The Impact of Consumer Credit Access on Unemployment: Extensions and Data

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1 Introduction

This online appendix includes data on credit use among the unemployed, robustness checks, and the full set of equations for the extensions in the main paper (Herkenhoff [2013]).

I establish a few stylized facts: (i) 34% of unemployed households used their credit cards in 2007 as opposed to 17% in 1989, (ii) of those unemployed using their cards, on average they had charges equal to 25% of their average prior monthly income in 2007, (iii) 53% were carrying a credit balance in 2007 (which actually declined relative to 1989), and (iv) 16% did not have enough liquid assets to pay off that balance, (iv) 27% of unemployed households are carrying balances from month to month in 2007 as opposed to 18% in 1989, (v) those monthly balances doubled to 201% of monthly income from 1989 to 2007, (vi) of those unemployed households carrying balances in 2007, 61% did not have enough liquid assets to pay off that balance. In total, 16% (= .27*.61) of the unemployed have liquid assets less than their monthly balance. To proxy total liquid resources available to households, I also establish two more facts from the SCF: (i) the mean ratio of the unused credit limit to annual gross income grew from 12% in 1989 to 34% in 2007, and (ii) the mean ratio of liquid assets plus unused credit to income also grew from 79% in 1989 to 93% in 2007.

To gauge the importance of default to unemployed households, I provide a formal analysis of default triggers using the 2007-2009 SCF and tabulating the DTI ratios of defaulters. I find that unemployment is the strongest predictor of default while divorce, medical payments, and other triggers are weaker predictors of default. I also find that the debt to income ratios of defaulters exceed 200%.

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I include robustness checks regarding the timing of the shocks in the paper. I show that credit expansions which occur at any point during the recession or during the recovery yield the same general results as the main paper.

Lastly, I provide the full set of equations associated with the long-lived credit relationship model and the on-the-job-search model. Workers are not immediately allowed to search after job loss in the equations below, purely for notational reasons. Likewise, the flow utility of leisure is suppressed. In the code used to generate the results in the paper, both features are present.

2 Data Appendix

2.1 Unemployed Households & Credit Use Over Time

Table 1 includes detailed data on the time series for credit card use presented in Herkenhoff [2013]. Specifically, the time series concern bankcards such as Visa, Mastercard, and American Express which represent the vast majority of credit cards (Evans and Schmalensee [2005]). The sample is restricted to heads of household who are labor force participants; there are no age restrictions. The Survey of Consumer Credit did not provide weights in 1970 and 1977.

2.2 Charges, Balances, and Limits of the Unemployed

Primary causal evidence that the unemployed borrow to replace income is provided by Sullivan [2008] and Hurd and Rohwedder [2010]. Using an indirect approach, Sullivan [2008] finds that unemployed households with low assets increase unsecured debt by 11-18 cents per dollar of lost income (this effect holds in both the Panel Study of Income Dynamics and Survey of Income and Program Participation). Using a more direct approach, Hurd and Rohwedder [2010] find that 18% of unemployed households self-report using unsecured credit to replace lost income. Their study is based on the 2009 RAND American Life Panel.

To provide a snapshot of credit use among wealthy households, Table 2 shows the monthly bankcard charges (new credit card charges as of the survey date), balances (current balance less most recent payments as of the survey date), and limits (aggregate limit across all cards as of the survey date) by heads of households in the 1989 and 2007 Survey of Consumer Finances.\(^1\) Table 2 yields a few stylized facts: (i) 34% of unemployed households used their

\(^1\)An important note is that ‘charges’ refers to the new amount charged to the credit card on the most recent bill as of the SCF survey date. This is not the same as the increase in the balance of the credit card which is unobserved. 1989 was the first year in which charge data, default data, and credit limit was collected.
Table 1: Time Series Data from Herkenhoff [2013]

<table>
<thead>
<tr>
<th></th>
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</thead>
<tbody>
<tr>
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<td>0.13 0.13 111</td>
<td>0.18 0.18 3434</td>
</tr>
<tr>
<td>1977</td>
<td>0.13 0.13 78</td>
<td>0.38 0.38 2563</td>
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<td>0.20 0.20 276</td>
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<td>1992</td>
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<td>0.32 0.38 176</td>
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<tr>
<td>2009p</td>
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<td>0.74 0.81 3857</td>
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<tr>
<td>2010</td>
<td>0.45 0.44 416</td>
<td>0.65 0.68 6482</td>
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<td>0.12 0.12 276</td>
<td>0.21 0.20 4262</td>
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<td>1992</td>
<td>0.25 0.23 177</td>
<td>0.33 0.27 3906</td>
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<td>1995</td>
<td>0.25 0.26 176</td>
<td>0.37 0.31 4299</td>
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<td>1998</td>
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<td>2004</td>
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<td>0.27 0.28 128</td>
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<td>0.46 0.38 3857</td>
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<td>2009p</td>
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<td>0.33 0.31 416</td>
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<td>330 330 402</td>
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<tr>
<td>1983</td>
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<td>786 810 839</td>
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<td>1989</td>
<td>1282 1136 18</td>
<td>1822 2020 794</td>
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<td>1992</td>
<td>2811 2481 41</td>
<td>2199 2493 1070</td>
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<td>1995</td>
<td>3913 4419 45</td>
<td>2972 3389 1338</td>
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<td>1998</td>
<td>5656 5958 39</td>
<td>4081 4806 1316</td>
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<td>2001</td>
<td>6031 7386 32</td>
<td>3897 4577 1433</td>
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<td>2007</td>
<td>6419 7242 36</td>
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<td>2007p</td>
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<td>7347 8707 1463</td>
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<td>8417 10923 1221</td>
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<td>6250 6451 128</td>
<td>6957 7787 1934</td>
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<td>1970</td>
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<td>0.23 0.23 224</td>
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<td>1977</td>
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<td>0.55 0.51 32</td>
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<td>1.27 1.29 1308</td>
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<td>2.23 2.23 32</td>
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<td>2004</td>
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<td>2009p</td>
<td>1.90 1.93 78</td>
<td>1.60 1.66 1204</td>
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<tr>
<td>2010</td>
<td>1.89 1.91 127</td>
<td>1.38 1.37 1919</td>
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</table>
credit cards in 2007 as opposed to 17% in 1989, (ii) of those unemployed using their cards, on average they had charges equal to 25% of their average prior monthly income in 2007, (iii) 53% were carrying a credit balance in 2007 (which actually declined relative to 1989), and (iv) 16% did not have enough liquid assets to pay off that balance.

Table 2: Credit Card Charges, Credit Card Balances, and Credit Card Limits

<table>
<thead>
<tr>
<th></th>
<th>Mean 1989</th>
<th>Mean 2007</th>
<th>Obs. 1989</th>
<th>Obs. 2007</th>
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<tr>
<td>Charges</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fraction of All Households with Positive Charges Last Month</td>
<td>0.40</td>
<td>0.53</td>
<td>3143</td>
<td>4417</td>
</tr>
<tr>
<td>Fraction of Unemployed Households with Positive Charges Last Month</td>
<td>0.17</td>
<td>0.34</td>
<td>105</td>
<td>128</td>
</tr>
<tr>
<td>Last Month’s Charges for Unemployed Households with Charges&gt;0 (Nominal)</td>
<td>231</td>
<td>840</td>
<td>20</td>
<td>44</td>
</tr>
<tr>
<td>Last Month’s Charges to Monthly Income for Unemployed Households with Charges&gt;0</td>
<td>0.19</td>
<td>0.25</td>
<td>20</td>
<td>44</td>
</tr>
<tr>
<td>Fraction of Unemployed Households Carrying Positive Balance with Charges&gt;0</td>
<td>0.78</td>
<td>0.53</td>
<td>20</td>
<td>44</td>
</tr>
<tr>
<td>Balance to Monthly Income for Unemployed Households with Charges&gt;0</td>
<td>0.99</td>
<td>1.18</td>
<td>20</td>
<td>44</td>
</tr>
<tr>
<td>Fraction of Unemployed Households with Less Liquid Assets Than Last Month’s Charges</td>
<td>0.04</td>
<td>0.16</td>
<td>20</td>
<td>44</td>
</tr>
<tr>
<td>Balances</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fraction of All Households Carrying Positive Balance</td>
<td>0.29</td>
<td>0.41</td>
<td>3143</td>
<td>4417</td>
</tr>
<tr>
<td>Fraction of Unemployed Households Carrying Positive Balance</td>
<td>0.18</td>
<td>0.27</td>
<td>105</td>
<td>128</td>
</tr>
<tr>
<td>Avg. Balance for Unemployed Households with Balance&gt;0 (Nominal)</td>
<td>1262</td>
<td>6419</td>
<td>18</td>
<td>36</td>
</tr>
<tr>
<td>Avg. Balance to Monthly Income for Unemployed Households with Balance&gt;0</td>
<td>1.92</td>
<td>2.01</td>
<td>18</td>
<td>36</td>
</tr>
<tr>
<td>Fraction of Unemployed Households with Less Liquid Assets Than Monthly Balance</td>
<td>0.43</td>
<td>0.61</td>
<td>18</td>
<td>36</td>
</tr>
<tr>
<td>Credit Limit</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Credit Limit to Annual Income, All Bankcard Holders</td>
<td>0.16</td>
<td>0.40</td>
<td>2107</td>
<td>3417</td>
</tr>
<tr>
<td>Credit Limit to Annual Income, Unemployed Bankcard Holders</td>
<td>0.18</td>
<td>0.41</td>
<td>30</td>
<td>58</td>
</tr>
<tr>
<td>Unused Credit Limit, Unemployed Bankcard Holders (Nominal)</td>
<td>2626</td>
<td>21593</td>
<td>30</td>
<td>58</td>
</tr>
<tr>
<td>Unused Credit Limit to Annual Income, Unemployed Bankcard Holders</td>
<td>0.12</td>
<td>0.34</td>
<td>30</td>
<td>58</td>
</tr>
<tr>
<td>Maximum Available Liquid Assets</td>
<td>0.79</td>
<td>0.93</td>
<td>3143</td>
<td>4417</td>
</tr>
</tbody>
</table>

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

Table 2 also shows that (i) 27% of unemployed households are carrying balances from month to month in 2007 as opposed to 18% in 1989, (ii) those monthly balances doubled to 201% of monthly income from 1989 to 2007, and (iii) of those unemployed households carrying balances in 2007, 61% did not have enough liquid assets to pay off that balance. In total, 16% (= .27*.61) of the unemployed have liquid assets less than their monthly balance.

To measure potential self-insurance opportunities, Table 2 also measures credit limits. Unemployed households have an unused credit limit to annual income ratio of 34%, meaning that they could charge 34% of their annual income to their credit cards before having to pay overage fees. Even though the mean liquid asset to income ratio has declined considerably

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2Credit limits are not strict. Herkenhoff [2012b] provides estimates of the fraction of households over their credit limit using Equifax data.
from .67 in 1989 to .59 in 2007, the maximum available amount of liquid assets increased (i.e. the sum of liquid assets plus unused credit limits increased). The ratio of unused credit limits plus liquid assets to income went from an average of 79% in 1989 to 93% in 2007.\(^3\)

### 2.3 Default (Not Bankruptcy) as Unemployment Insurance

Default, which I define to be 60+ days late on a required loan payment, occurs 6× more often than bankruptcy and is used for consumption smoothing in response to high frequency income shocks such as unemployment whereas bankruptcy is a low frequency event.\(^4\) Using surveys to directly measure this mechanism, Hurd and Rohwedder [2010] find that at least 36% of households self-report at least some degree of default in response to job loss. While Hurd and Rohwedder [2010] do not report debt to monthly income ratios, Table 3 shows that in the SCF, defaulting households have debt to monthly income ratios in excess of 200%, and 23% of non-mortgagors who were out of a job over the last 12 months defaulted on at least one of their obligated loan payments during that same time period.\(^5\) I provide a formal analysis of default triggers using the 2007-2009 SCF and I find that unemployment is the strongest predictor of default while divorce, medical payments, and other triggers are weaker predictors of default. However, the main point of this paper is that default is an insurance mechanism that leads to longer unemployment spells making any such regression analysis subject to endogeneity.

<table>
<thead>
<tr>
<th>Table 3: Basic Default Tabulations, 2009 SCF</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Percent of Employed Non-Mortgagors who Defaulted in Last 12mo.</strong></td>
</tr>
<tr>
<td>---------------------------------------------</td>
</tr>
<tr>
<td>8.40%</td>
</tr>
<tr>
<td><strong>Percent of Non-Mortgagors with Positive Duration Unemployment Spell in Last 12mo. who Defaulted in Last 12mo.</strong></td>
</tr>
<tr>
<td>Balance to Avg. Monthly Income Ratio of Non-Mortgagors with Positive Duration Unemployment Spell in Last 12mo. who Defaulted in Last 12mo.</td>
</tr>
<tr>
<td>---------------------------------------------</td>
</tr>
<tr>
<td>2.10</td>
</tr>
</tbody>
</table>


\(^3\)Let \(L\) be liquid assets, \(I\) be annual income, \(U\) be unused credit, then this ratio is constructed as \(\frac{L+U}{I}\).

\(^4\)See Herkenhoff [2012b] for more on default triggers. See Livshits et al. [2007] for more on bankruptcy triggers.

\(^5\)The SCF does not report the minimum payment which is necessary for a better understanding of the consumption smoothing benefits of default from unsecured credit. The focus is on non-mortgagors in order to measure the consumption smoothing role of default; this is in contrast to mortgage defaults which, in some cases, can be attributed to price changes alone. However, Herkenhoff [2012a] and Gerardi et al. [2013] use precisely timed PSID data to show that mortgagors default primarily in response to job loss and most of these defaults are for consumption smoothing rather than strategic purposes.
2.4 Default Trigger Analysis

This use of default by unemployed households is relatively unexplored in the literature due to data limitations. To conduct the analysis, I again use the 2007-2009 Survey of Consumer Finances (SCF) panel. The panel aspect allows me to control for changes in medical bills, divorce shocks, and other factors related to default (these are the trigger events usually emphasized in the bankruptcy literature, see Livshits et al. [2007] and Chatterjee et al. [2007]).

In the analysis below, I restrict the sample to working age heads of household who are labor force participants, have at least one unsecured loan, and are non-mortgagors. Overall, there are 710 observations in the restricted sample, 13% of which have defaulted over the prior 12 months. It is important to note that default, defined to be 60+ days late on any obligated loan payment, is measured over the prior 12 months. The actual date of default is unknown. Likewise, unemployment spells are measured over the prior 12 months and aggregated together. Therefore, the timing and length of any single unemployment spell is unknown. Since there is no direct measurement of medical expenditures in the SCF, I proxy medical bills with other unsecured debt payments which includes medical loan payments.

Table 4 illustrates the unemployment and default results. In each specification the dependent variable is a 60+ days late default indicator over the last 12 months. Columns (1) and (3) show that unemployed non-mortgagors are between 8% and 15% more likely than employed non-mortgagors to report a default over the prior 12 months. A causal interpretation of these estimates is tenuous since the survey suffers from time aggregation bias, and the main point of this paper is that the unemployment regressor is endogenous: default can protract unemployment spells via the self-insurance it provides the unemployed and, more obviously, unemployment is a default trigger. Moreover, selection into the status of being a non-mortgagor and unobserved heterogeneity also pose problems to the causal interpretation of these results. I will turn to a structural model below to avoid such problems.

2.5 Liquid Assets to Income

Table 5 includes data on liquid assets to income among all households. The definitions use to construct the series are given below:

- Net Liquid Assets: Checking Accounts + Saving Accounts + Money Market Accounts + CDs + Government Savings Bonds/Bills/Corporate/Muni/Other Bonds + Stock + Mutual Funds - Bankcard Debt

- Income: Gross Total Family Income (Includes wages and salaries as well as business income)

6See Gerardi et al. [2013] for more on the role of unemployment in default using precisely timed questions in the PSID.
Table 4: Dependent Variable is 60+ Days Late Default Indicator over Last 12 Months, Logit (Average Marginal Effects)

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
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<tbody>
<tr>
<td>Unemployed Over Last 12 mo. (d)</td>
<td>0.154***</td>
<td>0.0924***</td>
<td>0.0825***</td>
</tr>
<tr>
<td></td>
<td>(0.0359)</td>
<td>(0.0309)</td>
<td>(0.0287)</td>
</tr>
<tr>
<td>Change in Income 2007 to 2009</td>
<td></td>
<td></td>
<td>0.0399</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.0524)</td>
</tr>
<tr>
<td>Change in Other Loan Payments 2007 to 2009 (Incl. Medical Loans)</td>
<td></td>
<td>-0.0452</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.0360)</td>
</tr>
<tr>
<td>Divorce (d)</td>
<td></td>
<td>-0.0938***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0353)</td>
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<td>Balance Sheet Controls</td>
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<td>Demographics</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
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<td>710</td>
<td>710</td>
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<tr>
<td>Pseudo R2</td>
<td>0.0439</td>
<td>0.0927</td>
<td>0.131</td>
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</table>

Notes. Robust t-statistics in parentheses. Asterisk legend: *** p<0.01, ** p<0.05, * p<0.1. SCF working age heads who are labor force participants with at least 1 required credit payment over the last 12 mo. Demographic controls include, age, race, sex, marital status, education. Balance sheet controls include liquid assets to income, illiquid assets to income, and credit card debt to income. Average marginal effects reported in columns (1)-(3). Observations are unweighted.

Table 5: Net Liquid Asset to Income Distribution, SCF

<table>
<thead>
<tr>
<th>Variable</th>
<th>p10</th>
<th>p25</th>
<th>p50</th>
<th>p75</th>
<th>p90</th>
<th>Obs.</th>
</tr>
</thead>
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<td>1970</td>
<td>0</td>
<td>0.0375</td>
<td>0.260019</td>
<td>1.831551</td>
<td>26.36062</td>
<td>3401</td>
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<td>1977</td>
<td>0</td>
<td>0.022727</td>
<td>0.133333</td>
<td>0.829286</td>
<td>4.25</td>
<td>2312</td>
</tr>
<tr>
<td>1983</td>
<td>0</td>
<td>0.011737</td>
<td>0.08904</td>
<td>0.43586</td>
<td>1.538462</td>
<td>3665</td>
</tr>
<tr>
<td>1989</td>
<td>0</td>
<td>0.003488</td>
<td>0.083333</td>
<td>0.445652</td>
<td>2.3143</td>
<td></td>
</tr>
<tr>
<td>1992</td>
<td>-0.01271</td>
<td>0.002</td>
<td>0.079231</td>
<td>0.508333</td>
<td>1.867677</td>
<td>3906</td>
</tr>
<tr>
<td>1995</td>
<td>-0.03158</td>
<td>0</td>
<td>0.0608</td>
<td>0.43</td>
<td>1.691429</td>
<td>4299</td>
</tr>
<tr>
<td>1998</td>
<td>-0.027</td>
<td>0.004167</td>
<td>0.098246</td>
<td>0.666667</td>
<td>2.554622</td>
<td>4305</td>
</tr>
<tr>
<td>2001</td>
<td>-0.02636</td>
<td>0.005556</td>
<td>0.102564</td>
<td>0.6825</td>
<td>2.698473</td>
<td>4442</td>
</tr>
<tr>
<td>2004</td>
<td>-0.06533</td>
<td>0</td>
<td>0.045556</td>
<td>0.335</td>
<td>1.75</td>
<td>4519</td>
</tr>
<tr>
<td>2007</td>
<td>-0.07414</td>
<td>0</td>
<td>0.041667</td>
<td>0.29375</td>
<td>1.59996</td>
<td>4417</td>
</tr>
<tr>
<td>2010</td>
<td>-0.0648</td>
<td>0</td>
<td>0.030784</td>
<td>0.209677</td>
<td>1.411111</td>
<td>6482</td>
</tr>
</tbody>
</table>

### 2.6 Credit Card Transition Rates

The table below shows the quarterly transition rates among Equifax primary sample members over the number of accounts open (in aggregate and also specifically among credit holders). The gross transitions into and out of credit card ownership suggest there are large amounts of turnover in credit card ownership.

<table>
<thead>
<tr>
<th>Number of Open Credit Lines</th>
<th>Next Quarter</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>0</td>
<td>91.94</td>
</tr>
<tr>
<td>1</td>
<td>6.03</td>
</tr>
<tr>
<td>2</td>
<td>0.79</td>
</tr>
<tr>
<td>3</td>
<td>0.22</td>
</tr>
<tr>
<td>4</td>
<td>0.07</td>
</tr>
<tr>
<td>5</td>
<td>0.05</td>
</tr>
<tr>
<td>6</td>
<td>0.01</td>
</tr>
<tr>
<td>7</td>
<td>0.01</td>
</tr>
<tr>
<td>8</td>
<td>0.01</td>
</tr>
<tr>
<td>9</td>
<td>0.01</td>
</tr>
<tr>
<td>10</td>
<td>0</td>
</tr>
<tr>
<td>11</td>
<td>0</td>
</tr>
<tr>
<td>12</td>
<td>0.5</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Number of Open Bankcards</th>
<th>Next Quarter</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>0</td>
<td>93.49</td>
</tr>
<tr>
<td>1</td>
<td>4.82</td>
</tr>
<tr>
<td>2</td>
<td>0.73</td>
</tr>
<tr>
<td>3</td>
<td>0.2</td>
</tr>
<tr>
<td>4</td>
<td>0.1</td>
</tr>
<tr>
<td>5</td>
<td>0.06</td>
</tr>
<tr>
<td>6</td>
<td>0.04</td>
</tr>
<tr>
<td>7</td>
<td>0.03</td>
</tr>
<tr>
<td>8</td>
<td>0.03</td>
</tr>
<tr>
<td>9</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>0</td>
</tr>
<tr>
<td>11</td>
<td>0</td>
</tr>
<tr>
<td>12</td>
<td>0.43</td>
</tr>
</tbody>
</table>

The weighted average probability of losing a credit line is 10.37% based on the table above which implies an average credit relation of roughly 2.4 years.

---

7This data is taken from [Herkenhoff [2012b]].
3 Saving Composition: Flow of Funds

Does the decline in liquid asset holdings actually matter for the aggregate? Table 7 shows that roughly 34% of household assets are liquid as of 2007. Liquid assets are a significant fraction of the household balance sheet and thus contribute significantly to capital formation in the United States.

Table 7: Flow of Funds Analysis

<table>
<thead>
<tr>
<th>Account</th>
<th>As of 2007 (in 2007 Dollars)</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Assets</td>
<td>81,115</td>
<td>All Household/Non-Profit Assets</td>
</tr>
<tr>
<td>Non-Financial Assets</td>
<td>28,217</td>
<td>Real-Estate, Software, and Equipment</td>
</tr>
<tr>
<td>Real Estate</td>
<td>23,487</td>
<td></td>
</tr>
<tr>
<td>Deposits</td>
<td>52,898</td>
<td></td>
</tr>
<tr>
<td>Credit Market Instruments</td>
<td>4,865</td>
<td>Foreign deposits, Checkable deposits and currency, Time and savings deposits, Money market fund shares</td>
</tr>
<tr>
<td>Corporate Equities</td>
<td>10,448</td>
<td></td>
</tr>
<tr>
<td>Mutual Fund Share</td>
<td>4,869</td>
<td></td>
</tr>
<tr>
<td>Pensions</td>
<td>13,236</td>
<td></td>
</tr>
<tr>
<td>Liquid Asset Ratio (Deposits+Credit Market Instruments+Corporate Equities+Mutual Fund Shares)/Assets</td>
<td>0.34</td>
<td></td>
</tr>
</tbody>
</table>

4 Structural Change in Lending Markets

There have been many structural changes to consumer credit markets over the last 4 decades. In terms of regulations, there were many changes to credit markets that favored consumers and led to a boom in credit: Regulation Z (Truth in Lending,1968) standardized the credit industry to increase transparency on credit terms; the Fair Credit Reporting Act of 1970 entitled consumers to receive free credit reports once a year to dispute information; the Bankruptcy Reform Act of 1978 strengthened Chapter 13 significantly; the Equal Credit Opportunity Act of 1974 banned redlining; and finally, the Fair Credit Billing Act of 1974 was a means for consumers to dispute credit charges.
As Berger et al. [1995] show, banking efficiency changed dramatically over the course of the 1980s. There were roughly 13,000 ATMs in 1979 and 109,000 ATMS by 1994; likewise, the cost of processing an electronic deposit fell by a factor of 8 from .09 cents to .01 cents per transaction. Mester [1997] also explains that prior to credit scoring, small business loans took 3 to 4 weeks to process. After the introduction of credit scoring, small business loans took a few mere hours to process. Credit scoring grew dramatically during the 1980s, culminating in Equifax going public in 1987.

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

5 Extension: Long-Lived Credit Relationships

5.1 Long-Lived Credit Relationships: Households

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

With long term lending relationships, lenders understand that households who are not necessarily borrowing today may borrow in the future. Lenders are forward looking and rationally discount to the present the expected future profits of lending to such a household. Therefore households who are not planning on immediately borrowing may still receive credit offers (i.e. there is an incentive to accumulate and create credit relationships even if there is no immediate borrowing). Just as in a labor market in which a worker matches with a firm and then chooses how many hours to work, in this asset market households match with lenders and then choose how much to borrow. Even in the case that the household does not borrow, the household is still matched with the lender.

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

A household’s state vector consists of the current employment status $e \in \{W, U\} \equiv \mathcal{W}$ (the value function will be denoted $W$ if employed, $U$ if unemployed), credit access status $a \in \{C, N\}$ [this is now a persistent state], the current wage $w \in \mathcal{W} \equiv [\underline{w}, \overline{w}] \subseteq [0, 1]$ if employed or unemployment benefits $z \in \mathcal{Z} \equiv [\gamma w, \gamma \overline{w}] \subseteq [0, 1]$ where $\gamma \in (0, 1)$ if unemployed, net assets $b \in \mathcal{B} \equiv [\underline{b}, \overline{b}] \subseteq \mathbb{R}$, age $t \in \mathbb{N}_T \equiv \{1, \ldots, T\}$, and the aggregate state
\[ \Omega. \]

The aggregate state \( \Omega \) includes three components. The first component is aggregate productivity \( y \in \mathcal{Y} \), the second component is aggregate credit conditions \( A \in \mathcal{A} \), and the third component is an infinite dimensional object \( \mu \) which summarizes the distribution of households across all state variables, i.e. \( \mu : \{ W, U \} \times \{ C, N \} \times W \cup Z \times \mathcal{B} \times N_T \rightarrow [0, 1]. \)

An unemployed \( (U) \) household’s access to credit is determined by their past asset accumulation \( b \), their unemployment benefit income \( z \), their age \( t \), and the aggregate state \( \Omega = (y, A, \mu) \) which includes labor productivity \( y \), aggregate credit conditions \( A \), and the distribution of households across states \( \mu \). Let \( A\psi(\theta_{U,t}^C(z, b; \Omega)) \) be the probability that an unemployed person with assets \( b \) and benefits \( z \) is extended credit. \( \theta_{U,t}^C(z, b; \Omega) \) is the submarket tightness for unemployed agents with benefits \( z \) and assets \( b \):

\[
U_t(z, b; \Omega) = A\psi(\theta_{U,t}^C(z, b; \Omega))U_t^C(z, b; \Omega) + (1 - A\psi(\theta_{U,t}^C(z, b; \Omega)))U_t^N(z, b; \Omega) \quad \forall t \leq T
\]

At the end of the period, after realizing the aggregate state, unemployed agents look for jobs paying \( \tilde{w} \). Each submarket is indexed by a wage and \( p(\theta_{t}^L(\tilde{w}; \Omega')) \) is the probability of successfully matching to an employer paying \( \tilde{w} \) (the wage is fixed over the duration of employment). The function \( \theta_{t}^L(\tilde{w}; \Omega') \) is the submarket tightness (vacancy to looker ratio) for an age \( t \) agent in market \( \tilde{w} \) given the aggregate state \( \Omega' \).

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

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

In this scenario, credit access \( a \in \{ C, N \} \) is a persistent state. For those with access to credit (i.e. their credit application is approved), their choice set for assets includes loans, i.e. the asset choice is unrestricted \( b \in \mathcal{B} \). Thus, the problem solved by an unemployed agent \( (U) \) with credit access \( (C) \) is given below:

\[
U^C_t(z, b; \Omega) = \max_{b' \in \mathcal{B}, D \in [0, 1]} u(c) - x(D) + \eta \\
+ (1 - s(D)) \cdot \beta \mathbb{E} \left[ \max_{\tilde{w} \in W} p(\theta_{t+1}^L(\tilde{w}; \Omega')) W_{t+1}^C(\tilde{w}, b'; \Omega') + \left( 1 - p(\theta_{t+1}^L(\tilde{w}; \Omega')) \right) U_{t+1}^C(z, b', \Omega') \right] \\
+ s(D) \cdot \beta \mathbb{E} \left[ \max_{\tilde{w} \in W} p(\theta_{t+1}^L(\tilde{w}; \Omega')) W_{t+1}^C(\tilde{w}, b'; \Omega') + \left( 1 - p(\theta_{t+1}^L(\tilde{w}; \Omega')) \right) U_{t+1}^N(z, b', \Omega') \right] \quad \forall t \leq T
\]

\[
U_{T+1}^C(z, b; \Omega) = 0
\]
such that the law of motion for aggregates is taken as given and the budget constraint is satisfied,

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

\[ \Omega' = (\mu', A', y') \]
\[ \mu' = \Phi(\Omega, A', y') \]
\[ y' \sim F(y' | y) \]
\[ A' \sim G(A' | A). \]

Notice that the bond price \( q_{U,t}(z, b', D; \Omega) \) now depends on the default decision. I assume that if the household defaults, no loanable funds will be made available to the household. This type of ‘universal default rule’ will be discussed in more detail below in Section 5.2.

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

For those **without access to credit** (i.e. credit application is rejected), the problem is similar, except the household’s asset choice \( b' \) is restricted to be positive, \( b' \in \mathbb{R}^{++} \).

\[
U^N_t(z, b; \Omega) = \max_{b' \geq 0, D \in [0,1]} u(c) - x(D) + \beta \mathbb{E} \left[ \max_{\tilde{w} \in W} p(\theta_{t+1}^L(\tilde{w}; \Omega')) W_{t+1}(\tilde{w}, b'; \Omega') \right. \\
\left. + \left(1 - p(\theta_{t+1}^L(\tilde{w}; \Omega'))\right) U_{t+1}(z, b'; \Omega') \right] \quad \forall t \leq T
\]

\[
U^N_{T+1}(z, b; \Omega) = 0
\]
such that the budget constraint holds

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

Employed agents in this economy face a similar credit constraint to unemployed agents. At the start of the period, employed agents are able to obtain access to credit markets with probability \( A\psi(\theta_{W,t}^C(w, b; \Omega)) \) that depends on the vector of households attributes. Households therefore have the following value function:

\[
W_t(w, b; \Omega) = A\psi(\theta_{W,t}^C(w, b; \Omega)) W_t^C(w, b; \Omega) + (1 - A\psi(\theta_{W,t}^C(w, b; \Omega))) W_t^N(w, b; \Omega) \quad \forall t \leq T
\]

\( \delta_{t+1}(w; y) \) is the state contingent job separation rate and there is a \( \gamma \) replacement rate on wage income upon job loss.
The only other household value function that changes is for an employed (W) household with credit access (C):

\[
W_t^C(w, b; \Omega) = \max_{b' \in B, D \in [0, 1]} u(c) - x(D)
\]

\[
+ (1 - s(D)) \cdot \beta \mathbb{E} \left[ (1 - \delta_{t+1}(w; y')) W_{t+1}^C(w, b'; \Omega') + \delta_{t+1}(w; y') \left\{ \max_{\tilde{w} \in W} p(\theta_L^{t+1}(\tilde{w}; \Omega')) W_{t+1}^C(\tilde{w}, b'; \Omega') \right. \\
+ \left. (1 - p(\theta_L^{t+1}(\tilde{w}; \Omega'))) U_{t+1}(\gamma w, b'; \Omega') \right\} \right]
\]

\[
+ s(D) \cdot \beta \mathbb{E} \left[ (1 - \delta_{t+1}(w; y')) W_{t+1}(w, b'; \Omega') + \delta_{t+1}(w; y') \left\{ \max_{\tilde{w} \in W} p(\theta_L^{t+1}(\tilde{w}; \Omega')) W_{t+1}(\tilde{w}, b'; \Omega') \right. \\
+ \left. (1 - p(\theta_L^{t+1}(\tilde{w}; \Omega'))) U_{t+1}(\gamma w, b'; \Omega') \right\} \right]
\]

such that the law of motion for aggregates (1) is taken as given and the budget constraint is satisfied,

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

For those who are employed and do not have credit access, they face the same problem except their asset choice is restricted to be positive, \(b' \geq 0\).

\[
W_t^N(w, b; \Omega) = \max_{b' \geq 0, D \in [0, 1]} u(c) - x(D) + \beta \mathbb{E} \left[ (1 - \delta_{t+1}(w; y')) W_{t+1}(w, b'; \Omega') + \delta_{t+1}(w; y') U_{t+1}(\gamma w, b'; \Omega') \right]
\]

Such that the budget constraint is satisfied:

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

### 5.2 Long-Lived Credit Relationships: Saving and Lending Institutions

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

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

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

\[
\Xi(D) = \begin{cases} 
0 & \text{if } D > D \\
1 & \text{if } D = D
\end{cases}
\]
As before, households make take it or leave it offers to lenders taking into account the proportional minimum servicing fee. This assumption guarantees lenders the proportional minimum servicing fee $\tau$ on a per-period basis and allows me to express the bond pricing function in a familiar form. Let $D_{e',t+1}(w', \hat{b}; \Omega')$ be the policy function implied by the household’s problem, then the bond price can be written as,

$$q_{e,t}(w, \hat{b}, \hat{D}; \Omega) = \begin{cases} 
\bar{s} \mathbb{E}\left[\left(1-D^\prime_{e',t+1}(w', \hat{b};\Omega')\right) \right] + (1-\bar{s}) \mathbb{E}\left[\left(1-D^C_{e',t+1}(w', \hat{b};\Omega')\right) \right], & \hat{b} \in B_-, \ \hat{D} = D \\
0, & \hat{b} \in B_-, \ \hat{D} > D \\
\frac{1}{1+r_f}, & \hat{b} \in B_+
\end{cases}$$

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

$$Q_t(e, w, b; \Omega) = (1 - \mathbb{E}(\hat{D})) \left\{ q_{e,t}(w, \hat{b}, \hat{D}; \Omega) \bar{s} + \frac{1}{1+r_f} \mathbb{E}\left[\left(1-D^\prime_{e',t+1}(w', \hat{b};\Omega')\right) \cdot \hat{b} \right] - (1-\bar{s}) \cdot \frac{1}{1+r_f} \mathbb{E}\left[\left(1-D^C_{e',t+1}(w', \hat{b};\Omega')\right) \cdot \hat{b} \right] 
+ (1 - \bar{s}) \cdot \frac{1}{1+r_f} \mathbb{E}\left[Q_{t+1}(e', w', \hat{b};\Omega')\right] \right\} \big|_{b=b^*_t(a,w,b;\Omega), \ \hat{D}=D^*_t(a,w,b;\Omega), \ e \in \{W,U\}, \ b \in B}$$

5.3 Long-Lived Credit Relationships: Firms

The firm problem remains unchanged

6 Extension: On the Job Search (OJS)

6.1 OJS: Firms

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

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

$$V_t(a, w, b; \Omega) = -\kappa + q(\theta^L_t(a, w, b; \Omega))J^a_t(w, b; \Omega)$$
With free entry it must be the case that profits are competed away. Thus, \( \theta_L(t, a, w, b; \Omega) \) for \( a \in \{C, N\} \) is given by,

\[
\theta_L(t, C, w, b; \Omega) = q^{-1}\left(\frac{\kappa}{J_C(t, w, b; \Omega)}\right) \text{ if } \theta_L(t, C, w, b; \Omega) > 0
\] (2)

Due to the timing assumption, firms meet those without credit who, after matching, will then go into the market and attempt to find credit (these may be those who defaulted, or those who had an exogenous breakup, or those who simply did not have credit to begin with).

\[
\theta_L(t, N, w, b; \Omega) = q^{-1}\left(\frac{\kappa}{J_N(t, w, b; \Omega)}\right) \text{ if } \theta_L(t, N, w, b; \Omega) > 0
\] (3)

The value of an ongoing match is similar to Menzio and Shi [2009, 2011]. Notice that the expectation \( \mathbb{E}_{\Omega'} \) is over the aggregate state vector which includes the distribution of people across states (I will omit the subscript from now on):

\[
J_C(t, w, b; \Omega) = y - w + (1 - d(D^*)) \beta \mathbb{E}_{\Omega'} \left[ (1 - p(\theta_{t+1}^C(C, \tilde{w}^*, b^*; \Omega'))) \cdot (1 - \delta_{t+1}(w, y')) \cdot J_C(t+1, w, b^*; \Omega') \right]
\]

\[
+ d(D^*) \beta \mathbb{E}_{\Omega'} \left[ (1 - p(\theta_{t+1}^L(N, \tilde{w}^*, b^*; \Omega'))) \cdot (1 - \delta_{t+1}(w, y')) \cdot J_{t+1}(w, b^*; \Omega') \right]
\]

\[
J_t(w, b; \Omega) = A\psi(\theta_W^C(w, b; \Omega)) J^C_t(w, b; \Omega) + (1 - A\psi(\theta_W^C(w, b; \Omega))) J^N_t(w, b; \Omega)
\]

such that the aggregate law of motion is taken as given,

\[
\Omega' = (\mu', A', y')\\
\mu' = \Phi(\Omega, A', y')\\
y' \sim F(y' | y)\\
A' \sim G(A' | A)
\]

Note that firms take the household’s policy functions as given. Specifically, the firm knows that the wage posting decision of the households depends on the credit status and that the household uses the policy function \( \tilde{w}^C = \tilde{w}_{W,t+1}^C(w, b; \Omega) \) if the credit relation persists, otherwise \( \tilde{w}^N = \tilde{w}_{W,t+1}^N(w, b; \Omega) \). The firm also knows the default policy function \( D^* = D_{W,t}^C(w, b; \Omega) \) and bond policy function \( b^* = b_{W,t}^C(w, b; \Omega) \) of the household.

And I will assume that zero profit matches are destroyed with probability 1.\(^8\)

\[
\delta_{t}(w, y) = \begin{cases} 
1 & \text{if } t > T \text{ or } y < w \\
\delta & \text{if } y > w 
\end{cases}
\]

\(^8\)There is efficiency loss here since future surplus might be positive even though today’s profits are zero. I can no longer solve the social planners problem, but this assumption allows me to ignore the household’s surplus (which depends on several states) in calculating the equilibrium market tightness.
For firms matched with employees that do not have credit:

\[ J^N_t(w, b; \Omega) = y - w + \beta \mathbb{E}_{\Pi} \left[ (1 - p(\theta^L_{t+1}(N, \tilde{w}^N, b^*; \Omega))) \cdot (1 - \delta_{t+1}(w; y')) \cdot J_{t+1}(w, b^*; \Omega') \right] \]

such that \( \tilde{w}^N = \tilde{w}^N_{W,t+1}(w, b; \Omega) \) since they do not have credit, \( D^* = D^N_{W,t}(w, b; \Omega) \), and \( b^* = b^*_{W,t}(w, b; \Omega) \) are chosen optimally by the household (contingent on the initial state with is no credit \( N \)) and as before,

\[ J_t(w, b; \Omega) = A \psi(\theta^C_{W,t}(w, b; \Omega)) J^C_t(w, b; \Omega) + (1 - A \psi(\theta^C_{W,t}(w, b; \Omega))) J^N_t(w, b; \Omega) \]

### 6.2 OJS: Household Problem

An unemployed \( (U) \) household’s access to credit is determined by their past asset accumulation \( b \), their unemployment benefit income \( z \), their age \( t \), and the aggregate state \( \Omega = (y, A, \mu) \) which includes labor productivity \( y \), aggregate credit conditions \( A \), and the distribution of households across states \( \mu \). Let \( A \psi(\theta^C_{U,t}(z, b; \Omega)) \) be the probability that an unemployed person with assets \( b \) and benefits \( z \) is extended credit. \( \theta^C_{U,t}(z, b; \Omega) \) is the submarket tightness for unemployed agents with benefits \( z \) and assets \( b \):

\[
U_t(z, b; \Omega) = A \psi(\theta^C_{U,t}(z, b; \Omega)) U^C_t(z, b; \Omega) + (1 - A \psi(\theta^C_{U,t}(z, b; \Omega))) U^N_t(z, b; \Omega) \quad \forall t \leq T
\]

At the end of the period, after realizing the aggregate state, unemployed agents look for jobs paying \( \tilde{w} \). Each submarket is indexed by a vector \( (a, \tilde{w}, b; \Omega') \) and \( p(\theta^L_t(a, \tilde{w}, b'; \Omega')) \) is the probability of successfully matching to an employer paying \( \tilde{w} \) (the wage is fixed over the duration of employment). The function \( \theta^L_t(a, \tilde{w}, b'; \Omega') \) is the submarket tightness.

For those with access to credit, their choice set for assets includes loans, i.e. the asset choice is unrestricted \( b \in B \). Thus, the problem solved by an unemployed agent \( (U) \) with credit access \( (C) \) is given below:

\[
U^C_t(z, b; \Omega) = \max_{\psi \in \mathcal{B}, D \in [0,1]} u(c) - x(D) + \delta \mathbb{E} \left\{ \max_{\tilde{w} \in \mathcal{W}} p(\theta^L_{t+1}(N, \tilde{w}, b'; \Omega')) W_{t+1}(\tilde{w}, b'; \Omega') + (1 - p(\theta^L_{t+1}(N, \tilde{w}, b'; \Omega'))) U_{t+1}(z, b'; \Omega') \right\} \\
+ (1 - \delta) \mathbb{E} \left\{ \max_{\tilde{w} \in \mathcal{W}} p(\theta^L_{t+1}(C, \tilde{w}, b'; \Omega')) W_{t+1}(\tilde{w}, b'; \Omega') + (1 - p(\theta^L_{t+1}(C, \tilde{w}, b'; \Omega'))) U^C_{t+1}(z, b'; \Omega') \right\} \quad \forall t \leq T
\]

\[
U^C_{T+1}(z, b; \Omega) = 0
\]

Such that the law of motion for \( \Omega \) holds and the budget constraint is satisfied,

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

the household takes the law of motion for the aggregate state as given,

\[
\Omega' = (\mu', A', y')
\]

\[
\mu' = \Phi(\Omega, A', y')
\]

\[
y' \sim F(y' | y)
\]

\[
A' \sim G(A' | A)
\]
For those without access to credit (i.e., their credit application is rejected), the problem is similar, except the household’s asset choice \( b' \) is restricted to be positive, \( b \in \mathbb{R}_{++} \).

\[
U_t^N(z, b; \Omega) = \max_{b' \geq 0, D \in [0,1]} u(c) - x(D) + \beta \mathbb{E} \left[ \max_{\tilde{w} \in \tilde{W}} p(\theta_{t+1}^L(N, \tilde{w}, b'; \Omega')) W_{t+1}(\tilde{w}, b'; \Omega') + \left(1 - p(\theta_{t+1}^L(N, \tilde{w}, b'; \Omega'))\right) U_{t+1}(z, b'; \Omega') \right] \forall t \leq T
\]

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

such that the budget constraint holds

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

Employed agents in this economy face a similar credit constraint to unemployed agents. At the start of the period, employed agents are able to obtain access to credit markets with probability \( A \psi(\theta_{W,t}^C(w, b; \Omega)) \) that depends on the vector of households attributes. Households therefore have the following value function:

\[
W_t(w, b; \Omega) = A \psi(\theta_{W,t}^C(w, b; \Omega)) W_t^C(w, b; \Omega) + (1 - A \psi(\theta_{W,t}^C(w, b; \Omega))) W_t^N(w, b; \Omega) \forall t \leq T
\]

\( \delta_{t+1}(w; y) \) is the state contingent job separation rate and there is a \( \gamma \) replacement rate on wage income upon job loss. If they have access to the credit market, their dynamic programming problem is given by:

\[
W_t^C(w, b; \Omega) = \max_{b' \in B, D \in [0,1]} u(c) - x(D) + s(D) \cdot \beta \mathbb{E} \left[ (1 - \delta_{t+1}(w; y')) \left\{ \max_{\tilde{w} \in \tilde{W}} p(\theta_{t+1}^L(N, \tilde{w}, b'; \Omega')) W_{t+1}(\tilde{w}, b'; \Omega') + \left(1 - p(\theta_{t+1}^L(N, \tilde{w}, b'; \Omega'))\right) W_{t+1}(w, b'; \Omega') \right\} + \delta_{t+1}(w; y') U_{t+1}(\gamma w, b; \Omega') \right]
\]

\[
+ (1 - s(D)) \cdot \beta \mathbb{E} \left[ (1 - \delta_{t+1}(w; y')) \left\{ \max_{\tilde{w} \in \tilde{W}} p(\theta_{t+1}^L(C, \tilde{w}, b'; \Omega')) W_{t+1}(\tilde{w}, b'; \Omega') + \left(1 - p(\theta_{t+1}^L(C, \tilde{w}, b'; \Omega'))\right) W_{t+1}(w, b'; \Omega') \right\} + \delta_{t+1}(w; y') U_{t+1}(\gamma w, b; \Omega') \right]
\]

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

Such that the laws of motion for \( \Omega \) and \( z \) hold and the budget constraint is satisfied:

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

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

$W_t^N(w, b; \Omega) = \max_{b' \geq 0, D \in [0, 1]} u(c) - x(D) + \beta \mathbb{E} \left\{ (1 - \delta_{t+1}(w; y')) \left( \max_{\tilde{w} \in \mathcal{W}} p(\theta_{t+1}^L(N, \tilde{w}, b'; \Omega')) W_{t+1}(\tilde{w}, b'; \Omega') + (1 - p(\theta_{t+1}^L(N, \tilde{w}, b'; \Omega')) W_{t+1}(w, b'; \Omega') \right) + \delta_{t+1}(w; y') U_{t+1}(\gamma w, b'; \Omega') \right\}$

Such that the aggregate laws of motion hold and the budget constraint is satisfied:

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

### 6.2.1 On the Job Search: Lending Institutions

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

$$Q_t(e, w, b; \Omega) = (1 - \Xi(\hat{D})) \left\{ q_{e,t}(w, \hat{b}, \hat{D}; \Omega) \hat{b} - \hat{d} \cdot \frac{1}{1 + r_f} \mathbb{E} \left[ (1 - D_{e,t+1}(w', \hat{b}; \Omega')) \cdot \hat{b} \right] - (1 - \hat{d}) \cdot \frac{1}{1 + r_f} \mathbb{E} \left[ (1 - D_{e,t+1}(w', \hat{b}; \Omega')) \cdot \hat{b} \right] + (1 - \hat{d}) \cdot \frac{1}{1 + r_f} \mathbb{E} \left[ Q_{t+1}(e', w', \hat{b}; \Omega') \right] \right\}$$

such that the universal default rule is given by,

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

and the bond price is given by,

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

### 7 Extension: Piece-Rate Wages

Instead of looking for jobs paying wage $w$, workers enter in contracts for a fraction $\alpha$ of production, i.e. the wage is $\alpha y$:

$$U^C(z, b; \Omega) = \max_{b' \in \mathcal{B}, D \in [0, 1]} u(c) - x(D) + \beta \mathbb{E} \left\{ \max_{\tilde{\alpha} \in \mathcal{W}} p(\theta^L(\tilde{\alpha}; \Omega')) W(\tilde{\alpha}, b'; \Omega') + \left( 1 - p(\theta^L(\tilde{\alpha}; \Omega')) \right) U(z, b'; \Omega') \right\}$$
8 Extension: Benefit Eligibility and Expiration

In this extension, unemployment benefit eligibility is random. Agents receive eligibility upon job loss with probability $p_e$. An agent that is eligible receives $\gamma \%$ of their wage. An agent that is ineligible receives $z$ in the period of job loss. Let $\lambda_I$ be the probability of conducting immediate search after job loss. Let $p_\tau$ be the probability benefits expire. If benefits expire, agents also receive $z$.

\[
W^L_t(w, b; \Omega) = \max_{b' \in B, D \in [0, 1]} u(c) - x(D) + s(D) \cdot \beta \mathbb{E}\left[ \left( 1 - \delta_{t+1}(w; y') \right) \left( \max_{\omega \in W} \lambda p(\theta^L_{t+1}(N, \bar{w}, b'; \Omega')) W_{t+1}(\bar{w}, b'; \Omega') \right.ight.
\]
\[
+ \left. \left( 1 - \lambda p(\theta^L_{t+1}(N, \bar{w}, b'; \Omega')) \right) W_{t+1}(w, b'; \Omega') \right)
\]
\[
+ \delta_{t+1}(w; y') \left[ \max_{\omega \in W} \lambda p(\theta^L_{t+1}(N, \bar{w}, b'; \Omega')) W_{t+1}(\bar{w}, b'; \Omega') \right.
\]
\[
+ \left. \left( 1 - \lambda p(\theta^L_{t+1}(N, \bar{w}, b'; \Omega')) \right) \left[ p_e U_{t+1}^C(\gamma w, b'; \Omega') + (1 - p_e) U_{t+1}(\bar{z}, b'; \Omega') \right] \right]
\]
\[
+ \left. \left( 1 - s(D) \right) \cdot \beta \mathbb{E}\left[ \left( 1 - \delta_{t+1}(w; y') \right) \left( \max_{\omega \in W} \lambda p(\theta^L_{t+1}(C, \bar{w}, b'; \Omega')) W^C_{t+1}(\bar{w}, b'; \Omega') \right.ight.
\]
\[
+ \left. \left. \left( 1 - \lambda p(\theta^L_{t+1}(C, \bar{w}, b'; \Omega')) \right) W^C_{t+1}(w, b'; \Omega') \right) \right)
\]
\[
+ \delta_{t+1}(w; y') \left[ \max_{\omega \in W} \lambda p(\theta^L_{t+1}(C, \bar{w}, b'; \Omega')) W^C_{t+1}(\bar{w}, b'; \Omega') \right.
\]
\[
+ \left. \left. \left( 1 - \lambda p(\theta^L_{t+1}(C, \bar{w}, b'; \Omega')) \right) \left[ p_e U^C_{t+1}(\gamma w, b'; \Omega') + (1 - p_e) U^C_{t+1}(\bar{z}, b'; \Omega') \right] \right) \right]
\]

\[
U^C_t(z, b; \Omega) = \max_{b' \in B, D \in [0, 1]} u(c) - x(D) + s(D) \cdot \beta \mathbb{E}\left[ \left( \max_{\omega \in W} p(\theta^L_{t+1}(N, \bar{w}, b'; \Omega')) W_{t+1}(\bar{w}, b'; \Omega') \right.ight.
\]
\[
+ \left. \left. \left( 1 - p(\theta^L_{t+1}(N, \bar{w}, b'; \Omega')) \right) \tilde{U}_{t+1}(z, b'; \Omega') \right) \right]
\]
\[
+ \left. \left. \left( 1 - s(D) \right) \cdot \beta \mathbb{E}\left[ \left( \max_{\omega \in W} p(\theta^L_{t+1}(C, \bar{w}, b'; \Omega')) W^C_{t+1}(\bar{w}, b'; \Omega') \right.ight.
\]
\[
+ \left. \left. \left. \left( 1 - \lambda p(\theta^L_{t+1}(C, \bar{w}, b'; \Omega')) \right) \left( 1 - p(\theta^L_{t+1}(C, \bar{w}, b'; \Omega')) \right) \tilde{U}^C_{t+1}(z, b'; \Omega') \right) \right) \right]\]

\[
\tilde{U}^C_{t+1}(z, b'; \Omega') = p_z U^C_{t+1}(z, b'; \Omega') + (1 - p_z) U^C_{t+1}(z, b'; \Omega')
\]
In this section, I discuss back-of-the-envelope elasticities and explain why dynamic considerations matter for understanding the impact of consumer credit on job finding over the business cycle. Consider the case when $\beta = 0$, the labor market matching function is the min function $M(u, v) = \min\{u, v\}$. Fix output per worker to be $y$. The job finding rate of the household is therefore a linear function of $y - w$. Consider the following problem solved by the worker:

$$\max_w (y - w)(-1)e^{(-1)(w+(1-D)b)} + (1 - (y - w))(-1)e^{(-1)[p_c(z+(1-D)b-b)+(1-p_c)(z+(1-D)b)]}$$

First order conditions suffice:\(^9\)

$$e^{(-1)(w+(1-D)b)} + (y - w)e^{(-1)(w+(1-D)b)} + (-1)e^{(-1)[p_c(z+(1-D)b-b)+(1-p_c)(z+(1-D)b)]} = 0$$

Rearranging, it must be the case that the optimal wage is chosen such that:

$$(1 + (y - w)) = e^{(w)(-1)[p_c(z-b)+(1-p_c)z]}$$

Without dynamic effects, Figure 1 illustrates that when productivity falls, the gap in job finding rates between those with credit access and those without also narrows. In that sense, credit access has a large effect on unemployment in good times. Only once dynamic wait-and-see effects are allowed does credit access lower the reservation wage disproportionately in bad times.

Now consider linearizing the function $e^w$ around $w = 0$.

$$1 + y - w = (1 + w) \cdot (1 + p_c b - z)$$

Rearranging, this yields the following expression for the optimal wage:

$$\frac{1 + y - (1 + p_c b - z)}{(1 + (1 + p_c b - z))} = w$$

$$\frac{\partial w}{\partial p_c} = -\frac{b}{(1 + (1 + p_c b - z))} \left(1 + \frac{1 + y - (1 + p_c b - z)}{(1 + (1 + p_c b - z))}\right)$$

\(^9\) Check concavity:

$$f(w) = -w(-1)e^{(-1)(w+(1-D)b)} = we^{(-1)(w+(1-D)b)}$$

F.O.C.

$$f'(w) = we^{(-1)(w+(1-D)b)}(-1) + e^{(-1)(w+(1-D)b)} = e^{(-1)(w+(1-D)b)}(1 - w)$$

$$f''(w) = e^{(-1)(w+(1-D)b)}(-1) + e^{(-1)(w+(1-D)b)}(1 - w)(-1)$$

$$= e^{(-1)(w+(1-D)b)}((-1) + (1 - w)(-1)) = (-1)e^{(-1)(w+(1-D)b)}(2 - w)$$

since $w \in [0, 1]$, this is concave.
The elasticity of the job finding rate with respect to credit conditions is therefore given below:

\[
\frac{\partial w}{\partial p_c} \frac{p_c}{w} = -\frac{b}{(1 + (1 + p_c b - z))} \left(1 + \frac{(1 + y - (1 + p_c b - z))}{(1 + (1 + p_c b - z))}\right) \frac{p_c}{w}
\]

Given the following parameters: a maximum loan equal to 50% of monthly wages \(b = -0.5\); a quarterly credit finding rate of 25% \(p_c = 0.25\); a benefit replacement rate of 50% \(z = 0.5\); wage of unity \(w = 1\); and productivity that is 1% above trend \(y = 1.01\); a 1% increase in the approval rate raises the wage by 0.20% which is the same as lowering the job finding rate by 0.20%. A 10% increase in approval rates is normal in the recovery phase of a business cycle. Such a movement would result in a 2.0% reduction in job finding rates during the recovery.

What this analysis is missing is prior asset positions. And the general equilibrium effects on the asset distribution were shown to offset this reduction in job finding rates almost entirely.

A similar elasticity can be found with respect to the lower bound on borrowing:

\[
\frac{\partial w}{\partial b} \frac{b}{w} = -\frac{p_c}{(1 + (1 + p_c b - z))} \left(1 + \frac{(1 + y - (1 + p_c b - z))}{(1 + (1 + p_c b - z))}\right) \frac{b}{w}
\]

This effect is similar to credit access. In a side extension, Nakajima [2012] considered the aggregate implications of lowering the borrowing limit but found limited impacts since there was near zero borrowing in his equilibrium. I calibrate to liquid wealth and the dynamic
model endogenizes $b$ making access to credit the relevant margin for understanding the impact of credit on business cycles.

10 Robustness Checks: Timing and Servicing Fees

In this section, I consider altering the timing of the credit expansions and lowering the exogenous minimum servicing fee. I find that the results are robust to the various timing assumptions for the credit expansions, and that the lower the spread, the greater the impact of consumer credit on unemployment. Figures 2-3 show the credit expansion occurring 2 quarters after the recession, Figures 4-5 show the credit expansion occurring 4 quarters after the recession, and Figures 6-7 show the credit expansion occurring on the date of the recession with a minimum servicing fee of 4% as compared to the 8% used in the paper. With each of these timing assumptions, the same result rings true: credit expansions anytime during the recovery slows employment growth.
Figure 2: Transition Experiment with Alternative Timing (2Q Lag of Credit Expansion): Labor Productivity & Credit Match Efficiency Inputs, 2001 Recession

Figure 3: Percentage Change in employment, 2001 Recession
Figure 4: Transition Experiment with Alternative Timing (2Q Lag of Credit Expansion): Labor Productivity & Credit Match Efficiency Inputs, 2001 Recession

Figure 5: Percentage Change in employment, 2001 Recession
Figure 6: Transition Experiment with Low Servicing Fee ($\tau = 4\%$): Labor Productivity & Credit Match Efficiency Inputs, 2001 Recession

Figure 7: Percentage Change in employment Low Servicing Fee ($\tau = 4\%$), 2001 Recession
Figure 8: Alternate Credit Expansion Timing: Credit Match Efficiency Inputs, 2001 Recession

Figure 9: Alternate Credit Expansion Timing: Percentage Change in employment, 2001 Recession
11 Technology Adoption Coming out of Recessions

Recent work by Comin and Mestieri [2013] has illustrated that technology diffusion is greatly impacted by business cycles, and diffusion is strongly procyclical. Figure 10 illustrates the adoption of Numerical Control Turning Machines in the UK, relative to GDP. Alexopoulos [2011] details that technology diffusion tends to lead the business cycle with the correlation between the number of books published on computer technology today and GDP next year being .47. Berger et al. [2011] provides data on the adoption of credit scoring technologies based on a random sample of 300 respondent banks. The respondent banks outlined the year of credit scoring adoption. Figure 11 illustrates credit technology diffusion among those banks. While the earliest date of adoption was truncated in the survey to 1994, the series is clearly procyclical. Barren and Staten [2003] describe the adoption of tiered-pricing coming out of the 1990s recession:

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

Figure 12 illustrates the effects of two-tier pricing coming out of the 1990-1991 recession. The result was a large decline in rates as card companies adopted risk scoring.
Figure 10: Procyclical Technology Diffusion, Comin and Mestieri [2013]

Figure 5: Diffusion of Numerical Control Turning Machines in the UK

Figure 11: Fraction of Community Banks Adopting Consumer Credit Scoring, Derived from Data Presented in Berger et al. [2011]
Figure 12: Credit Scoring Technology Diffusion, Barren and Staten [2003]
12 Credit Supply Coming out of Recessions

Figure 13 illustrates annual times series for credit card offers per capita, taken from Synovate/Ipsos and Mintel Comperemedia (who recently acquired by Synovate). What we see is that there is large growth in credit offers per capita both going into recessions as well as during the recovery. In an alternate calibration, I directly map my model’s credit offers per capita to this data. I infer annual movements in credit matching efficiency to target this measure of credit supply.

Figure 13: Credit Card Offers Per Capita
13 Alternate Timing of Impulse Response Shocks

This section explores what happens to employment dynamics in response to credit shocks 1-quarter before the recession, and 4-quarters before the recession.

What we see is that the trough of employment is significantly lower when credit expands 1 quarter before the recession, and employment remains depressed during the recovery. However, as the wealth distribution shifts and households pay off the loans they took out during the recession, the economy with increased credit actually reaches its pre-recession levels of employment faster.

14 Spreads

As in standard models of default, during bad times (low output in standard sovereign default models Arellano [2008]), the spread is relatively lower. Negative correlation between the spread and output is counterfactual. This correlation is the result of a changing pool of borrowers, and the relative value of credit access during recessions. In recessions, while default risks increase for the unemployed, employed households now value access to credit and thus are less likely to repay loans. As a result, borrowing costs decline for a large subgroup of households, and average spreads tend to decline during recessions. There is however significant heterogeneity in credit markets which is discussed in the paper.
Figure 14: Inputs, IRF, Credit Expansion 1 Quarter Prior to Recession

Figure 15: Percentage Change in employment, IRF, Credit Expansion 1 Quarter Prior to Recession
Figure 16: Inputs, IRF, Credit Expansion 4 Quarters Prior to Recession

Figure 17: Percentage Change in employment, IRF, Credit Expansion 4 Quarters Prior to Recession
Figure 18: Unemployment Rate, IRF, Credit Expansion 4 Quarters Prior to Recession
Figure 19: Credit Spread, IRF, Credit Expansion 5 years Prior to Recession
15 Impact of Credit Access on Job Finding Rates over Recession by Assets Class

Figures 20 and 21 depict the job finding rates among households, split by asset holdings, with and without credit access in the impulse response experiment where credit expands 5 years before the recession.

The interesting thing is that households which have already borrowed considerably are impervious to the business cycle. Those households are desperate for a job, the interest rates they face are relatively high, and so it doesn’t matter to them whether productivity is 1.02 or 1.01. For other subgroups with low amounts of saving that may potentially rely on borrowing during a recession, their job finding rates are disproportionately affected by their ability to access credit. Figure 22 and 23 depict the fraction of households in each of these asset subgroups.
Figure 20: Job Finding Rate of Unemployed Households without Credit, Grouped by Assets

Figure 21: Job Finding Rate of Unemployed Households with Credit, Grouped by Assets
Figure 22: Fraction of Unemployed Households without Credit, Grouped by Assets

Figure 23: Fraction of Unemployed Households with Credit, Grouped by Assets
16 Ballparking the Numbers

In this section, I compare the implied elasticity of the job finding rate with respect to liquid asset access among low-wealth households in my model to the SIPP counterpart analyzed in Chetty [2008]. Chetty [2008] finds that among households in the lowest quartile of wealth, after 1 quarter, a 5% increase in the replacement rate of UI leads to a 12% reduction in the quarterly job finding rate. Figure 25 repeats Chetty [2008]'s results with a marker added at 12 weeks (1 quarter). Chetty [2008] also reports results for the impact of receiving a severance payment on job finding hazards. The specific amount received in severence is not available in Chetty [2008]'s data, however he provides a loose estimate that roughly 1 year of job-tenure translates into 1 week of severance pay. Households were employed for roughly 7.5 years in Chetty [2008]'s sample. He finds that access to this amount of liquid assets lowers the quarterly job finding rate by approximately 8%. I find that having credit access in my model allows agents to replace roughly 6 weeks of lost wages (this is the maximum, and there are no taxes in my model), and lowers the quarterly job finding rate by approximately 9.6% among households with zero net worth, 7.3% among households with moderate negative net worth, and 6.7% for households with severe negative net worth (defined in Section 6 of the main paper). Taking taxes into account, the tax-free 6 week potential replacement of income from borrowing in my model is roughly comparable to a taxable increase of severance payments that replace 7 to 10 weeks of income.

Figure 24: Chetty’s Results for UI

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10 This is a 5% increase for 26 weeks.
11 Chetty [2008] writes, “Lee Hecht Harrison (2001) reports results from a survey of severance pay policies of human resource executives at 925 corporations in the U.S. in 2001... Using the percentages reported in this table for non-exempts (hourly workers) and coding the < 1 week category as 0.5 weeks, I compute that on average, individuals receive 1.35 weeks of severance pay per year of service.”
Figure 25: Chetty’s Results for Access to Liquid Assets

References


