War, Collateral Damage, and Firm-Level Consequences

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Abstract

How much has the war in Ukraine damaged the collateral of Ukrainian firms, and how much collateral damage has that caused the Ukrainian financial system? We address this question using unusually rich high-frequency supervisory data of Ukrainian banks combined with a survey of banks on the location and condition of corporate borrowers' collateral between February and November 2022. Using an instrumental variables approach, we find that the war damages collateral, and the reduced value of collateral lowers firms' ability to borrow and raises firm defaults. The results imply reduced investment and lower economic growth for Ukraine in the future.

Keywords: war, collateral damage, probability of default, credit, Ukraine

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Introduction

There are many costs of war. Compared to the loss of life and limb, the permanent physical and psychological scars, the atrocities, and the destruction of families, hopes, and dreams, the economic costs may pale in importance, yet they remain considerable. Having reliable estimates of these costs and how they affect behavior has important implications for future recovery and reconstruction.

In this paper, we examine some of the firm-level consequences of war in Ukraine, particularly the period since February 24, 2022, when Russia launched a full-scale invasion building on its earlier grabbing of territory and causing the armed conflict from 2014. Our focus is on firm-level outcomes in financial markets, costs that take place through collateral damage, literally.

Our empirical analysis relies on a remarkable database we have linked together that contains detailed information on all large corporate loans in Ukraine outstanding from February to November 2022. The data include measures of the value and location of different types of collateral posted for each loan, information from summer 2022 on the loss of or damage to the collateral, and basic characteristics of the corporate borrowers and loan terms. With these data, we are able to assess how collateral damage affects firm-level default, the probability of default, and access to new borrowing.

This research is directly related to previous studies of the "collateral channel" through which a shock to collateral value can generate multiplier effects by affecting borrowing ability [Barro, 1976, Bernanke and Gertler, 1989, Chaney et al., 2012, Gan, 2007]. The most common type of "shock" studied in this literature is changes in real estate prices, associated with macroeconomic fluctuations. Our work is also related to studies of figurative "collateral damage," which mostly focus on how war reduces international trade [Glick and Taylor, 2010]. To our knowledge, however, no previous research has studied the literal damage to collateral value taking place during a war, and how that causes further collateral damage in financial markets.

Our results also add to the scarce but growing literature on the implications of Russia's war in Ukraine for the Ukrainian economy. Notable contributions to that literature include Gorodnichenko et al. [2022]. Since February 2022, there have also been extensive efforts by economists to analyze and quantify the caused losses to different sectors of the Ukrainian economy, such as infrastructure, agriculture, and the labor market, among others. One such example includes "Russia will pay"[1] project with the goal to estimate all material damage caused to Ukraine's civilian infrastructure.

The paper continues in the next section with a background overview of the Ukrainian banking sector, followed by discussions of data, empirical strategy, results, and conclusion.

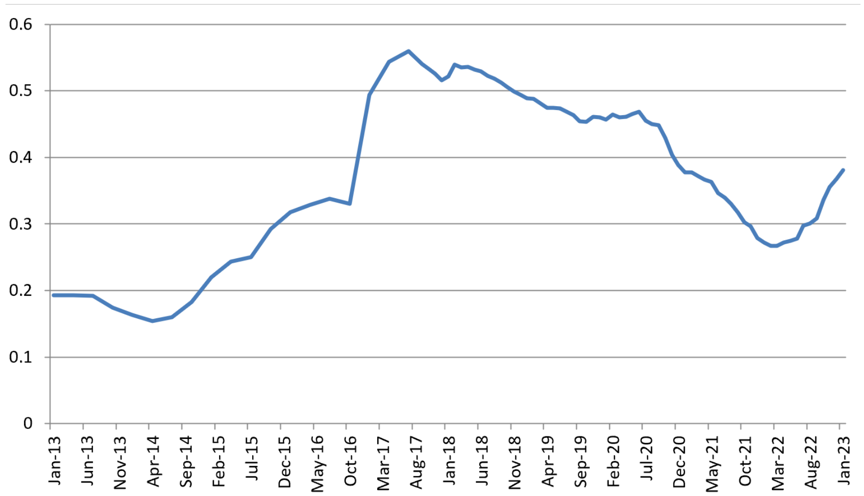
Overview of Banking Sector in Ukraine

During the past two decades, the banking sector in Ukraine underwent several macroeconomic crises and policy related changes. The quality of corporate portfolios deteriorated dramatically in 2014-2015 due to the macroeconomic shock caused by the annexation of Crimea, the military conflict in Donetsk and Luhansk regions, and large-scale structural imbalances in the economy [National Bank of Ukraine, June 2016]. The crisis impacted not only firms located in regions directly affected by Russia's aggression, but the whole Ukrainian economy. Losses for banks were smaller if the pre-shock quality of assets had not been overestimated and risks not been systematically hidden and accumulated since the crisis in 2008-2009. There was little control over banks issuing loans to related parties, business groups, and low-quality borrowers. The concentration of loans in foreign currency was high at that time. As a result, the macroeconomic shock in 2014-2015 triggered old hidden risks in the banking sector and significantly damaged the performance of all corporate borrowers. The share of non-performing loans increased to a maximum of 58 percent in 2017 as banks recognized losses and fully complied with new regulations.

Recognition of the true quality of corporate portfolios was an important condition for

[1]https://kse.ua/russia-will-pay/

Figure 1: Share of Non-Performing Loans

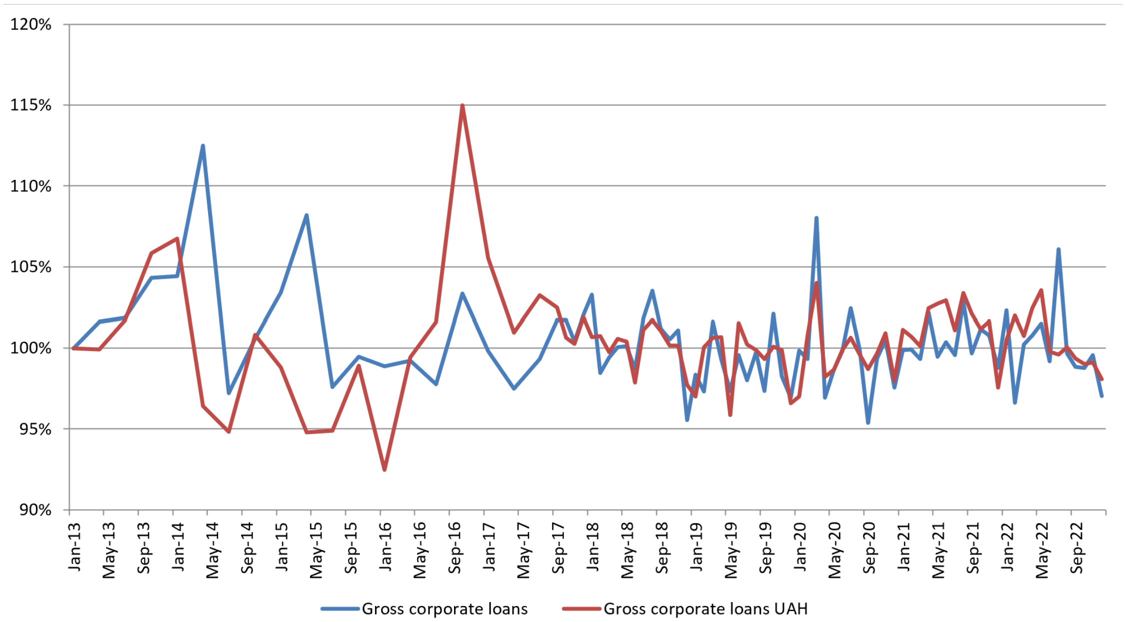


Source: National Bank of Ukraine

the development of further policies and recovery of corporate lending in the future. The National Bank of Ukraine (NBU) was institutionally reformed and finally gained its political independence. In the following years, the NBU implemented Basel regulations regarding the assessment of credit risk, limitation of related party lending, and overall concentration of large exposures [National Bank of Ukraine, December 2016]. More than 100 banks exited the market because of a lack of equity, nontransparent ownership structure, money laundering, bank fraud, etc. One of the largest domestic banks was nationalized. Along with other macroeconomic policies, the banking sector started recovering in 2016-2017. Corporate lending was reviving as the cost of loans was decreasing, and demand was gradually rising [National Bank of Ukraine, December 2017].

By the onset of the pandemic, the banking sector in Ukraine was transparent, liquid and profitable due to proper banking supervision and efficient regulations. As a result, banks were fully capitalized with a high margin of safety and diversified corporate portfolios. The pandemic did not cause significant losses [National Bank of Ukraine, June 2020]. The industries most affected by the pandemic had only moderate exposure in Ukrainian banks

Figure 2: Loans to Corporate Borrowers



Source: National Bank of Ukraine

[National Bank of Ukraine, December 2020]. In 2021, corporate lending was recovering, with lending to small and medium-size borrowers increasing most rapidly [National Bank of Ukraine, December 2021]. The share of non-performing loans was declining.

Although the full-scale invasion by Russia has caused a deep crisis, the Ukrainian banking system has generally continued to function well, maintaining liquidity and continuing to issue loans [National Bank of Ukraine, June 2022]. In the first months of full-scale war, corporate lending was growing, driven mostly by the state support program Affordable Loans 5–7–9% [National Bank of Ukraine, December 2022]. At the same time, as banks receive more recent data about their corporate borrowers and loan-related collateral, credit losses and the share of non-performing loans go up. Since February 2022, banks have reported an overall 9 percent increase in non-performing loans [National Bank of Ukraine, December 2022]. The ongoing war and systematic attacks on power infrastructure are causing significant deterioration of business performance and, consequently, higher credit losses for banks.

The NBU expects total losses from credit risk will therefore continue to increase. For estimating banking sector's losses, the regulator launched additional surveys for banks aimed at collecting detailed information regarding large exposures and collateral conditions.

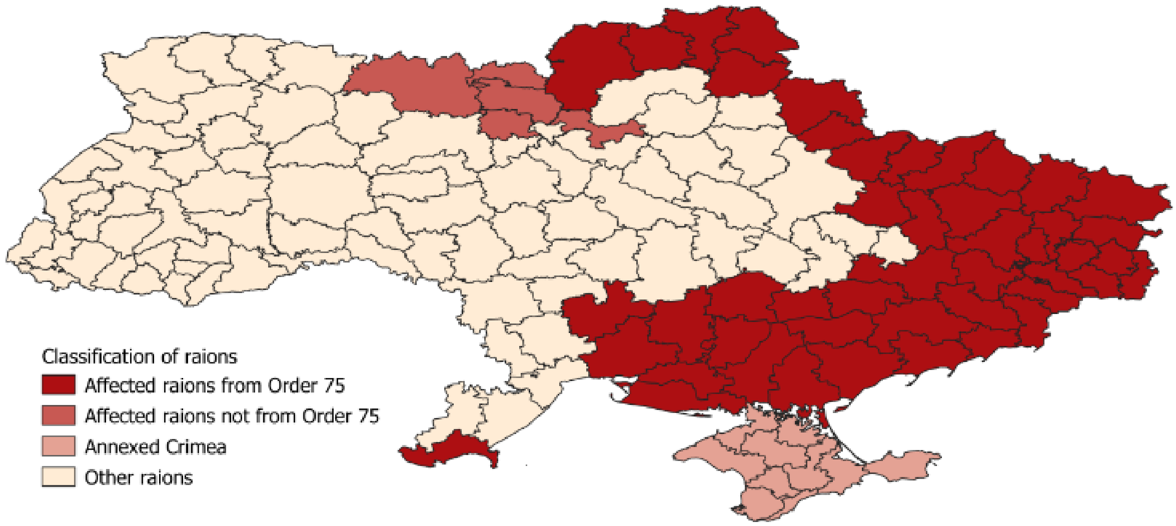
Data and Sample Construction

We use several datasets to analyze the effect of collateral damage on various firm outcomes. Bank-borrower-collateral location level data were collected by the NBU in the one-off survey of the largest Ukrainian banks on different collateral conditions as of July 1, 2022 (hereafter *survey*). The *survey* includes information on up to the 100 largest corporate borrowers from each of 66 banks that collectively hold 96 percent of the total loan portfolio in the Ukrainian banking system. The initial sample contains 2,774 unique bank-borrower pairs. Further, we exclude borrowers with unsecured loans or loans with highly-liquid collateral (deposits, etc.) and borrowers for which banks did not provide information about the collateral location. The resulting *survey* sample contains the micro-level data for 58 banks and 2,090 unique bank-borrower pairs of collateral location, collateral conditions (damaged, destroyed, no information, loss of control or not affected), and type of collateral asset (e.g. residential real estate, transportation, etc.).*Collateral asset* in the *survey* data is a collateral of a specific type (land, transportation, equipment, residential or commercial real estate, integrated property, or other) that was located in specific raion. For example, a borrower might have two collateral assets that are *land* but are located in different raions. For each borrower in the survey, we have the information on their collateral assets and their locations.

We merge these survey data with the supervisory loan data (hereafter *loan data*), monthly administrative data reported by all banks to the NBU for outstanding corporate loans above UAH 2 mln, and loans issued to related parties. This rich dataset contains information on bank-borrower-loan level and characteristics such as exposure at default, collateral value, type of collateral asset, credit risk, maturity, interest rate, etc. *Collateral asset* in the *loan* data is a collateral of a specific type (land, transportation, equipment, real estate, integrated property, or other) associated with a specific loan contract. These data also contain information about the quality of borrowers, including default and the probability of default. We use these data to obtain information on collateral values and to calculate outcome variables as of November 1, 2022.

To identify the locations of the borrowers, we use data from financial statements collected by the State Statistical Service of Ukraine. These data allow us to identify the borrower's raion of registration and 2-digit industry code. We then classify all raions as either affected or non-affected using two sources. First, we code a raion as affected if it was indicated in Order 75 of the Ministry of Reintegration of the Temporarily Occupied Territories of Ukraine "On approval of the list of territorial communities which are located in the area of fighting, under temporary occupation, or encirclement (blockade)" since April 25, 2022, and thereafter. Second, we use the information from public sources to compile the list of raions that were temporarily occupied and then liberated prior to April 25, 2022. We treat a raion as affected if at least one territorial community within a raion was located in the area of fighting, under temporary occupation, or blockade. The map of affected raions is illustrated in Figure 3.

Figure 3: Classification of raions affected by Russia's invasion



To construct the sample for the analysis, we start with the *survey* and restrict it to corporate borrowers only. For each borrower and collateral asset, we create a dummy variable *ColAffected* which takes the value of 1 if the collateral asset was located in the affected raion. We also construct the collateral condition variables *damaged*, *destroyed*, *loss of control*, and *no information* which correspond to the possible conditions of the collateral asset from the survey. The unit of observation in this sample is bank-borrower-collateral asset type (land, transportation, equipment, etc.) and its condition. We then merge the borrowers from the *survey* with the *loan data* by bank-borrower-collateral type as of February and November 2022. This expands the data because loan data is on bank-borrower-loan-collateral asset level. We then use loan data to calculate outcome variables and main variable of interest. We complement this data with the information on 2-digit industry code and location of borrower registration from the financial statements. This allows us to create variable *BorrAffected* which takes the value of 1 for the borrower registered in the affected raion.

The main question we address is whether the change in collateral value affected the outcomes for Ukrainian firms. We study four outcomes. The first is *Default* as of November

2022 and it takes a value of 1 for the borrowers that were in default as of November 1, 2022. The second outcome, *PDChange*, is the difference between the probability of default as of November 2022 and the probability of default as of February 2022. Probability of default (PD) is the bank's estimate of the likelihood that a borrower will be unable to meet its debt obligations. PD calculation is mostly based on the financial state of a borrower. PD is one of the main inputs for a credit risk assessment.

To measure whether damaged collateral affected opportunities to get new loans, our final outcomes are *NewLoan* and *ShareNewLoans*. *NewLoan* takes the value of 1 if a borrower had at least one new loan between February and November 2022 and is 0 otherwise. *ShareNewLoans* is defined as the ratio of the sum of new loans as of November (new are the loans initiated between March and November, and still outstanding in November) to the sum of all outstanding loans as of February 2022.

We construct our main variable of interest, the measure of change of collateral value *ColChange* from the *loan data*. *ColChange* is defined as the ratio of collateral-loan ratio as of February to collateral-loan ratio as of November 2022:

$$ColChange_{clibj} = \frac{ColSumNov_{clibj}/LoanSumNov_{libj}}{ColSumFeb_{clibj}/LoanSumFeb_{libj}} \tag{1}$$

where $ColSumNov_{clibj}$ ($ColSumFeb_{clibj}$) is value of collateral asset c of loan l for borrower i from industry j in bank b as of November (February) and $LoanSumNov_{clibj}$ ($LoanSumFeb_{clibj}$) is outstanding amount of loan l for borrower i from industry j in bank b as of November (February). To calculate this measure, we use collateral value adjusted for the NBU's liquidity coefficients by collateral type and restrict our sample only to the loans that we can track over time (loans that were outstanding as of February and November). This ensures that we calculate the change in the collateral value for the same loan, and the change is not driven by the change in the structure of loan portfolio.

Table 1 reports summary statistics on firm outcomes for the entire sample and by collateral condition. Between February and November, default probabilities and defaults have increased, and borrowers experienced, on average, a 14 percent increase in the share of new loans. However, borrowers with any damage to their collateral have a higher probability of default, higher default rate, and lower shares of new loans as of November 2022 compared to the borrowers that did not report any damage to their collateral. Moreover, borrowers with any damage to their collateral experience a decrease in their collateral value between February and November, while borrowers with no damage face a slight increase in their collateral value. Overall, about 8 percent of all collateral assets in the sample have been either damaged, destroyed, have lost control, or there is no information about their conditions.[2]

Table 1: Outcomes by Collateral Condition

Collateral condition	**PD change**	**Default**	**Share new loans**	**New loans**	**Collateral change**	**N**
All collateral assets	0.14	0.09	0.14	0.19	0.99	5667
Any damage	0.21	0.34	0.09	0.15	0.74	476
No damage	0.09	0.12	0.15	0.20	1.02	5161
Missing	0.02	0.00	0.01	0.08	1.04	30

Notes: Columns 1 through 4 report mean values of PD change, Default, New loans and Share of new loans where the unit of observation is borrower. Column 5 reports the mean of ratio of collateral-loan ratios where the unit of observation is borrower-loan-collateral asset. Any damage=1 if any of collateral asset was damaged, destroyed, have lost control or there is no information about the condition of this collateral asset. PD change = change in probability of default from February to November 2022. Default = 1 if borrower defaulted as of November 2022. Share new loans = ratio of new loans initiated between March and November (and outstanding as of November) relative to all loans in February. New loans = 1 if borrower had at least one new loan between February and November. Collateral change is a ratio of collateral-loan ratios in February and November.

Table 2 provides a breakdown of collateral conditions by the location (raion) of the collateral and raion of the borrower registration. It is notable that across all collateral conditions that indicate any damage to collateral, most of the collateral assets are located

[2]This percentage may well be interpreted as a lower bound because it pertains to July (the survey date) rather than November and because borrowers may fail to report damaged collateral to the banks.

in the affected raions. Out of all collateral assets that experienced no damage, about 25 percent were located in the affected raions. There is also substantial overlap between different collateral conditions: one collateral asset for a specific borrower may have more than one condition. The reason behind this is that *survey* reports information for each bank, borrower, collateral asset, and collateral raion level, and a particular borrower can have more than one asset of the same collateral type located in different raions and different conditions.

Table 2: Collateral Condition and Collateral Location

Collateral condition	**Collateral in affected raions**	**Collateral in other raions**
Damaged	66	29
Destroyed	9	0
Loss of control	330	1
No information	117	7
Not damaged/destroyed/lost	1,287	3,874
Missing condition	15	15

Notes: One collateral asset can have several collateral conditions. Out of 95 damaged collateral assets, 69 have lost control and there is no information on 3 others. Out of 9 destroyed collateral assets, 5 have lost control. Out of 124 with no information, 3 are damaged and 52 have lost control.

Table 3 further explores the differences across borrowers in outcomes and changes in collateral value by the location of the borrower and collateral, as well as participation in the state loan program. We find that borrowers who are registered in affected raions and borrowers with collateral in affected raions have higher default rates and probability of default as of November compared to February. Also, these borrowers experience a decrease in their collateral value and are less likely to get new loans. Table 3 further confirms that most of the new loans in the sample were issued through the state loan support program, although only 94 borrowers get new loans through this state program.

Table 3: **Outcomes by Location and Participation in the State Loan Program**

	PD change	Default	New loans	Collateral change	Number of borrowers	N
Borrower in affected raion	0.16	0.17	0.13	0.96	277	1,170
Borrower not in affected raion	0.08	0.13	0.15	1.01	765	4,497
Collateral in affected raion	0.13	0.16	0.11	0.94	183	1,741
Collateral not in affected raion	0.08	0.14	0.15	1.02	859	3,926
State loan program	0.05	0.00	0.61	1.14	94	823
No state loan program	0.11	0.15	0.11	0.97	948	4,844

Notes: Columns 1 through 3 report mean values of PD change, Default, and Share of new loans where the unit of observation is borrower. Column 4 reports the mean of ratio of collateral-loan ratios between February and November where the unit of observation is borrower-loan-collateral asset.

Empirical Strategy

When studying the effect of the change in collateral value on firm outcomes, we face an identification problem. In particular, the same (or different) shock may affect the borrower's financial health as well as the value of collateral. Therefore, we need to separate collateral damage and damage to the borrower. Our baseline estimating equation relates change in collateral value to firm outcomes:

$$DV_{ibj} = \beta * ColChange_{libjc} + \gamma * ColAffected_{ibjc} + \omega * BorrAffected_{ibj} + \theta_b + \alpha_j + \epsilon_{ibjc} \quad (2)$$

where $ColChange_{libjc}$ is ratio of collateral-loan ratio as of November to collateral-loan ratio as of February for collateral asset c of loan l for borrower i, $ColAffected_{ibjc} = 1$ if any part of the collateral asset is located in an affected raion, $BorrAffected_{ibjc} = 1$ if borrower is registered in affected raion. θ_b and α_j measure bank and industry fixed effects, respectively. The inclusion of the controls for borrower location is the first step to disentangling the effect of collateral damage net of the damage to the borrower.

To address the identification problem more directly, we utilize the richness of the data and employ an instrumental variable approach by instrumenting ratio of collateral-loan ratios

$ColChange_{libjc}$ with dummies for collateral conditions (*damaged, destroyed, loss of control, no information*). As an alternative specification, we create a single dummy (*AnyDamage*) that takes the value of 1 if the collateral asset was either damaged, destroyed, lost, or there is no information about its condition. This approach allows us to disentangle the effect of the change in collateral value driven by the damage, destruction, loss of control, or absence of information about the collateral asset and not by the overall worsening of market conditions caused by the war. In various specifications, we control for *ColAffected*, and sometimes additionally *BorrAffected*, to account for generalized exposure to the war at the raion level, implying that the instrument reflects idiosyncratic damage resulting from that exposure. Another function of this approach is that the change in collateral value may be measured with error, for instance, if firms keep reporting the same value to banks despite changed circumstances and banks cannot verify value independently. In this case, instrumenting provides a multiple indicator method of reducing bias associated with measurement error.

Table 4 reports estimates from the first-stage regression of ratio of collateral-loan ratios *ColChange* on the dummy *AnyDamage*. The results are consistent across specifications and show that there is a strong negative relationship between any damage and change in collateral value suggesting that collateral assets that were either damaged, destroyed, lost control, or if there is no information about their conditions, experience a decline in value compared to those that were not damaged. Table A1 in the Appendix further breaks down *AnyDamage* in separate dummies for *damaged*, *destroyed*, *loss of control*, and *no information*. The results suggest that the overall negative effect is driven by the collateral assets that borrowers lost control of. The rest of the dummies are not consistently significant and results are noisy likely due to small number of assets within each category and possibly because of overlap between the categories for collateral condition.

Table 4: **Change in Collateral Loan Ratio and Collateral Condition**

	(1)	(2)	(3)	(4)	(5)
Any damage	-0.277***	-0.294***	-0.318***	-0.284***	-0.284***
	(0.076)	(0.090)	(0.098)	(0.098)	(0.098)
Collateral in affected raion				-0.060**	-0.056
				(0.028)	(0.036)
Borrower in affected raion					-0.007
Bank FE		✓	✓	✓	✓
Industry FE			✓	✓	✓
Observations	5,667	5,667	5,499	5,499	5,499
R-squared	0.047	0.101	0.140	0.144	0.144

Notes: Table shows the results of OLS regression with ratio of collateral-loan ratio as of November to collateral-loan ratio as of February as dependent variable. The unit of observation is collateral asset. *Any damage* takes on the value of 1 if any of collateral asset was damaged, destroyed, lost control or there is no information about its condition. In parentheses, heteroskedasticity-robust standard errors that correct for correlation of error terms at borrower level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To further ensure that the effect we identify comes via the collateral channel and is not driven by the aggregate effect of the war on borrowers, we perform a robustness analysis by excluding the types of collateral assets that are most likely to be used in the production process (equipment and integrated property). The remaining types include land, residential real estate, transportation, and others.

Results

The regression results examining the outcomes of collateral damage for default and the change in default probability are presented in Table 5. All estimated coefficients on the variable of interest, the change in collateral value, are estimated to be negative. They are much larger and more significant in the IV specifications, which may reflect high measurement error in the change in collateral value. The point estimate in column (2) implies that a 10 percent decline in collateral value raises the default rate by eight percentage points, against a 12 percent unconditional mean for the default rate. The result in column (4) implies a corresponding 4.5 increase in banks' assessments of the probability of future default. This difference in the magnitude of the coefficients might imply that the banks underestimate the impact of war on the default probability of the borrowers.

Table 5: Defaults and Probability of Default

	(1)	(2)	(3)	(4)
	Default		Change in default probability	
	OLS	IV	OLS	IV
Change in collateral-loan ratio	-0.128**	-0.825***	-0.029	-0.451**
	(0.060)	(0.241)	(0.045)	(0.203)
Collateral in affected raion	0.014	-0.073*	-0.007	-0.059*
	(0.034)	(0.043)	(0.028)	(0.035)
Borrower in affected raion	0.096*	0.097**	0.166*	0.167***
	(0.057)	(0.048)	(0.048)	(0.046)
Bank FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Observations	5,499	5,499	5,499	5,499
First-stage F-stat		13.51		13.51
Mean dep. variable	0.122	0.122	0.121	0.121

Notes: Dependent variable is default as of November 2022 (columns 1-2) and change in default probability between February and November 2022 (columns 3-4). The unit of observation is collateral asset. In parentheses, heteroskedasticity-robust standard errors that correct for correlation of error terms at borrower level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The estimated coefficients on borrower location are generally consistent with a positive default effect of location in an affected raion. However, collateral location is estimated to have either a zero or opposite effect, possibly because the positive effect is already captured by the change in collateral value or by borrower location. Tables A2 and A3 show that the OLS regression in column (7) with only collateral location, omitting borrower location, produces large, positive, statistically significant coefficients of 0.074 and 0.096, for the default rate and bank's estimated probability, respectively. The IV result of much smaller coefficients in column (8) of those tables seems to reflect the fact that collateral location is highly correlated with collateral damage, which is hardly surprising in the context of a war.

Table 6 contains analogous results for the new borrowing outcomes, both as a dummy variable for any new loan and for the continuous variable measuring the ratio of new loans as of November 2022 to the level of borrowing as of February 2022. Again, the estimated coefficients are larger with the IV specification than with OLS. The results in column (2) imply that the probability of a new loan falls about 7.5 percentage points for each 10 percent fall in collateral value. Column (4) implies that the amount of new loans falls by close to 3 percentage points for the same decline. Again, borrower location more strongly affects the outcomes than collateral location.

Table 6: New Loans

	(1)	(2)	(3)	(4)
	New loans		Share of new loans	
	OLS	IV	OLS	IV
Change in collateral-loan ratio	0.222***	0.753***	-0.000	0.277***
	(0.047)	(0.165)	(0.050)	(0.068)
Collateral in affected raion	0.056	0.124**	0.013	0.048
	(0.048)	(0.054)	(0.041)	(0.039)
Borrower in affected raion	-0.072	-0.71	-0.061*	-0.061*
	(0.074)	(0.065)	(0.035)	(0.033)
Bank FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Observations	5,499	5,499	5,499	5,499
First-stage F-stat		13.51		13.51
Mean dep. variable	0.284	0.284	0.121	0.121

Notes: In columns 1 and 2, dependent variable is new loans which takes on the value of 1 if the borrower has obtained a new loan between February, and November 2022. In columns 3 and 4, dependent variable is new loans obtained between February and November, 2022 as a share of all outstanding loans as of February 2022. The unit of observation is collateral asset. In parentheses, heteroskedasticity-robust standard errors that correct for correlation of error terms at borrower level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

One potential problem with these estimates is that damage to collateral could affect a firm's production capability, worsening its financial condition through a different channel. For this reason, we exclude types of collateral that could be involved in production, such as equipment and integrated property. This exclusion pertains to about 1,500 collateral assets, shrinking the sample size. The remaining collateral types include land, transportation, and real estate, among others. Results in Tables 7 and 8 show estimated coefficients very similar to the main sample, even slightly higher in magnitude.

Table 7: Defaults and Probability of Default: Non-Production Assets

	(1)	(2)	(3)	(4)
	Default		Change in default probability	
	OLS	IV	OLS	IV
Change in collateral-loan ratio	-0.115**	-0.935***	-0.019	-0.540**
	(0.056)	(0.270)	(0.043)	(0.229)
Collateral in affected raion	0.015	-0.093*	0.006	-0.062
	(0.033)	(0.052)	(0.030)	(0.042)
Borrower in affected raion	0.099*	0.119**	0.162***	0.176***
	(0.058)	(0.057)	(0.052)	(0.054)
Bank FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Observations	3,913	3,913	3,913	3,913
First-stage F-stat		12.56		12.56
Mean dep. variable	0.128	0.128	0.128	0.128

Notes: Dependent variable is default as of November 2022 (columns 1-2) and change in default probability between February and November 2022 (columns 3-4). The unit of observation is collateral asset. In parentheses, heteroskedasticity-robust standard errors that correct for correlation of error terms at borrower level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: New Loans: Non-Production Assets

	(1)	(2)	(3)	(4)
	New loans		Share of new loans	
	OLS	IV	OLS	IV
Change in collateral-loan ratio	0.213***	0.785***	-0.004	0.301***
	(0.053)	(0.214)	(0.052)	(0.087)
Collateral in affected raion	0.077	0.154**	0.035	0.076
	(0.056)	(0.066)	(0.048)	(0.048)
Borrower in affected raion	-0.059	-0.073	-0.062	-0.069*
	(0.081)	(0.069)	(0.040)	(0.039)
Bank FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Observations	3,913	3,913	3,913	3,913
First-stage F-stat		12.56		12.56
Mean dep. variable	0.291	0.291	0.121	0.121

Notes: In columns 1 and 2, dependent variable is new loans which takes on the value of 1 if the borrower has obtained a new loan between February and November 2022. In columns 3 and 4, dependent variable is new loans obtained between February and November 2022 as a share of all outstanding loans as of February 2022. The unit of observation is collateral asset. In parentheses, heteroskedasticity-robust standard errors that correct for correlation of error terms at borrower level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Conclusion

What can economists, as economists, do to help Ukraine during this time of tremendous need? Perhaps not a great deal, but in this paper we try to do what we can. Constructing and analyzing a remarkable database on all large corporate loans allows us to assess changes in the value of loan collateral and their association with war since the Russian invasion of February 2022 until November.

We find that damage to collateral value has been substantial and that it has damaged firms' and banks' financial performance. Loan defaults and banks' assessments of future default probabilities both increased, while firm borrowing decreased in association with the decline in collateral value. We address potential endogeneity and measurement error concerns with an instrumental variables/multiple indicator strategy, while also controlling for bank and industry fixed effects and whether the borrower and collateral location are directly affected by invasion and occupation.

The results provide further evidence complementing that for the U.S. on the collateral channel in amplifying business cycles. They also demonstrate the importance of the indirect ("collateral") damage to Ukraine's financial system resulting from the war and begin to quantify part of the massive reconstruction effort that will be necessary soon, we hope, in the future.

References

Robert J Barro. The loan market, collateral, and rates of interest. *Journal of money, Credit and banking*, 8(4):439–456, 1976.

Ben Bernanke and Mark Gertler. Agency costs, net worth and business fluctuations." american economic review, march 1989, 14–31. *Financial Fragility and Economic Performance." Quarterly Journal of Economics*, pages 87–114, 1989.

Thomas Chaney, David Sraer, and David Thesmar. The collateral channel: How real estate shocks affect corporate investment. *American Economic Review*, 102(6):2381–2409, 2012.

Jie Gan. Collateral, debt capacity, and corporate investment: Evidence from a natural experiment. *Journal of Financial Economics*, 85(3):709–734, 2007.

Reuven Glick and Alan M Taylor. Collateral damage: Trade disruption and the economic impact of war. *The Review of Economics and Statistics*, 92(1):102–127, 2010.

Yuriy Gorodnichenko, Ilona Sologoub, and Beatrice Weder. *Rebuilding Ukraine: Principles and Policies*. CEPR Press, 2022.

Financial Stability Report. National Bank of Ukraine, June 2016. URL `https://bank.gov.ua/admin_uploads/article/FSR_062016_eng.pdf?v=4`.

Financial Stability Report. National Bank of Ukraine, December 2016. URL `https://bank.gov.ua/admin_uploads/article/FSR_122016_eng.pdf?v=4`.

Financial Stability Report. National Bank of Ukraine, December 2017. URL `https://bank.gov.ua/admin_uploads/article/FSR_2017-H2_eng.pdf?v=4`.

Financial Stability Report. National Bank of Ukraine, June 2020. URL `https://bank.gov.ua/admin_uploads/article/FSR_2020-H1_eng.pdf?v=4`.

Financial Stability Report. National Bank of Ukraine, December 2020. URL `https://bank.gov.ua/admin_uploads/article/FSR_2020-H2_eng.pdf?v=4`.

Financial Stability Report. National Bank of Ukraine, December 2021. URL `https://bank.gov.ua/admin_uploads/article/FSR_2021-H2_eng.pdf?v=4`.

Financial Stability Report. National Bank of Ukraine, June 2022. URL https://bank.gov.ua/admin_uploads/article/FSR_2022-H1_eng.pdf?v=4.

Financial Stability Report. National Bank of Ukraine, December 2022. URL https://bank.gov.ua/admin_uploads/article/FSR_2022-H2_eng.pdf?v=4.

Appendix

Table A1: Change in Collateral Loan Ratio and Collateral Condition

	(1)	(2)	(3)	(4)	(5)
Damaged	-0.054	0.011	-0.003	0.009	0.008
	(0.075)	(0.071)	(0.055)	(0.056)	(0.056)
Destroyed	-0.127**	-0.015	0.034	0.038	0.037
	(0.051)	(0.057)	(0.071)	(0.070)	(0.067)
No information	0.133	0.175*	0.175*	0.188**	0.187**
	(0.111)	(0.105)	(0.097)	(0.094)	(0.094)
Loss of control	-0.390***	-0.440***	-0.499***	-0.468***	-0.468***
	(0.076)	(0.090)	(0.098)	(0.100)	(0.099)
Collateral in affected raion				-0.049*	-0.045
				(0.026)	(0.030)
Borrower in affected raion					-0.006
					(0.039)
Bank FE		✓	✓	✓	✓
Industry FE			✓	✓	✓
Observations	5,667	5,667	5,499	5,499	5,499
R-squared	0.065	0.127	0.169	0.171	0.171

Notes: Table shows the results of OLS regression with the ratio of collateral-loan ratio as of November to collateral-loan ratio as of February as the dependent variable. The unit of observation is collateral asset. In parentheses, heteroskedasticity-robust standard errors that correct for correlation of error terms at borrower level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Defaults

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV	(9) OLS	(10) IV
Change in collateral-loan ratio	-0.158***	-0.861***	-0.141**	-0.738**	-0.140**	-0.815***	-0.128**	-0.819***	-0.128**	-0.825***
	(0.056)	(0.304)	(0.066)	(0.324)	(0.068)	(0.233)	(0.061)	(0.251)	(0.060)	(0.241)
Collateral in affected raion							0.074*	-0.012	0.014	-0.073*
							(0.039)	(0.033)	(0.034)	(0.043)
Borrower in affected raion									0.096*	0.097**
									(0.057)	(0.048)
Bank FE			✓	✓	✓	✓	✓	✓	✓	✓
Industry FE					✓	✓	✓	✓	✓	✓
Observations	5,667	5,667	5,667	5,667	5,499	5,499	5,499	5,499	5,499	5,499
First-stage F-stat		34.19		27.92		16.56		14.09		13.51
Mean dep. variable	0.124	0.124	0.124	0.124	0.122	0.122	0.122	0.122	0.122	

Notes: Dependent variable is default as of November 2022. The unit of observation is collateral asset. In parentheses, heteroskedasticity-robust standard errors that correct for correlation of error terms at borrower level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Probability of Default

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV	(9) OLS	(10) IV
Change in collateral-loan ratio	-0.022	-0.670**	-0.050	-0.593***	-0.045	-0.509**	-0.029	-0.442**	-0.029	-0.451**
	(0.053)	(0.283)	(0.053)	(0.230)	(0.052)	(0.200)	(0.048)	(0.221)	(0.045)	(0.203)
Collateral in affected raion							0.096**	0.046	-0.007	-0.059*
							(0.039)	(0.042)	(0.028)	(0.035)
Borrower in affected raion									0.166***	0.167***
									(0.048)	(0.046)
Bank FE			✓	✓	✓	✓	✓	✓	✓	✓
Industry FE					✓	✓	✓	✓	✓	✓
Observations	5,667	5,667	5,667	5,667	5,499	5,499	5,499	5,499	5,499	5,499
First-stage F-stat		34.19		27.92		16.56		14.09		13.51
Mean dep. variable	0.121	0.121	0.121	0.121	0.122	0.122	0.122	0.122	0.122	0.122

Notes: Dependent variable is change of probability of default between February and November, 2022. The unit of observation is collateral asset. In parentheses, heteroskedasticity-robust standard errors that correct for correlation of error terms at borrower level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Share of New Loans

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV	(9) OLS	(10) IV
Change in collateral-loan ratio	0.016	0.231***	0.017	0.237**	0.004	0.265***	-0.000	0.274***	-0.000	0.277***
	(0.038)	(0.062)	(0.040)	(0.100)	(0.048)	(0.071)	(0.051)	(0.067)	(0.050)	(0.068)
Collateral in affected raion							-0.025	0.010	0.013	0.048
							(0.036)	(0.033)	(0.041)	(0.039)
Borrower in affected raion									-0.061*	-0.061*
									(0.035)	(0.033)
Bank FE			✓	✓	✓	✓	✓	✓	✓	✓
Industry FE					✓	✓	✓	✓	✓	✓
Observations	5,667	5,667	5,667	5,667	5,499	5,499	5,499	5,499	5,499	5,499
First-stage F-stat		34.19		27.92		16.56		14.09		13.51
Mean dep. variable	0.120	0.120	0.120	0.120	0.121	0.121	0.121	0.121	0.121	0.121

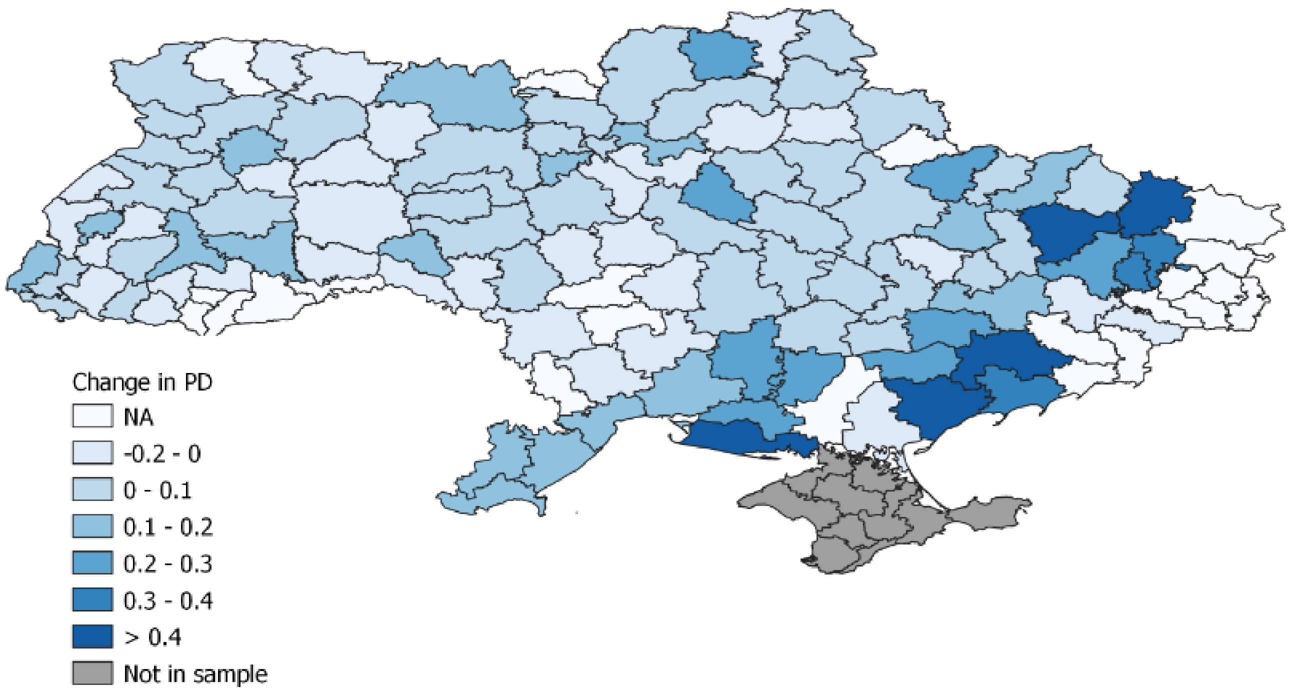
Notes: Dependent variable is new loans obtained between February and November 2022 as a share of all outstanding loans as of February,2022. The unit of observation is collateral asset. In parentheses, heteroskedasticity-robust standard errors that correct for correlation of error terms at borrower level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: New Loans

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV	(9) OLS	(10) IV
Change in collateral-loan ratio	0.244***	0.527***	0.221***	0.543***	0.220***	0.658***	0.222***	0.750***	0.222***	0.753***
	(0.048)	(0.134)	(0.043)	(0.137)	(0.048)	(0.125)	(0.047)	(0.164)	(0.047)	(0.165)
Collateral in affected raion							0.012	0.079	0.056	0.124**
							(0.063)	(0.067)	(0.048)	(0.054)
Borrower in affected raion									-0.072	-0.071
									(0.074)	(0.065)
Bank FE			✓	✓	✓	✓	✓	✓	✓	✓
Industry FE					✓	✓	✓	✓	✓	✓
Observations	5,667	5,667	5,667	5,667	5,499	5,499	5,499	5,499	5,499	5,499
First-stage F-stat		34.19		27.92		16.56		14.09		13.51
Mean dep. variable	0.280	0.280	0.280	0.280	0.284	0.284	0.284	0.284	0.284	0.284

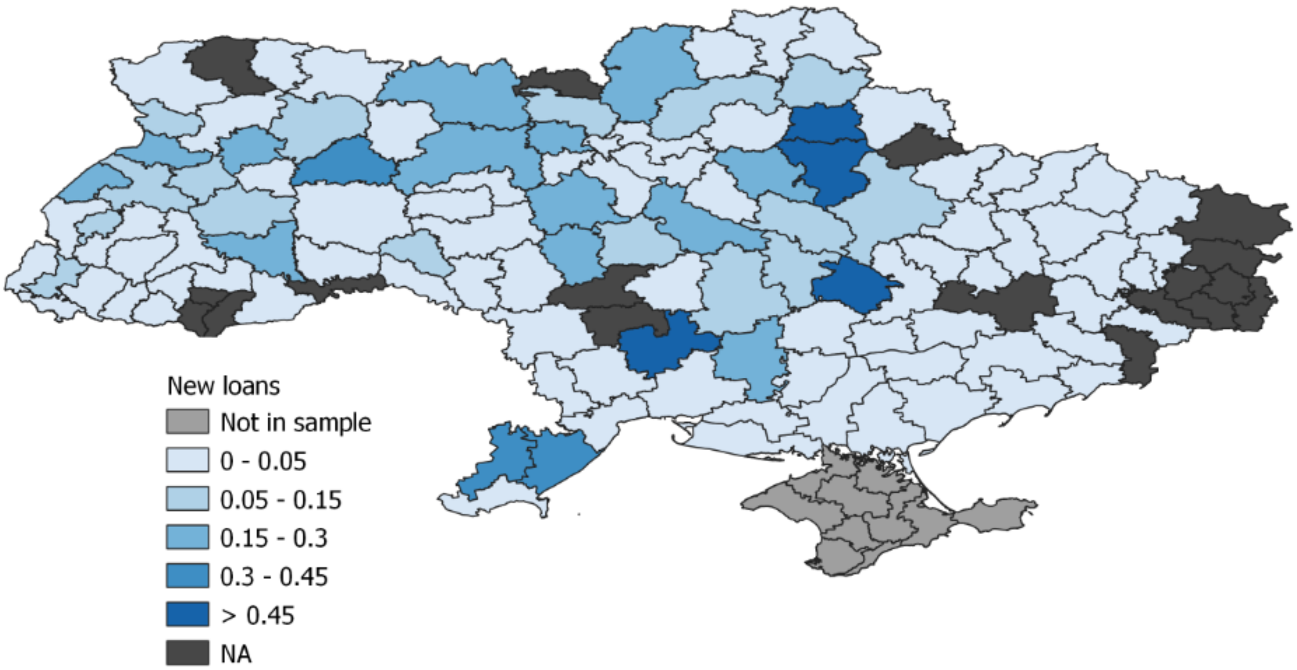
Notes: Dependent variable is new loans which takes on the value of 1 if the borrower has obtained a new loan between February and November 2022. The unit of observation is collateral asset. In parentheses, heteroskedasticity-robust standard errors that correct for correlation of error terms at borrower level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A1: Change in Probability of Default, 2022 (Survey Sample)



Notes: The map reports mean change in the probability of default in the survey sample between February and November 2022 by raion level. Dark shaded raions experienced the largest average increase in the probability of default between February and November 2022. Gray area refers to Crimea, which is not in the sample as Russia annexed it in 2014.

Figure A2: Share of New Loans, 2022 (Survey Sample)



Notes: The map reports mean share of new loans in the survey sample as of November 2022 by raion level. Dark blue raions experienced the largest average increase in the share of new loans between February and November 2022. Dark gray area indicates the raions that are not in the sample as there are no borrowers in the sample who are registered in these raions. Light gray area refers to Crimea, which is not in the sample as Russia annexed it in 2014.