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

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Abstract

We empirically and theoretically examine how consumer credit access affects displaced workers. Empirically, we link administrative employment histories to credit reports. We show that an increase in credit limits worth 10% of prior annual earnings allows individuals to take .15 to 3 weeks longer to find a job. Conditional on finding a job, they earn more and work at more productive firms. We develop a labor sorting model with credit to provide structural estimates of the impact of credit on employment outcomes, which we find are similar to our empirical estimates. We use the model to understand the impact of consumer credit on the macroeconomy. We find that if credit limits tighten during a downturn, employment recovers quicker, but output and productivity remain depressed. This is because when limits tighten, low-asset, low-productivity job losers cannot self-insure. Therefore, they search less thoroughly and take more accessible jobs at less productive firms.

Recent research by Kaplan and Violante [2014] has shown that many households, even those with large amounts of wealth, have very little liquid assets. At the same time, many of those households have significant amounts of credit access (Herkenhoff [2013]). This generates a potentially important consumption smoothing role for consumer credit if 'hand-to-mouth' households lose their jobs. While much is known about the impact of unemployment benefits on employment outcomes (*inter alia* Katz and Meyer [1990], Ljungqvist and Sargent [1998], Acemoglu and Shimer [1998], Chetty [2008], Mitman and Rabinovich [2012], and Hagedorn et al. [2013]), little is known about the role consumer credit plays in the search decisions of unemployed households, and even less is known about how this interaction affects the macroeconomy.[1] How does consumer credit affect job finding rates, replacement earnings, or the types of jobs workers take? How does access to consumer credit affect the allocation of workers to firms, and what does this imply for labor productivity, output, and employment dynamics?

We examine these questions empirically and theoretically. Empirically, we link individual credit reports with administrative employment records. We use this dataset to measure the impact of consumer credit access on job finding rates and re-employment earnings of displaced workers. We find that being able to replace 10% more of prior annual labor earnings with personal revolving credit allows medium-tenure displaced mortgagors to take .15 to 3 weeks longer to find a job, and, among those who find a job, they obtain a 0 to 1.7% greater annual earnings replacement rate. Moreover, individuals with greater access to credit find jobs at larger firms and more productive firms.

Our results are consistent with individuals using personal credit to fund longer unemployment spells so that they can search and find better job matches. These results show that independent of realized borrowing, the *potential* to borrow affects search decisions regardless if credit lines are actually drawn down. To our knowledge, we are the first to measure the elasticity of non-employment durations and the elasticity of earnings replacement rates with respect to consumer credit access.

Theoretically, we develop a general equilibrium labor sorting model with consumer credit. We use the model to structurally estimate the impact of credit limits on job search behavior and to assess the impact of consumer credit on the aggregate economy. In our model,

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[1]The nascent but growing literature on the topic has focused on two mechanisms, the self-insurance role of credit (e.g. Athreya and Simpson [2006], Herkenhoff [2013], Athreya et al. [2014]) and labor demand effects of credit (e.g. Bethune et al. [2013], Donaldson et al. [2014]). The equally sparse empirical literature on unemployment and borrowing is limited due to data constraints (Hurst and Stafford [2004], Sullivan [2008] among others) but recent inroads are being made with new account data (Baker and Yannelis [2015], Gelman et al. [2015], Ganong and Noel [2015], Kolsrud et al. [2015] among others).

heterogeneous credit-constrained workers accumulate human capital while working. When unemployed, they direct their search, as in Menzio and Shi [2010, 2011], for jobs among heterogeneous firms.[2] Firms differ with respect to capital and produce output by combining the human capital of workers with their own physical capital (for simplicity we refer to firm capital as physical capital, but this may also be thought of as intellectual capital). We assume supermodularity, meaning that firms with greater amounts of physical capital produce more with workers who have greater amounts of human capital. We therefore measure sorting in the model as the raw correlation coefficient between worker human capital and firm physical capital.[3] Which worker matches with which firm determines both output and labor productivity in this economy, and therefore the ability of unemployed households to self-insure, either through saving or borrowing, and search for higher physical capital jobs has the potential to change the path of a recovery.

Using this new theoretical framework, we make two quantitative contributions. First, we estimate the model using public data in order to provide a set of independent structural estimates of the elasticity of the duration of unemployment and the earnings replacement rate with respect to consumer credit access. We find an elasticity of duration with respect to unused credit of .61 (implying about a .7 week longer non-employment duration with a credit line worth 10% of prior income). This estimate falls in the middle of our reduced form estimates. We also estimate an elasticity of earnings with respect to unused credit, among those who find a job, of approximately 1.8%.

Second, given that the model produces earnings and duration elasticities that are consistent with the data, we use the model as a laboratory to examine the impact of credit on labor sorting, productivity, and the ensuing employment recovery during a recession. The main experiment we conduct using the model is to tighten borrowing limits during the 2007-2009 recession and then study the subsequent recovery. In particular, we simulate the 2007-2009 recession by feeding actual total factor productivity residuals into the model. During the recession, we permanently tighten borrowing limits, delivering roughly a 3 percentage point

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[2]Related theoretical work includes sorting models with frictions (inter alia Bagger and Lentz [2008], Eeckhout and Kircher [2011], Hagedorn et al. [2012], Bonhomme et al. [2014]), frictionless assignment models with borrowing constraints (Fernandez and Gali [1999], Legros and Newman [2002], and Strauss [2013]), and occupational choice under credit constraints (inter alia Neumuller [2014], and Dinlersoz et al. [2015]).

Our work is also related to Lentz [2009], Krusell et al. [2010] and Nakajima [2012a] who have studied the impact of savings on search decisions, and Guerrieri and Lorenzoni [2011] among others have looked at the role household borrowing constraints play in models with frictionless labor markets.

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

reduction in the fraction of households borrowing, and a 1 percentage point reduction in the aggregate debt to income ratio. Upon impact and throughout the recovery, the tighter credit limit depresses output per worker (labor productivity) by .28 percentage points and decreases overall output by .11 percentage points.

We find that when debt limits tighten, however, standard measures of sorting improve and remain elevated throughout the recovery. This happens as constrained households, who are also more likely to have low human capital, take jobs with low physical capital. Households with savings, who are more likely to have high human capital, are able to continue to search thoroughly for jobs with higher physical capital. Since sorting measures the correlation between human capital and physical capital, and since this correlation actually increases when debt limits tighten, standard measures of sorting improve. Sorting improves while output falls because the jobs that are being created during periods of tight debt limits are less-physical-capital-intensive jobs. What disconnects the positive comovement of sorting with labor productivity and output is the presence of firm investment and household credit constraints, both of which are typically absent in sorting models.

Lastly, when debt limits tighten during the recession, employment recovers more quickly. The mechanism is that when credit limits tighten, unemployed low-human-capital-borrowers lose their ability to self-insure and take relatively abundant jobs at less-capital-intensive firms. Constrained households take lower quality jobs relatively quickly, causing a tradeoff between the speed of the labor market recovery and the health of the recovery, measured by labor productivity and output.

Our contributions are both empirical and theoretical. Empirically, we build the first dataset to merge individual credit reports with administrative employment records and measure the impact of consumer credit access on job finding rates and re-employment earnings of displaced workers. Using several different instruments, we show that with increased credit displaced workers search longer and replace a higher fraction of their pre-displacement income. Theoretically, we develop the first labor sorting model with consumer credit. We build on existing labor sorting models such as Marimon and Zilibotti [1999], Shimer and Smith [2000], Shi [2001], Shimer [2001], Lise and Robin [2013] and Eeckhout and Sepahsalari [2014], by generating interactions between heterogeneous credit histories and the allocation of workers to firms. We build on the influential work of Lise and Robin [2013] who consider sorting over the business cycle with risk neutrality, and we complement the recent innovative work of Eeckhout and Sepahsalari [2014], who study assets and sorting, by allowing for bor-

4

rowing and productivity differences among workers. Our framework is tractable enough that it can be used by future researchers to study a variety of questions related to misallocation and credit access, including credit access among firms.

The paper proceeds as follows. We first describe our conceptual framework in Section 1. Section 2 describes the data. Sections 3 and 4 contain our empirical results. Section 5 presents the model, Section 6 describes the model estimation and structural estimates of the duration elasticity, Section 7 conducts the main counterfactual exercise of tightening debt limits, and Section 8 concludes.

1 Job Finding and Unsecured Credit

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

Hypothesis 1: Ceteris paribus, greater credit access among the unemployed increases non-employment durations.

Hypothesis 2: Ceteris paribus, greater credit access among the unemployed increases subsequent re-employment earnings.

It is important to note that because durations increase with greater credit access, the theoretic 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, *conditional* on finding a job, we test whether unemployed workers with

5

greater credit access find higher wage jobs.

2   Data and Definitions

Our main data source is a randomly drawn panel of 5 million TransUnion credit reports which are linked by a scrambled social security number to the Longitudinal Employment and Household Dynamics (LEHD) database. All consumer credit information is taken from TransUnion at an annual frequency from 2001 to 2008. The TransUnion data includes information on the balance, limit, and status (delinquent, current, etc.) of different classes of accounts held by individuals. The different types of accounts include unsecured credit as well as secured credit on mortgages.

The LEHD database is a quarterly matched employer-employee dataset that covers 95% of U.S. private sector jobs. The LEHD includes data on earnings, worker demographic characteristics, firm size, firm age, and average wages. Our main sample of earnings records includes individuals with credit reports between 2001 and 2008 from the 11 states for which we have LEHD data: California, Illinois, Indiana, Maryland, Nevada, New Jersey, Oregon, Rhode Island, Texas, Virginia, and Washington. Since job dismissal and reason of dismissal are not recorded in the LEHD, we follow Jacobson et al. [1993] and focus on mass layoffs.[4]

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.[5] 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).[6]

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

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

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

[6]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.

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 C.

We focus on revolving credit from TransUnion because it can be drawn down on short notice following job loss and paid-off slowly over time without any additional loan-applications or income-checks. Our main measure of credit access is therefore an individual's unused credit limit across all types of revolving debt (excluding mortgage related revolving debt) over annual earnings, measured prior to displacement.[7] We call this ratio the 'unused revolving credit limit ratio.'[8] The main components of revolving credit include bank revolving (bank credit cards), retail revolving (retail credit cards), and finance revolving credit (other personal finance loans with a revolving feature). In Appendix B.5 we use alternate measures of credit access prior to layoff including (i) credit scores, (ii) unused revolving credit inclusive of HELOCs, and (iii) total secured and unsecured unused credit.

3   Empirical Approach

The goal of this section is to estimate the impact of credit access on employment outcomes of displaced workers. While many authors, including Jacobson et al. [1993], have argued that mass layoffs are exogenous to worker characteristics, credit access upon layoff certainly is not. To solve this issue, we need to find a characteristic of workers that impacts credit limits and only impacts employment prospects through its impact on credit limits. To isolate such exogenous variation in credit limits, we use three sets of orthogonal instruments which we discuss in detail in the following sections: (i) bankruptcy flag removals, (ii) individual-specific account ages and (iii) geography instruments.

3.1   Bankruptcy Flag Removals

Our first strategy is to follow Musto [2004] who exploits the fact that bankruptcy flags are removed, by law, after ten years, and this gives rise to a large exogenous increase in credit

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

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

access which does not reflect changes in underlying credit worthiness or unobserved quality of the individual.[9] Consider the set of displaced workers who have a bankruptcy flag on their record prior to displacement, and let $Removal_{i,t}$ equal 1 if the worker has their bankruptcy flag removed in the year of displacement. Our empirical approach is to compare those who have their bankruptcy flag removed in the year of displacement (the treatment group) to those whose flags remain on their record in the year of displacement (the control group). We therefore implement the following specification in order to isolate the impact of increased credit access on outcome variables such as duration, $D_{i,t}$,

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

In this specification γ represents how much longer displaced workers take to find a job if their flag is removed relative to the control group of workers whose flags are not removed. The key identifying assumption for this specification is that the treatment and control group have identical outcomes if no treatment had occurred. We formally test this assumption in Appendix B.1 by showing that the main outcome variables for the treatment and control group are statistically indistinguishable prior to the flag removal. In particular, we show that mean earnings growth, time spent non-employed, firm size, and firm wage prior to layoff are statistically indistinguishable across the treatment and control group prior to layoff.

3.2 Gross and Souleles Instrument

Our second approach is based on 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.[10] We exploit these time-contingent changes in credit access by using the age of the oldest account as an instrument for credit limits.

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

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[9]Chapter 7 Bankruptcy flags (the most pervasive type of bankruptcy) remain on a worker's credit report for a statutory 10 years, whereas Chapter 13 flags are removed after 7 years. We cannot differentiate between these types of flag removal, but what matters for us is that the removal is statutory.

[10]As we discuss in Appendix B.4, the general mechanism is that credit issuers revise account limits based on set time intervals. The subsequent limit revision is a function of credit scores, and credit scores, by construction, positively weight account ages.

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

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

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

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

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. We argue and provide supporting evidence with over-identification tests that, after controlling for physical age as well as a host of other individual characteristics, that account age satisfies the exclusion restriction. In Appendix B.4 we discuss this instrument and the over-identification tests in more detail.

3.3 Saiz Instrument

Our last approach is based on Mian and Sufi [2012] who show that geographic constraints, such as the Saiz [2010] housing supply elasticity, significantly impact house price growth as well as leverage and are orthogonal to labor markets except through their impact on leverage (excluding real estate related sectors). Our analysis relies on the arguments made in Mian and Sufi [2012], but, rather than focusing on *realized leverage* (realized borrowing), the channel we emphasize is that geographic constraints impact house price growth, and house price growth is a determinant of *credit access*, and in particular, credit limits. We therefore use the MSA-level housing supply elasticity as the instrument, $s_{i,t}$, in the first stage regression (2) for credit limits.

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, 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 conditions, and (ii) housing wealth. We conduct a thought experiment to address the first challenge. While Mian and Sufi [2012] 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.

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 prior to 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.

To further address concerns over housing wealth and wealth more generally, we conduct two additional exercises. First, in Appendix B.2, we report OLS regressions of unemployment duration on unused credit, directly controlling for the OFHEO house price index. We show that the inclusion of house prices does not affect our point estimates. Second, in Appendix B.3, we use the 1998 to 2007 Survey of Consumer Finances (SCF) surveys, and we show that the relationship between non-employment duration and unused credit card limits (the only limit available in the SCF) is similar to our IV estimates and unaffected by the direct inclusion of self-reported home values, liquid assets, or illiquid assets.

Lastly, in Appendix B.4 we provide the closest possible test of whether or not the Saiz instrument is exogenous by using Hansen's J-test (over-identification test). The over-identification tests show that the level component of unused credit which is being isolated by the Saiz instrument satisfies the exclusion restriction.

3.4 Sample Descriptions and Summary Statistics

Based on these identification strategies, we use two samples in this paper.

i. **Displaced Bankrupt Sample:** Our first sample includes all displaced households who had a bankruptcy flag on their record in the year prior to displacement. We then split this sample into a treatment group of 1,000 individuals (to the nearest thousand) whose flags are removed in the year of displacement, and a control group of 17,000 individuals whose flags remain on their records throughout the displacement.[11] In order to garner enough observations to disclose this sample, we could only impose a tenure requirement of 1 year. Given the way we identify displacements, and our use of lagged credit prior to displacement, this sample covers the years 2002-2006.

ii. **Displaced Mortgagor Sample:** Our second sample includes displaced workers with mortgages who had at least 3 years of tenure at the time of displacement, and worked in a non-real-estate industry. These are standard restrictions used in the literature, e.g. Davis and Von Wachter [2011], to mitigate any issues associated with seasonal employment or weak labor-force attachment. Given these criteria we end up with a sample of 32,000 individuals (to the nearest thousand). This sample covers the years 2002-2006.

Table 1 includes summary statistics for both samples. All variables are deflated by the CPI, and the top 1% (and bottom 1% if the variable is not bounded below) of continuous variables are winsorized. Columns (1) and (2) of Table 1 summarize the displaced bankrupt sample. Our displaced bankrupt sample is split into a treatment and control group. On average the demographic characteristics between these two groups are quite close: imputed years of education is 13.8 years for those who have their flag removed (the treatment group) and 13.6 for those who do not have their flag removed (the control group) and average tenure is 4 years in the treatment group and 3.9 in the control group.

Individuals whose flags are removed are naturally older, with an average age of 44 in the treatment group and an average age of 42.4 in the control group. The treatment group earned $49k before displacement whereas the control group earned $43.5k. While there is a level difference in earnings, in Appendix B.1, we show that the main outcome variables

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

for the treatment and control group, including wage growth and time spent non-employed, are statistically indistinguishable prior to the flag removal. The treatment group takes 1.73 quarters to find a job on average after displacement, and their earnings replacement rate is 83%, whereas the control group takes 1.53 quarters on average to find a job after displacement, and their earnings replacement rate is 88%. We show in the regression analysis that follows that the difference in durations is significant after adjusting for composition, whereas the difference in earnings replacement rates is not.

Turning to the displaced mortgagor sample, Column (3) of Table 1 shows that average annual labor earnings prior to layoff was about $56k and that the average worker could replace 45% of their prior annual labor earnings with unused revolving credit.[12] After layoff, they took roughly 1.67 quarters to find a new job, and their annual earnings replacement rates were 81% one year after mass displacement, including zeros, similar to what Davis and Von Wachter [2011] find. Finally, the age of the oldest account is approximately 15 years on average in our sample. Column (4) of Table 1 shows that if we condition on displaced mortgagors who have a job in the year following displacement (i.e. in period $t + 1$), the average duration is .56 quarters, and the average earnings replacement rate is 1.02 (meaning a full recovery of earnings). By conditioning on employment, this sample drops earnings replacement rates equal to zero and thus parses out any effects of duration on earnings.

To summarize the raw correlations in the displaced mortgagor sample, Figure 1 plots the duration of non-employment by unused revolving credit to income deciles prior to layoff. Figure 2 plots the earnings replacement rate by unused revolving credit to income deciles prior to layoff for those individuals who found a job in the year following displacement. The deciles of unused revolving credit to income range from approximately zero to roughly 200%. Those in the top decile can approximately replace 2x their annual income with revolving credit. Both figures reveal a generally monotone increasing relationship between unused credit prior to layoff and both durations and earnings replacement rates, with a pronounced rise in the last decile of unused credit.

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[12]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.

4 Empirical Results

For each dependent variable, we show four sets of results corresponding to (1) OLS for the displaced bankrupt sample, (2) OLS for the displaced mortgagor sample, (3) the account age IV (GS-IV) for the displaced mortgagor sample, and (4) the geography IV (Saiz-IV) for the displaced mortgagor sample. Column (1) therefore relies on the bankrupt sample, and Columns (2) through (4) rely on the mortgagor sample. In every specification, our vector of controls ($X_{i,t}$) includes quadratics in age and tenure as well as sex, race and education dummies, lagged annual income, cumulative lagged earnings (to proxy for assets), 1-digit SIC industry dummies, lagged characteristics of the previous employer including the size, age, and wage per worker, a dummy for the presence of auto loans, an equity proxy (the highest mortgage balance observed less the current balance), HELOC limits (to proxy for available housing wealth upon layoff), as well as year dummies, the MSA unemployment rate, and MSA income per capita.

4.1 Duration Results

Table 2 illustrates the impact of unused credit on durations. Column (1) uses the displaced bankrupt sample, and shows the impact of a derogatory flag drop on duration. The point estimates imply that if an individual's bankruptcy flag is dropped in the year of displacement, they take on average .178 quarters longer to find a job (about 2 weeks longer), relative to the control group. Column (2), which uses the displaced mortgagor sample, illustrates the results from a simple OLS regression of duration on unused credit limits. The estimates reveal a duration elasticity of .25, which implies that being able to replace 10% more of prior annual income with unused credit is associated with an increase in duration of .3 weeks.[13]

   In Column (3) we instrument the unused credit limit with the Gross and Souleles [2002] instrument. We find a duration elasticity of .5 which implies that being able to replace 10% more of prior annual income with unused credit allows workers to take roughly .6 weeks longer to find a job. In Column (4), we instrument the unused credit limit with the Saiz [2010] instrument. We find a duration elasticity of 1.5 which implies that being able to replace 10% more of prior annual income with unused credit allows workers to take roughly

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[13].3 weeks comes from multiplying the 10% increase in credit access to income by the OLS coefficient and then multiplying again by 12 weeks per quarter (i.e. .3 weeks=.1*.25*12).

1.8 weeks longer to find a job.

To convert the bankruptcy flag removal result into an elasticity, Table 3 shows that a bankruptcy flag is associated with a contemporaneous increase in revolving credit limits equal to 7% of prior annual income and an increase in credit scores of 140 pts. This implies that being able to replace 10% of prior annual income allows displaced workers to take nearly 3 weeks longer to find a job (=.1*.178*12/.07). The size of this point estimate suggests that there are non-linear effects of credit access on durations since credit constrained households are reacting more per dollar of credit than less constrained households. In Section 4.4 we discuss these non-linearities in more detail.

Our estimates imply that $1 of additional unused credit limit is about half to three-quarters as potent for unemployment durations as $1 of unemployment benefit. Being able to replace 5% of annual earnings on a credit card is equivalent to a 10% increase in UI replacement rates for the typical 6-month duration of unemployment benefits. In the empirical UI literature, the impact of a 10% increase in the UI replacement rate for 6 months is to increase unemployment durations by .3 to 2 weeks with the modal estimate lying between .5 and 1 for the US (see Nakajima [2012b] and Card et al. [2015] for a summary of recent empirical and quantitative elasticities). Our estimates imply an equivalent elasticity with respect to credit of .15 to 1.5 weeks.

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

4.2 Earnings Replacement Rates

Earnings Replacement Rates Excluding Zeros: To avoid confounding annual replacement earnings with durations, in Table 4 we isolate the set of households who have positive earnings in each quarter during the year after layoff. Table 4 reveals that conditional on finding a job, those with greater credit access find higher wage jobs.

Column (1) of Table 4 shows that if an individual's bankruptcy flag is dropped in the year of displacement, there is a small negative, but statistically insignificant impact of credit access on earnings replacement rates. On the other hand, Columns (2) through (4) of Table

4 show that being able to replace 10% more of prior annual income increases the earnings replacement rate of job finders by .3% in the OLS regressions, by .8% using the Gross and Souleles instrument, and by 1.72% using the Saiz Instrument.

Earnings Replacement Rates Including Zeros: Table 5 illustrates the impact of unused credit on replacement rates of annual earnings, including zeros for those who do not find a job. The point estimates in Column (1) through (4) of Table 5 show that the impact of additional credit access on replacement earnings is statistically indistinguishable from zero. There are two competing forces generating this result: (i) durations increase with more credit access, depressing replacement earnings, (ii) of those who find a job, those who have more credit access find higher wages, increasing replacement earnings. In the sections that follow, we show that the model's self-insurance mechanism generates the same offsetting forces.

These results are, in general, 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 and insignificant effects, as well as negative effects in one case (see Nekoei and Weber [2015] for a summary). In Appendix C, we explore earnings replacement rates at longer horizons for this sample.

4.3   Size and Productivity of Firms

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 larger and more productive firms. Our main dependent variables include an indicator function if the worker finds a job at a firm in the 99th percentile of the firm size distribution or better ('Large Firm Dummy'), measured 1 year after displacement, as well as an indicator function if the worker finds a job at a firm in the 75th decile of the wage-per-worker distribution (aggregate wage bill divided by total employees), which is our proxy for productivity.[14] These deciles were chosen for comparability: i.e. firms in the 99th percentile of the size distribution comprise approximately 1/3 of employment, and firms in the 75th percentile of the wage-per-worker distribution comprise approximately 1/3 of employment. While not reported here, we find similar effects using alternate cutoffs that are either narrower or broader.

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[14]What we call firms in the text are State Employment Identification Numbers (SEINs) in the LEHD. SEINs aggregate all plants within a state.

Table 6 illustrates the impact of unused credit on the odds that a worker finds a job at a firm in the 99th decile of the size distribution or greater. Column (1) of Table 6 shows that displaced workers whose flags are removed are 3.9% more likely to work at a large firm relative to the control group. Columns (2) through (4) show that being able to replace 10% more of prior annual income increases the odds that a worker finds a job at a large firm by an insignificant amount in both the OLS and Gross and Souleles regressions, and by 4.7% using the Saiz Instrument.

Table 7 illustrates the impact of unused credit on the odds that a worker finds a job at a firm in the 75th decile of the wage-per-worker (our proxy for labor productivity) distribution or greater. Column (1) of Table 7 shows that displaced workers whose flags are removed are 2.95% more likely to work at a productive firm relative to the control group. Columns (2) through (4) show that being able to replace 10% more of prior annual income increases the odds that a worker finds a job at a productive firm by an insignificant amount in the OLS and Saiz regressions, and by 1.5% using the Gross and Souleles instrument.

While these results have mixed significance levels, the modal estimates are positive and significant, implying that those with greater credit access prior to layoff are more likely to be re-employed at larger and more productive firms.

4.4   Non-Linear Impact of Credit on Employment Outcomes

Our results reveal differences in responses to similarly sized increases in credit, suggesting that there are important non-linearities in both duration and earnings replacement rate elasticities. We construct several sets of results (available upon request) which stratify our samples by terciles of income and indebtedness. The lowest debt terciles exhibit the greatest sensitivity to credit, consistent with our finding that previously bankrupt households (who have very little debt and are credit constrained) have the greatest duration elasticities.

When we split the sample by income, we find more evidence of non-linearities. The middle tercile of the income distribution exhibits the strongest duration and earnings replacement rate elasticities, i.e. they are the most sensitive to credit. With any type of non-homothetic preferences (like Stone-Geary), very low income households must find a job immediately, which could rationalize this type of non-linearity at the low-end of the income distribution. In contrast, very high income households are probably unconstrained to begin with, and so

additional credit access will not induce any type of response.

4.5 Borrowing by Displaced Workers

One important point of our empirical section is that regardless of realized borrowing, the *potential* to borrow affects job search decisions regardless if the credit line is actually drawn down. Workers know that if their buffer stock of liquid assets is depleted, they can borrow, and this affects their job search decisions even if they never borrow. Existing work by Sullivan [2008] using the PSID and SIPP has shown that about 20% of workers borrow during unemployment, and it is precisely low wealth workers who borrow during unemployment. Recent work by ? has updated Sullivan [2008] through the great recession and found similar results, with greater borrowing occurring among low wealth households in the crisis.

We plot the distribution of bankcard borrowing among displaced workers. Figure 3, which is a smoothed density, plots the change in bankcard 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. Some workers borrow, consistent with Sullivan [2008], whereas some workers save, also consistent with Sullivan [2008]'s regression results. As a result, the net amount borrowed among displaced workers is close to zero, consistent with recent findings (e.g. Gelman et al. [2015], Ganong and Noel [2015], Kolsrud et al. [2015]). However, this masks quite large and economically significant heterogeneity in borrowing by displaced workers.

We further explore the role of borrowing by displaced workers in Figure 4 which illustrates the change in real revolving debt in the year of layoff relative to 1 year before layoff as a function of duration.[15] Figure 4 shows that borrowing is a weakly increasing function of unemployment duration, which suggests that those who were able to take the longest to find a job were those who were able to borrow the most. The graph is a raw mean, and the standard error is a standard error for the mean, so there is significant composition bias still present in the graph. To address these concerns, Table 8 illustrates regression results for the relationship between non-employment duration and borrowing, controlling for as many characteristics of workers as possible. Column (1) omits controls, and Column (2) includes controls. The coefficient in Column (2) implies that for every additional quarter of non-

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[15]To obtain more power in the graph, durations are recoded to increase sample sizes, (i.e. durations of length 0 or 1 are coded as 1, durations length 2 to 3 are coded as 3, 3-4=4,5-6=6,7-8=8, 9=9).

employment, workers borrow on average \$200, which is a relatively small average amount. As discussed above, however, this regression masks the significant heterogeneity of how much displaced workers borrow, which we are exploring in future research.

5 Model

Given our IV estimates are inherently local estimates, we build a structural model that we use to obtain independent 'global' estimates of the unemployment duration and earnings replacement rate elasticities. We then use the model to conduct our main experiment which is to consider how changes in aggregate borrowing limits impact the allocation of workers to firms, output, and productivity.

Let $t = 0, 1, 2, \ldots$ denote time. Time is discrete and runs forever. There are three types of agents in this economy. A unit measure of risk averse finitely-lived households, a continuum of risk neutral entrepreneurs that run the endogenously chosen measure of operating firms, and a unit measure of risk neutral lenders.

As in Menzio et al. [2012], there are $T \geq 2$ overlapping generations of risk averse households that face both idiosyncratic and aggregate risk. Each household lives T periods deterministically and discounts the future at a constant rate $\beta \in (0,1)$. Every period households first participate in an asset market where they make asset accumulation, borrowing, and bankruptcy decisions. After the asset market closes, households enter the labor market where they direct their search for jobs.[16] Let $c_{t,t+t_0}$ and $L_{t,t+t_0}$ respectively denote the consumption and hours worked of an agent born at date t in period $t + t_0$. The objective of a household is to maximize the expected lifetime flow utility from non-durable consumption and leisure.

$$\mathbb{E}_t \left[\sum_{t_0=1}^{T} \beta^{t_0} u(c_{t,t+t_0}, 1 - L_{t,t+t_0}) \right]$$

From this point on we will drop time subscripts and focus on a recursive representation of the problem. We assume that labor is indivisible, such that the household consumes its

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[16]The way directed search is modeled in this paper rules out the possibility that wage gains may simply reflect differences in bargaining power and outside options.

entire time endowment while employed $L = 1$, and vice verse for the unemployed.

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

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

Let $M(u, v)$ denote the matching function, and define the labor market tightness to be the ratio of vacancies to unemployment. Since there is directed search, there will be a separate labor market tightness for each submarket. In each submarket, there is a job finding rate for households, $p(\cdot)$, that is a function of the labor market tightness $\theta_t(h, k; \Omega)$, such that $p(\theta_t(h, k; \Omega)) = \frac{M(u_t(h,k;\Omega), v_t(h,k;\Omega))}{u_t(h,k;\Omega)}$. On the other side of the market, the hiring rate for firms $p_f(\cdot)$ is also a function of the labor market tightness and is given by $p_f(\theta_t(h, k; \Omega)) = \frac{M(u_t(h,k;\Omega), v_t(h,k;\Omega))}{v_t(h,k;\Omega)}$. When households enter the labor market, they choose which capital intensity (k) submarket to search in.[17] Once matched with a firm, a worker produces $f(y, h, k) : \mathcal{Y} \times \mathcal{H} \times \mathcal{K} \to \mathbb{R}_+$ and keeps a share α of this production.[18]

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

[18]This a similar assumption to Kaplan and Menzio [2013], and is only made for tractability purposes. Directed search models with commitment to one submarket, including Shi [2001], find that firms optimally post unique wages that are monotone in workers' types, but other models in which firms do not commit to any given submarket, such as Shimer [2001], find non-monotone wages in workers' types within any given job, in some cases. Empirically, wage profiles are concave in education and decreasing for higher levels of

At the beginning of every period, households with debt positions $b < 0$ make a default decision. In the present formulation, the default punishment is similar to Ch. 7 bankruptcy in the United States. A household in bankruptcy has a value function scripted by B and cannot save or borrow. With probability λ, a previously bankrupt agent regains access to asset markets. If a household is in good standing (i.e. they have regained access to asset markets), its value function is scripted with a G, and the household can freely save and borrow.

The problem of an unemployed household in good standing is given below. To suppress an additional state variable, we allow unemployment benefits $z(k)$ to be a function of the worker's prior wage, but only through its dependence on k.[19]

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

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

Such that

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

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

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

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

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

For households who default, they are excluded from both saving and borrowing. There is an

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education. We can allow for this by introducing flexible functional forms for production.

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

exogenous probability λ that they regain access to asset markets:

$$U_t^B(b, h, k; \Omega) = u(c, 1) + \lambda \beta \mathbb{E}\bigg[\max_{\tilde{k}} p(\theta_{t+1}(h', \tilde{k}; \Omega')) W_{t+1}(0, h', \tilde{k}; \Omega')$$

$$+ \big(1 - p(\theta_{t+1}(h', \tilde{k}; \Omega'))\big) U_{t+1}(0, h', k; \Omega')\bigg]$$

$$+ (1 - \lambda)\beta \mathbb{E}\bigg[\max_{\tilde{k}} p(\theta_{t+1}(h', \tilde{k}; \Omega')) W_{t+1}^B(0, h', \tilde{k}; \Omega')$$

$$+ \big(1 - p(\theta_{t+1}(h', \tilde{k}; \Omega'))\big) U_{t+1}^B(0, h', k; \Omega')\bigg], \quad t \leq T$$

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

Such that

$$c \leq z(k)$$

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

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

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

A similar problem holds for the employed. The value functions are denoted with a W for employed households, and at the end of every period, employed households face layoff risk δ. If they are laid off, since the period we will ultimately use is 1 quarter, we must allow the workers to search immediately for a new job.[20] We relegate the employed value functions to Appendix D.

5.1 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

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

the inequality below:

$$q_{e,t}(b', h, k; \Omega) \leq \frac{\mathbb{E}\left[1 - D_{e',t}(b', h', k'; \Omega')\right]}{1 + r_f} \tag{5}$$

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

5.2 Firms

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

The entrepreneur, when attempting to create a firm, is subject to a financing constraint. When a firm is not yet operational, the firm does not have access to perfect capital markets. The firm must borrow the money, $b_f < 0$ to finance the initial capital investment. We assume the firm is not subject to the aggregate debt limit.[21] If the firm fails to find an employee, the firm defaults and the capital is lost.[22]

When deciding whether or not to post a vacancy, the firm solves the following problem. It chooses capital $k \in \mathcal{K}$ and what types of workers, indexed by human capital and age $(h, t) \in \mathcal{H} \times \mathbb{N}_T$, to hire. In the event that the worker is hired, the firm has access to perfect capital markets and repays b_f immediately. 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 $q_{f,t}(b, k, h; \Omega)$ denote the

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[21]This is because we want to isolate the impact of household credit limits on the macroeconomy. In future work, we are exploring the role of firm constraints on sorting.

[22]We are envisioning specific assets with low liquidation value, however, in Appendix J.4 we allow for an explicit partial liquidation by the lender (capital is denoted in units of the final consumption good, and so this amounts to capital reversibility).

bond price faced by the firm. Then the problem a firm solves when attempting to recruit a worker is given below (recall b is negative if borrowing),

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

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 (note that k is implicitly related to b_f in the equation above),

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

Using the fact that Equation (6) holds with equality under free entry and that Equation (7) must also hold with equality, the market tightness in each submarket which is 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 α. We assume the firm keeps a share $1 - \alpha$ of its production, and workers receive the remaining share α of production. Of that remaining output, firms must then pay a fixed cost f_c.[23] The value function for the firm is given by,

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

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

There are three stark assumptions implicit in this value function, (i) zero liquidation value of capital, (ii) static capital, and (iii) no on-the-job search. In Appendix J we allow capital to have a nonzero liquidation value and we allow firms to dynamically invest in capital. We do not explicitly model on-the-job search due to tractability (it would require firms

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[23]The representative entrepreneur will make exactly zero profits across plants and over time, even if some firms are temporarily making negative profits. When calibrating the model this fixed cost will serve to generate a small surplus for firms, and help the model match quantitative features of the data.

knowing workers' asset policy functions, see Herkenhoff [2013] for a model with one sided heterogeneity, credit, and OJS), but by allowing firms to invest in capital, we mitigate workers' incentives to switch jobs. In fact, with frictionless capital adjustment, firms set capital to the surplus maximizing value and workers have no incentive to leave the firm.

5.3   Equilibrium: Definition, Existence and Uniqueness

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 ($\{D_{e,t}(\mathbf{x})\}_{t=1}^{T}$), and 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 $\theta_t(h, k; \Omega)$, processes for aggregate shocks $(y, \underline{b})$, and an aggregate law of motion $\Phi(\Omega, y', \underline{b}')$ 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.

We use the same tools as Shi [2009] and Menzio and Shi [2011] to solve for a Block Recursive Equilibrium in which policy functions and prices do not depend on the aggregate distribution μ (even though it fluctuates over time and can be recovered by simulation). However, policy functions still depend on aggregate productivity, y, and the borrowing limit, $\underline{b}$.

In Appendix E, we prove two propositions which we will use in the numeric portion of the paper. First, a Block Recursive Equilibrium exists in this economy, and thus to solve the model economy, we only need to solve the first 'block' of the equilibrium i.-iii. ignoring iv., and then we can simulate to recover the dynamics of μ. Furthermore, we establish that certain classes of utility, matching, and production functions yield uniqueness.

24

6 Calibration

The parameters are calibrated so that the model's stochastic steady state is consistent with 1970-2007 averages. Stochastic steady state means that aggregate total factor productivity (y) still fluctuates but that the borrowing limit ($\underline{b}$) is constant forever.[24] The period is set to one quarter. We calibrate the productivity process to match the Fernald et al. [2012], non-utilization adjusted total factor productivity series. The series is logged and band pass filtered to obtain deviations from trend with periods between 6 and 32 quarters. Aggregate productivity deviations are assumed to fluctuate over time according to an AR(1) process:

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

Estimation yields $\rho = 0.894$ and $\sigma_e = 0.00543$, and the process is discretized using Rouwenhurst's method.

We set the annualized risk free rate to 4%. In stochastic steady state, we set $\underline{b} = -.5$, which is non-binding for all agents in our simulations. We set the job destruction rate to a constant 10% per quarter, $\delta = .1$ (Shimer [2005]). For the labor market matching function, we use a constant returns to scale matching function that yields well-defined job finding probabilities:

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

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

Preferences are given below, where η is the flow from leisure, and L=1 for employed persons and L=0 otherwise:

$$u(c, 1 - L) = \frac{c^{1-\sigma} - 1}{1 - \sigma} + \eta(1 - L)$$

We set the risk aversion parameter to a standard value, $\sigma = 2$. The life span is set to $T = 80$ quarters (20 years), and newly born agents are born unemployed, with zero assets, in good credit standing, and with a uniform draw over the grid of human capital. The household share of income, α, is set to $\frac{2}{3}$, and the production function is Cobb-Douglas,

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[24]A long sequence of productivity shocks is drawn according to the AR(1) process for y and held fixed. A large number of agents (N=30,000) is then simulated for a large number of periods (T=270 quarters, burning the first 100 quarters). Averages are reported over the remaining 170 quarters across $R = 10$ repetitions. Appendix K describes the solution algorithm in detail.

$f(y, h, k) = yh^a k^{(1-a)}$ with parameter $a = \frac{2}{3}$. The bankruptcy re-access parameter $\lambda = .036$ generates the statutory 7 year exclusion period.

The remaining 8 parameters including the discount factor β, the unemployment benefit z, the utility penalty of bankruptcy χ, the entry cost of firms κ, the fixed cost of operations f_c, the flow from leisure η, the human capital appreciation $p_{+\Delta}$ rate, and the human capital depreciation $p_{-\Delta}$ rate are calibrated jointly to match 8 moments: the fraction of households with liquid asset to income ratios less than 1%, the immediate consumption loss from unemployment, the bankruptcy rate, the unemployment rate, the relative volatility of unemployment to productivity, the autocorrelation of unemployment, the wage growth of 25 year olds, and the long term consumption losses from layoff. We do not directly target the duration elasticity or earnings replacement rate elasticity.

The household discount factor $\beta = .988$, which implies a discount rate of about 5% per annum, is calibrated to match the fact that 25.4% of households have a ratio of liquid assets to annual gross income less than one percent.[25] We argue that for high frequency search models (in which unemployment durations are very short), that liquid wealth is the relevant calibration target since it isolates the portion of wealth that can be drawn down in response to a temporary income shock (such as job loss). As Kaplan and Violante [2014] show, it is precisely access to liquid assets that determines the response of households to income shocks.

The unemployment benefit is set to a constant, $z(k) = .101$ $\forall k$, in order to match the observed consumption losses following job loss.[26] This value of z yields an average UI replacement rate of approximately 40% for the lowest human capital workers (Shimer [2005]), but implies significantly lower UI replacement rates of 10% for higher human capital workers, in line with Chodorow-Reich and Karabarbounis [2013].

The labor vacancy posting cost $\kappa = .034$ is chosen to target a mean U6 unemployment rate of 8.9% which is the 1994-2007 average,[27] and we set the bankruptcy utility penalty

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[25]See Kaplan and Violante [2014] and Herkenhoff [2013]. The data is from the SCF (and it predecessor survey the Survey of Consumer Credit). For each household, we sum cash, checking, money market funds, CDS, corporate bonds, government saving bonds, stocks, and mutual funds less credit card debt over annual gross income. We take the mean of this liquid asset to income ratio across households in each survey year, and then we average over 1970 to 2007 to arrive at the moment.

[26]Browning and Crossley [2001] find 16% consumption losses after 6 months of unemployment for Canadians, and as they explain, scaling food consumption losses in Gruber [1994] results in 15% consumption losses in the year of layoff for US households in the PSID. We therefore target a 15% consumption loss from the quarter prior to initial displacement until the end of the 1st year of layoff, 4 quarters after initial displacement.

[27]Since there is no concept of "marginally-attached" workers or part-time employment in the model, U6

$\chi = .077$ to generate the average bankruptcy rate in the US from 1970-2007 of approximately .1% per quarter.[28]

The processes for human capital are calibrated to generate 1.05% wage growth per quarter while employed, as well as the long term consumption losses of displaced households.[29] These processes are governed by two parameters $p_{-\Delta}$ and $p_{+\Delta}$.

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

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

In the calibration below, the grid for human capital, $h \in [.5, .6, .7, .8, .9, 1]$, as well as the step size, $\Delta = .1$, between grid points are taken as given. Our estimates are $p_{-\Delta} = .143$ and $p_{+\Delta} = .077$, which imply that once every year-and-a-half, unemployed agents in the model expect to fall one rung on the human capital ladder. This generates between 10% to 20% earnings losses (depending on the initial human capital) per annum, which is smaller than the 30% per year Ljungqvist and Sargent [1998] target.

In terms of the flow utility of leisure, we follow most of the quantitative search and matching literature by setting η to target a labor market moment. We choose $\eta = .237$ to match the autocorrelation of unemployment since the flow utility of leisure determines unemployed households' willingness to remain out of work.

We calibrate the fixed cost of operations for firms $f_c = .100$, which determines how sensitive firms are to productivity shocks, to match the observed volatility of unemployment to productivity.

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is a better measure of unemployment for the model. The data is available from 1994:Q1 to present.

[28]The bankruptcy rate is .41% per annum from 1970-2007 according to the American Bankruptcy Institute (accessed via the Decennial Statistics).

[29]Our measure of wage growth in the data is the median 2-year real-income growth rate for households aged between 25 and 30 in the PSID between 2005 and 2007. In the data, the median growth rate among this subset of households was 8.8% (we condition on at least 1k of earnings in each year). Converting this estimate to quarters yields a quarterly income growth rate of 1.05%. Assuming agents are born at 25, our model measure of wage growth is at the midpoint of that interval, measured among 27.5 year olds in the model. Using the 2005-2011 PSID, we calculate a full consumption recovery (1% higher relative to pre-layoff consumption) 2 years after layoff for unemployed households who have zero duration spells. For distressed layoffs, Saporta-Eksten [2013]'s estimates long-run consumption losses of approximately 8% two years after initial displacement. We take the average of these two estimates and target a 3% consumption loss.

Table 9 summarizes the parameters, and Table 10 summarizes the model's fit relative to the targeted moments. The key targeted moments that control the sensitivity of agents to credit are the consumption drop upon layoff, which is most directly controlled by z (UI), and the long term consumption loss which is controlled by $p_{-\Delta}$ (the human capital depreciation rate), and the model matches those targeted moments quite well. While the model produces less volatility than the data in response to productivity shocks, as we show in the next section, the model succeeds at replicating the elasticity of replacement rates and durations with respect to credit, both of which were non-targeted moments. In other words, the responsiveness of agents to credit in our model matches the observed responsiveness in the data, independent of the model's ability to generate volatility.

The fundamental tension in the model is between generating borrowing/bankruptcies and matching the business cycle facts: intuition would suggest that lowering the discount factor would be the best way to generate borrowing/bankruptcies but doing so only exacerbates the models ability to match business cycle facts.[30] The more impatient are agents, the more they want to work immediately, regardless of productivity, which dampens business cycle dynamics. Because of the two sided heterogeneity, we cannot deploy the simple fixes in Hagedorn and Manovskii [2008]; raising the value of leisure will, at best, make only the lowest-human-capital agents indifferent between working and not, and reducing firm surplus will, at best, make only the lowest-capital firms sensitive to productivity movements. The remainder of the distribution of workers and firms will not, in general, respond to productivity shocks. We discuss this more in Appendix F.

6.1 Non-Targeted Moments: Model Estimates of Duration and Earnings Replacement Rate Elasticities

In this section, we use the model generated policy functions to simulate a large mass of agents and estimate the 'global' duration and replacement earnings elasticities with respect to credit access.[31] Since the model's debt pricing schedule does not have an explicit credit

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[30]To then generate more borrowing, the calibration moves into regions the parameters which penalize default.

[31]We calculate the duration and replacement earnings elasticities using 30,000 agents simulated for 270 periods (burning the first 100 periods), while holding the aggregate state fixed at $y = 1$, and defining $\underline{b}_H$=-.1 and $\underline{b}_L$=-.5. Agents hold the same rational beliefs over the transition rate $P_{\underline{b}}$ between $\underline{b}_H$ and $\underline{b}_L$ as Section 7.

limit, we define the credit limit to be the minimum of the level of debt where the bond interest rate first exceeds 30% per quarter and the exogenous debt limit $\underline{b}$.[32] We isolate newly laid off agents, and then we compute each agent's optimal search decision under loose $(\underline{b} = \underline{b}_L)$ and tight exogenous debt limits $(\underline{b} = \underline{b}_H > \underline{b}_L)$, ceteris paribus.

This calculation is feasible as the policy function of each agent is contingent on the realization of Ω which includes the exogenous debt limit $\underline{b}$. So at each decision node, encoded in this policy function is the search decision of the agent if debt limits tighten as well as if debt limits remain slack. 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.[33] Appendix G provides more detail on the way we calculate the model's elasticities.

Table 11 compares the model's global elasticities to the data. The first row of Table 11 shows that if unused credit to income increases by 10% in the model, then agents take .72 (=.608*12*.1) weeks longer to find a job. This falls in the mid-range of our OLS and IV estimates. However, the elasticity calculated in the model is a 'global' elasticity and is conceptually different from the local average treatment effect identified by the IVs.

The second row of Table 11 shows that the model replacement rate elasticity (inclusive of 0s) is -.024, which is quite small and in line with the insignificant coefficients found in the data. To understand why this is the case, we decompose earnings losses in the model into two offsetting components: (i) access to additional credit depresses job finding rates which tends to lower replacement earnings, and (ii) access to additional credit increases the capital intensity of submarkets searched by agents which tends to raise replacement earnings.

To capture the first component, the third row of Table 11 shows that when debt limits expand by 10% of prior annual income, job finding rates fall by 1.1% as workers can better self-insure while searching more thoroughly for jobs. This tends to decrease the replacement earnings of agents, since unemployed workers have an earnings replacement rate of zero. To capture the second component, the fourth row of Table 11 shows that being able to replace 10% more of prior income with credit allows agents in the model to search in submarkets with

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[32]Only .03% of the agents in the model will ever borrow at real quarterly rates above 30%. The results are robust to alternate definitions of this effective debt limit.

[33]The intuition is simple and is formally shown in the existence proof. $J_T(h, k; y) = f(y, h, k)$ does not depend on $\underline{b}$, and working back, neither does $J_t(h, k; y)$ for arbitrary t. Therefore, using the free entry condition, $\theta_t(h, k; y)$, which pins down the menu of operating submarkets, will not either.

2.7% greater intellectual or physical capital intensity. This 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 near-zero replacement earnings elasticity observed in the model.

The fifth row of Table 11 is designed to remove any duration effects from the replacement earnings elasticity. This row shows that among job finders at t+1 (the year after layoff), being able to replace 10% more of prior income with credit results in a 1.8% greater earnings replacement rate, which falls toward the high end of our IV estimates.

Lastly, we can compare the impact of bankruptcy flag removal on duration and replacement rates in both the model and data. The final two rows of Table 11 show that following flag removal, displaced workers take .066 quarters longer to find a job, whereas in the data this number is .178. Following flag removal, agents earn .7% more in the model, whereas in the data, the impact on replacement earnings is insignificant.

Overall, we believe the model's self-insurance mechanism generates replacement rate elasticities (both inclusive and exclusive of 0s) as well as duration elasticities that are in line with our IV estimates.

7 Main Quantitative Experiment

Based on the model's success at replicating key non-targeted micro moments, we now aggregate across individual agents to explore how credit access impacts the macroeconomy. In particular, we study the way changes in borrowing limits impact the path of output, labor market sorting and therefore productivity during the 2007-2009 recession. We do so by comparing aggregate outcomes across two economies, both of which have the same beliefs about debt limit transitions $P_{\underline{b}}$:

1. **Tight Debt Limit Economy:** The debt limit tightens from $\underline{b} = -.5$ (a non-binding value) to $\underline{b} = -.1$ in 2008-Q4 (the first quarter in which the aggregate consumer credit limit declined[34]), and stays there permanently. As we discuss below, the new debt limit generates a similar debt to income (DTI) and borrowing contraction as the data.

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[34]2014 Q1 New York Fed Consumer Credit Report, Page 7, time series entitled 'Credit Limit and Balance for Credit Cards and HE Revolving.'

2. **Constant Debt Limit Economy:** The debt limit $\underline{b} = -.5$ remains constant throughout the simulation.

In the experiments below, both economies are simulated in their ergodic stochastic steady states with the non-binding debt limit, $\underline{b} = -.5$, for a large number of periods. We then feed in a realized set of shocks that replicates, as approximated on a grid, the path of the Fernald et al. [2012] productivity residuals from 1974-Q1 to 2012-Q4. The borrowing limit is held constant at $\underline{b} = -.5$ through 2008-Q4 in both economies, for simplicity. In 2008-Q4, one economy has the limit tighten to $\underline{b} = -.1$, and it remains there permanently.

We impose that both economies have the same beliefs over debt transitions. Let $p_{l,l}$ be the probability of remaining in the 'low' debt limit state, $\underline{b} = -.1$, and let $p_{h,h}$ be the probability of remaining in the 'high' debt limit state, $\underline{b} = -.5$. Then the transition matrix for the debt limit $\underline{b}$ is given by $P_{\underline{b}} = \begin{pmatrix} p_{l,l} & 1 - p_{l,l} \\ 1 - p_{h,h} & p_{h,h} \end{pmatrix}$. Agents understand that if the debt limit tightens, it is permanent, so we set $p_{l,l} = 1$. And, agents also understand that once every 34 years (from 1974 to 2008), debt limits will tighten, so we set $p_{h,h} = .9926$. On average, therefore, agents are rational.

We show in Table 12 that the model economy replicates the liquid wealth of displaced households leading up to the crisis. Furthermore, approximately 14% of agents in the model borrow, and of those that borrow, they replace 9.8% of lost income using unsecured credit which is in line with Sullivan [2008]'s findings. We then document in Table 13 that the new debt limit $\underline{b} = -.1$ delivers roughly the same magnitude decline in both borrowing and debt to income (DTI) ratios as the data.

7.1   Model Results

Figure 5 illustrates the path for the exogenous component of productivity y and the path for the borrowing limit $\underline{b}$. These are the two inputs in the experiment. Each plot contains two dashed lines that correspond to differing degrees of debt limit tightening. The dashed blue line corresponds to the economy where limits tighten to $\underline{b} = -.1$, and, for the sake of robustness, we also include the dash-dot red line which corresponds to the economy where limits tighten to $\underline{b} = -.2$ (this delivers a drop in DTIs half as severe as the $\underline{b} = -.1$ economy).

Table 13 shows that the fraction of households borrowing falls by 3.09 percentage points

in the economy in which the aggregate limit tightens to $\underline{b} = -.1$ and 1.21 percentage points when the aggregate debt limits tightens to $\underline{b} = -.2$. Economy-wide debt to income ratios fall by 1.09 percentage points and .53 percentage points, respectively. In the data, the fraction of households that stopped borrowing fell by 6.77 percentage points from 2007 to 2010 (measured in the SCF) while the debt to income ratio fell by .86 percentage points from 2007 to 2010 (measured in the SCF).[35]

Figure 6 plots the percentage change in employment during the 2007-2009 recession across the economy with a tighter debt limit versus the economy with a fixed debt limit. When debt limits tighten, employment tends to increase, persistently. The mechanism is that with looser credit limits, unemployed households borrow to smooth consumption while thoroughly searching for capital-intensive jobs. If debt limits tighten, they lose their ability to self-insure, and, as a result, take low-capital-intensity jobs that are relatively quick to find. In other words, when limits tighten, low-asset job losers take relatively less productive employment opportunities. This introduces a strong tension between recovery speed and recovery health, as workers find jobs more quickly but these jobs are of lower quality.

As Figure 9 shows, the aggregate capital stock held by entrepreneurs drops severely relative to the economy in which debt limits are held constant. This is entirely driven by new entrepreneurial entrants posting more vacancies in submarkets with less capital, and constrained households searching for jobs in those submarkets. The time it takes for the aggregate capital stock to recover to its pre-recession levels is as much as 6 quarters longer in the economy in which debt limits tighten.

Because households become more constrained and take jobs in which there is less capital per unit of labor, Figure 7 shows that measured labor productivity, defined as output over employment, declines when debt limits are tightened. The economy in which debt limits tighten the most has a .28 percentage point lower labor productivity as compared to the economy with constant debt limits, and this productivity gap persists throughout the recovery. In Appendix J, when we allow for capital investment to change over the course of a match, the labor productivity decline is slightly less pronounced because firms have the ability to invest more in existing matches during the recovery.

In terms of production, the impact of tighter debt limits on aggregate output is theoretically ambiguous: households find jobs faster, but the jobs workers find are less productive.

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[35]While not reported here for the sake of space, the bankruptcy rate reaches .97% in the model in the quarter in which limits are tightened, which is in line with ABI bankruptcies per capita.

However, Figure 8 shows that quantitatively the reduction in capital per worker is so severe that output falls by .11 percentage points.

The mechanism at the heart of the output decline involves a reallocation of workers from high capital firms to low capital firms. To understand this reallocation in greater detail, we now turn to standard measures of sorting. Figure 10 plots the percentage change in the correlation between human capital, h, and firm capital, k, during the 2007-2009 recession. Figure 11 plots the corresponding percentage change in the Spearman rank correlation coefficient between human capital, h, and firm capital, k, as well (workers are ranked by h, and firms are ranked by k, and the Spearman Rank correlation coefficient is the resulting correlation between the numeric ranks of workers and firms). The raw correlation coefficient between worker human capital and firm physical capital is approximately $+.33$.

Figures 10 and 11 show that in the economy in which debt limits are tighter, these standard measures of sorting *improve*. The mechanism behind this sorting improvement is that in the economy in which debt limits tighten, unemployed agents with low-human-capital cannot borrow to smooth consumption while thoroughly searching for jobs. Therefore, they take jobs that are less-capital-intensive, but more abundant. On average, since low human capital workers are less productive (recall the assumption of supermodularity), tighter debt limits force these 'low quality' workers to take 'low quality' jobs. As such, standard measures of sorting improve, even as output falls, since they do not take into account the investment decisions of firms. In this economy, these standard measures of sorting are not good proxies for either productivity or output, even with a supermodular production function.[36] In Appendix H, we show that households would be willing to give up .09% of lifetime consumption to live in a world in which borrowing limits do not tighten in 2007, even though standard measures of sorting would be lower in that world.

Allowing firms to invest and workers to save are standard assumptions in most neoclassical business cycle models but are often difficult to incorporate in search theoretic models. The fact that standard measures of sorting move in the opposite direction of output and productivity under these mild assumptions raises important questions about the welfare implications of sorting patterns derived from search theoretic models with linear utility or under the assumption of fixed firm types.

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[36]In Appendix I we explore alternate measures of sorting in more detail, including other measures of mismatch proposed in the literature. We show that alternate measures of mismatch, such as distance from surplus maximizing match (Lise and Robin [2013]), are countercyclical in the model. This general pattern of countercyclical mismatch is in line with the data, e.g. Moscarini and Vella [2008] and Şahin et al. [2012].

7.2 Robustness: Capital Investment and Liquidation Value

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

8 Conclusions

Our paper provides the first estimates of the impact of credit constraints on job finding rates and subsequent replacement wages of displaced workers. Using new administrative data, we find that medium-tenure displaced mortgagors, in response to being able to replace 10% of their annual income with revolving credit, take .15 to 3 weeks longer to find a job but obtain an earnings replacement rate that is 0 to 1.7% greater. Furthermore, displaced individuals with greater credit access tend to find jobs at larger and more productive firms.

We develop a labor sorting model with credit to provide structural estimates of the impact of credit on the duration of unemployment and how much income displaced individuals replace in their new job. The model yields estimates of approximately .7 and 1.8%, respectively for the duration of unemployment and the income replacement rate, which are similar to our empirical estimates.

We then use the model to understand the impact of consumer credit on productivity, output, and employment. The model shows that tighter debt limits during recessions may increase employment during the recovery, but depress both productivity and output. This tension between the speed of recovery and health of recovery is at the heart of the mechanism: tighter debt limits force constrained households to cut their job search short, taking relatively unproductive jobs that are more abundant.

Our empirical and quantitative findings have implications for the way both policy-makers and economists think about the optimal provision of unemployment insurance (Marimon and Zilibotti [1999], Acemoglu and Shimer [1998], Shimer and Werning [2005]) and the response

of labor markets to monetary policy (Gornemann et al. [2012], Auclert [2014]). The fact that increases in credit access can *reduce* job finding rates by easing household credit constraints brings into question the ability of the Federal Reserve Bank to effectively meet the mandate of "maximum employment, stable prices and moderate long-term interest rates."

We view this paper as the beginning of a research agenda which uses new micro data and theory to understand how consumer credit impacts the allocation of households to firms. The next step in our research agenda is to measure the impact of consumer credit constraints on the other side of the market, on the Schedule C entrepreneurs and the workers they hire (Herkenhoff et al. [2016]).

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Table 1: Summary Statistics for Displaced Mortgagor and Displaced Bankrupt Samples

	(1) Bankrupt Sample	(2)	(3) Mortgagor Sample	(4)
	Treatment	Control	All	Employed at t+1
Age	44.0	42.4	44.1	43.4
Tenure	4.0	3.9	5.9	5.9
Imputed Years of Education	13.8	13.6	13.9	13.9
Lagged Annual Earnings	$48,893	$43,527	$56,108	$57,733
Lagged Unused Revolving Credit to Income	0.12	0.07	0.45	0.41
Lagged Unused Total Credit to Income	0.30	0.22	0.77	0.71
Duration of Non-Employment (In Quarters)	1.73	1.53	1.67	0.56
Replacement Rate (Annual Earnings Year t+1/Annual Earnings Year t-1)	0.83	0.88	0.81	1.02
Lagged Months Since Oldest Account Opened	165.8	163.0	181.7	179.0
Observations (Rounded to 000s)	1000	17000	32000	21000

Notes. Sample selection criteria in Section 3.4. Lagged refers to (t-1), the year before displacement.

Table 2: Dependent Variable is Duration. Columns: (1) OLS with Bankruptcy Flag Drop, (2) OLS with Displaced Mortgagors, (3) IV using Gross and Souleles Instrument, (4) IV using Saiz instrument.

	(1)	(2)	(3)	(4)
		Dependent Variable is Duration		
	OLS-Flag Drop	OLS	IV-GS	IV-Saiz
Unused Revolving Credit to Income Ratio		0.249***	0.514***	1.513**
		(0.0258)	(0.115)	(0.630)
Flag Drop (d)	0.178**			
	(0.0792)			
Demographic, Industry, MSA, & Lagged Earnings Controls	Y	Y	Y	Y
HELOC Limits and Equity Proxy	Y	Y	Y	Y
R2 (1st Stage for IVs)	0.033	0.048	0.134	0.101
Angirst Pischke FStat Pval	-	-	0	0.000138
Round N	18000	32000	32000	32000

*Notes. Std. errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Cols. (1) to (3) use robust std. errors, and Col. (4) uses MSA clustered std. errors. Col. (1) uses displaced bankrupt sample. Cols. (2) to (4) use displaced mortgagor sample. Unused Revolving Credit to Income measured 1 year prior to layoff. Demographic controls include quadratic in age & tenure, race, sex and education dummies as well as year & auto loan dummies. Industry controls include 1-digit SIC dummies and size, age, and wage per worker of prior firm. MSA controls include real per capita GDP and the MSA unemployment rate. Lagged earnings controls include prior real annual earnings and cumulative real annual earnings to proxy for assets. Equity proxy is highest observed mortgage balance less current mortgage balance. HELOC limits include combined home equity limits.*

Table 3: Impact of Bankruptcy Flag Removal on Credit Access, OLS. Column (1) Dependent Variable is Revolving Credit Limit to Income, and Column (2) Dependent Variable is Credit Score.

	(1) Credit Limit to Inc	(2) Credit Score
Flag Drop (d)	0.0689***	140.1***
	(0.00962)	(6.257)
Demographic, Industry, MSA, & Lagged Earnings Controls	Y	Y
HELOC Limits and Equity Proxy	Y	Y
R2	0.056	0.126
Round N	18000	18000

*Notes. Robust Std. errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Same control definitions as Table 2.*

Table 4: Dependent Variable is Replacement Rate, Measured 1 Year After Layoff Relative to 1 Year Before Layoff. Sample Includes Those With Jobs 1 Year After Layoff.

	(1)	(2)	(3)	(4)
		—— DV is Replacement Rate, Among Employed at t+1 ——		
	OLS-Flag Drop	OLS	IV-GS	IV-Saiz
Unused Revolving Credit to Income Ratio		0.0332***	0.0847***	0.172**
		(0.00344)	(0.0139)	(0.0872)
Flag Drop (d)	-0.0126			
	(0.0111)			
Demographic, Industry, MSA, & Lagged Earnings Controls	Y	Y	Y	Y
HELOC Limits and Equity Proxy	Y	Y	Y	Y
R2 (1st Stage for IVs)	0.146	0.082	0.117	0.0872
Angirst Pischke FStat Pval	-	-	0	2.48e-05
Round N	12000	21000	21000	21000

Notes. Same as Table 2.

Table 5: Dependent Variable is Replacement Rate, Measured 1 Year After Layoff Relative to 1 Year Before Layoff. Sample includes everyone, even those with replacement rates of 0.

	(1)	(2)	(3)	(4)
		—Dependent Variable is Replacement Rate—		
	OLS-Flag Drop	OLS	IV-GS	IV-Saiz
Unused Revolving Credit to Income Ratio		-0.00531	0.0169	-0.129
		(0.00437)	(0.0176)	(0.148)
Flag Drop (d)	-0.0230			
	(0.0140)			
Demographic, Industry, MSA, & Lagged Earnings Controls	Y	Y	Y	Y
HELOC Limits and Equity Proxy	Y	Y	Y	Y
R2 (1st Stage for IVs)	0.047	0.044	0.134	0.101
Angirst Pischke FStat Pval	-	-	0	0.000138
Round N	18000	32000	32000	32000

Notes. Same as Table 2.

Table 6: Dependent Variable is Dummy if Firm is in 99th Decile of Size Distribution or Greater ('Large Firm Dummy'). Sample Includes Those With Jobs 1 Year After Layoff.

	(1)	(2)	(3)	(4)
		—Dependent Variable is Large Firm Dummy—		
	OLS-Flag Drop	OLS	IV-GS	IV-Saiz
Unused Revolving Credit to Income Ratio		-0.000220	0.0282	0.471**
		(0.00505)	(0.0257)	(0.234)
Flag Drop (d)	0.0392**			
	(0.0176)			
Demographic, Industry, MSA, & Lagged Earnings Controls	Y	Y	Y	Y
HELOC Limits and Equity Proxy	Y	Y	Y	Y
R2 (1st Stage for IVs)	0.056	0.061	0.117	0.0872
Angirst Pischke FStat Pval	-	-	0	2.48e-05
Round N	12000	21000	21000	21000

Notes. Same as Table 2.

Table 7: Dependent Variable is Dummy if Firm is in 75th Decile of Wage Per Worker Distribution or Greater ('Productive Firm Dummy'). Sample Includes Those With Jobs 1 Year After Layoff.

	(1)	(2)	(3)	(4)
	—————Dependent Variable is Productive Firm Dummy—————			
	OLS-Flag Drop	OLS	IV-GS	IV-Saiz
Unused Revolving Credit to Income Ratio		-0.00375	0.153***	-0.251
		(0.00459)	(0.0248)	(0.322)
Flag Drop (d)	0.0295*			
	(0.0164)			
Demographic, Industry, MSA, & Lagged Earnings Controls	Y	Y	Y	Y
HELOC Limits and Equity Proxy	Y	Y	Y	Y
R2 (1st Stage for IVs)	0.217	0.229	0.117	0.0872
Angirst Pischke FStat Pval	-	-	0	2.48e-05
Round N	12000	21000	21000	21000

Notes. Same as Table 2.

Table 8: Dependent Variable is Change in Real Revolving Debt 1 Year After Layoff Minus 1 Year Before Layoff.

	(1) Change in Revolving Debt	(2) Change in Revolving Debt
Duration of Unemployment	48.93	196.9***
	(54.67)	(55.37)
Constant	2,676***	-1,857
	(153.5)	(2,236)
Demographic, Industry, MSA, & Lagged Earnings Controls	N	Y
HELOC Limits and Equity Proxy	N	Y
R-squared	3.17e-05	0.025
Round N	32000	32000

Notes. Robust Std. errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Same control definitions as Table 2.

Table 9: Summary of Model Parameters.

	Pre-Calibrated	
Variable	Value	Description
ρ	0.894	Autocorrelation of Productivity Process
σ_e	0.00543	Std. Dev. Of Productivity Process
r_f	4%	Annualize Risk Free Rate
δ	10%	Quarterly Layoff Rate
ζ	1.6	Matching Function Elasticity
σ	2	Risk Aversion
α	0.66	Household share of income
a	0.66	Cobb-Douglas Labor Share
λ	0.036	Bankruptcy Re-Access
$\underline{b}$	-0.5	Non-binding debt limit

	Jointly-Estimated	
Variable	Value	Description
κ	0.034	Firm Entry Cost
z	0.101	UI
$p_{-\Delta}$	0.143	Depreciation Rate of Human Cap.
$p_{+\Delta}$	0.077	Appreciation Rate of Human Cap.
β	0.988	Discount Factor
f_c	0.100	Fixed Cost
η	0.237	Flow Utility of Leisure
χ	0.077	Bankruptcy Utility Penalty

Table 10: Model Calibration

	Model	**Target**	**Variable**	**Value**	**Source**
Unemployment Rate	8.93%	8.90%	κ	0.034	BLS, U6 1994-2007
Consumption Drop 1 Yr After Layoff	0.846	0.84	z	0.101	Browning & Crossley (2001)
Consumption Drop 2 Yrs After Layoff	0.971	.97	$p_{-\Delta}$	0.143	Saporta-Eksten (2013) / PSID 2005-2011
Quarterly Income Growth Rate 25yo	1.078%	1.05%	$p_{+\Delta}$	0.077	PSID, 2005-2007
Fraction of Households with Liquid assets to Income Ratio<1%	0.093	0.254	β	0.988	SCF, 1974-2007
Vol U/ Vol y	2.686	9.5	f_c	0.100	Shimer (2005)
Autocorr Unempl	0.730	0.94	η	0.237	Shimer (2005)
Bankruptcy rate	0.01%	0.10%	χ	0.077	ABI, 1970-2007

Table 11: Non-Targeted Moments: Model Elasticities vs. Data Elasticities

	Model	Data: OLS	Data: IV-GS	Data: IV-Saiz	Data: Flag Removal
Duration Elasticity	0.608	.249***	.514***	1.513***	-
Replacement Elasticity (including 0s)	-0.024	-0.005	0.0169	-0.129	-
Job Finding Elasticity	-0.11	-	-	-	-
Capital Elasticity	0.27	-	-	-	-
Replacement Elasticity, Job Finders at t+1	0.18	.033***	.0847***	.172***	-
Duration after Flag Removal	0.066	-	-	-	0.178***
Replacement rate after Flag Removal	0.007	-	-	-	-0.023

Notes. Model estimates derived from simulating 30,000 agents in steady state with productivity held at $y = 1$ for T=270 (discarding the first 100 periods) and computing job finding behavior under counterfactually looser limits. See Section 6.1 and Appendix G for more details. Data estimates from Tables 2 through 4.

Table 12: Liquid Wealth Distribution: Model vs. Data, 2007

	Model Job Losers, 2007	Data Job Losers, 2007	Model All HHs, 2007	Data All HHs, 2007
p10	-0.04	-0.02	0.03	-0.07
p25	0.05	0.00	0.17	0.00
p50	0.18	0.01	0.28	0.04
p75	0.36	0.08	0.42	0.30
p90	0.51	0.21	0.54	1.60
Mean	0.21	0.22	0.29	0.59
N	120,000	57	120,000	4385

Notes. 2007 SCF liquid wealth calculated as the sum of savings, checking, money market, mutual funds, CDs, bonds, and stocks less credit card debt, taken as ratio to gross family income. Job losers defined as those who made the transition from employed to unemployed in the last quarter, in both model and data.

Table 13: Reduction in Borrowing When Borrowing Limit Tightens, Model v. Data.

	Δ Fraction of HHs Borrowing	Δ DTI
Debt limit tightened from $\underline{b} = -.5$ to $\underline{b} = -.1$	-3.09%	-1.09%
Debt limit tightened from $\underline{b} = -.5$ to $\underline{b} = -.2$	-1.21%	-0.53%
Data	-6.77%	-0.86%

Notes: All Differences Computed using 2007 and 2010 SCF. DTI is Change Unsecured Revolving Consumer Credit to Annual Family Income. Fraction Borrowing Change is Difference in Fraction of Households Carry Positive Balances. Means Weighted Using Survey Weights. Model statistics calculated as difference in average of quarterly values over same corresponding years.

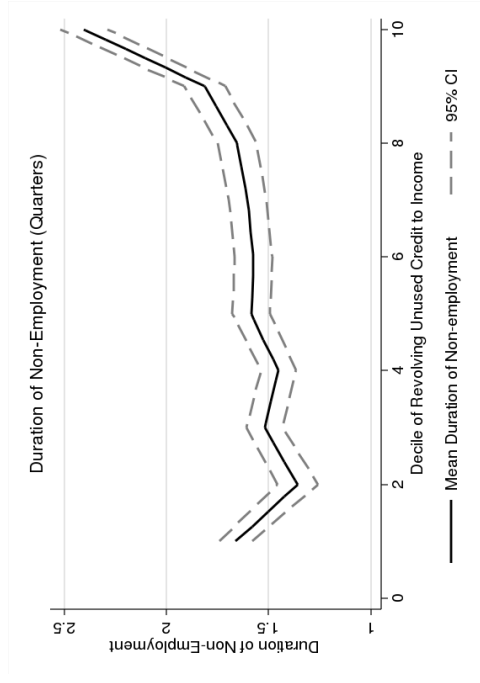Figure 1: Non-Employment Duration by Unused Revolving Credit to Income Decile, *prior to layoff*

Duration of Non-Employment (Quarters)

Mean Duration of Non-employment — — — 95% CI

Figure 2: Replacement Earnings 1 Year After Layoff (Including 0s) by Unused Revolving Credit to Income Decile, *prior to layoff*
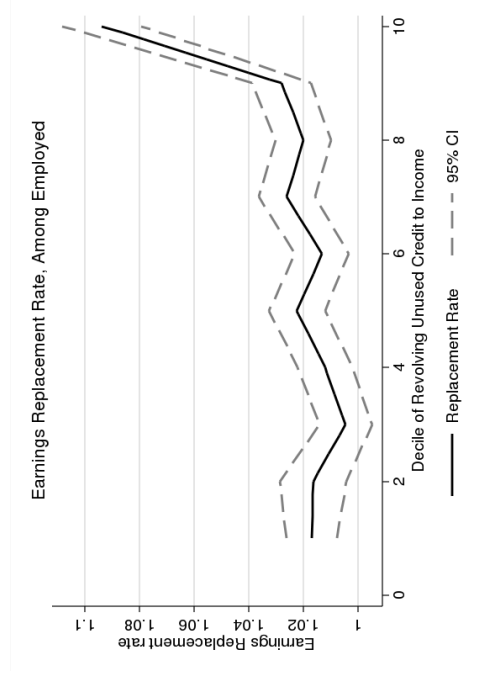

Earnings Replacement Rate, Among Employed

Replacement Rate — — — 95% CI

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

Kernel Density of Change in Revolving Balances
Year of Layoff Minus Year Before Layoff
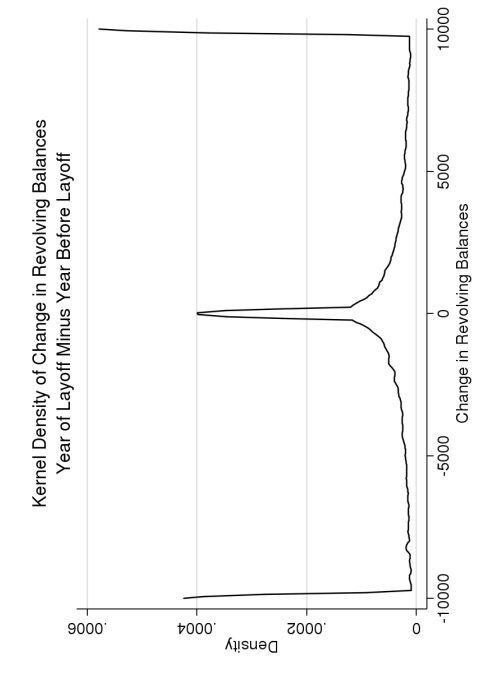
Figure 4: Change in Real Revolving Balance between Year of Layoff Minus 1 Year Before Layoff as Function of Non-Employment Duration
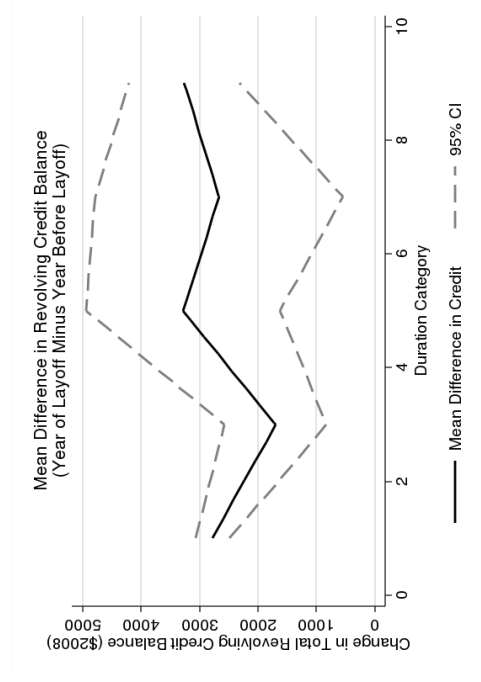

Mean Difference in Revolving Credit Balance
(Year of Layoff Minus Year Before Layoff)

Mean Difference in Credit — — — 95% CI

Figure 5: Experiment Input: Exogenous Aggregate Productivity (y) and Borrowing Limit $\underline{b}$, 2007-2009 Recession

Figure 6: Percentage Change in Employment Per Capita

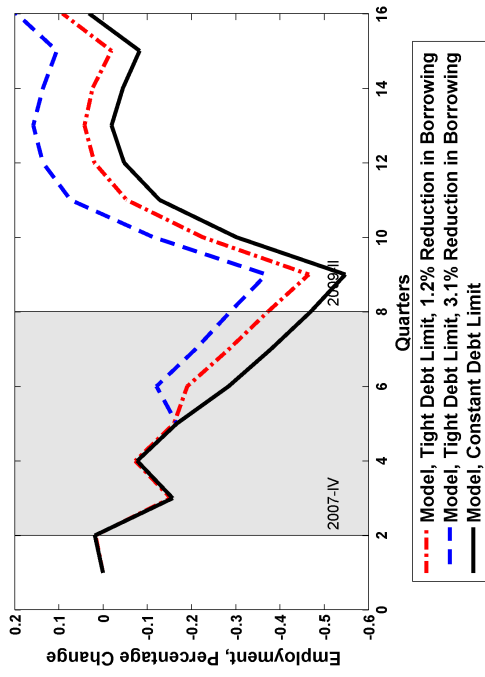Figure 7: Labor Productivity, 2007-2009 Recession
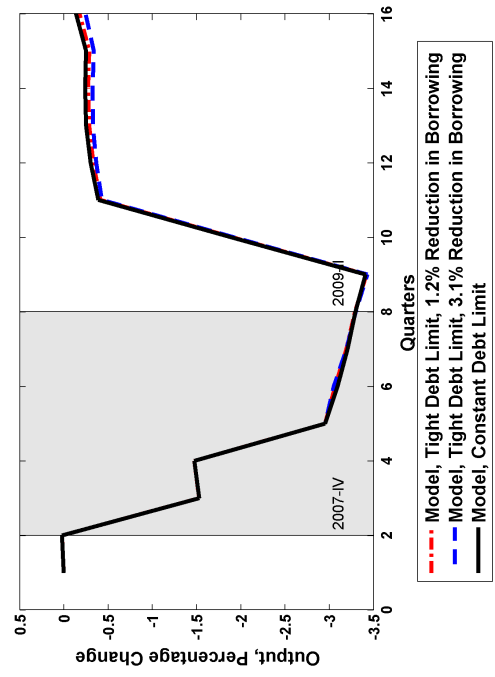
Figure 8: Aggregate Output

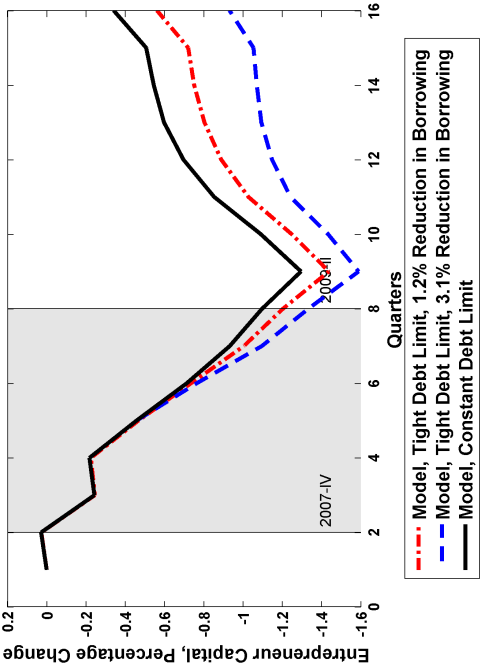Figure 9: Aggregate Firm Capital, 2007-2009 Recession

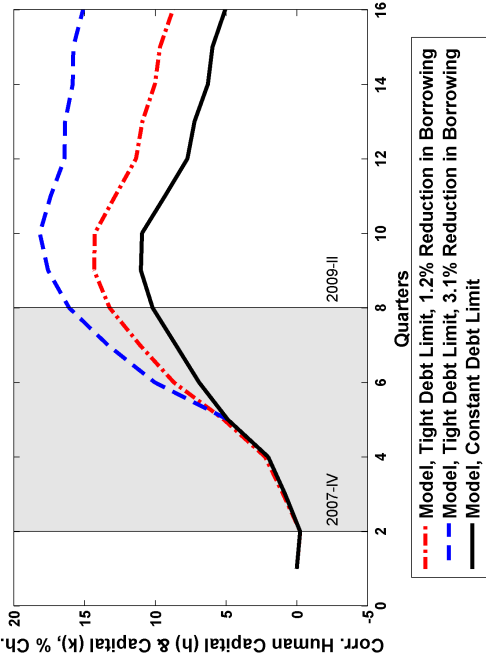Figure 10: Correlation Between Human Capital (h) and Firm Capital (k)
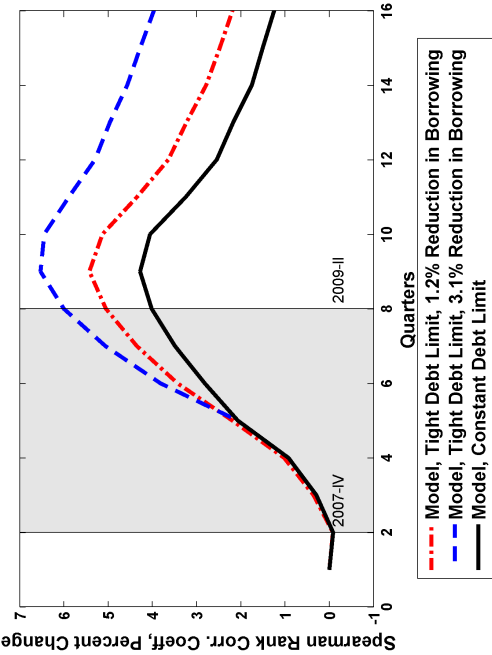

Figure 11: Spearman Rank Correlation Coefficient Between Human Capital (h) and Firm Capital (k)

Online Appendix Not For Publication

A Data Appendix

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

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

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

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

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

A.1 Employment and Duration Definitions

Our main concept of employment is end of quarter employment, as in Abowd et al. [2009]. For example, to be counted as employed at the end of quarter 1 at employer X, the worker in question must have had positive earnings at employer X in quarter 1 and quarter 2. Our earnings threshold is $500 in each quarter, and we find no significant impact on our results for greater earnings thresholds. If a mass displacement occurs at employer X in quarter 2 (i.e. 30% of their employees leave or they close, see the following section), and the worker

separates from employer X (meaning the worker is not end of quarter employed at employer X in quarter 2), then we count the worker as mass displaced. If the worker becomes end of quarter employed at employer Y in quarter 2, then the non-employment duration spell is marked as a zero. If the worker is end of quarter employed at employer Y in quarter 3, then the duration is 1 quarter, and so on. We truncate durations at 9 quarters. In Section C.1, we adjust these spells for partial quarters of non-employment duration using the earnings gap method, and we also adjust for self-employment. We have also used other measures of employment, and we find no significant impact on our results.

A.2   Identifying Mass Layoffs

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

A.3   TransUnion Variables

The unsued revolving credit limit ratio is defined as,

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

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

B   Robustness Checks

B.1   Verifying Assumptions for Bankruptcy Flag Removal Regressions

For the simple difference estimator used in the bankruptcy flag removal regressions to be valid, we must verify that the treatment and control group have similar means prior to layoff. Let $t = 0$ denote the year of removal, let $Y_{i,t}$ denote outcome variables of interest (wage growth, time spent unemployed, etc.), and let $treat_{i,t}$ be an indicator if the household is in the treatment group. Let $X_{i,t}$ include the same baseline demographic controls as the regressions in the text. We therefore run the following regressions for $t = -1$ (the year before layoff) and $t = -2$ (two years before layoff):

$$Y_{i,t} = \gamma_{i,t} Treat_{i,t} + \beta X_{i,t} + \epsilon_{i,t}$$

We show in Table 14 that the treatment and control group have insignificant mean differences in the outcome variables of interest for both $t = -1$ and $t = -2$. This implies that the two groups have identical trends and levels leading up to the flag removal. Therefore, the assumptions underlying the simple difference estimator hold, and our estimates should, in theory, be unbiased.

Table 14: Testing Identical Means and Parallel Trends for Bankrupt Sample, Treatment vs. Control.

Comparison of treatment and control group <u>1</u> year prior to layoff			
	Reject equal means at X% sig. level?		
	X=1%	X=5%	X=10%
Dependent variable is wage growth (w(t)/w(t-1))	N	N	N
Dependent variable is indicator if non-employed in Q1	-	-	-
Dependent variable is indicator if non-employed in Q2	-	-	-
Dependent variable is indicator if non-employed in Q3	-	-	-
Dependent variable is indicator if non-employed in Q4	-	-	-
Dependent variable is firm size	N	N	N
Depdent variable is firm productivity	N	N	N

Comparison of treatment and control group <u>2</u> years prior to layoff			
	Reject equal means at X% sig. level?		
	X=1%	X=5%	X=10%
Dependent variable is wage growth (w(t)/w(t-1))	N	N	N
Dependent variable is indicator if non-employed in Q1	N	N	N
Dependent variable is indicator if non-employed in Q2	N	N	N
Dependent variable is indicator if non-employed in Q3	N	N	N
Dependent variable is indicator if non-employed in Q4	N	N	N
Dependent variable is firm size	N	N	N
Depdent variable is firm productivity	N	N	N

Notes. Robust standard errors. Sample conditions on employment 1 year prior to layoff, so time spent non-employed is the same (by construction) in the year before layoff.

B.2 House Prices and the Relationship Between Credit, Non-Employment Durations, and Replacement Rates

Table 15 illustrates the main OLS regressions with direct house price controls. The house price control we include in the regression is the OFHEO All-Transaction House Price Index for MSAs.[37] Column (1) shows the baseline OLS result with no equity proxies or house prices, and the coefficient implies that being able to replace 10% more of prior annual income allows a household to take .3 weeks longer to find a job (=.258*.1*12). Column (2) adds in the house price index, and the coefficient remains the same. Column (3) includes both the equity proxies used in the text as well as the house price index, and the coefficient still remains the same. Columns (4) through (6) illustrate the same results for the replacement rate among the sample of households who found a job in the year after layoff. In each case, the replacement rate 1 year after layoff is hardly impacted by the inclusion of house price controls.

These results suggest that whether the house is worth 200k or 220k does not affect short term job search decisions directly. Only if the job loser can use the equity of the home to smooth consumption, should the value of the home impact short term job search decisions. While one may argue that households can sell their house to tap equity, since the average job loss spell in our data is quite short, it is unlikely that a worker who is laid off will be able to secure additional home equity lines, refinance or vacate the home immediately and sell the house. As Piazzesi et al. [2015] show empirically, even in the best of markets, it takes over 1 quarter for the median homeowner to sell their home, once it is listed. Empirically, in our dataset, we do not see households disproportionately taking out mortgages or paying off mortgages around displacement.

The fact that house price increases do not necessarily imply households are wealthier, nor that they should consume more, is actively debated in the literature (see both sides of the literature in Calomiris et al. [2009], among others). As most theoretic studies show, a household may attempt to sell the house, but they must buy a new one or rent thereafter, mitigating housing wealth effects. There is also mixed evidence regarding housing lock (see both sides of the literature discussed in Karahan and Rhee [2011]), suggesting that housing wealth may not matter for selling decisions as well. We find very little evidence of interstate movers or intrastate movers in our sample around job loss. If we drop movers, our IV regression results remain unchanged in terms of sign, significance, and magnitude.

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[37]This is publicly avaiable from the OFHEO website. The index is normalized to 100 in 1995.

Table 15: Baseline OLS regressions with Direct Controls for OFHEO House Prices (Source: LEHD/TransUnion 2002-2006)

	(1) Duration	(2) Duration	(3) Duration	(4) Replacement Rate	(5) Replacement Rate	(6) Replacement Rate
Unused Revolving Credit to Income Ratio	0.258***	0.248***	0.242***	0.0335***	0.0327***	0.0324***
	(0.0257)	(0.0258)	(0.0259)	(0.00344)	(0.00344)	(0.00345)
Demographic, Industry, MSA, & Lagged Earnings Controls	Y	Y	Y	Y	Y	Y
OFHEO HPI Index	N	**Y**	**Y**	N	**Y**	**Y**
HELOC Limits and Equity Proxy	N	N	**Y**	N	N	**Y**
R2	0.047	0.048	0.049	0.082	0.083	0.083
Round N	32000	32000	32000	21000	21000	21000

Notes. Clustered standard errors at MSA level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. OFHEO HPI Index is the OFHEO All-Transaction House Price Index measured in the year prior to layoff. Revolving Unused Credit to Income measured 1 year prior to layoff. Demographic controls include quadratic in age & tenure, race, sex and education dummies as well as year & auto loan dummies. Industry controls include 1-digit SIC dummies. MSA controls include real per capita GDP and the MSA unemployment rate. Lagged earnings controls include both lagged real annual earnings, and cumulative lagged real annual earnings to proxy for assets.

B.3 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 12 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 prior to 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, very similar to the IV estimate in the LEHD/TransUnion sample considered in the text.

Figure 12: **Survey of Consumer Finances:** Correlation of Unemployment Durations (in Weeks) on Unused Credit (Source: 1998-2007 SCF)

SCF Unemployment Duration in Weeks
by Decile of Unused Credit to Income Decile

Source: 1998, 2001, 2004, and 2007 SCF, Sample includes 24-65yo heads with positive duration over prior 52 weeks and positive credit card limit.

Important: Unemployment duration measured over prior year
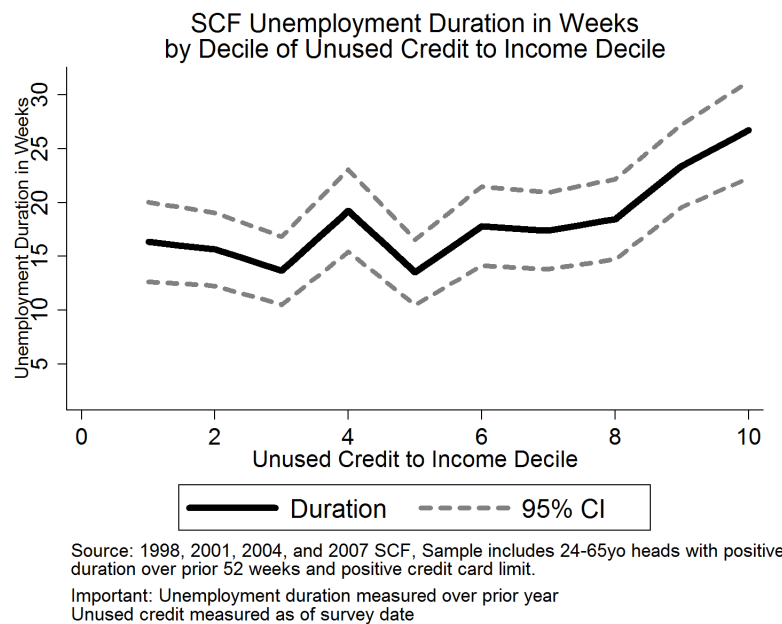Unused credit measured as of survey date

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 Durations 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.4 Over-Identification Tests

In this section we discuss the assumptions underlying the Gross and Souleles instrument, and we use the fact that we have two different instruments in order to conduct over-identification tests. In summary, the Saiz and Gross and Souleles instruments pass over identification tests at the 5% significance level, suggesting that they are satisfying exclusion restrictions. However, there is no true test of exogeneity.

For the Gross and Souleles instrument to be valid, it must be both relevant and exogenous. What makes the Gross and Souleles instrument relevant is that a large component, approximately 15%, of a credit score is solely based on length of credit history.[38] By simply having an account open, you credit score increases and affects your credit limits.[39] Empirically, the first stage is very strong, as evidenced by the small p-values in the Stock-Yogo weak identification tests ('Weak Id'), where the null is that the instruments are weak.

For the age of the oldest account to be a valid instrument for credit limits, it must not only be a strong determinant of credit limits, but it can only have an impact on employment prospects through credit limits (exogeneity). The main challenge to exogeneity is that the age of an account is related to the physical age of the individual. Since the age of an account is how scoring companies proxy for physical age, by conditioning on physical age (which we observe but scoring companies do not), we are able to isolate changes in credit scores simply due to variation in account age, that have nothing to do with physical age.[40]

Lastly, since we have multiple instruments, we show that both the Gross and Soueles instrument and Saiz instrument pass over-identification tests. For individual i, $l_{i,t}$ is unused credit, $g_{i,t}$ is the age of the oldest account, $s_{i,t}$ is the supply elasticity, and $X_{i,t}$ is a vector of characteristics including quadratics in age and tenure. To conduct the over-identification tests, we implement the following specifications:

$$l_{i,t-1} = \pi_1 s_{i,t} + \pi_2 g_{i,t} + BX_{i,t} + u_{i,t} \tag{10}$$

---

[38] See 'Your Credit Score,' prepared by Fair Isaac Corporation and available from http://www.consumerfed.org/pdfs/yourcreditscore.pdf

[39] Limits are then revised upward as credit scores increase. As Gross and Souleles [2002] explain, credit issuers revise account limits regularly, and the length of time an account was open is a determinant of these credit limit revisions. They write, "many issuers will not consider (or are less likely to consider) an account for a line change if it has been less than six months or less than one year since the last line change" (p.7).

[40] The reason they do this is that the Equal Credit Opportunity Act bans the use of age, race, or sex in determining credit score, and so the credit scoring companies use account age as a proxy for physical age.

These first-stage estimates of π_1, π_2 and B are used to isolate the exogenous component of the unused credit limit ratio, $\hat{l}_{i,t-1}$. The second stage regression is then used to estimate how this exogenous variation in credit impacts employment outcomes such as duration, $D_{i,t}$.

$$D_{i,t} = \gamma \hat{l}_{i,t-1} + \beta X_{i,t} + \epsilon_{i,t} \tag{11}$$

The main idea behind the over-identification tests is to predict $\hat{l}_{i,t-1}$ using one instrument, e.g. $s_{i,t}$, and then verify that the other instrument, $g_{i,t}$, is uncorrelated with the resulting residuals.

Table 17 illustrates the main results using both the Saiz and Gross and Souleles instruments in the first stage. We see that the instruments pass the over-identification tests (in particular, we implement Hansen's J-test). The null is that the instruments are valid, and so larger p-values indicate the fact that we cannot reject the null that the instruments are valid. The instruments pass the J-test at both 1% and 5% significance levels. In terms of point estimates, Table 17 shows that our main results hold: credit limits positively impact durations (Column (1)), earnings replacement rates (Column (2)), and firm productivity (Column (4)).

Table 17: Over Identification Tests with Saiz and Gross & Souleles instrument. (Source: 2002-2006 LEHD/TransUnion)

Dep Var	(1) Duration	(2) Replacement Rate	(3) Large Firm Dummy	(4) Productive Firm Dummy
		Over ID Tests with Saiz-IV and GS-IV		
Unused Revolving Credit to Income Ratio	0.656***	0.0970***	0.0860	0.0987*
	(0.112)	(0.0157)	(0.0534)	(0.0521)
Demographic, Industry, MSA, & Lagged Earnings Controls	Y	Y	Y	Y
HELOC Limits and Equity Proxy	Y	Y	Y	Y
R2 (1st Stage for IVs)	0.137	0.120	0.120	0.120
Angirst Pischke FStat Pval	0	0	0	0
Pval Weak Id Null Weak	6.41e-05	4.46e-05	4.46e-05	4.46e-05
Jtest Pval Null Valid	0.134	0.290	0.0622	0.230
Round N	32000	21000	21000	21000

Notes. Clustered std. errors at MSA level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Same control definitions as Table 2.

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

In Table 18, we use alternate endogenous regressors: (i) unused revolving credit to income, including HELOCs (ii) total unused credit, including all types of secured (including HELOCs and mortgage debt) and unsecured debt (we define 'total unused credit to income' as the total credit limit less the amount currently borrowed over annual earnings, where the ratio is measured 1 year prior to layoff)[41], and (iii) credit scores (this corresponds to TransUnions bankruptcy model, and ranges from 0 to 1000, with higher scores indicating less credit risk).

Columns (1) and (2) of Table 18 illustrate that revolving unused credit, inclusive of HELOCs, has a similar effect on duration and replacement rates (conditional on being employed at $t+1$), respectively, as the baseline definition in the text (which excludes HELOCs). Likewise, Columns (3) and (4) of Table 18 illustrate that total unused credit has a similar effect on duration and replacement rates. Columns (5) and (6) of Table 18 are more difficult to interpret, since the units are in terms of the TU bankruptcy model ('credit score'), but in general, if an individual has a higher score prior to layoff, they take longer to find a job, and they find higher replacement rates, conditional on finding a job.

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

Table 18: Alternate Measures of Access to Credit. IV estimates using the Saiz Instrument. (Source: 2002-2006 LEHD/TransUnion)

	Saiz House Supply Elasticity					
	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var	Duration	Replacement Rate (Among Employed at t+1)	Duration	Replacement Rate (Among Employed at t+1)	Duration	Replacement Rate (Among Employed at t+1)
Unused Revolving Credit to Income Ratio (Incl. HELOCs)	1.269**	0.162**				
	(0.525)	(0.0755)				
Total Unused Credit to Income Ratio			1.508**	0.134**		
			(0.589)	(0.0616)		
Credit Score					0.00238**	1.087***
					(0.000957)	(0.0665)
Demographic, Industry, MSA, & Lagged Earnings Controls	Y	Y	Y	Y	Y	Y
HELOC Limits and Equity Proxy	Y	Y	Y	Y	Y	Y
R2 (1st Stage for IVs)	0.137	0.0896	0.104	0.117	0.110	0.113
Angirst Pischke FStat Pval	2.13e-05	1.39e-05	7.32e-05	4.48e-06	2.32e-05	2.78e-06
Round N	32000	21000	32000	21000	32000	21000

*Notes. Clustered Std. errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Displaced mortgagor sample in Cols. (1), (3), and (5). Displaced mortgagor sample, conditional on employment at t+1, in Cols. (2), (4), and (6). Credit score is the TU bankruptcy score prior to layoff. Unused Revolving Credit to Income Ratio and Total Unused Credit to Income Ratio measured prior to layoff. Same control definitions as Table 2.*

C   Replacement Earnings 2 Years After Layoff

Consider the set of households who find a job 1 year after layoff. In the main text, Table 4 illustrates 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 19 analyzes wages 2 years after layoff for this same sample. Within this sample, the OLS estimates in Column (1) imply that replacement earnings are .3% higher, 2 years after layoff, for households who can replace 10% more of their lost income with unused credit. The Saiz instrument in Column (2) and the bankruptcy flag removal in Column (3) yield insignificant results, whereas the Gross and Souleles estimates in Column (3) imply that within this sample, replacement earnings are .9% higher, 2 years after layoff, for households who can replace 10% more of their lost income with unused credit. While the results are mixed, the earnings gains in Table 4 persist 2 years after layoff for at least 2 of the specifications considered in the main text.

Table 19: 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)	(3)	(4)
	——— DV is Replacement Rate at $t+2$, Among Employed Sample ———			
	OLS	IV-Saiz	IV-GS	OLS-Flag Drop
Unused Revolving Credit to Income Ratio	0.0383***	0.180	0.0916***	
	(0.00441)	(0.122)	(0.0171)	
Flag Drop (d)				-0.00598
				(0.0136)
Demographic, Industry, MSA, & Lagged Earnings Controls	Y	Y	Y	Y
HELOC Limits and Equity Proxy	Y	Y	Y	Y
R2 (1st Stage for IVs)	0.078	0.0872	0.117	0.120
Angirst Pischke FStat Pval	-	2.48e-05	0	-
Round N	21000	21000	21000	12000

Notes. Same as Table 2.

C.1 Self-Employment and the Earnings Gap Method

Table 20 redoes the main analysis in two different ways. Column (1) is a regression of duration on unused credit where the self-employed with more than 5k in annual Schedule C earnings are counted as employed. Column (2) infers the length of unemployment duration using the earnings gap method. Using quarterly earnings prior to layoff as the base (E_{q-1}), then those who find a job within the first quarter of layoff will have spent $1 - E_q/E_{q-1}$ fraction of the quarter unemployed. Table 20 illustrates that the main results are robust to these alternate definitions.

Table 20: 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 (Self-Employment)	(2) Duration (Earnings Gap Method)
Unused Revolving Credit to Income Ratio	1.334**	1.532**
	(0.646)	(0.623)
Demographic, Industry, MSA, & Lagged Earnings Controls	Y	Y
HELOC Limits and Equity Proxy	Y	Y
R2 (1st Stage for IVs)	0.101	0.101
Angirst Pischke FStat Pval	0.000138	0.000138
Round N	32000	32000

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

D   Employed Value Functions

For employed households, value functions are denoted with a W, and at the end of every period, employed households face layoff risk δ. If they are laid off, since the period is 1 quarter, we must allow the workers to search immediately for a new job.[42]

$$W_t^G(b, h, k; \Omega) = \max_{b' \geq \underline{b}} u(c, 0) + \beta \mathbb{E}\Big[(1 - \delta)W_{t+1}(b', h', k; \Omega')$$

$$+ \delta\Big\{ \max_{\tilde{k}} p(\theta_{t+1}(h', \tilde{k}; \Omega'))W_{t+1}(b', h', \tilde{k}; \Omega')$$

$$+ \big(1 - p(\theta_{t+1}(h', \tilde{k}; \Omega'))\big)U_{t+1}(b', h', k; \Omega')\Big\}\Big], \quad t \leq T$$

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

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,

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

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

$$W_t^B(b, h, k; \Omega) = u(c, 0) + \lambda\beta\mathbb{E}\Big[(1 - \delta)W_{t+1}(0, h', k; \Omega')$$

$$+ \delta\Big\{ \max_{\tilde{k}} p(\theta_{t+1}(h', \tilde{k}; \Omega'))W_{t+1}(0, h', \tilde{k}; \Omega')$$

$$+ \big(1 - p(\theta_{t+1}(h', \tilde{k}; \Omega'))\big)U_{t+1}(0, h', k; \Omega')\Big\}\Big]$$

$$+ (1 - \lambda)\beta\mathbb{E}\Big[(1 - \delta)W_{t+1}^B(0, h', k; \Omega')$$

$$+ \delta\Big\{ \max_{\tilde{k}} p(\theta_{t+1}(h', \tilde{k}; \Omega'))W_{t+1}^B(0, h', \tilde{k}; \Omega')$$

$$+ \big(1 - p(\theta_{t+1}(h', \tilde{k}; \Omega'))\big)U_{t+1}^B(0, h', k; \Omega')\Big\}\Big], \quad t \leq T$$

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

---

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

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,

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

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

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

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

E   Characterizing Existence and Uniqueness

In this section, we characterize both the existence and uniqueness of a block recursive equilibrium for the model economy. These propositions are useful for numeric exercises since they will establish that (i) all equilibria are block recursive, and (ii) for certain classes of utility, matching, and production functions, the equilibrium is unique. The proofs use a similar methodology to Menzio et al. [2012], extended to an environment with two-sided heterogeneity. We begin with Proposition E.1 which is the existence result for a Block Recursive Equilibrium. Without loss of generality, we set the firm fixed cost f_c to zero.

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

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

in the last period of life,

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

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

In this last period of life, the saving and borrowing policy function $b'_{e,T}(b, h, k; y, \underline{b})$ 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,

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

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

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

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

Now stepping back to the labor search problem, the firm's value function will be independent of μ as well,

$$J_T(h, k; \Omega) = (1 - \alpha)f(y, h, k) + \beta \cdot 0$$
$$= J_T(h, k; y, \underline{b})$$

And the labor market tightness will also be independent of μ,

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

$$= \theta_T(h, k; y, \underline{b})$$

The household at age $T - 1$ (note that the primes below simply note that age $T - 1$ risk over y and $\underline{b}$ 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,

$$\max_{k \in \mathcal{K}} \ p(\theta_T(h', k; y', \underline{b}')) W_T(b', h', k; y', \underline{b}') + \big(1 - p(\theta_T(h', k; y', \underline{b}'))\big) U_T(b', h', k; y', \underline{b}') \quad (12)$$

So long as k lies in a bounded interval, the extreme value theorem guarantees at least one solution to this problem. As we will see below, for certain classes of production functions, only one solution exists. For the current exposition, assume the production function lies within this class, and a unique solution exists.

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

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

$$= q_{U,T-1}(b', h, k; y, \underline{b})$$

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

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

$\square$

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

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

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

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

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

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

Substituting,

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

The minimum supportable debt is given by,

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

$\square$

Now, we turn to uniqueness. In Lemma (E.3) we provide sufficient conditions for the economy to admit a unique, Block Recursive Equilibrium. Lemma E.3 demonstrates that for a broad range of production functions and utility functions, the model admits a unique solution, and so there is no equilibrium selection implicitly taking place in the numeric exercises. Removing uncertainty in the proof is only for the sake of closed form solutions to the firm problem, and as long as the utility function of the household is additively separable in leisure, the proof holds.

Lemma E.3. *In addition to the assumptions in Proposition E.1, let the production function be Cobb-Douglas, i.e. $f(y, h, k) = yh^{1-a}k^a$ ($0 < a < 1$), let the matching function be given by $M(u, v) = u^{\frac{1}{2}}v^{\frac{1}{2}}$, let $\chi \to \infty$ (no default for households), the value of leisure is zero, and assume there is no uncertainty over human capital h, aggregate productivity y, or the borrowing limit $\underline{b}$. Then if the utility function is negative, increasing, and concave (e.g. $\frac{c^{1-\sigma}-1}{1-\sigma}$ for $\sigma > 1$ or $u(c) = -e^{-c}$), the household labor search problem (equation (12)) admits a unique solution.*

Proof. The non-stochastic firm problem can be solved by hand, and under the hypotheses

of the present lemma, it is directly proportional to capital,

$$J_t(h,k) = \frac{(1-\alpha)f(y,h,k)}{1-\beta(1-\delta)} - \frac{(\beta(1-\delta))^{T-t+1}(1-\alpha)f(y,h,k)}{1-\beta(1-\delta)} \propto k^a$$

Under the assumption $M(u,v) = u^{\frac{1}{2}}v^{\frac{1}{2}}$, the equilibrium market tightness $\theta_t(h,k)$ can be solved by hand.

$$\kappa = \theta_t(h,k;\Omega)^{-\frac{1}{2}}\left[J_t(h,k;\Omega) - (1+r_f)\cdot\frac{k}{\theta_t(h,k;\Omega)^{-\frac{1}{2}}}\right]$$

Solving for θ_t yields,

$$\left(\frac{\kappa + (1+r_f)k}{J_t(h,k;\Omega)}\right)^{-2} = \theta_t(h,k;\Omega)$$

The household job finding rate is therefore given by,

$$\left(\frac{J_t(h,k;\Omega)}{\kappa + (1+r_f)k}\right) = p(\theta_t(h,k;\Omega))$$

For κ and r_f sufficiently small,

$$p(\theta_t(h,k;\Omega)) \propto k^{a-1}$$

The constant worker share α in combination with the non-negative and increasing production function implies that the wage a worker receives is concave and increasing in k. Note that the composition of two non-decreasing concave functions in k preserves concavity in k, i.e. $\tilde{u}(k) = u(w(h,k) + \mu)$ is concave in k for arbitrary μ. Let $\underline{u}$ be the outside option of the household if they remain unemployed. Since the probability of finding a job is directly proportional to k^{a-1}, the household chooses k to maximize

$$k^{a-1}\tilde{u}(k) + (1 - k^{a-1})\underline{u}$$

Since $-k^{a-1}$ is concave, we ignore the second term (the idea will be to show the first term is concave, and then use the fact that the sum of two concave functions is concave). The condition for the first term to be concave is given by,

$$\underbrace{(a-1)(a-2)k^{a-3}\tilde{u}(k)}_{(-)} + \underbrace{2(a-1)k^{a-2}\tilde{u}'(k)}_{(-)} + \underbrace{k^{a-1}\tilde{u}''(k)}_{(-)} < 0$$

Under the hypotheses that $u < 0$, $u' > 0$, $u'' < 0$ (note, these properties transfer to $\tilde{u}$), and $0 < a < 1$, the labor search problem of the household is strictly concave and one solution exists for k.

$\square$

Table 21: Business Cycle Moments for Model During Main Simulation (1974 to 2012) vs. Data

Model							
x	u_1	v	θ	y	$\tilde{k}$	UE Rate	Default Rate*
SD(x)/SD(y)	2.69	1.66	1.91	1.00	0.97	1.66	0.00
Autocorr(x)	0.73	0.39	0.78	0.82	0.79	0.40	0.13
Corr($\cdot$,x)							
u	1.00	-0.19	-0.74	-0.72	-0.73	-0.87	-0.14
Data							
x	u_1	v	θ	y	$\tilde{k}$	UE Rate	Default Rate*
SD(x)/SD(y)	9.50	10.10	19.10	1.00	-	5.90	6.07
Autocorrelation	0.94	0.94	0.94	0.88	-	0.91	0.92
Corr($\cdot$,x)							
u_1	1.00	-0.89	-0.97	-0.41	-	-0.95	0.55

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

F Business Cycle Moments

Table 21 displays the business cycle moments for the main model in the text versus the data. The table makes the shortcomings of the model quite clear: the model is unresponsive to productivity shocks (Shimer [2005] and more recently Chodorow-Reich and Karabarbounis [2013]). Why does the Hagedorn and Manovskii [2008] calibration not work in this context? They noticed that the flow utility from non-employment must be large enough to make workers nearly indifferent between working and not working: workers then become sensitive to small movement in productivity and wages. It is impossible to make every type of worker indifferent between working and not working with significant heterogeneity and a constant unemployment benefit or flow utility of leisure. The only paper to our knowledge to address

this issue is Lise and Robin [2013] who make the flow utility of non-employment a function of the workers type, the workers type squared, the aggregate state, and interactions between the workers type and the aggregate state.

G   Calculating Model Elasticities

In this section, we use the model generated policy functions to estimate the duration and replacement earnings elasticities with respect to credit access.[43]   Since the debt pricing schedule does not have an explicit credit limit, we define the credit limit to be the maximum of either the level of debt where the bond interest rate first exceeds 30% per quarter (denote this level of debt $b_{30}(\cdot)$) or the exogenous debt limit $\underline{b}$.[44]   Therefore, we define the credit limit for an agent with state vector $\mathbf{x}$ as $L(\mathbf{x}) = \min\{-b_{30}(\mathbf{x}), -\underline{b}\}$. We isolate newly laid off agents (let I_δ denote this set of agents, and let N_δ denote its cardinality), and then we compute each agent's optimal search decision under loose ($\underline{b} = \underline{b}_L$) and tight exogenous debt limits ($\underline{b} = \underline{b}_H > \underline{b}_L$), ceteris paribus. What makes this calculation feasible is that the policy function of each agent is contingent on the realization of Ω which includes the exogenous debt limit $\underline{b}$. So at each decision node, encoded in this policy function is the search decision of the agent if debt limits tighten as well as if debt limits remain slack. 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.[45]

We compute the change in unemployment duration, weighted by the distribution of job

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[43]We calculate the duration and replacement elasticities using 30,000 agents simulated for 270 periods (burning the first 100 periods), while holding the aggregate state fixed at $y = 1$, and defining $\underline{b}_H$=-.1 and $\underline{b}_L$=-.5. Agents hold the same rational beliefs over the transition rate $P_{\underline{b}}$ between $\underline{b}_H$ and $\underline{b}_L$ as Section 7.

[44]Only .03% of the agents in the model will ever borrow at real quarterly rates above 30%. The results are robust to alternate definitions of this effective debt limit.

[45]The intuition is simple and is formally shown in the existence proof. $J_T(h, k; y) = f(y, h, k)$ does not depend on $\underline{b}$, and working back, neither does $J_t(h, k; y)$ for arbitrary t. Therefore, using the free entry condition, $\theta_t(h, k; y)$, which pins down the menu of operating submarkets, will not either.

losers after moving from an exogenous limit $\underline{b} = \underline{b}_L$ to $\underline{b} = \underline{b}_H$ as follows,[46]

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

Define $\frac{\Delta(L_t + b_t)}{Y_{t-1}}$ as the change in the unused credit to income ratio that the agent faces if the exogenous debt limit is tightened.[47] The model implied duration elasticity is therefore given by,

$$\epsilon_{dur} = \frac{\Delta Dur_t}{\left(\frac{\Delta(L_t + b_t)}{Y_{t-1}} \right)} = 0.608$$

In other words, if unused credit to income increased by 10%, then agents would take .72 weeks longer to find a job. This falls in the mid-range of our IV estimates. However, the elasticity calculated in the model is a 'global' elasticity and is conceptually different from the local average treatment effect identified by the IV.

Next, we calculate the elasticity of replacement earnings with respect to credit, including households who do not find a job and thus have a replacement rate of zero. Let $e_i \in \{W, U\}$ denote employment status and $\mathbb{I}$ be the indicator function. Then define $R_t(\underline{b})$ as the earnings replacement rate, $R_t(\underline{b}) = \frac{1}{N_\delta} \sum_{i \in I_\delta} \frac{\mathbb{I}(e_i=W)*4\alpha f(y_t, h_{i,t}, k^*(b_{i,t}, h_{i,t}, k_{i,t}; y_t, \underline{b})) + 0*(\mathbb{I}(e_i=U))}{4\alpha f(y_{i,t-1}, h_{i,t-1}, k_{i,t-1})}$ The model implied replacement earnings elasticity is therefore given by,

$$\epsilon_{Rep} = \frac{R_t(\underline{b}_H) - R_t(\underline{b}_L)}{\left(\frac{\Delta(L+b)}{Y_{t-1}} \right)} = -.024$$

Similar to data replacement rate (inclusive of 0s) in Table 5, the model replacement rate (inclusive of 0s) produces a small, slightly negative, earnings replacement rate elasticity of -.024. To understand why this is the case, we can decompose earnings losses into two offsetting components: (i) access to additional credit depresses job finding rates which tends to lower replacement earnings, and (ii) access to additional credit increases the capital intensity of submarkets searched by agents which tends to raise replacement earnings. We can compute each of these components separately. Define the job finding rate for agents as $JF_t(\underline{b}) =$

---

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

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

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

$$\epsilon_{JF} = \frac{JF_t(\underline{b}_H) - JF_t(\underline{b}_L)}{\left(\frac{\Delta(L+b)}{Y_{t-1}}\right)} = -0.11$$

This implies that when debt limits expand by 10% of prior annual income, job finding rates fall by 1.1% as workers can better self-insure while searching more thoroughly for jobs. This tends to decrease the replacement earnings of agents, since unemployed workers have an earnings replacement rate of zero.

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

$$\epsilon_K = \frac{K_t(\underline{b}_H) - K_t(\underline{b}_L)}{\left(\frac{\Delta(L+b)}{Y_{t-1}}\right)} = .27$$

In other words, being able to replace 10% more of prior income with credit allows agents in the model to search in submarkets with 2.7% greater intellectual or physical capital intensity. This 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 near-zero replacement earnings elasticity observed in the model.

Next, we calculate the elasticity of replacement earnings with respect to credit among job finders. By isolating job finders, we implicitly drop zeros from the replacement rate calculation. Let $I_e(\underline{b})$ denote the set of job finders at the end of period t. Let $N_{\delta,e}$ denote the cardinality of $I_\delta \cap I_e(\underline{b})$, which is the set of laid off households who find a job at the end of period t. Define replacement earnings among this set of households as $R_{t,e}(\underline{b}) = \frac{1}{N_{\delta,e}} \sum_{i \in I_\delta \cap I_e(\underline{b}_L)} \frac{4\alpha f(y_t, h_{i,t}, k^*(b_{i,t}, h_{i,t}, k_{i,t}; y_t, \underline{b}))}{4\alpha f(y_{i,t-1}, h_{i,t-1}, k_{i,t-1})}$. Lastly, define $\frac{\Delta(L_{t,e}+b_{t,e})}{Y_{t-1,e}}$ to be the change in credit limits to income of those who find a job at the end of period t under borrowing limit $\underline{b}_L$.[48] The model implied replacement earnings elasticity, among the employed, is therefore given

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

by,

$$\epsilon_{Rep,e} = \frac{R_{t,e}(\underline{b}_H) - R_{t,e}(\underline{b}_L)}{\left(\frac{\Delta(L_{t,e}+b_{t,e})}{Y_{t-1,e}}\right)} = .18$$

This implies that in the model, among job finders, being able to replace 10% more of prior income with credit results in a 1.8% greater earnings replacement rate, which falls toward the high end of our IV estimates. In summary, the model's self-insurance mechanism generates replacement rate elasticities (both inclusive and exclusive of 0s) as well as duration elasticities that are in line with our IV estimates.

G.1 Bankruptcy Flag Removal in Model v. Data

We further explore non-targeted moments in this section by comparing the response of duration and replacement rates to bankruptcy flag removal. We do so by isolating the set of newly laid off agents with prior bankruptcies in the model (i.e. agents in bad standing), I_b. Each of these agents' policy function includes their optimal search decision if their flag is removed and their optimal search decision if the flag is not removed (i.e. they remain in bad standing). Let $Dur_{no\ bk}$ denote the duration of agents if their flag is removed (where duration is computed based on their search decisions as in Section F), and let Dur_{bk} denote the duration of agents if their flag remains on their record. We then compute $\Delta Dur = Dur_{no\ bk} - Dur_{bk} = .066$, which implies that following bankruptcy flag removal, agents take about $\frac{3}{4}$ of a week longer to find, relative to the counterfactual of not having their flag removed. In Section 4 we showed that following flag removal, individuals in the data take 2 weeks longer to find a job relative to the control group of those whose flags are not removed.

If we do the same for replacement earnings, $\Delta Rep = Rep_{no\ bk} - Rep_{bk} = .007$. In Section 4 we showed that following flag removal, there is an insignificant impact on replacement earnings relative to the control group of those whose flags are not removed. We find a relatively small impact on replacement earnings in the model, implying a .7% increase in replacement earnings following flag removal. We cannot rule this effect out based on our empirical point estimates.

H   Welfare

To compute the welfare implications of tighter debt limits (and the subsequent greater amounts of sorting), we measure what fraction of lifetime consumption a newly born agent would be willing to give up in order to live in a world with looser debt limits ($\underline{b} = -.5$) as opposed to living in a world with debt limits which are initially loose and then tighten in 2008 to $\underline{b} = -.1$. Let c_t, e_t, and D_t denote consumption, employment, and default decisions when the debt limit is loose from 1970 to 2012. Let c_t^b, e_t^b, and D_t^b denote consumption, employment, and default decisions when the debt limit is loose until 2008, after which it permanently tightens to $\underline{b} = -.1$. We compute the welfare gain as follows:

$$
\Delta_W = \left[\frac{\sum_{t=0}^{\infty} \beta^t \left[\frac{(c_t^b)^{1-\sigma}}{1-\sigma} + \eta \mathbb{I}(e_t^b = U) - \chi D_t^b \right] - \sum_{t=0}^{\infty} \beta^t [\eta \mathbb{I}(e_t = U) - \chi D_t]}{\sum_{t=0}^{\infty} \beta^t \left[\frac{(c_t)^{1-\sigma}}{1-\sigma} \right]} \right]^{1/(1-\sigma)} - 1
$$

For the cohort of agents 'born' (i.e. enter the workforce) between 1989 and 1994 and are of prime age during the crisis, we compute that this cohort of agents would be willing to give up .09% of lifetime consumption

I   Alternate Measures of Sorting and Mismatch

In this appendix we describe three measures of 'sorting', broadly defined. The first comes from Lise and Robin [2013], which is to measure the distance from the optimal surplus maximizing match. Let $S_t^a(b, h, k; \Omega) = W_t^a(b, h, k; \Omega) + J_t(h, k; \Omega) - U_t^a(b, h, k; \Omega)$ denote surplus of worker h matched to firm k. Since the cost of capital is paid up-front, the surplus maximizing capital (in any match) is $\bar{k}$ (the upper bound on capital). The distance from the surplus maximizing match is therefore proportional to $D = \int_k \frac{\bar{k}-k}{\bar{k}} \mu_e(k) dk$ where $\mu_e(k)$ is the marginal distribution of employed workers across capital levels. We also compute measures of productivity dispersion including the coefficient of variation of capital per worker, $CV_k = \frac{\int_k k^2 \mu_k dk - (\int_k k \mu_e(k)) dk)^2}{\int_k k \mu_e(k) dk}$, and the coefficient of variation of labor productivity $CV_l = \frac{\int_k \int_h (h^a k^{a-1})^2 \mu_e(k,h) \ dh \ dk - (\int_k \int_h h^a k^{a-1} \mu_e(k,h) \ dh \ dk)^2}{\int_k \int_h h^a k^{a-1} \mu_e(k,h) \ dh \ dk}$ where $\mu_e(k, h)$ is the joint pdf of employed individuals over capital and human capital. Figures 13 and 14 illustrate the sorting measures in the economy in which credit limits are constant during the recession and an economy in which credit limits tighten. There are two key points to take away from the figures, 1.

these measures of mismatch and productivity dispersion are countercyclical, similar to Lise and Robin [2013] (who also include both measures – surplus maximizing distance and labor productivity dispersion), and 2. these measure deteriorate even more when credit limits tighten, i.e. there truly is more mistmatch when limits tighten.

Figure 13: Recession Experiment: Alternate Measure of Sorting, Loose Limits $\underline{b} = -.5$
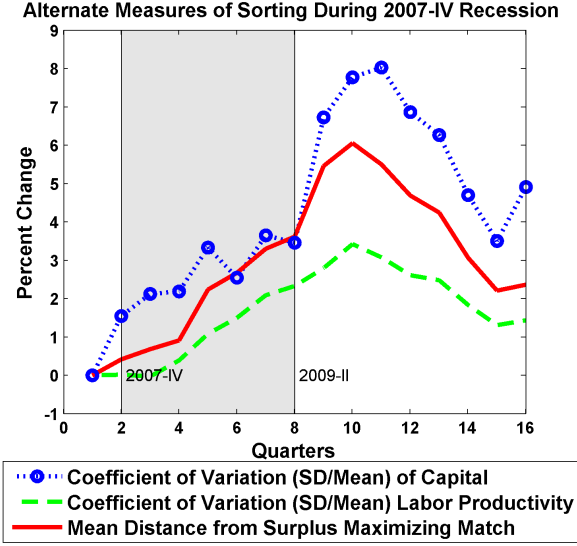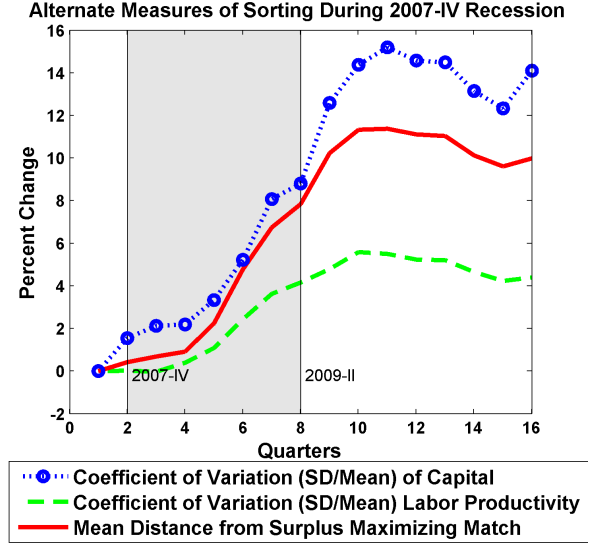
Figure 14: Recession Experiment: Alternate Measure of Sorting, Tight Limits $\underline{b} = -.1$ (Source: LEHD/TransUnion)

J Model Robustness: Capital Investment and Liquidation

J.1 Model with Firm Investment

Now assume that Firms can invest in capital, depending on the worker's type. The problem of an unemployed household is unchanged. The value functions for employed borrowers who default as well as the discrete default decision are formulated in an identical fashion to that of the unemployed, except workers must now forecast the investment decision of the firm.

Timing assumption: New capital is not operable immediately.

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

$$W_t^B(b, h, k; \Omega) = u(c, 0) + \lambda \beta \mathbb{E}\Big[(1-\delta)W_{t+1}(0, h', \mathbf{k'}; \Omega')$$

$$+ \delta\Big\{ \max_{\tilde{k}} p(\theta_{t+1}(h', \tilde{k}; \Omega'))W_{t+1}(0, h', \tilde{k}; \Omega')$$

$$+ \big(1 - p(\theta_{t+1}(h', \tilde{k}; \Omega'))\big)U_{t+1}(0, h', \mathbf{k}; \Omega')\Big\}\Big]$$

$$+ (1-\lambda)\beta\mathbb{E}\Big[(1-\delta)W_{t+1}^B(0, h', \mathbf{k'}; \Omega')$$

$$+ \delta\Big\{ \max_{\tilde{k}} p(\theta_{t+1}(h', \tilde{k}; \Omega'))W_{t+1}^B(0, h', \tilde{k}; \Omega')$$

$$+ \big(1 - p(\theta_{t+1}(h', \tilde{k}; \Omega'))\big)U_{t+1}^B(0, h', \mathbf{k}; \Omega')\Big\}\Big], \quad t \leq T$$

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

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,

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

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

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

J.2 Lenders

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

J.3 Entrepreneurs

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

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

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

$$i = k' - k$$

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

In the results below, we choose a quadratic adjustment cost $\Gamma(x) = x^2$. We see that the presence of firm investment does not significantly alter the main set of results. Figure 15 illustrates employment with the quadratic adjustment cost, Figure 16 illustrates sorting (the correlation between human capital and capital), Figure 17 illustrates firm capital, and Figure 18 illustrates labor productivity. Figure 17 shows that firm capital recovers much faster as firms invest in more capital per worker as productivity recovers and human capital grows.

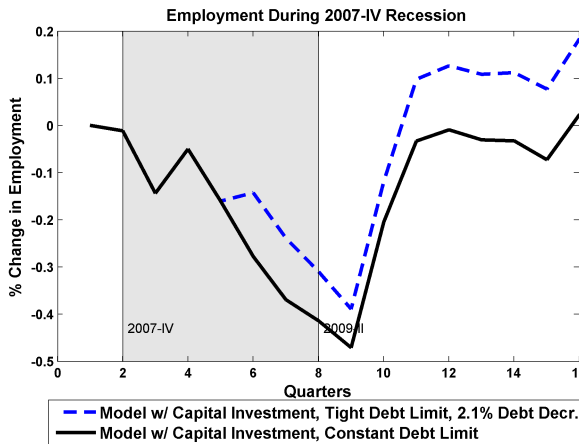Figure 15: Allowing for Capital Investment: Employment

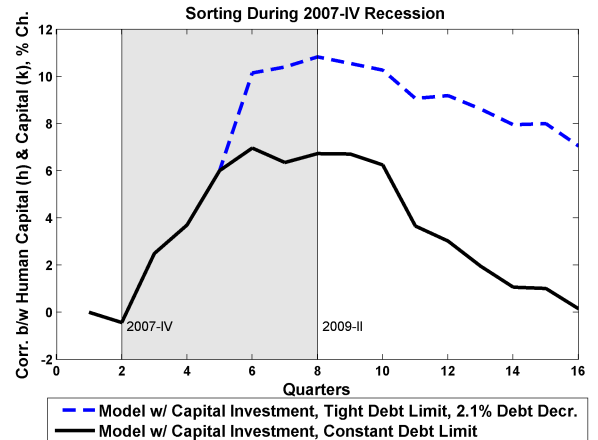Figure 16: Allowing for Capital Investment: Corr. B/w Human Capital (h) and Firm Capital (k)

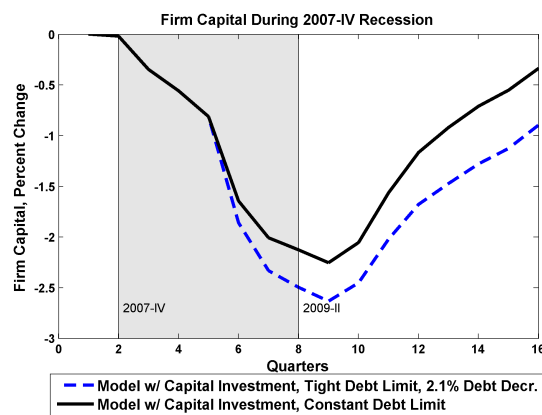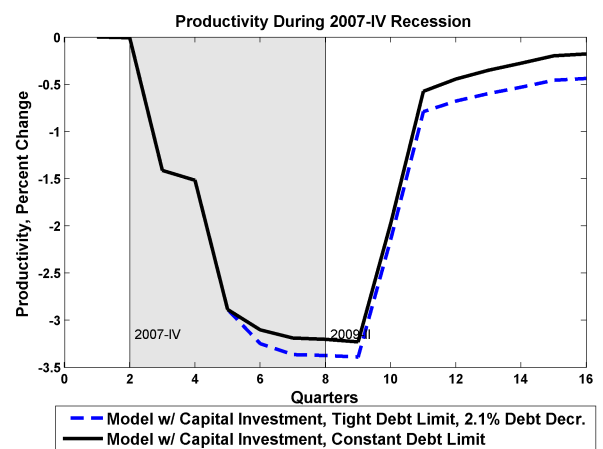Figure 17: Allowing for Capital Investment: Agg. Firm Capital, 2007-2009 Recession

Figure 18: Allowing for Capital Investment: Labor Productivity, 2007-2009 Recession

Firm Capital During 2007-IV Recession

Model w/ Capital Investment, Tight Debt Limit, 2.1% Debt Decr.
Model w/ Capital Investment, Constant Debt Limit

Productivity During 2007-IV Recession

Model w/ Capital Investment, Tight Debt Limit, 2.1% Debt Decr.
Model w/ Capital Investment, Constant Debt Limit

J.4   Liquidation

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

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

In the results below, we choose $\chi_f = .25$ which is relatively low, but it allows us to preserve the calibration, approximately. For larger values of χ_f, the same aggregate patterns emerge, except we must significantly expand the capital grid to a point that it becomes computationally infeasible. Figures 19 and 20 illustrate the model's main results with liquidation values. Employment rises while productivity falls in both cases, which is the same pattern that emerged when tighter debt limits were imposed in an economy with no liquidation value.

Figure 19:   Liquidation Value Experiment: Employment, 2007-2009 Recession

Figure 20:   Liquidation Value Experiment: Labor Productivity, 2007-2009 Recession
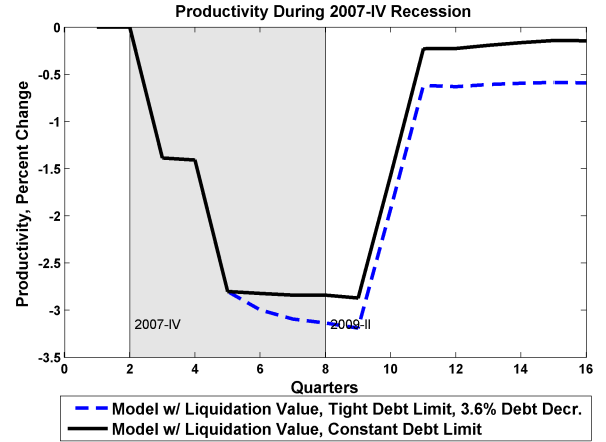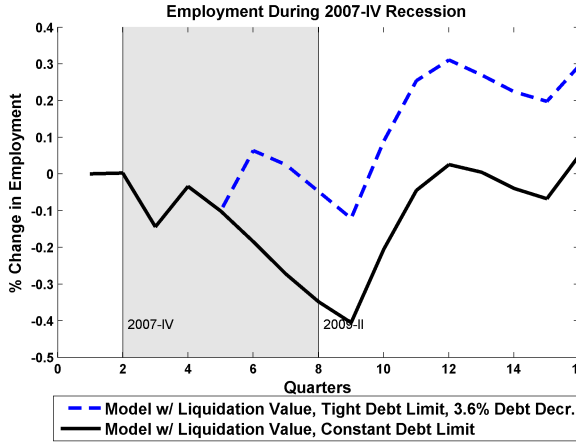
K Solution Algorithm

We solve the model using value function iteration on a discrete grid. Capital lies between [0.025,1] with 40 evenly spaced grid points including the ends of the grid. Bonds lie on the grid [-.5,1.5] with 81 evenly spaced grid points. The human capital grid is 6 evenly spaced grid points including the end of the grid over [.5,1]. The aggregate shock is discretized with 4 states using Rouwenhorst's method. The aggregate bond limit is discretized with 2 possible values $\underline{b} \in \{-.5, -.1\}$.

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. Fix the aggregate shock path for all simulations (in the main experiment we feed in actual TFP realizations approximated on the grid). Use policy functions from the household problem to simulate 30,000 households for 270 periods, 10 times, burning the first 100 periods. We report averages over the 10 simulations.