUE (LEHD-TU | 0.23 | 0.05 |
| | | | $\overline{w}_{firm} > p99$ elasticity among EUE (LEHD-TU | 0.00 | 0.00 |
| | | | $<$ 40 years old, Duration elasticity (LEHD-TU) | 0.27 | 0.26 |
| | | | $<$ 40 years old, $\overline{w}_{firm} > p75$ elasticity among EUE (LEHD-TU) | 0.31 | 0.12 |
| | | | $>$ 40 years old, Duration elasticity (LEHD-TU) | 0.32 | 0.31 |
| | | | $>$ 40 years old, $\overline{w}_{firm} > p75$ elasticity among EUE (LEHD-TU) | 0.33 | 0.22 |
| | | | $<$median utilization, Duration elasticity (LEHD-TU) | 0.29 | 0.20 |
| | | | $<$median utilization, $\overline{w}_{firm} > p75$ elasticity among EUE (LEHD-TU) | 0.32 | 0.12 |
| | | | $>$median utilization, Duration elasticity(LEHD-TU) | 1.00 | 0.59 |
| | | | $>$median utilization, $\overline{w}_{firm} > p75$ elasticity among EUE (LEHD-TU) | 0.33 | 0.33 |

*Notes. 2004 steady state computed by simulating N=200,000 agents for T=250 quarters, discarding the first 100 quarters. Averages are reported over the remaining 150 quarters across $R = 3$ repetitions. To estimate the regression analysis, we take the final cross-section of the simulated model at $T = 350$, and we repeatedly lay off all individuals (since layoff is exogenous, the set of laid off households is representative) 100 times. We stack these representative layoffs into a panel which we use for computing the model-implied elasticities.*

# G Solution Algorithm

We solve the model using value function iteration on a discrete grid. Capital lies in the interval [0.01,4.0] with 120 grid points including the ends of the grid. We evenly space 10 grid points from .01 to 1.0, where agents do not often search, and we evenly space 110 grid points from 1.0 to 4.0, where agents search most commonly. Bonds lie on the grid [-0.6643]∪[-0.65,2.0] with 107 evenly spaced grid points over the interval [-0.65,2.0], including zero. The human capital grid is 5 evenly spaced grid points including the end of the grid over [0.5,1.5]. 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.

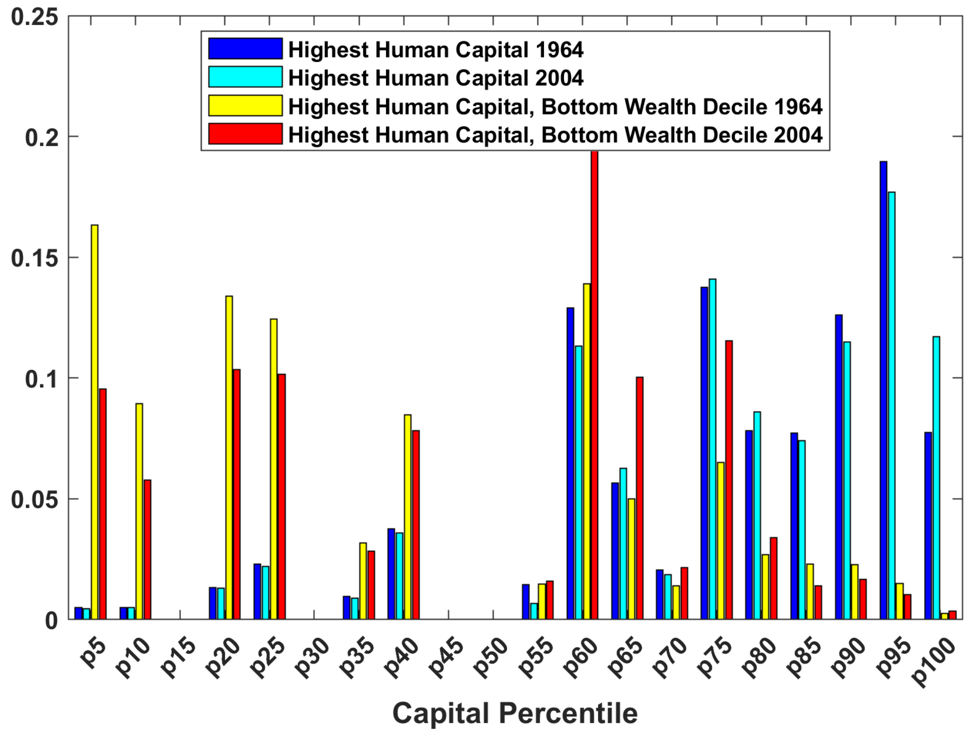
vii. Repeat i to vi until $t = 1$.

viii. Use policy functions from the household problem to simulate N=200,000 agents for T=250 quarters, discarding the first 100 quarters. Averages are reported over the remaining 150 quarters across $R = 3$ repetitions.

# H High human capital and sorting

Figure 17 plots the sorting patterns among high human capital workers. Those with the highest human capital who are constrained (i.e., they are in the lowest west decile) sort into

Figure 17: Sorting among the highest human capital workers




low $k$ jobs. Access to credit improves their ability to obtain high $k$ jobs, however they do not reach the upper percentiles $p99$ and above of the capital distribution. Thus, the model is simultaneously (1) consistent with the empirical regressions and (2) generates improvements in sorting from high human capital workers.

Figure 18 plots the general sorting patterns between human capital, assets, and capital. Higher assets and higher human capital workers sort into higher capital jobs. The non-monotonicity is driven by the initial sorting of low-wealth young agents along the bottom rungs of the job ladder.

Figure 18: Sorting by human capital and assets