Finance, Employment, and Survival: Evidence from Bank Liquidations in Ukraine
Extended Abstract

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This version: January 31, 2024

Abstract

We estimate the value of specific banking relationships to corporate borrowers using detailed loan data for 2007-19 linked to universal firm-level panel data from Ukraine, where a major financial reform led to the liquidation of 104 banks. We find that 70 percent of firms receive loans from a single "main bank," and less than 13 percent of those whose main bank is liquidated manage to get a subsequent loan from a new lender. Our results suggest that firms losing lender relationships because of liquidation experience employment decreases averaging around 13 percent in the first post-liquidation year and about 26 percent over the five years following the liquidation, conditional on survival. We also find that affected firms are 14 percent less likely to survive through 2019, controlling for firm size, productivity, and industry fixed effects.

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1 Introduction

How important is a relationship with a bank to a firm's performance and survival? If firms can easily switch among different sources of credit supply, then the loss of any one source may have little implication for the firms that have borrowed from that source. However, to the extent that relationships are sticky, so that switching is costly, then the loss of the credit source may negatively impact firms, reducing growth and survival.

Such disruptions often occur during recessions and financial crises, as over-extended banks reduce their exposure, leaving their borrowers in the lurch. For instance, Chodorow-Reich (2014) uses the shock of the Great Recession to compare 2008-9 employment changes at 2000 firms that borrowed from banks with varying degrees of vulnerability to the financial crisis, in particular through links to Lehman Brothers. In another type of identification strategy, Kwaja and Mian (2008) examine effects on banks and their borrowers after a nuclear test that produced foreign currency exchange restrictions, and which tended to hurt banks with more foreign currency holdings. In each of these cases, the credit shock is macro in the sense that it is simultaneous and similar in origin, if not in magnitude, for all banks and firms. Moreover, the analysis uses changes in the health/liquidity of banks, but does not use variation based on their survival.

In this paper, our identification strategy is based on bank liquidations resulting from a large-scale financial reform in Ukraine beginning in 2014 and largely complete by 2017. In total, 104 banks out of 186 operating in 2013 were dissolved during these years. The corporate loans at these banks accounted for 40 percent of of all such loans in 2013. As we show, these banks offered loans that were similar to banks that were not liquidated in terms of interest rates and maturity terms, although they tended to be smaller than those from banks that were not liquidated. The data also show no differences in the characteristics of firms to which they lent.

Using monthly loan-borrower data from the National Bank in Ukraine and combining them with annual firm-level financial statements data, we trace the employment dynamics

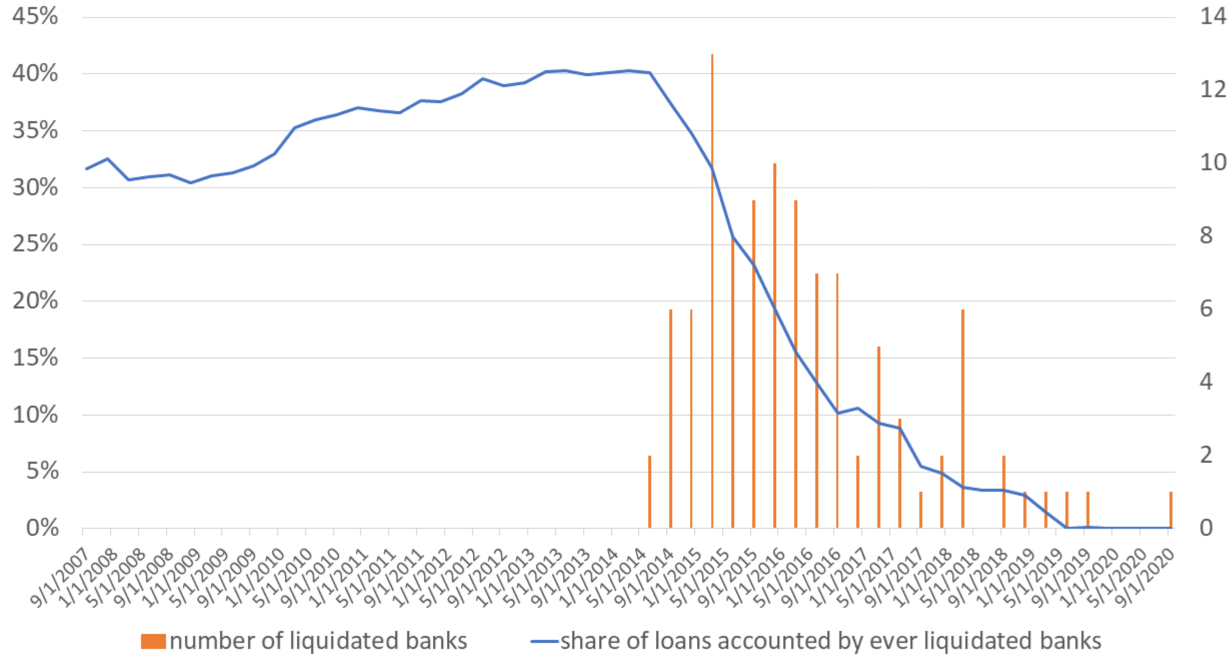

Figure 1: Share of loans accounted by ever liquidated banks and number of liquidated banks

and survival of the firms whose main bank has been liquidated between 2014 and 2019. Our results suggest that bank liquidations resulted in around 13 percent employment decrease in the first post-liquidation year and amounted to 26 percent over the five years following the liquidation of the main bank. We also find that affected firms were 14 percent less likely to survive through 2019, controlling for firm size, productivity, and industry fixed effects.

2 Data and Methods

In this study, we use unusually rich data in coverage and in the length of time series. The main data source for the firm-level data used to compute employment is the national statistical office (Derzhkomstat in Ukrainian), which supplies annual enterprise performance statement, balance sheet statement, and financial results statement for 2010-2020. Employment and output data come from the enterprise performance statement. Employment is defined as the average number of enlisted employees in the year, while output is net sales after indirect taxes. We combine firm level data with the unique loan-borrower-bank data. These data come from the Form 613: all banks are required to submit this form monthly to the National Bank of Ukraine and reflect the transactions of the borrowers whose total liabilities towards the bank are at least 70,000 US dollars.[1] In other words, this data covers borrowers with large portfolios in banks registered in Ukraine. This monthly panel data, available between 2007 and 2020, contains unique loan and borrower identifiers, information on loan characteristics such as loan size, loan currency, interest rate, maturity, collateral, and others.

We start our empirical strategy by establishing persistence in lending relationships in our data. Following Chodorow-Reich (2014), we estimate the persistence equation in the following form:

$$Lender_{ijt} = \beta * PrevLender_{ijt} + \alpha_j + \mu_t + \phi_k + \epsilon_{ijt}, \tag{1}$$

where i, j, and t index borrower, lender, and year, respectively. *Lender* takes value of 1 for bank j that issued a new loan to borrower i in year t. *Lender* equals 0 for all other potential banks that were active in year t. *PrevLender* takes on the value of 1 for bank j that issued a new loan to borrower i in year $t-1$. The model controls for bank, year, and industry fixed effects. Results in Table 1 show that a bank that served as the previous lender of a borrower has a 78 percentage point greater likelihood of serving as the new lead lender. The persistence of the banking relationship is also reflected in the number of banks each firm borrowed from between 2007 and 2019. Figure 2 illustrates that 70 percent and 20 percent of the firms in the loan data had a single bank and two banks, respectively. The stickiness of the banking relationship is more pronounced for firms that borrowed from liquidated banks only: almost 90 percent of them borrowed from a single bank between 2007 and 2019.

[1] Form № 613 ”Report on the concentration of risks on active operations of the bank with counterparties and persons related to the bank”

Table 1: Banking relationship regressions

	(1)	**(2)**	**(3)**
Previous lender	0.813***	0.813***	0.789***
	(0.004)	(0.004)	(0.004)
Year FE	NO	YES	YES
Bank FE	NO	NO	YES
Industry FE	YES	YES	YES
N		44,337,102	
Number of borrowers		26,143	
Number of loans		309,870	
Number of banks		212	
R2	0.664	0.664	0.669

Notes: Dependent variable is a binary variable and equals one for the bank that is a current lender for each borrower. The sample includes borrowers between 2007 and 2020. Regressions are estimated using OLS. In parentheses, heteroskedasticity-robust standard errors that correct for correlation of error terms at borrower level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Although most of the firms in the sample had a relationship with a single bank only (see Figure 2), we introduce the concept of the main bank, which also helps us estimate the effect of the liquidations for the firms that could have been the most affected by the bank closures. Main bank in year t for borrower i is defined as the bank that accounted for the largest share of outstanding loans (measured in current prices) for borrower i in years t, $t-1$, and $t-2$. Outstanding loans are measured as of January of each year. Then we classify the borrower as "treated" or affected by the liquidation if the bank that was liquidated in year t was the borrower's main bank in year t.

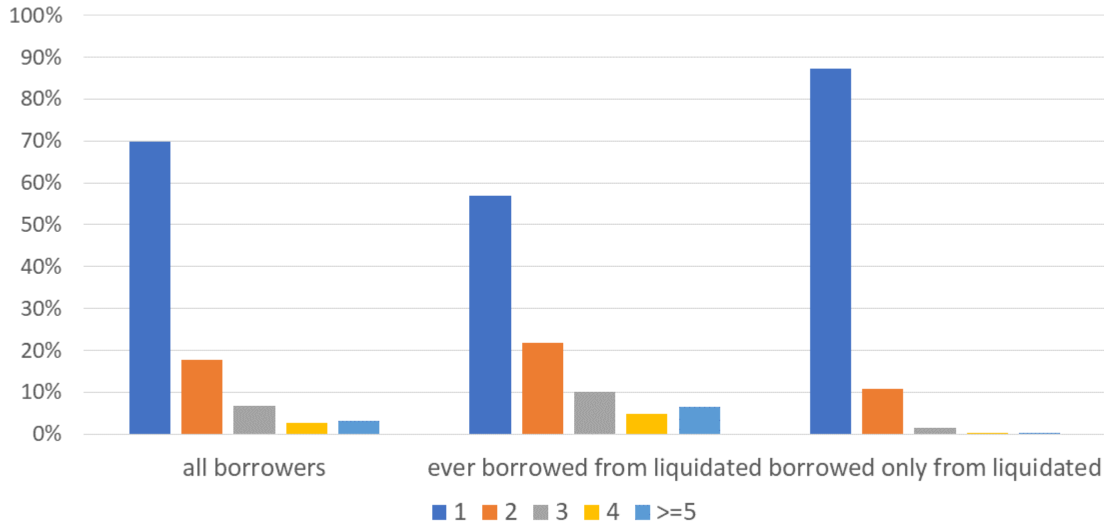

Figure 2: Number of banking relationships by type of borrower

We then merge loan data with firm-level data to create employment panel: 26,714 out of 30,503 borrowers (or 88% borrowers) in the loan data are matched with employment data and have non-missing employment and industry codes. The investigation of matching patterns presented in Table 2 shows that firms that borrowed from ever-liquidated banks only had the worst match with employment data. Also, those firms are smaller on average than other types of borrowers.

To estimate the effect of bank liquidations on employment dynamics, we use the following model:

$$Emp_{ijt} = \beta * Treated_i + \gamma * Treated_i Post_{it} + D_{tj} + \alpha_i + \epsilon_{ijt}, \tag{2}$$

where i, j, t index borrower, borrower's industry, and year, respectively. Emp_{ijt} is log employment; $Treated_i$ equals 1 for firms that had bank that was liquidated in year t as their main bank. $Post_{it}$ is borrower-specific post dummy which equals 1 in all post-liquidation

Table 2: **Employment characteristics of borrowers**

Type of borrower	**Number of firms in large loans data**	**Number of firms with employment data**	**Mean**	**Standard deviation**
Borrow from never liquidated bank only	19,965	18,019	234	2319
Borrow from both types of banks	2,378	2,297	461	3203
Borrow from ever liquidated banks only	8,205	6,398	83	419

years. We also include vector of industry-year interactions D_{tj} to account for industry specific shocks that might have affected firm's employment. We estimate Equation 2 by OLS and FE (including firm fixed effect) to account for the unobserved and observed differences between firms that are fixed over time. For OLS regression, α_i are zeros.

3 Results

Estimates of Equation 2 are presented in Table 3. The OLS results confirm the observation from 2 that treated firms are smaller on average. Therefore, the inclusion of fixed effects is crucial to account for these differences. Column 2 of Table 3 shows that firms that had liquidated bank as their main bank experienced 26 percent employment decreased in the years following the liquidation.

We further investigate the dynamics of the liquidation effect as well as test for possible pre-liquidation dynamics in employment through an event study for years prior and after the liquidation. Employment dynamics is measured relative year=0 (liquidation year). Underlying regression includes firm fixed effects and industry-year interactions. Pre- and post-dummies are always zeros for not-treated firms. Figure 3 shows corresponding coefficients and 99 percent confidence intervals, suggesting that there are no employment trends in the pre-liquidation period for treated firms. Also, we observe an initial employment drop of 13 percent in the first post-liquidation year, and the negative effect monotonically increases

Table 3: Estimated Employment Effect of Bank Liquidations

	(1) OLS	(2) FE
Treated	-0.441***	
	(0.035)	
Treated*Post	0.095**	-0.258***
	(0.043)	(0.034)
Constant	2.398***	2.842***
	(0.000)	(0.219)
Industry*Year FE	YES	YES
Observations	247,272	
Number of treated firms	2,683	
Number of firms	28,995	

Notes: In parentheses, heteroskedasticity-robust standard errors that correct for correlation of error terms at borrower level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

and reaches 42 percent 5 years following the liquidation.

Note that the employment effect estimated in Equation 1 includes only the borrowers that survived in the post-liquidation period. Indeed, many firms were not able to switch to another bank and exited the data altogether. To test for this relationship formally, we estimate survival regression where the dependent variable is the likelihood of survival through 2019 (last year in the data), controlling for firm's age, employment and labor productivity in 2010, and treatment dummy. This regression is estimated using logit model and marginal effects are presented in Table 4. The survival regression results show that older, larger, and more productive firms are more likely to survive through 2019. Also, treated firms are 14 percent less likely to survive through 2019.[2]

[2]Note that the regression sample in column 2 reduces in half when we control for employment and productivity in 2010. Firms that entered after 2010 are not included in columns 2 through 4. However, results in column 4 suggest that the change in Treated coefficient in column 2 compared to column 1 is result of employment inclusion not change in the sample composition.

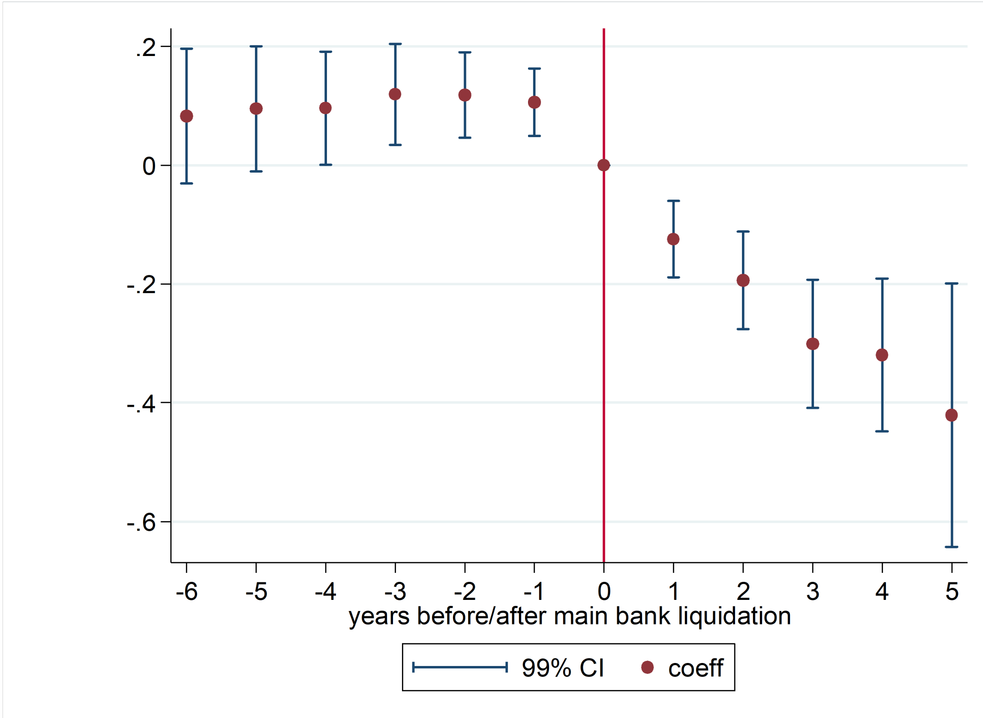

Figure 3: Employment Dynamics

Table 4: Survival analysis

	(1)	(2)	(3)	(4)
Age	-0.003***	0.026***	0.031***	0.034***
	(0.000)	(0.000)	(0.000)	(0.000)
Treated	-0.078***	-0.132***	-0.142***	-0.072***
	(0.009)	(0.011)	(0.012)	(0.012)
Employment		0.068***	0.049***	
		(0.001)	(0.001)	
Labor Productivity			0.014***	
			(0.001)	
Industry	YES	YES	YES	YES
Observations	641,420	277,600	234,791	234,791

Notes: Dependent variable: Survive=1 if firm survived through 2019. The sample includes all firms that were ever in employment data between 2010 and 2019. Estimates represent marginal effects from logit regressions. In parentheses, heteroskedasticity-robust standard errors that correct for correlation of error terms at borrower level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.