

The Impact of Consumer Credit Constraints on Earnings, Sorting, and Job Finding Rates of Displaced Workers

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1 Introduction

Earnings losses after layoff are severe on average and differ significantly across individuals (Jacobson et al. [1993], Jacobson et al. [2005], Couch and Placzek [2010], Davis and von Wachter [2011]). While much is known empirically and theoretically about the impact of unemployment benefits on earnings losses (Ljungqvist and Sargent [1998], Saporta-Eksten [2013]), little is known about the role consumer credit plays in the earnings losses of displaced workers, their job finding rates, and the subsequent quality of jobs they take. To answer this question, we merged confidential, quarterly, individual employment records from the Census with proprietary individual credit reports based on social security numbers. Our first contribution is to use this new administrative panel dataset to measure the impact of consumer credit access on job finding rates and re-employment earnings of displaced workers. We find that credit constrained workers have earnings losses that are [X]% greater than unconstrained households, and that the job finding rates of credit constrained workers are [X]% greater than unconstrained households.

To understand the impact of credit access on sorting, employment, output, and productivity, we introduce risk aversion into a model with heterogeneous workers and firms, building on the influential prior work by Eeckhout and Kircher [2010], Eeckhout and Kircher [2011] and Hagedorn et al. [2012]. In our model, heterogeneous credit-constrained workers accumulate human capital while working and direct their search for jobs among heterogeneous

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credit-constrained firms while unemployed. We find that an increase in credit limits equal to $[X]\%$ of GDP (decreases or) increases employment by $[X]\%$, increases output by $[X]\%$, and increases productivity by $[X]\%$. The mechanism is that credit access acts as a safety net, allowing workers to sort into better matches with firms.

The role of unsecured credit in unemployed households' job finding decisions is being actively debated in the profession, with several papers arguing that unsecured credit markets are not useful for insurance purposes (Athreya et al. [2009] and Bethune [2015]) while others have argued that they are (Hurst and Stafford [2004], Herkenhoff [2013], and Albanesi and Nosal [2014]). Existing empirical studies by Sullivan [2008] and Hurd and Rohwedder [2010] identify significant changes in borrowing behavior among the unemployed with approximately 20% of households directly self-reporting borrowing during unemployment, and nearly 36% reporting some form of default (default may have been an important channel for consumption smoothing during the 2007-2009 crisis, see Mulligan [2008] and Herkenhoff and Ohanian [2012]). A common mistake in the reduced form literature has been to assume that credit markets only impact individuals if they borrow and draw down their credit lines; however, what actually matters is the stock of resources available to the household, and studies based on survey data lack accurate credit limit data (including the SCF which only asks about 1 credit line and lacks any high frequency panel information). In the model outlined below, households with large limits who never draw down their lines of credit will have more resources on hand and take longer to find jobs. Therefore, aggregate credit limits (a measure of resources on hand), is a better measure of ability to self-insure than realized borrowing. To our knowledge, no existing studies have addressed the impact of credit access on either job finding rates or subsequent job quality.

Our identification strategy relies on a similar instrumental variable as Gross and Souleles [2002]. Gross and Souleles [2002] exploit exogenous variation in the timing of credit limit increases solely due to the length of time since an account was opened. Conditional on age and income, which are two observables in our dataset, we exploit plausibly exogenous heterogeneity in account ages as an instrument for credit limits. We isolate displaced households as in Jacobson et al. [1993], and then we split households into several age-income bins. *Within each age-income bin*, our first stage regression consists of estimating the impact of credit history length on credit limits (this is by construction conditional on age and income). The second stage regression then uses the predicted first-stage credit limits as an input to determine the impact of a 1\$ increase in credit limit on the quarterly job finding rate of any given household in our dataset. Our main result is that a 1,000\$ increase in credit limits leads to an $X\%$ reduction in job finding rates.

These results have several implications for the way both policy-makers and economists think about the optimal provision of unemployment insurance (Shimer and Werning [2005], Chetty [2008], Michaillat [2012]) and the response of labor markets to monetary policy (Bernanke and Blinder [1992], Galí [2010]). The fact that increases in credit access can actually *reduce* job finding rates brings into the question the ability of the Federal Reserve Bank to effectively meet the dual mandate of "maximum employment, stable prices and

moderate long-term interest rates.” These findings bring about several continuation policy questions: What should the optimal mix of unemployment insurance and credit limits be? And how can default regimes affect labor market outcomes?

2 Literature

Prior to the 2007-2009 crisis, the interaction between private unemployment insurance mechanisms, such as credit cards and bankruptcy, and public unemployment insurance mechanisms, such as unemployment insurance and welfare, received relatively little attention in the literature. Notable exceptions include [Athreya and Simpson \[2006\]](#) who consider bankruptcy provisions and unemployment insurance, [Lentz \[2009\]](#) who considers unemployment insurance in a model of savings, and [Shimer and Werning \[2005, 2007\]](#) who consider optimal unemployment insurance in a model of hidden savings (agents are allowed to borrow in this framework). More recently however, the profession has begun to think about the way labor markets are affected by private consumption smoothing mechanisms such as home equity loans ([Hurst and Stafford \[2004\]](#)), default arrangements ([Athreya and Simpson \[2006\]](#), [Han and Li \[2007\]](#), [Gordon \[2011\]](#), [Herkenhoff and Ohanian \[2012\]](#), [Herkenhoff \[2012\]](#), [Chen \[2012\]](#), [Dobbie and Song \[2013\]](#), [Albanesi and Nosal \[2014\]](#)), mortgage modifications ([Mulligan \[2008, 2012\]](#) and [Herkenhoff and Ohanian \[2011\]](#)), and other combinations of spousal labor supply and assets ([Blundell et al. \[2012\]](#) and citations therein).

The literature that studies the impact of liquid assets on job finding rates has produced largely mixed results. Using variation in severance payments, recent research by [Chetty \[2008\]](#) found a strong impact of liquid asset access on job finding rates. Using experimental data collected by a payday lending company in Oregon, [Zinman \[2010\]](#) finds mixed results regarding the impact of payday loan access on employment outcomes and other financial outcomes.¹ The Oregon policy capped the interest rate on all loans at 10\$ per 100\$ of loans and set the minimum loan term to 31 days (max APR of 150%). This is binding for payday lenders who often charge 390% APR. In their sample, they only have 1040 payday borrowers, where 520 are in the baseline respondent sample from Oregon and the remaining set of households are a control group in Washington. After the cap, households did not borrow as much, and those who did substituted into overdraft and other expensive forms of liquidity. He finds that restricting credit access actually increases unemployment. He posits that households use payday loans for productive uses to avoid missing work such as repairing one’s car. The same is true in many structural models such as [Lentz \[2009\]](#) and [Nakajima \[2012\]](#) who justify imposing savings-only constraints because, as [Lentz \[2009\]](#) points out,

¹[Karlan and Zinman \[2010\]](#) study the impact of extending four-month loans at 200% APR in South Africa. They find these loans significantly increase the likelihood that a borrower is employed 6 to 12 months after taking a loan. They argue that the mechanism is that these households use the credit to pay for health treatment and auto repairs – shocks that would potentially require them to miss work, personally fix the problem, and be fired had they not had the resources to pay for it.

“The vast majority of the spell observations are characterized by wealth levels such that a change in the lower wealth bound below the minimum wealth observation has no effect on worker behavior.” Recently however, [Herkenhoff \[2013\]](#) has found significant impacts of credit on employment behavior.

In the unemployment insurance literature, several papers including [Katz and Meyer \[1990\]](#), [Meyer \[1991\]](#), [Rothstein \[2011\]](#), [Hagedorn et al. \[2013\]](#), and [Card et al. \[2015\]](#) have measured the impact of unemployment benefits (replacement rates and length) on job finding rates, and [Addison and Blackburn \[2000\]](#) (see citations therein) among other have considered the impact of unemployment benefits on re-employment earnings, finding significant but often times small effects. To our knowledge, we are the first to empirically measure the impact of credit access on employment outcomes. Our advances to this area of the literature are contingent on the observation that there are significant differences between unemployment insurance and credit access: (i) credit lines can be drawn down before an unemployment spell begins producing strong offsetting effects on job finding behavior (see [Herkenhoff \[2013\]](#)), (ii) credit lines are supposed to be repaid and interest rates are idiosyncratic which has the potential to change what type of wages workers search for, (iii) informal bankruptcy and formal bankruptcy provide workers with alternate forms of self-insurance that may be more valuable in downturns when credit is scarce, (iv) monetary policy disproportionately impacts credit carrying households.

When we turn to the impact of credit on sorting and replacement wages, we adopt the methodology laid out in the long literature on earnings losses ([Jacobson et al. \[1993\]](#), [Jacobson et al. \[2005\]](#), [Couch and Placzek \[2010\]](#), [Davis and von Wachter \[2011\]](#), [Saporta-Eksten \[2013\]](#)). We contribute to this literature by showing how credit constraints impact the *extensive* margin of employment, as well as the traditional intensive measure of earnings. In many of these studies, the impact of job loss on earnings is inferred from annual data which smooths out much of the important high-frequency variation in job finding rates. Notable exemptions include the concurrent work by Rogerson et al [2015, in progress] (we need to ask Richard for a draft).

3 Description of the LEHD

Quarterly earnings data is taken from the Longitudinal-Employer Household Dynamics (LEHD) database which is a matched employer-employee dataset that covers 95% of U.S. private sector jobs. 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. Our earnings data span from 1995 to 2008 for 11 states: California, Maryland, Illinois, Texas, Indiana, Nevada, New Jersey, Oregon, Rhode Island, Virginia, and Washington.

To measure displacements we follow [Jacobson et al. \[1993\]](#), and focus on 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 corresponding closure in the LBD. To ensure that there was actually a mass layoff, we then verify that fewer than 35% of workers move to any other single SEIN. This removes mergers, firm name-changes, and spin-offs from our sample. Following [Davis and von Wachter \[2011\]](#), we limit ourselves to workers with at least 3 years of tenure.

4 Description of TransUnion Data

All consumer credit information is taken from TransUnion at an annual frequency from 2001 to 2012. TransUnion is one of the three largest credit scoring companies in the United States, and it has a similar market share to Equifax and Experian. Our main sample is a 5% random sample of individuals with credit reports from the 11 states for which we have LEHD data. The TransUnion data is then merged based on social security numbers to the LEHD. Table [X] illustrates our match rates. We are able to successfully match [X]% of observations between the two datasets. In some instances, households may have a credit report, but no prior employment history (as would be the case for a house wife), while in other instances, households may have an employment history without a credit report.

Our data includes information on the balance, limit, and status (delinquent, current, etc.) of different classes of accounts held by individuals. We describe the data in detail below.

5 Summary Statistics

We have [X] displaced workers between 2001 and 2008. For comparisons to non-displaced workers, we have a 10% random sample of non-displaced workers with credit reports in 2001 ([Y] observations). We therefore have a balanced panel of [X] + [Y] observations from 2001 to 2008.

Table 1 includes summary statistics of displaced and non-displaced workers in 2001. Table [X] summarizes the main variables of interest in our study. On average consumers have [X] accounts open with an average balance of [X]. [X] % are mortgagors, whereas in the census, [Y] % are mortgagors. The mean earnings in the sample is [X], and in the CPS, mean earnings is [Y].

Table 1: Summary Statistics, 2001 Cross-Section

	Displaced	Non-Displaced
Years of Education		
Tenure Prior to Displacement		
Share in SIC 10		
Share in SIC 20		
Fraction with Mortgages		
Bankcard Limits		
Bankcard Balance		
Bankcard Utilization Rate		
Age of Oldest Account		
Months on File		
Number of Bankruptcies		
Number of Foreclosures		
Number of Accounts in Collection		
Income		
Bankcard Debt to Income		
Total Debt to Income		
Limits to Income		
Observations		

6 Empirical Approach

The goal of this section is to estimate the impact of credit access on job finding rates among displaced workers. While most of the literature including [Jacobson et al. \[1993\]](#) and [Couch and Placzek \[2010\]](#) have argued that mass layoffs are exogenous to worker characteristics, credit access upon layoff certainly is not. The goal is to find a characteristic of households that impacts credit limits, and only impacts employment prospects through its impact on credit limits. To isolate the exogenous variation in credit limits, we follow [Gross and Souleles \[2002\]](#) who use the timing of credit limit expansions, which are based on credit card industry conventions, to instrument credit limits. [Gross and Souleles \[2002\]](#) exploit exogenous variation in the timing of credit limit increases solely due to the length of time since an account was opened. Conditional on age and income, which are two observables in our dataset, we exploit plausibly exogenous heterogeneity in account ages as an instrument for credit limits.

We hypothesize, and test below, that the age of the oldest open account is a valid instrument for credit limits. For that to be true, the age of the oldest open account must be a strong determinant of credit limits (relevance), but not have an impact on employment prospects except through credit limits (exogeneity). The first stage of the 2-step instrumental variable regression demonstrates the relevance of the age of the oldest open account for credit limits.

However, using the *unconditional* age of the oldest open account as an instrument for credit access violates the exogeneity condition; it is related to age and therefore wages and employment prospects. However, conditional on age and annual earnings (two observables in our dataset), we show that the age of the oldest open account is a valid instrument for credit limits. Our approach is to separate individuals into $j \in \{1, \dots, J\}$ age-earnings bins (in exercise below, we use 25 bins). We then show that within each age-earnings bin, the instrument formally passes the J-test, where the over-identification comes from adding in the square of the oldest account and length of credit history as additional instruments. And, within each of the j age-earnings bins, we demonstrate exogeneity informally by regressing a series of labor market measures on the age of the oldest account and bankcard limits to show that the age of the oldest account, after controlling for bankcard limits, is never a significant predictor of either income or job finding rates. Only through its impact on bankcard limits does the age of the oldest account impact labor market outcomes.

Conditional on the age of a person, there are a number of reasons that are orthogonal to labor market outcomes that would result in different ages of credit accounts. Natural churn of accounts expiring and accounts opening will generate different values for the age of the oldest open credit account. However, in other instances, the age of the oldest open account may plausibly be related to important variables affecting labor market outcomes. Age of the oldest account impacts the credit score of the household, and in marginal cases, credit score may determine employment outcomes. For most households, however, credit score is not the marginal determinant of employment. For instance a credit score of 690

versus 790 would have no impact on employment outcomes. A credit score of 610 versus 710 might. Prior bankruptcies may preclude employment. So in our robustness checks, we limit our sample to prime credit score (above 680) households only with no prior history of bankruptcy, and we show that our results hold true. Age of the oldest open account may also be correlated with assets, education, earnings, and other demographics variables, and so we include proxies for equity and auto holdings, imputed education, lagged earnings, and standard demographic controls such as tenure, sex, race, etc. to address this. As shown below, conditional on observables, age of the oldest open credit account satisfies tests of both relevance and exogeneity.

Consider the sample of households laid-off due to plant closure. Let $J_{i,t+1}$ be an employment indicator for individual i in quarter $t + 1$. Let $l_{i,t}$ denote the the age of the oldest open credit account of that individual in quarter t . Let $X_{i,t}$ include unemployment duration, demographics controls, credit history controls (including the credit score), prior employment/wage controls, and aggregate economic controls. Consider the linear probability model (LPM) for simplicity:

$$J_{i,t+1} = \gamma l_{i,t} + \beta X_{i,t} + \epsilon_{i,t}$$

Our coefficient of interest is γ , which is the impact of credit limits on the quarterly job finding hazard, *ceteris paribus*. As discussed above, unused credit limits $l_{i,t}$ are endogenous. Simultaneity bias is particularly worrisome. Employment prospects tomorrow (and therefore income growth) determine credit limits, and credit limits determine employment prospects via their impact on liquidity. To circumvent this endogeneity, we use an instrumental variables approach where our instrument is the age of the oldest open account (in particular, the oldest open bankcard account).

Let $a_{i,t}$ denote age of the oldest open account. Split households into j experience-age bins at date t . The model we estimate is given below:

$$J_{i,t+1} = \gamma_j \hat{l}_{i,t}^j + \beta X_{i,t} + \epsilon_{i,t} \quad \forall j \in 1, \dots, J$$

Within each of the j bins, the first-stage regression is to predict credit limits as a function of credit history.

$$l_{i,t}^j = \pi^j a_{i,t}^j + \beta X_{i,t}^j + u_{i,t}^j \quad \forall j \in 1, \dots, J$$

The identifying assumptions are $E[l_{i,t}^j h_{i,t}^j] \neq 0$ and $E[\hat{l}_{i,t}^j \epsilon_{i,t} \mid j] = 0$, i.e. conditional on the experience-age bin, the predicted increase in credit limits due to length of credit history is exogenous.

7 Results

Table [X] illustrates the main regression without conditioning on age and earnings, and without instrumenting credit limits. In general, bankcard limits and job finding rates are negatively correlated. An increase in bankcard limits of 1,000% reduces the job finding rates by [X]. If we interact the term with age and earnings bins, we see that low earnings, young households are impact the most.

Table [Y] instruments the credit limit with the age of the oldest account. The presence of other non-housing, non-auto assets would tend to bias the results in the opposite direction; households with low assets take out credit cards earlier to circumvent liquidity constraints and therefore have older accounts. Therefore households with older accounts, and larger limits due to the older accounts, actually have fewer assets – these low-asset households with old accounts should find jobs faster, but what we see is the opposite.

A 1,000\$ increase in credit limits reduces the quarterly job finding rate of displaced households by [X]%. On average, households with low earnings are more sensitive to changes in credit limits. This is consistent with [X] who shows that an increase in credit limits, *ceteris paribus*, reduces job finding rates by [X]%.

Table [N] describes the impact of credit limits on replacement wages. On average, a 1,000\$ increase in credit limits increases the replacement rate of wages by [X]%.

8 Model

Let $t = 0, 1, 2, \dots$ 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 representative risk neutral entrepreneur that runs 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 and bankruptcy decisions. After the asset market closes, households enter the labor market where they direct their search for jobs. Let $c_{t,t+t_0}$ and $h_{t,t+t_0}$ respectively denote the consumption and leisure 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.

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

From this point on we will drop time subscripts and focus on a recursive representation of the problem. I assume that labor is indivisible, such that the household consumes its entire time endowment while employed $h = 1$, and vice versa for the unemployed.

Households are heterogeneous along several dimensions. Let $b \in \mathcal{B} \subset \mathbb{R}$ 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 $h \in \mathcal{H} \subset \mathbb{R}_+$ denote the human capital of the worker. Workers also differ with respect to the capital $k \in \mathcal{K} \subset \mathbb{R}_+$ 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.

The aggregate state of the economy includes three components: (i) labor productivity $y \in \mathcal{Y} \subset \mathbb{R}_+$ and (ii) the risk free rate $r_f \in \mathcal{R} \subset \mathbb{R}_+$, and (iii) the distribution of agents across states $\mu : \{W, U\} \times \{G, B\} \times \mathcal{B} \times \mathcal{H} \times \mathcal{K} \times \mathbb{N}_T \rightarrow [0, 1]$. Let $\Omega = (y, r_f, \mu) \in \mathcal{Y} \times \mathcal{R} \times M$ summarize the aggregate state of the economy where M is the set of distributions over the state of the economy. Let $\mu' = \Phi(\Omega, r'_f, y')$ be the law of motion for the distribution.

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.

$$U_t^G(b, h, k; \Omega) = \max_{b' \in \mathcal{B}} u(c, 1) + \beta \mathbb{E} \left[\max_k p(\theta_t(h', k; \Omega')) W_{t+1}^G(b', h', k; \Omega') \right. \\ \left. + (1 - p(\theta_t(h', k; \Omega'))) U_{t+1}^G(b', h', k; \Omega') \right], \quad t \leq T$$

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

Such that

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

I assume that human capital abides by the following law of motion:

$$h' = \mu(h)$$

And the aggregate law of motion is taken as given:

$$y' \sim F(y' \mid y) \\ r'_f \sim F(r'_f \mid r_f) \\ \mu' = \Phi(\Omega, y', r'_f)$$

For households who default, they are excluded from both saving and borrowing. Their is an exogenous probability λ that they regain access:

$$\begin{aligned}
U_t^B(b, h, k; \Omega) = \max_{b' \in \mathcal{B}} & u(c, 1) + \lambda \beta \mathbb{E} \left[\max_k p(\theta_t(h', k; \Omega')) W_{t+1}(b', h', k; \Omega') \right. \\
& \left. + (1 - p(\theta_t(h', k; \Omega'))) U_{t+1}(b', h, k; \Omega') \right] \\
& + (1 - \lambda) \beta \mathbb{E} \left[\max_k p(\theta_t(h', k; \Omega')) W_{t+1}^B(b', h', k; \Omega') \right. \\
& \left. + (1 - p(\theta_t(h', k; \Omega'))) U_{t+1}^B(b', h, k; \Omega') \right], \quad t \leq T
\end{aligned}$$

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

Such that

$$c \leq z(h, k)$$

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:

$$U_t(b, h, k; \Omega) = \max \left\{ U_t^G(b, h, k; \Omega), U_t^B(0, h, k; \Omega) \right\}$$

A similar problem holds for the employed.

8.1 Firms

There is a risk neutral entrepreneur that operates a constant returns to scale production function. The entrepreneur invests in capital $k \in \mathcal{K} \subset \mathbb{R}_+$ and posts vacancies to attract workers in the frictional labor market.

The entrepreneur is subject to a financing constraint. In the first period of trying to attract a worker, the firm does not have access to perfect capital markets. The firm must borrow the money to finance the initial capital and vacancy cost. If the firm fails to find an employee, the firm defaults and the capital is lost [perhaps it is reclaimed by the entrepreneur?].

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 $(h, t) \in \mathcal{H} \times \mathbb{N}_T$ to hire. In the event that the worker is hired, the firm has access to perfect capital markets and repays b immediately. In the event that no worker can be found, the firm defaults.

Capital is denominated in units of the final consumption good. Let $q_{f,t}(b, k, h; \Omega)$ denote the bond price faced by the firm.

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

such that

$$\kappa + k \leq q_{f,t}(b, k, h; \Omega)b$$

In equilibrium, this constraint holds with equality:

$$b = \frac{\kappa + k}{q_{f,t}(b, k, h; \Omega)}$$

The bond price is given by:

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

Therefore, the amount borrowed is

$$b = (1 + r_f) \cdot \frac{\kappa + k}{p_f(\theta_t(h, k; \Omega))}$$

Therefore, every submarket that is entered with positive probability must satisfy:

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

$$\kappa = p_f(\theta_t(h, k; \Omega)) J_t(h, k; \Omega) - (1 + r_f)(\kappa + k)$$

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

For tractability, we assume that workers and firms split output according to a constant piece-rate α . The value function for the firm is therefore

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

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

9 Earnings Losses After Layoff, Constrained v. Unconstrained Households

Let $i \in \{0, 1, \dots, N\}$ denote the individual, let $j \in \{0, 1, \dots, J\}$ denote the group of the individual, and let $t \in \{0, 1, \dots, T\}$ denote time. Let θ_i denote the individual fixed effect of the individual i . This is designed to capture ability and other unobserved heterogeneity (as well as static observables) that determine wages.

Let $D_{ijt}^k = 1$ if individual i is k periods before or after displacement at date t . Let $\gamma_{j,t}$ denote group specific time trends. Let μ_t denote dummies for each year so that $\mu_t = 1$ at date t . In general, the wage of individual i , in group j , at date t is given by,

$$w_{ijt} = \mu_t + \theta_i + \gamma_{j,t} + \sum_{k=-16}^{16} \delta_j^k \cdot D_{ijt}^k + u_{ijt}$$

In particular, we are interested in how earnings losses differ across constrained and unconstrained individuals. Let I_f be an indicator that the individual is constrained.

$$w_{ijt} = \mu_t + \theta_i + \gamma_{j,t} + \sum_{k=-16}^{16} \delta_j^{k,f} \cdot D_{ijt}^k \times I_f + u_{ijt}$$

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A Data Sources

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 1\$ for 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. Firm age and size are then taken from the Business Dynamics Statistics (BDS) which is a private-sector longitudinal business database.

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 source of the demographic information is the Person Characteristic File (PCF), and the Composite Person Record (CPR). Information on sex, date of birth, place of birth, citizenship, and race. CPR contains annual place of residence information.

The LEHD is also matched with the Survey of Program Participation (SIPP), and the March Current Population Survey (CPS). Identifiers information for both of these matches is incorporated in the LEHD dataset.

A.1 Imputations

The unit-to-worker (U2W) imputation allocates workers to workplaces everywhere except Minnesota. This imputation is based on job histories and place-of-residence. 30-40% of state-level employment is concentrated in employers that operate more than one establishment within the state.

In terms of demographics, 3% of individual records did not link, so they impute the sex, age, etc. based on earnings and employment histories. About 10% of geography data on place of residence is missing, so it is imputed. They use observables to impute the probability the person lives in a certain county. No geography below county level is imputed.

The education level is imputed based on a match between the Decennial Census 1990 and the LEHD data. This education imputation is being replaced by a probabilistic record link to the Census 2000 data. About 1 in 6 people acquire a directly reported educational attainment as of 2000.