Loan Types and the Bank Lending Channel

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Using credit-registry data for Spain and Peru, we show that four main types of commercial credit—namely, asset-based loans, cash-flow loans, trade finance and leasing—are easily identifiable and represent the bulk of corporate credit. Importantly, the bank lending channel varies across these loan types. Aggregate credit supply shocks previously identified in the literature are most strongly correlated with supply shocks in asset-based loans, while the correlation is weaker for cash-flow loans, trade finance, and leasing. We also revisit two well-known studies on the bank lending channel and find that results are sensitive to accounting for loan heterogeneity.

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Worldwide, much of commercial credit consists of four distinct types of loans: (i) asset-based loans (or "ABL"), (ii) "cash-flow" loans, (iii) trade finance, and (iv) leasing.[1] All of these loans are senior and secured; however, they differ in the type of collateral that backs them (or, to be precise, the net recovery from the sale of collateral). Using credit registry data from both an advanced economy, Spain, and an emerging market, Peru, we document the universal use and economic importance of these types of credit and empirically examine how these different types of credit impact the bank credit channel.

The core characteristics of collateral are its liquidation value, pledgeability, and durability. These characteristics are at the heart of the existence of different types of commercial credit. These do not have to be intrinsic characteristics of the physical asset, but can also be differences in repossession of collateral, as in the case of asset-based loans versus leasing (e.g., Eisfeldt and Rampini, 2009; Gavazza, 2011; Rampini and Viswanathan, 2013). Lease financing is an arrangement where the creditor finances an asset and the firm uses it in exchange for fixed rental payments. From a collateral perspective, ABL are comparable to leases: both are secured by large, typically registered physical assets with a relatively clear liquidation value (for example, a building or an airplane). The difference, as emphasized by Eisfeldt and Rampini (2009), is that leasing separates ownership and use of the asset, making it easy to repossess the asset by the lender in case of a default. So the pledged physical asset can be (and often is) identical across these two different types of loans, but the recovery in default is different due to the difference in pledgeability.

[1] These different types of credit are widely acknowledged by the industry and bank regulators. We abstract from factoring, which is the sale of accounts receivables, as opposed to borrowing against them as one would do in cash-flow based financing. Factoring generally constitutes a negligible fraction of commercial credit.

A significant fraction of commercial credit is what is called "cash-flow loans." Lian and Ma (2018) estimate that as much as 80% of syndicated credit in the U.S. is cash-flow based. The difference between ABL and cash-flow loans can again be understood from the perspective of the collateral used to secure the credit. As already mentioned, in the case of ABL, the borrower pledges specific physical assets to secure the loan. In the case of cash-flows loans, the lender has a senior claim on all unencumbered assets of the company; that is, the lender has a first claim on all proceeds from asset liquidations (excluding assets that were already pledged).[2] Overall, the collateral in cash-flow lending differs from ABL and leasing in several dimensions: it is oftentimes less durable, has lower liquidation value due to its less standardized nature, and has lower pledgeability due to uncertainty about its value (e.g., intellectual property or retailer inventory) or lack of title (e.g., office furniture). Indeed, a typical credit agreement for a cash-flow loan does not have a comprehensive list of what represents a collateral in the transaction. It is its senior secured position in the capital structure—and not the claim over specific assets—that allows it to have recovery in case of a default.[3] As a result, in the credit assessment of the cash-flow loan, the emphasis is *not* on the value of collateral (as in the case of an ABL), but on the borrower's ability to pay the interest and amortization (hence, the label "cash-flow loan").

The last significant category of commercial credit—trade finance—backs business-to-business (B2B) transactions.[4] This type of credit is backed by a bilateral contract, such as a

[2] It is common for a company that has many hard assets to split its collateral using a subsidiary structure and get an asset-based loan backed by hard assets in parallel to a cash-flow based loan backed by all other remaining assets.

[3] A standard credit agreement also includes a series of "catch-all" restrictions on asset sales, which helps to preserve the recovery in default.

[4] Not to be confused with "trade credit," which is credit granted directly by companies to their business clients.

contract for delivery of goods. Amiti and Weinstein (2011) provide a detailed insight into the working of trade finance.[5] The loan in this case is backed by the goods that are being transacted, so the collateral is well identified, valued (and insured), and the title of the good is in transfer (so it is not yet part of what will become collateral of a cash-flow loan). Trade finance is probably closest to cash-flow loans, but the pledgeability of the collateral in this case is higher. To be fair, there are other unique features of the trade credit, as it involves multiple counterparties and the credit risk in this case is no longer simply that of the borrower.

There are also other distinctions in terms of processes and sources of capital among the four lending categories. However, we want to highlight that in practice one often observes that borrowers have multiple loans outstanding of different loan type, and that the collateral for these different loan types can be partitioned without generating conflict among creditors. Importantly, what emerges from the earlier discussion is that different loan types carry different credit risks and involve different practices for mitigating negative shocks. Different loan types would also be differentially affected by fluctuations in the value of collateral.

In view of the above, accounting for the loan type is pivotal for at least two reasons:

First, failing to account for loan type leads to a mismeasurement of the credit channel effect. The methodology in Khwaja and Mian (2008), henceforth KM,—the workhorse of the literature focused on transmission of financial shocks to the real economy—performs a within-firm cross-sectional comparison of lenders' behavior. This approach relies on the assumption that firm-specific changes in credit demand are constant across lenders, hence

[5] Although Amiti and Weinstein (2011) focus on international trade, the arrangements used in local trade have similar feature, as trade concerns a delivery of contracted goods.

the estimated differences can be attributed to differences in credit supply. But, to the degree that there is a correlation between investment opportunities and credit type, and if different lenders provide different loan types to a given borrower, the identifying assumption that the borrower's credit demand is fixed across lenders is violated.[6] (See Appendix 1 for a more detailed description of the biases that arise when using the KM methodology without accounting for loan heterogeneity.) Accounting for loan type can also enhance our general understanding of the transmission of bank credit supply shocks. For instance, if collateral prices have been on the rise, and we observe that credit shocks are primarily driven by asset-based loans, then the collateral channel is likely to be an important driver in the transmission of shocks.

Second, a substantial number of borrowers in most economies rely on a single loan type. Historically, this number was 60% in Spain and 42% in Peru. Also, as we will show, the type of loans used by these firms tends to be very persistent. The overlap between the sample of borrowers that, at a given point in time, rely on one lender (the sample discarded in the KM approach) and the sample of borrowers that rely on one loan is not perfect, but substantial. About 79% of single-lender borrowers are also single-loan type for Spain; this number is 69% for Peru. This means that understanding results by loan type matters more broadly for the generalizability of the results that build on the KM methodology.[7] KM

[6] We know that large lenders can provide any loan type. This is not to say that you could easily switch the type of credit across existing lenders. For example, if a given borrower has a cash-flow loan with bank "A" and an ABL with bank "B", then it is likely to go back to bank "A" when it needs to increase its cash-flow loan. As we said, different loan types are about different credit risk, the type of screening and monitoring is likely to be specific to a given loan type. So information frictions in lender switching—for a given loan type—are likely.

[7] Using monthly observations, Ioannidou, Ongena, Peydró (2015) find that 46% of borrowers in Bolivia have only one lender at a given point in time. Bolton, et al. (2016)

estimation relies on a fraction of larger firms in the economy to estimate the lower bound of the credit supply, as firms excluded from the estimation are likely to be more bank-dependent.

To illustrate these points, we use credit registry data from Spain and Peru. We show that in both countries the bulk of bank commercial credit can be grouped into four main types: asset-based loans, cash-flow loans, trade financing, and leasing. The first two types of loans are the most common type of credit in both countries, both in terms of number and volume of loans. For instance, in 2004, asset-based loans accounted for 39.1% and cash-flow loans accounted for 48.2% of total commercial credit by banks in Spain. For Peru, these figures are 43.5% and 35.8%, respectively. The average size of asset-based loans is much larger than that of the other forms of credit, averaging about 1.0 million euros in the case of Spain and 6.4 million Soles in the case of Peru.

Applying the methodology proposed by Amiti and Weinstein (2018), we find that credit supply shocks vary by type of loans. This approach separates the bank lending channel from the firm-borrowing channel, as in KM, by saturating the regression with firm-time and bank-time fixed effects while accounting for general equilibrium conditions at the aggregate level. Overall credit supply shocks are most strongly correlated with supply shocks in asset-based loans, while the correlation is weaker for cash-flow loans, trade finance, and leasing.

Next, we revisit two well-known studies of the bank lending channel in order to explore to what extent heterogeneity in loan characteristics matters in practice.

show that this number for Italy is 60%, and, according to Morais et al. (2019) 79% of Mexican firms tend to have one lender. Quarterly data used in Khwaja and Mian (2008) for Pakistan, Iyer et al. (2014) for Portugal, and Baskaya et al. (2017) for Turkey show that the fraction of borrowers with one lending relationship is 90%, 25%, and 54%, respectively.

Specifically, we re-estimate the baseline specifications in Jimenez et al. (2012) and Bentolila et al. (2018) separately for different loan types using loan-level data from the Spanish credit register. Jimenez et al. (2012) applies the KM methodology to Spanish data to assess how variation in bank capital interacts with changes in monetary policy rates to influence credit growth. They find that lower interest rates spur loan growth especially at lowly capitalized banks, consistent with a risk-taking channel of monetary policy. Bentolila et al. (2018) applies the KM methodology to Spanish credit register data to estimate the effects of government bailouts on bank lending following the 2007-2008 global financial crisis (GFC). They find that banks that were bailed out by the Spanish government curtailed lending relative to the other banks during the GFC, consistent with a credit channel being related to bank strength. We find that the results on the bank lending channel in these two studies are sensitive to the type of loan considered. Specifically, the results in Jimenez et al. (2012) are mainly driven by cash-flow loans, while ABL loans exhibit a different pattern in the estimates. Similarly, we find that the results in Bentolila et al. (2018) are mainly driven by cash-flow loans and not by ABL loans.[8]

Bernanke and Gertler (1989, 1995) argue that monetary policy affects the external finance premium of firms by altering the agency costs, associated with asymmetric information between borrowers and lenders about the quality of firm investments. Easing monetary policy increases cash flows and collateral value, thus leading to a reduction in agency costs, which, in turn, makes it easier for the firm to borrow. While this theory does not have clear predictions for different loan types, arguably, the liquidation value of cash-flow loans is more sensitive to changes in agency costs, in which case monetary policy

[8] Note that these are cross-sectional estimates, whereas Amiti and Weinstein (2018) focus on the time-series behavior of the credit shocks.

should affect cash-flow loans more so than loans based on hard collateral. Similarly, if in the financial crisis the rise in agency costs was dominating the impact on collateral, it would explain why we find that the results in Bentolila et al. (2018) are primarily driven by cash flow loans. Alternatively, cash-flow loans may be more sensitive to monetary policy shocks because they tend to be of shorter maturity than asset-based loans.

In this paper, we build on and contribute to a number of strands of literature. First, we contribute to the literature on how the supply of credit is influenced by monetary policy and financial shocks including Kashyap et al. (1993), Bernanke and Gertler (1995), Kashyap and Stein (2000), and the set of papers that trace the impact of credit market disruptions on real outcomes including Kashyap, Lamont and Stein (1994), and Chodorow-Reich (2013).

Naturally, our paper contributes to the large body of empirical studies that build on Khwaja and Mian (2008) and use loan-level data to measure effects of credit shocks and their transmission. We will specifically replicate Jimenez et al. (2012) and Bentolila et al. (2018). Perhaps closest to our research are recent papers by Paravisini et al. (2017), which considers lender specialization, and Jimenez et al. (2019), which incorporates firm-level general equilibrium adjustments. Both studies refine the KM methodology.

Finally, there is the emerging literature focused on quantifying the aggregate effects of credit shocks on real outcomes, such as investment and output. We specifically build on Amiti and Weinstein (2018) and show that accounting for loan types is also relevant in evaluating the drivers of aggregate effects.

The paper proceeds as follows. Section 1 discusses the data from the Spanish and Peruvian credit registry. Section 2 shows patterns of use of different types of commercial loans by borrowers. Section 3 presents results of estimating credit supply shocks accounting for loan heterogeneity. Section 4 presents results of estimating cross-sectional effects of the bank credit channel accounting for loan heterogeneity. Section 5 concludes.

1 Data

In the analysis, we use credit registry data from two countries: Spain and Peru. Credit registries (or credit bureaus) are depositories of loan level information typically collected and maintained by the central bank for purposes of monitoring and regulation. They are also regularly used by local lenders to verify the credit history of a prospective borrower. To the extent that the type of credit is key information for assessing credit risk, information on the type of credit should be recorded in a credit registry and in any other major loan-level database. That is indeed the case in Spanish and Peruvian credit registries.[9] We elaborate on this below.

Typically, a credit registry tracks loan stock, that is, outstanding credit amount with monthly or quarterly frequency. One cannot observe individual loans in such data, but instead one observes lending relationships for a given borrower at a given point in time. Empirical work building on Khwaja and Mian (2008) generally constrains the analysis to observations in periods when the borrower has more than one lending relationship outstanding. As discussed earlier, this substantially limits the sample of borrowers used in the estimation. In our data, restricting the sample to firms with multiple lending relationships drops the number of unique borrowers by 50 percentage points for Spain and 39 percentage points for Peru. Naturally, once one accounts for loan type this further

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We specify the frequency because in some cases we were not certain if the authors refer to the number of unique borrowers or number of borrower-month/quarter observations.

[9] Similarly, in the United States, widely available data on syndicated loan origination such as DealScan can be used to identify the types of credit by looking at *Market segment* and *Loan type*.

restricts the sample of unique borrowers covered in the analysis. This is because, in the KM approach, borrowers that had one lender per loan type would be part of the analysis (as long as there is more than one lender/loan type.) Once we account for the loan type, these borrowers drop from the sample. Given this constraint, in what follows we will consider quarterly observations as a less restrictive time-unit of observation.

1.1 The Spanish CIR dataset

The Central Credit Register (*Central de Información de Riesgos* or *CIR* in Spanish) is maintained by the Banco de España in its role as primary banking supervisory agency, and contains detailed monthly information on all outstanding loans over 6,000 euros to non-financial firms granted by all banks operating in Spain since 1995. Given the low reporting threshold, virtually all firms with outstanding bank debt will appear in the CIR. We also use a dataset on loan applications, or, more precisely, bank requests for firm information which are interpreted as loan applications.[10] By matching the monthly records on loan applications with the stock of credit we infer whether the loan materialized. If not, either the bank denied it or the firm obtained funding elsewhere. This loan granting information is available from February 2002 onwards and is the same data used by Jimenez et al. (2012). Because several of the results will build on Jimenez et al. (2012), we restrict the Spanish sample to the 2002:Q1-2010:Q4 period. However, the descriptive statistics by loan type generalize to a longer sample.

[10] Banco de España can fine those banks requesting information without intent of loan origination.

In the Spanish data, we identify four main loan types based on two first-order variables: *Clase* or loan-risk class and *Garantia* or collateral.[11] From the indicator of type of risk, we consider the following three categories:[12] trade finance or "*crédito comercial*" (*clase A*) in Spanish, commercial and industrial (C&I) loans or "*crédito financiero*" (*clase B*), and leasing or "*operaciones de arrendamiento financiero*" (*clase K*). That is, leasing and trade finance in the Spanish data can be identified using solely *Clase* variable. To separate between asset-based and cash-flow based loans we turn to information on collateral. Spanish credit registry focuses on non-personal collateral ("*garantia real*") that includes assets like real estate, naval mortgages, securities, deposits, and merchandise (i.e., hard collateral). As mentioned earlier, it is the senior secured status (and contractual restriction on asset sales) that imply that the loan has collateral. The definition of collateralization in Spanish and Peruvian credit registries only concerns whether the loan is collateralized by hard assets. In the Spanish data, we know whether the value of the loan is collateralized by hard assets at (i) 100%, (ii) [50%; 100%); or (iii) is not collateralized. However, 98% of the loans in the data either have 100% real collateral or no real collateral. We categorize C&I loans "with collateral" as ABL, and cash-flow loans otherwise.

Consistent with our categorization of loan types, in Appendix Table A1, we use balance-sheet information taken from Almunia et al. (2018) available for the firms in the

[11] For full details see Circular 3/1995, de 25 de septiembre, a entidades de crédito, sobre la Central de Información de Riesgos (available at https://www.boe.es/buscar/pdf/1995/BOE-A-1995-22113-consolidado.pdf).

[12] We exclude guarantees and other contingent claims that are recorded in the Spanish data: "*avales, cauciones y garantías*" account for around 10% in number of loans and "*riesgo indirecto*" for around 6%. All the other types represent between 0.02% and 0.89% and are thus negligible. In terms of volume, these figures are even smaller.

Spanish sample, and confirm that firms with higher share of fixed assets over total assets rely more on ABL lending. In particular, asset tangibility has a strong economic and statistical power in explaining borrower's reliance on asset-based loan, yet practically no economic power on whether it uses leasing. On the other hand, the correlation between asset tangibility and borrower's share of cash-flow lending is negative. These results are robust to inclusion of controls for firm's age, size, leverage, and industry.

1.2 The Peruvian CIR dataset

Similar to the Spanish data, the Central Credit Register of Peru is maintained by the bank supervisory agency whi1ch in this case is the Superintendencia de Banca y Seguros (SBS). The data available to us covers a period between January 2001 and April 2018.[13] The sample is constraint to credit to firms with sales above 20 million Soles in sales (about $6 at the current exchange rate). We further focus on lending by banks, finance companies and "cajas".[14] Microcredit institutions are excluded from the sample.

We assign loans into four basic types using variable called *Cuenta*, which describes the type of loan as well as the collateral used in this transaction. We assign as asset-based credit the following loans types: "garantía hipotecaria," "garantías preferidas," "garantías preferidas autoliquidables," "garantías preferidas de muy rápida realización," and "otras garantías." That is, we count as ABL loans with the following collateral: real estate, other collateral with stand-alone title, deposits and other liquid

[13] Peruvian data has a structural break in 2010:Q2 at which point the Credit Registry applied a new filter for corporate loans. This should not affect the estimates of the supply shocks, however, this compositional shift in the data will be apparent in the descriptive statistics.
[14] Several countries have community banks and cajas, their origin and stated main objective is different than banks, however, they often act as traditional lenders.

financial securities, and other collateral. The values of *Cuenta* that got assigned to cash-flow based lending included: "*líneas de crédito*" (revolving lines) and "*préstamos*." "*Créditos-comercio exterior*" (loans for international trade) were assigned to the trade finance category. Finally, leasing is identified as "*arrendamiento financiero*." The types of credit that do not fall into one of these categories represent, on aggregate, about 10% of all loans and 20% of total commercial loan volume.

Note that for Peru we only capture international trade, whereas for Spain we capture all type of credit backing B2B transaction. As such the behavior of trade financing is not directly comparable across the two countries.

2 Use of different type of secured bank credit

In Table 1, we report descriptive statistics by loan type for 2004, 2008, and 2012. Panel A corresponds to the Spanish sample, and Panel B presents the same statistics for Peru. In line with evidence from the U.S. syndicated loan market presented by Lian and Ma (2018), cash-flow loans are an essential form of bank credit representing about half of all commercial credit in Spain and about a third of all commercial credit in Peru by loan volume or loan number. However, the universe of bank credit shows that asset-based credit is also pivotal, and perhaps not surprisingly even more so for an emerging economy. According to Djankov et al. (2008), debt enforcement tends to be weaker in emerging markets, making it more difficult to recover value in case of a default, rendering collateralized debt more attractive. ABL corresponds to about 40% of lending volume in Spain, but only about a quarter of all outstanding loans; whereas in Peru ABL in the past ten years had represented about 50% of lending volume and close to 40% of all loans.

[TABLE 1]

Turning to the evolution over time, Figure 1 illustrates that there is heterogeneity in the patterns across loan types suggesting that the Spanish credit boom was mostly driven by ABLs. The average size of ABL loans doubled during the boom, but it was then adjusted. Also, the increase in total credit was fourfold during the boom for ABLs while it was three- and two-fold for leasing and cash-flow lending, respectively. Similarly, the rise in ABL seems to be at the heart for the credit expansion experienced in Peru. Consistent with the weaker creditor protection that we expect for an emerging market, leasing (often a direct alternative to ABL) plays a substantial role as well.

[FIGURE 1]

In order to account for loan-specific heterogeneity when revisiting the bank lending channel literature, we need to condition the sample not only on borrowers with multiple lending relationships in a given quarter, but also require that there are multiple relationships within the same loan type. Note that this does not necessarily mean that the number of observations would drop relative to the sample in a KM-style estimation. For example, if a borrower has two lenders and each lender has an ABL and a trade-financing loan outstanding, our sample would have two borrower-quarter clusters (with two observations each), whereas KM-style estimation would have one (with two observations). However, if each lender has only one loan-type, and the loan types are non-overlapping, our sample would have zero qualifying observations (KM-style estimation would still have one observation). Also, while the number of overall observations could increase, the number of unique borrowers, or number of observations per loan-type cannot exceed the one in KM-style estimation. Table 2 gives insight into the overall impact on the sample. In the Spanish data, the number of unique borrowers drops by 13% once we account for loan type. In the Peruvian data, the drop is 8%. In both datasets the average loan size goes down because previously it was aggregated at the lender-quarter level across different loan types. We also see that the typical number of lenders per borrower after conditioning on loan type is about 3.

[Table 2]

To emphasize the importance of accounting for loan type for the generalizability of results out of sample, in Figure 2 we show the fraction of firms that use different loan types. This figure is constructed using the four loan-types for the last quarter of 2004, 2008, and 2012. The sample corresponds to the full credit registry, unconditional on the number of lenders per borrower. For Spain, we find that the majority of borrowers rely on one loan type: in 2004, this number was 60%, and it increases slightly in later years. For Peru, we can see that at least prior to the financial crisis (that is, before "Peruvian miracle" period) a large fraction of the borrowers relied on a limited number of loan types: in 2004, 83% of borrowers relied on two or one loan type, and, in 2008, this number was 73%.[15] [16]

[FIGURE 2]

Table 3 instead provides insight into the persistence of usage of a particular loan type. For each country, we present three matrices that correspond to different periods.

[15] These differences in the use of one or more loan type do not appear related to borrowing from one or more banks. Figure A1 shows that the distribution of loan type is broadly similar for borrowers with multiple lenders and borrowers with single lenders.

[16] "Over the past decade, Peru has been one of Latin America's fastest-growing economies, with an average growth rate 5.9 percent in a context of low inflation (averaging 2.9 percent)." Source: https://www.worldbank.org/en/country/peru "Peru At-A-Glance" accessed May 31, 2019. As mentioned earlier 2010 in the Peruvian data is also characterized by a reporting switch.

The analysis follows borrowers that at the end of a given year have only one loan type; each row corresponds to the starting loan type. (We count all borrowers with one loan type at the year end, even if in the past they had loans of other types.) The first matrix looks at the probability that 1 year later (at the end of the next year) the borrower has a given loan type (indicated in columns). The sample is conditional on the borrower remaining in the credit registry sample at the end of the period. That is, borrowers that leave the sample are not counted. To summarize the results, we first take an average across borrowers within year, and then report the average across years. The borrower can migrate to more than one type of credit. As a result, each row can add up to more than 100%. That said, if loan types are irrelevant, and the assignment is random, the benchmark would be 25%.

Taking Peru as an example, we see that 94.9% of borrowers that have asset-based loan will have an asset-based loan next year, and only 0.6% of them will completely substitute to a different loan type. However, we can see that about 17% of borrowers that exclusively rely on asset-backed loan expand into cash-flow based loans. The typical maturity of a loan in Peru is about one year, so this result is unlikely to be mechanical. However, we also report results for a 3-year window (bottom panel). Overall, even at the longer horizon, the loan type appears to be very persistent for each of the loan types. There is also little mobility of the loan type during the financial crisis (middle panel). Similarly, we see very little loan migration in the Spanish sample, indicating that loan type choices are persistent.

[TABLE 3]

3 Credit supply shocks and loan heterogeneity

Amiti and Weinstein (2018), henceforth AW, develop an empirical methodology for constructing aggregate supply and demand shocks using matched bank-firm loan data (the AW application is based on a sample of around 150 banks and 1,600 listed firms in Japan from 1990 to 2010). As the authors point out, many studies have shown that bank shocks matter for loan supply, however, that tells us little about how important is bank loan supply in determining aggregate variables such as investments and employment. The AW methodology builds on the following specification:

$$\Delta \ln L_{fbt} = \alpha_{bt} + \eta_{ft} + \varepsilon_{fbt} \tag{1}$$

where ΔlnL_{fbt} refers to loan growth by firm *f* from bank *b* in time *t* measured as log changes, α_{bt} refers to the "bank-lending channel", and η_{ft} refers to the "firm-borrowing channel". One approach to identify both channels is to empirically estimate (1) in a regression framework that is saturated with firm-time and bank-time fixed effects. AW show that this procedure is inefficient because it ignores general equilibrium considerations. For instance, a firm cannot borrow more without at least one bank willing to lend more (and vice versa). The core of AW's methodological insight is that one can account for general equilibrium conditions at the aggregate level by imposing that total credit growth is recovered by summing up the sequences of the estimated fixed effects so that the *R*-squared of the regression is equal to one by construction.

Using annual data from the Spanish CIR covering the period 2002-2010, we estimate equation (1) with the AW methodology and recover a sequence of bank-year and firm-year fixed effects that we interpret as bank credit supply shocks and firm demand shocks. These shocks are labelled as "All loans (ALL)" because they are based on total credit encompassing all loan types at the bank-firm-year level as in the original

AW approach. We next construct four alternative samples in which each bank-firm-year observation refers to credit exposure from a particular loan category. The AW methodology is then applied to each subsample and four different supply shocks are estimated for each bank in the sample: trade finance loans (TF), cash-flow loans (CF), asset-based loans (ABL), and leasing loans (LEA) shocks.

[Figure 3]

Figure 3 compares the original AW shocks estimated from total credit at the bank-firm level with the bank shocks resulting from each loan category. Panel A corresponds to Spain and Panel B corresponds to Peru. The takeaway is that the correlation is positive but relatively small. For Spain, the correlations range from 0.001 in the case of leasing to 0.282 for asset-based loans. For Peru, the range is from 0.001 to 0266; the lowest and highest numbers correspond to leasing and cash-flow lending. It is striking that—with the exception of trade finance which captures different things for the two countries—the magnitudes of errors resulting from omission of accounting for loan type are very similar for the two countries. This points to the similarities in the behavior of different types of credit across countries. Wide variation in errors across loan-types suggests that banks' credit supply is different depending on loan type contrary to the implicit assumption in the AW approach. Indeed, there are banks with an estimated positive shock from total credit (AW original setting) and a negative shock identified from, for instance, cash-flow loans, which definitely indicates that loan heterogeneity matters for the identification of bank supply shocks. Note that we focus here on bank shocks but the patterns are similar in the case of the estimated firm shocks shown in Figure A2 in the Appendix.

While the evidence in Figure 3 is already suggestive, the patterns in Table 4 are even more revealing of the importance of loan heterogeneity for identifying bank credit supply shocks. In particular, Table 4 shows that in all the six cases the estimated correlations are basically zero for both countries, which clearly points to loan-specific credit supply shocks at the bank level.

[Table 4]

Finally, we also estimated equation (1) on the Spanish data considering two alternative sets of fixed effects: if we regress credit growth on a set of bank-year and firm-year fixed effects, we explain 29 percent of the total variation in credit growth (*R*-squared = 0.29). However, if we instead include bank-loan-year and firm-loan-year fixed effects, the variation explained increases to 41 percent (*R*-squared = 0.41). We thus conclude that loan type heterogeneity matters to explain differences in credit growth.

4 Re-examining the bank lending channel of monetary policy

In this section, we revisit two well-known studies of the bank lending channel in order to explore to what extent heterogeneity in loan characteristics matters in practice. Specifically, for each of the four loan types identified above, we re-estimate the baseline specifications in Jimenez et al. (2012) and Bentolila et al. (2018) which both use Spanish data. Our identification is thus based on differences across banks within the same firm and loan type pair. Intuitively, we compare the same firm borrowing cash-flow loans from a bank affected by the shock with the same firm borrowing cash-flow loans from another bank not affected by the shock. Hence, we ensure that differences across banks cannot be driven by bank specific demand depending on the type of loan.

To provide a first insight into the role of loan type, our first exercise consists of regressing credit growth at the loan level on different sets of fixed effects. In the Spanish data, if we regress credit growth on firm-quarter fixed effects, we explain 28 percent of the total variation in credit growth (R-squared = 0.28). However, if we instead include firm-loan type-quarter fixed effects, the variation explained increases to 39 percent (R-squared = 0.39). The corresponding numbers for Peru are 0.23 and 0.42. This shows that loan type heterogeneity matters to explain differences in credit growth across banks within each firm.

4.1 Monetary policy and the bank lending channel

In this section, we re-estimate the baseline specification in Jimenez et al. (2012) considering two alternative dependent variables, namely, credit growth for the intensive margin and new loans for the extensive margin. Credit growth is based on annual log differences winsorized between -100% and +200%, and the new loan dummy takes value 1 when a bank-firm-loan type triplet first appears in the sample and zero otherwise. The sample covers the period 2002:Q1 to 2010:Q4.

When controlling for (firm x loan type x quarter) fixed effects we estimate the following model:

$$Y_{flbt} = \beta_{IC}\Delta IR_t \times CAP_{bt-1} + \beta_{IL}\Delta IR_t \times LIQ_{bt-1} + \tag{2}$$

$$+\beta_{GC}\,\Delta GDP_t \times CAP_{bt-1} + \beta_{GL}\Delta GDP_t \times LIQ_{bt-1} + Controls_{t-1} + \eta_{ilt} + \varepsilon_{flbt}$$

where f, b, and t refer to firm, bank, and quarter, respectively. l refers to the loan type, and η_{ilt} corresponds to (firm x loan type x quarter) fixed effects. Even though a large fraction of the borrowers relies on one loan type, many borrowers use more than lender by loan type, which is what ultimately allows us to do the replication exercise. ΔIR_t is the annual change in 3-month Spanish interbank interest rate. ΔGDP_t is annual growth of real GDP. CAP_{bt-1} and LIQ_{bt-1} refer to the capital and liquidity ratios at the bank level. With a minor exception, controls are as in Jimenez et al. (2012). Banks characteristics include log total assets, doubtful assets ratio, return on assets, capital ratio, and liquidity ratio. Firm controls include: (i) ratio of equity over total assets, (ii) ratio of the current assets over total assets, (iii) the log of the total assets of the firm (in 2008 euros), (iv) the log of one plus the firm's age in years, (v) return on assets, (vi) a dummy variable that equals one if the firm had doubtful loans the month before the loan was requested and zero otherwise, (vii) a dummy variable that equals one if the firm had doubtful loans any time previous to the month before the loan was requested and zero otherwise, (viii) the log of one plus the duration of the relationship between firms and bank (in month), and (ix) the log of the number of bank relationships. Regressions also include doubtful loan ratio of the industry in which the firm operates, and the log of the number of banks in the province where the firm is located. In terms of explanatory variables, the only differences between our analysis and Jimenez et al. (2012) are twofold. First, GDP data is not the same due to data revisions by the National Statistics Institute (e.g. new base year in 2010). Second, some controls (e.g. Herfindahl index in the sector and number of banks in the province) are not included because they are not readily available.

Estimates are reported in Table 5. In order to analyze the role of loan heterogeneity, we cannot use loan application data because we do not observe the loan type of the rejected applications (i.e., the zeros). Instead, in columns (1) through (4), we start by reproducing the Jimenez et al. (2012) results using credit registry data. Regressions in columns (5) through (8) control for (firm x loan type x quarter) fixed effects and are the results of interest. Note that we restrict the sample to be the same through all specifications, i.e., we use only multibank firm-loan type-quarter triplets.

[TABLE 5]

Overall, the explanatory power increases, but the magnitude of the effects seems relatively unaltered when including loan type fixed effects. Note however that the estimates in Table 5 can be interpreted as a weighted average of the different effects by loan type with weights given by the number of observations. In Table 6, we report the estimates by loan type. All specifications include firm-quarter fixed effects. The strongest specifications, the one that can be interpreted as identification of credit supply, are the ones corresponding to interactions with bank capitalization and liquidity (Table 6, Panel B).

The estimates in Table 6 indicate that cash-flow loans are at the root of the overall results in Jimenez et al. (2012). Indeed, cash-flow loans represent around 53% of the total number of loans (11 out of 21 million observations). Interestingly, ABL loans, which were central to the Spanish credit boom, present a different pattern in the estimates.

[TABLE 6]

4.2 The global financial crisis and the bank lending channel

Using data from the Spanish credit registry, Bentolila et al. (2018) estimate the real consequences of the global financial crisis shock through the credit channel. In particular, they exploit differences across banks that were bailed out by the Spanish government ("weak banks") versus the rest ("healthy banks"). Bentolila et al. (2018) consider a first-stage regression at the bank-firm level showing that weak banks curtailed lending relative to the other banks during the global financial crisis. The identification assumption in this first stage is based on Khwaja and Mian (2008) exploiting within firm variation across banks.

In this section, we re-estimate the first-stage regression in Bentolila et al. (2018) at the bank-firm-loan type level. More formally:

$$\textit{Credit growth}_{flb} = \pi \textit{Weak bank}_b + \textit{Bank}_b + \eta_{fl} + \varepsilon_{flb} \tag{3}$$

where, as before, *f*, *b*, and *l* refer to firm, bank, and type of loan, respectively. The dependent variable is credit growth between 2006:Q4 and 2010:Q4. The unit of observation is bank-firm-loan type level. *Weak bank,* a dummy identifying bailed out banks, is the explanatory variable of interest. *Bank* is a set of bank controls, namely, log total assets, doubtful assets ratio, return on assets, capital ratio, and liquidity ratio. We also include as a control log of (one plus) the length of the bank-firm-loan relationship, measure in month. All specifications include firm-loan type fixed effects (instead of firm fixed effects as in Bentolila et al. 2018).

The results are ported in Table 7. Column (1) corroborates the finding in Bentolila et al. (2018) that, for a given firm, weak banks reduced credit supply vis-a-vis healthy banks. Column (2) shows that this result is similar when including firm-loan type fixed effects. However, results by individual loan type indicate that cash-flow based loans are at the root of this finding. Estimated effects are not significant for asset-based loans and trade finance. Also the number of cash-flow loans is larger than that of ABLs, trade finance and leasing together.

[TABLE 7]

5 Conclusions

Practitioners commonly refer to four distinct loan types: asset backed loans, cash-flow loans, trade financing and leasing. At the heart of this distinction is the speed and size of recovery in default. Some of these types of credit had been directly or indirectly studied in the literature, however this distinction has been overlooked by the literature focused on the conditions of bank credit supply. Yet, as we show, such distinction is important as a large fraction of companies in any economy relies on a single loan type, and these loan types tend to be very persistent. Moreover, given that the quality of measurement of supply effects is central to several of the studies using narrow fixed effect identification, accounting for the loan type is an important identifying assumption.

This paper uses bank-firm matched credit register data from two largely unrelated countries—Spain and Peru—to show that, the four loan types are easily identifiable in the credit registry data. We show that these four loan types represent the bulk of the commercial credit in both economies, and, importuntately, that bank lending channel varies by loan type. Credit supply shocks are most strongly correlated with supply shocks in asset-based loans, while the correlation is weaker for cash-flow loans, trade finance, and leasing.

We revisit two well-known studies on the bank lending channel using Spanish data and find that results are sensitive to accounting for loan heterogeneity. Our results imply that not accounting for loan heterogeneity can bias estimates of the bank lending channel and more generally suggest that it is important to account for heterogeneity in loan type in analyses of the economic significance of credit market disruptions. While our study makes a first step to quantifying the importance of loan heterogeneity, more research is needed to improve our understanding of the credit type choices that firms make and how these choices influence the transmission of financial shocks.

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FIGURE 1. CREDIT EVOLUTION BY LOAN TYPE

Panel A. Spain

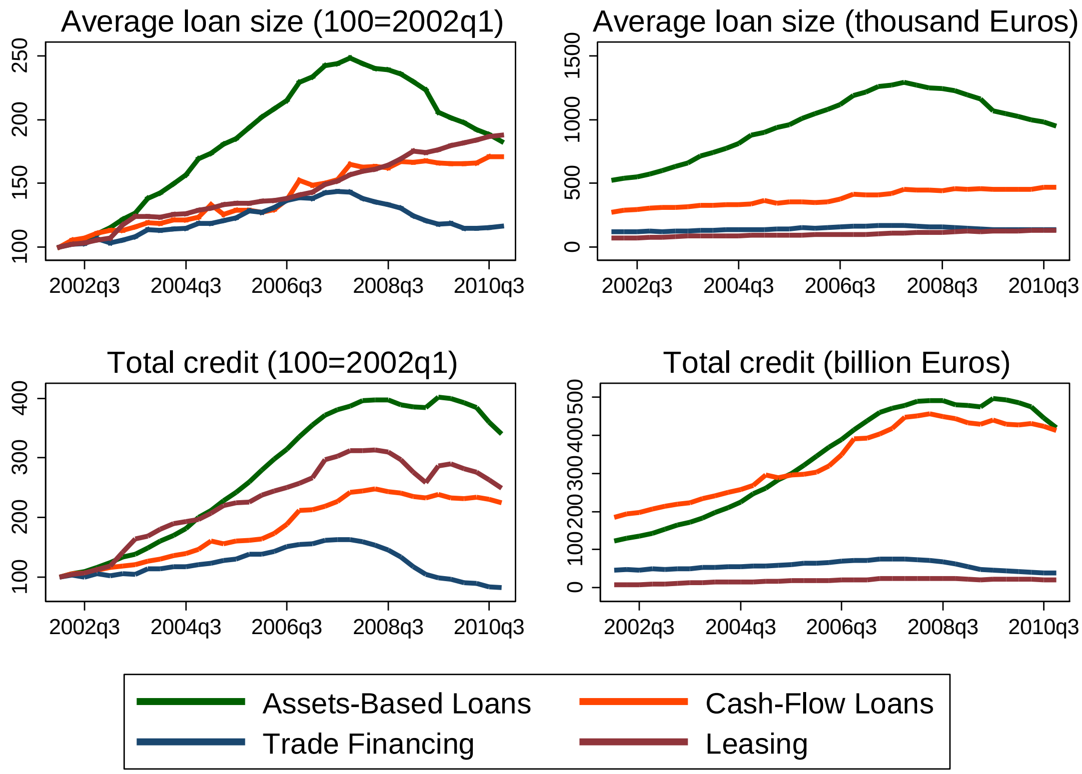


FIGURE 1. CONT.

Panel B. Peru

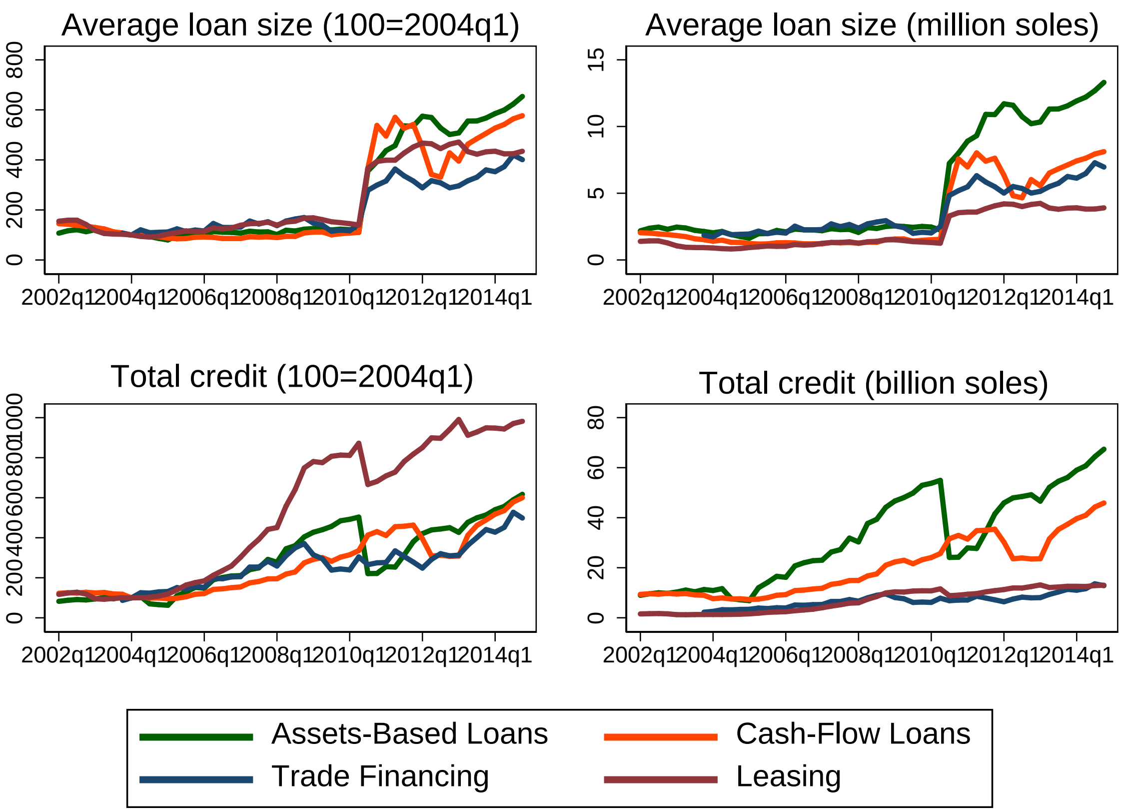
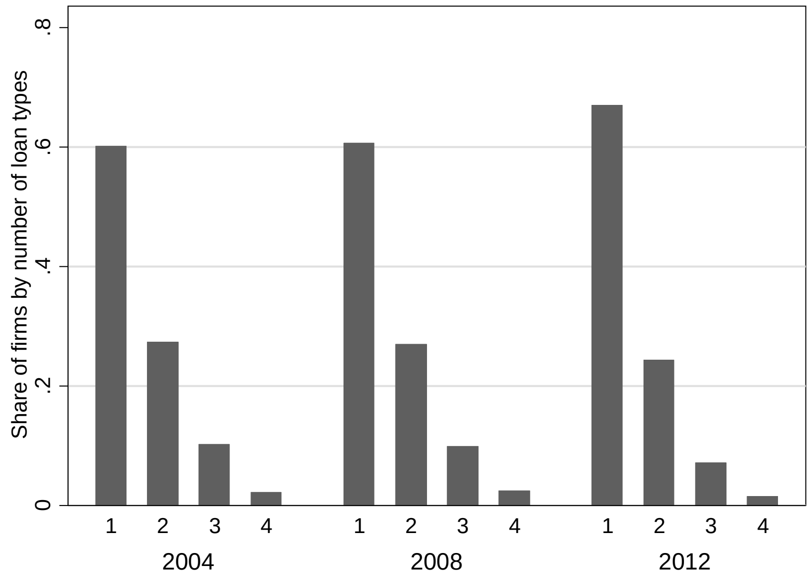


FIGURE 2—USE OF DIFFERENT LOAN TYPES

This figure illustrates the fraction of firms that use different loan types. To construct this figure we exclude loans not classified as asset-based, cash-flow lending, trade financing or leasing; thus, the maximum number of loan types that a borrower can use is 4. The sample otherwise corresponds to the full credit registry, unconditional on the number of lenders per borrowers. For each year, we use the last quarter.

Panel A. Spain



Panel B. Peru

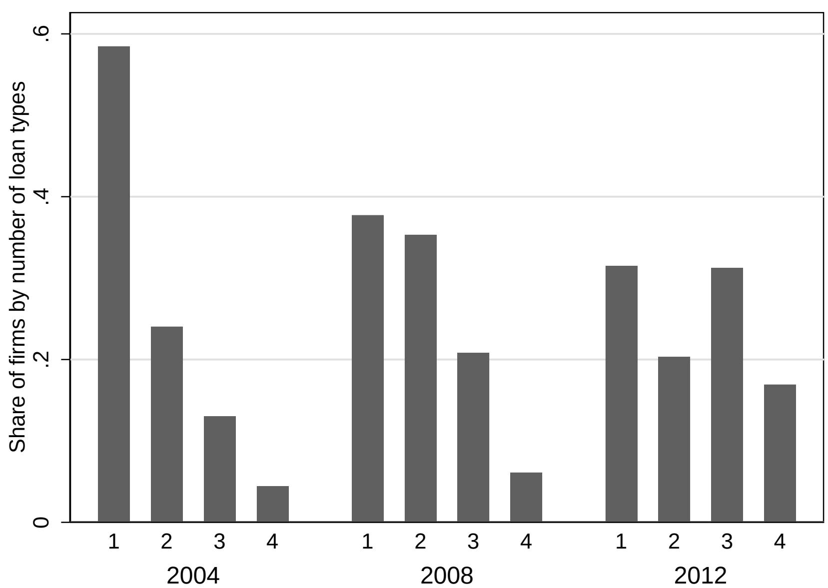
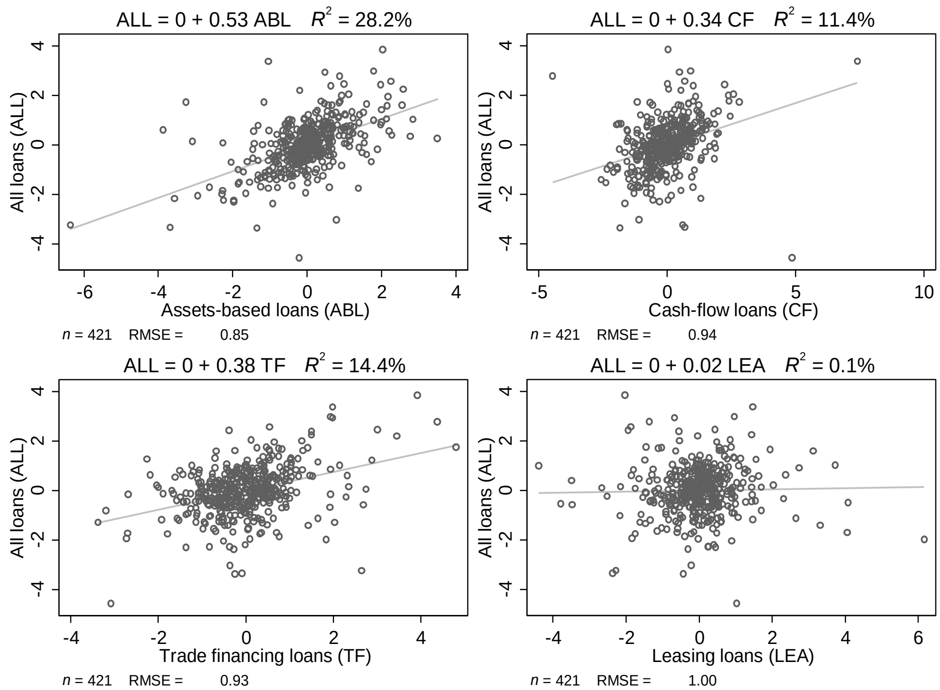


FIGURE 3: AMITI AND WEINSTEIN (2018) BANK SHOCKS BY LOAN TYPE

This figure plots Amiti and Weinstein (2018) bank shocks computed for the full sample against bank shocks computed by loan type. Panel A shows the results using data from Spain and panel B using data from Peru.

Panel A. Spain



Panel B. Peru

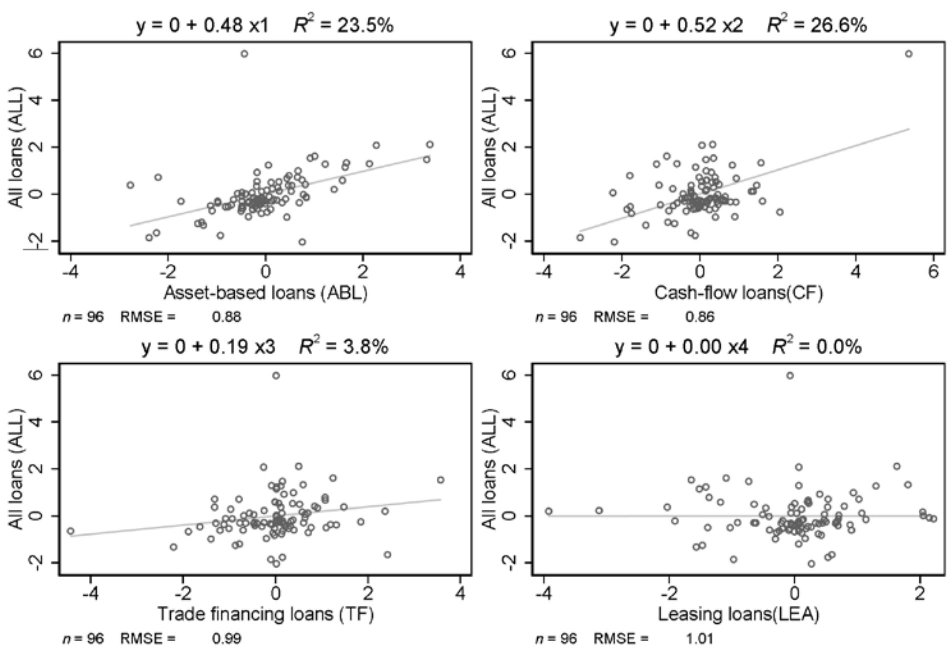


TABLE 1—DESCRIPTIVE STATISTICS BY LOAN TYPE

The numbers correspond to the full sample of loans, including borrowers with one lender. Both panels exclude loans that do not fall into one of the four loan-type categories.

Panel A.1: Prevalence of different loan types – Spain

Loan Type	% of loan volume (value-weighted)			% of loan number (equally-weighted)		
	2004	2008	2012	2004	2008	2012
Asset-based lending	39.1%	43.7%	41.8%	14.7%	17.9%	26.5%
Cash-flow loans	48.2%	47.4%	51.7%	48.8%	50.4%	53.4%
Trade financing	9.0%	5.7%	4.0%	22.5%	18.8%	12.4%
Leasing	3.7%	3.1%	2.5%	14.0%	12.9%	7.7%
	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Panel A.2: Loan size (outstanding balance) – Spain

	Loan size ('000 Euro)				
	Mean	S.D.	Median	1^{st} %	99^{th} %
Asset-based lending	1,001.93	5,977.96	171.00	9.00	15,000.00
Cash-flow loans	389.56	10,360.94	36.00	6.00	4,800.00
Trade financing	141.64	585.57	52.00	6.00	1,486.00
Leasing	100.82	716.62	24.00	6.00	1,199.00

TABLE 1—CONT.

Panel B.1: Prevalence of different loan types – Peru

Loan Type	% of loan volume (value-weighted)			% of loan number (equally-weighted)		
	2004	2008	2012	2004	2008	2012
Asset-based lending	43.5%	52.8%	51.7%	35.0%	42.7%	32.6%
Cash-flow loans	35.8%	24.5%	27.3%	41.2%	34.1%	35.0%
Trade financing	14.3%	11.6%	8.1%	11.9%	8.1%	10.8%
Leasing	6.4%	11.1%	12.8%	11.8%	15.2%	21.6%
	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Panel B.2: Loan size (outstanding balance) – Peru

	Loan size ('000 Peruvian Soles) sample average: $1 USD = S./ 3.13				
	Mean	S.D.	Median	1st %	99th %
Asset-based lending	6,436.4	60,712.7	437.5	0.02	88,014.8
Cash-flow loans	3,744.9	26,742.2	202.1	1.0	63,446.9
Trade financing	4,382.6	14,114.0	1,113.5	22.3	49,557.8
Leasing	2,410.0	17,483.8	235.2	1.4	34,139.8

TABLE 2—SAMPLE SIZE ACCOUNTING FOR LOAN TYPE

Empirical models that use within borrower-quarter variation in lenders behavior rely on the sample of borrowers with multiple lending relationships outstanding at a given point in time. The purpose of this table is to illustrate the effect on the sample of accounting for the loan type. For Spain, loan amounts are expressed in thousands of euros. For Peru, loan amounts are expressed in thousands of Peruvian Sol. On average for the sample, 1 US dollar equals 3.13 Sol.

Panel A: Spain

	Number of unique borrowers	Number of lenders per borrower			Obs.	Average loan size
		Mean	Median	99^{th} %		
Borrowers with multiple lenders per quarter	637,977	4.1	3	16	30,981,561	650.53
Accounting for loan type	554,785	3.8	3	14	33,350,337	528.76
Asset-based lending	132,860	3.0	2	12	4,158,440	1,655.90
Cash-flow loans	428,560	3.8	3	16	17,238,781	511.40
Trade financing	236,317	4.2	3	14	9,848,025	166.12
Leasing	73,661	2.8	2	9	2,105,091	140.77

Panel B: Peru

	Number of unique borrowers	Number of lenders per borrower			Obs.	Average loan size
		Mean	Median	99^{th} %		
Borrowers with multiple lenders per quarter	15,102	4.0	3	10	498,329	9,5157
Accounting for loan type	13,862	3.4	3	8	944,148	5,274.2
Asset-based lending	9,576	3.5	3	8	359,160	7,298.8
Cash-flow loans	9,616	3.2	3	8	341,705	4,341.1
Trade financing	1,726	3.8	3	8	95,118	4,634.0
Leasing	3,843	3.2	3	7	148,165	2,929.2

TABLE 3—PERSISTENCE OF LOAN TYPE FOR BORROWERS

This table follows the migration of loan type for the same borrower (i) one year later, and (ii) three years later. We also separately report the result for the financial crisis period 2007-2009. The sample is conditional on borrowers that start with one loan type and remain in the Credit Registry. We consider loan migrations to be cases where the borrower took out new loans of a different loan type than its loan types in the previous year. The columns correspond to the loan type in the subsequent years. The numbers correspond to the average across years, that is, years are equally-weighted in the calculation. The borrower can migrate to more than one type of credit. As a result, each row can add up to more than 100%. Each individual number is capped at 100%. In Panel B, all reported numbers are different from zero at 1% confidence level.

Panel A: Spain

	Loan type in the following period:			
Initial loan type:	Asset-based lending	Cash-flow based lending	Trade financing	Leasing
	Full sample, 1-year later			
Asset-based lending	95.09%	8.49%	2.78%	3.12%
Cash-flow based lending	5.29%	95.57%	4.09%	3.88%
Trade financing	5.93%	9.77%	85.18%	5.73%
Leasing	6.45%	8.05%	5.36%	82.22%
	2007-2009, 1-year later			
Asset-based lending	95.75%	4.86%	2.11%	1.69%
Cash-flow based lending	4.94%	94.91%	2.76%	2.17%
Trade financing	6.51%	4.55%	81.97%	2.81%
Leasing	6.74%	4.91%	4.21%	78.08%
	Full sample, 3-years later			
Asset-based lending	90.79%	14.41%	3.43%	5.70%
Cash-flow based lending	11.20%	91.05%	5.42%	7.11%
Trade financing	12.78%	16.28%	74.12%	10.10%
Leasing	14.10%	13.73%	6.82%	55.11%

Panel B: Peru

Initial loan type:	Asset-based lending	Cash-flow based lending	Trade financing	Leasing
	Loan type in the following period:			
	Full sample, 1-year later			
Asset-based lending	94.9%	17.3%	2.0%	4.6%
Cash-flow based lending	22.5%	97.5%	3.1%	6.0%
Trade financing	36.8%	39.9%	90.3%	14.8%
Leasing	50.5%	31.9%	5.7%	93.9%
	2007-2009, 1-year later			
Asset-based lending	84.8%	28.0%	1.4%	6.6%
Cash-flow based lending	35.1%	96.5%	2.8%	9.6%
Trade financing	35.5%	36.4%	87.0%	19.6%
Leasing	44.2%	42.8%	4.2%	95.3%
	Full sample, 3-years later			
Asset-based lending	86.3%	36.3%	4.6%	14.0%
Cash-flow based lending	44.7%	91.8%	6.3%	16.7%
Trade financing	57.3%	71.5%	63.5%	39.9%
Leasing	76.0%	59.5%	9.3%	79.6%

TABLE 4—VIS-À-VIS COMPARISON OF LOAN-SPECIFIC BANK SHOCKS

This table presents results of regressing Amiti and Weinstein (2018) bank shocks estimated by loan type on each other. For example, regressing bank shocks estimated for asset-based loans on bank shocks estimated for cash-flow based loans produces a slope of -0.05 and an *R*-squared of 0.003 (reported in parenthesis).

Panel A: Spain

	Asset-based	Cash-flow	Trade
Cash-flow	-0.05 (0.3%)	--	--
Trade	-0.05 (0.2%)	0.04 (0.2%)	--
Leasing	-0.01 (0.0%)	0.02 (0.0%)	-0.04 (0.2%)

Panel B: Peru

	Asset-based	Cash-flow	Trade
Cash-flow	0.15 (2.4%)	--	--
Trade	0.06 (0.4%)	0.13 (1.7%)	--
Leasing	-0.00 (0.0%)	0.14 (2.0%)	-0.12 (1.5%)

TABLE 5—REPLICATION OF JIMENEZ ET AL. (2012)

The table reports the estimated coefficients and robust standard errors (in parentheses) clustered at the bank-quarter level from linear probability models estimated using least squares. Central variables of interest are: the annual change of Spanish 3-month interbank interest rates (Δ*IR*); the annual change of Spanish GDP in real terms (Δ*GDP*); the ratio of bank's equity over total assets (*CAP*); and the ratio of bank's liquid assets over the total assets (*LIQ*). All regressions include controls as in Jimenez et al. (2012). For each borrower controls include: (i) ratio of equity over total assets, (ii) ratio of the current assets over total assets, (iii) the log of the total assets of the firm (in 2008 euros), (iv) the log of one plus the firm's age in years, (v) return on assets, (vi) a dummy variable that equals one if the firm had doubtful loans the month before the loan was requested and zero otherwise, (vii) a dummy variable that equals one if the firm had doubtful loans any time previous to the month before the loan was requested and zero otherwise, (viii) the log of one plus the duration of the relationship between firms and bank (in month), and (ix) the log of the number of bank relationships. Specifications also include doubtful loan ratio of the industry in which the firm operates, and the log of the number of banks in the province where the firm is located. At the bank level we control for banks capital and liquidity, log of total assets, doubtful assets ratio, and return on assets. ***, ** and * indicate significance at 1%, 5% and 10% level respectively.

	Firm-quarter FE				Firm-loan type quarter FE			
Dependent variable	Credit growth		New loan		Credit growth		New loan	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔIR_t	-1.88***		-2.99***		-2.26***		-2.77***	
	(0.19)		(0.98)		(0.20)		(0.94)	
ΔGDP_t	2.98***		1.833***		3.27***		1.65***	
	(0.13)		(0.67)		(0.13)		(0.65)	
$\Delta IR_t \times CAP_{bt-1}$		35.55***		8.26***		35.91***		8.11***
		(6.06)		(3.18)		(6.21)		(3.08)
$\Delta IR_t \times LIQ_{bt-1}$		9.87***		4.81***		9.14***		4.93***
		(2.26)		(1.10)		(2.20)		(1.11)
$\Delta GDP_t \times CAP_{bt-1}$		-33.53***		-7.61***		-34.08***		-7.21***
		(4.19)		(1.99)		(4.36)		(1.94)
$\Delta GDP_t \times LIQ_{bt-1}$		-6.54***		-2.17***		-5.80***		-2.18***
		(1.35)		(0.60)		(1.35)		(0.60)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Firm FE	yes	--	yes	--	--	--	--	--
Firm-quarter FE	--	yes	--	yes	--	--	--	--
Firm-loan-quarter FE	--	--	--	--	yes	yes	yes	yes
R-squared	0.051	0.279	0.188	0.607	0.077	0.391	0.205	0.655
Adj. *R*-squared	0.032	0.008	0.171	0.460	0.048	0.049	0.180	0.461
Observations	21,089,782	21,089,782	21,089,782	21,089,782	21,089,782	21,089,782	21,089,782	21,089,782

Bank-quarters	5,299	5,299	5,299	5,299	5,299	5,299	5,299	5,299

TABLE 6—REPLICATION OF JIMENEZ ET AL. (2012) BY INDIVIDUAL LOAN TYPE

This table builds on results in Table 5 and reports the estimated coefficients from re-running specifications (1) through (4) by loan type. For example, regressions (2.a) though (2.d) that appear in Panel B correspond to Table 1, specification (2); the four columns correspond to four key loan types. As in Table 5, the central variables of interest are: the annual change of Spanish 3-month interbank interest rates (ΔIR); the annual change of Spanish GDP in real terms (ΔGDP); the ratio of bank's equity over total assets (CAP); and the ratio of bank's liquid assets over the total assets (LIQ). All regressions include the same controls as in Table 5. For each column, Panel A and B have the same number of observation and bank-quarter clusters; these are reported at the end of Panel B. ***, ** and * indicate significance at 1%, 5% and 10% level respectively.

Panel A: Only macro variables

Dependent variable	Credit growth				New loan			
	Asset-based	Cash-flow	Trade	Leasing	Asset-based	Cash-flow	Trade	Leasing
	(1.a)	(1.b)	(1.c)	(1.d)	(3.a)	(3.b)	(3.c)	(3.d)
ΔIR_t	-2.44***	-1.76***	-1.64***	-6.89***	-1.22**	-2.79***	-3.66***	-1.32
	(0.22)	(0.26)	(0.34)	(0.71)	(0.57)	(0.95)	(1.12)	(1.08)
ΔGDP_t	1.88***	2.18***	5.14***	7.12***	0.62	1.68***	2.10***	1.07
	(0.14)	(0.16)	(0.26)	(0.45)	(0.40)	(0.66)	(0.76)	(0.75)
Firm FE	yes	yes	yes	yes	yes	yes	yes	Yes
R-squared	0.404	0.383	0.379	0.452	0.642	0.657	0.663	0.627
Adj. R-squared	0.000	0.038	0.076	0.064	0.394	0.465	0.499	0.363

TABLE 6—CONT.

Panel B: Bank characteristics

Dependent variable	Credit growth				New loan			
	Asset-based	Cash-flow	Trade	Leasing	Asset-based	Cash-flow	Trade	Leasing
	(2.a)	(2.b)	(2.c)	(2.d)	(4.a)	(4.b)	(4.c)	(4.d)
$\Delta IR_t \times CAP_{bt-1}$	-16.39**	40.27***	51.17***	77.15**	-0.24	12.26***	3.66	18.52
	(7.28)	(9.56)	(12.65)	(20.07)	(3.32)	(2.52)	(4.77)	(26.73)
$\Delta IR_t \times LIQ_{bt-1}$	0.51	10.08***	11.95	8.53	5.35***	4.76***	5.22***	6.86
	(3.03)	(2.69)	(4.34)	(6.16)	(1.53)	(0.97)	(1.93)	(5.03)
$\Delta GDP_t \times CAP_{bt-1}$	-5.81	-42.80***	-5.97**	-56.19***	-0.01	-9.90***	-4.09*	-16.86
	(4.06)	(5.85)	(2.60)	(12.32)	(2.03)	(1.67)	(2.53)	(15.41)
$\Delta GDP_t \times LIQ_{bt-1}$	-1.11	-7.96***	-5.98***	0.53	-3.58***	-2.70***	-2.32**	-4.49
	(1.52)	(1.65)	(2.60)	(3.95)	(0.82)	(0.59)	(1.01)	(2.92)
Firm-quarter FE	yes	yes	yes	yes	yes	yes	yes	yes
R-squared	0.404	0.383	0.379	0.452	0.642	0.657	0.663	0.627
Adj. R-squared	0.000	0.038	0.076	0.064	0.394	0.465	0.499	0.363
Observations	2,565,678	11,220,553	6,015,637	1,257,936	2,565,678	11,220,553	6,015,637	1,257,936
Bank-quarters	4,908	5,240	4,523	2,267	4,908	5,240	4,523	2,267

TABLE 7—REPLICATION OF BENTOLILA ET AL. (2018) BY LOAN TYPE

The table reports the estimated coefficients and robust standard errors (in parentheses) clustered at the bank-quarter level from linear probability models estimated using least squares. Central variable of interest is *Weak bank* which is a dummy equal to 1 if the bank was bailed by the Spanish authorities and zero otherwise. All regressions include controls as in Bentolila et al. (2018). ***, ** and * indicate significance at 1%, 5% and 10% level respectively.

	All	All	Asset-based	Cash-flow	Trade	Leasing
	(1)	(2)	(3)	(4)	(5)	(6)
Weak bank	-7.61***	-8.06***	0.19	-11.35***	-4.59	-16.40***
	(3.01)	(2.90)	(2.08)	(2.78)	(4.61)	(4.63)
Controls	yes	yes	yes	yes	yes	yes
Firm FE	yes	--	--	--	--	--
Firm-loan type FE	--	yes	yes	yes	yes	yes
R-squared	0.356	0.452	0.453	0.446	0.442	0.493
Adj. *R*-squared	0.068	0.119	0.053	0.120	0.125	0.115
Observations	325,118	325,118	49,806	187,037	76,319	11,956
Banks	139	139	126	136	118	49
Firms	100,521	100,521	21,013	69,177	27,667	5,095

APPENDIX 1. ESTIMATES OF CREDIT SHOCKS IN THE PRESENCE OF LOAN HETEROGENEITY

Consider the following regression model of loan growth, following Khwaja and Mian (2008):

$$\Delta \ln L_{fbt} = \beta X_{bt} + \eta_{ft} + \varepsilon_{fbt} \quad \text{(A1)}$$

where ΔL_{fbt} refers to loan growth by firm *f* from bank *b* in time *t*, X_{bt} denotes a bank-specific shock (e.g., a liquidity shock due to nuclear tests in the case of Khwaja and Mian, 2008), and η_{ft} refers to a firm-specific demand shock. The expectation of the error term is assumed to be zero: $E[\varepsilon_{fbt}] = 0$.

Since Khwaja and Mian (2008), this type of empirical specification has been used to disentangle the firm-borrowing channel (demand shock η_{ft}) from the bank lending channel (supply shock βX_{bt}). The inclusion of time-varying firm fixed effects implies that identification is based on variation in credit across banks with the same firm, keeping firm credit demand constant across banks.

The crucial assumption is that firms' credit demand is the same across all banks. This assumption may be violated if firms' credit demand is bank specific. Such would be the case if different lenders are providing different types of credit. For example, a firm pursuing an acquisition of another company could get a cash-flow based loan from bank "A", and in parallel, it could get an asset-based loan to finance an equipment purchase from bank "B". Now, imagine a given firm experiences a demand shock leading to an increase in its demand for credit of the second type. If this is the case, the demand shock would apply only to the asset-based loan (bank "B") instead of overall credit (from both banks "A" and "B").

We can formalize the bias that arises when the true specification includes firm-loan specific shocks by decomposing the firm demand shock η_{ft} into two-components: $\eta_{ft} = \bar{\eta}_{ft} + \eta_{flt}$, namely, an overall firm demand shock ($\bar{\eta}_{ft}$) and a firm-loan specific shock (η_{flt}), where *l* denotes the loan type. The true model to be estimated would then be:

$$\Delta \ln L_{fblt} = \beta X_{bt} + \bar{\eta}_{ft} + \eta_{flt} + \varepsilon_{fblt} \quad \text{(A2)}$$

where ΔL_{fblt} refers to loan growth of loan type *l* by firm *f* from bank *b* in time *t*.

We can assess the magnitude of the bias by comparing different estimates of equation (A2). In particular, we can first estimate $\hat{\beta}_{FE}$ by including time-varying firm fixed effects $\bar{\eta}_{ft}$ in equation (A2) but without including time-varying firm-loan fixed effects η_{flt}:

$$\hat{\beta}_{FE} = \beta + \frac{cov(X_{bt}, \eta_{flt})}{var(X_{bt})} \tag{A3}$$

We can then estimate $\hat{\beta}_{LOAN}$ by including time-varying firm-loan type fixed effects (η_{flt}) in the regression. The inclusion of firm-loan type fixed effects implies that identification is based on variation across banks in credit with the same firm and the same type of loan. Since $\hat{\beta}_{LOAN} = \beta$, we can obtain the magnitude of the bias:

$$\hat{\beta}_{FE} - \beta_{LOAN} = \frac{cov(X_{bt}, \eta_{flt})}{var(X_{bt})} \tag{A4}$$

The empirical model in (A1) can be generalized, following Amiti and Weinstein (2018), to:

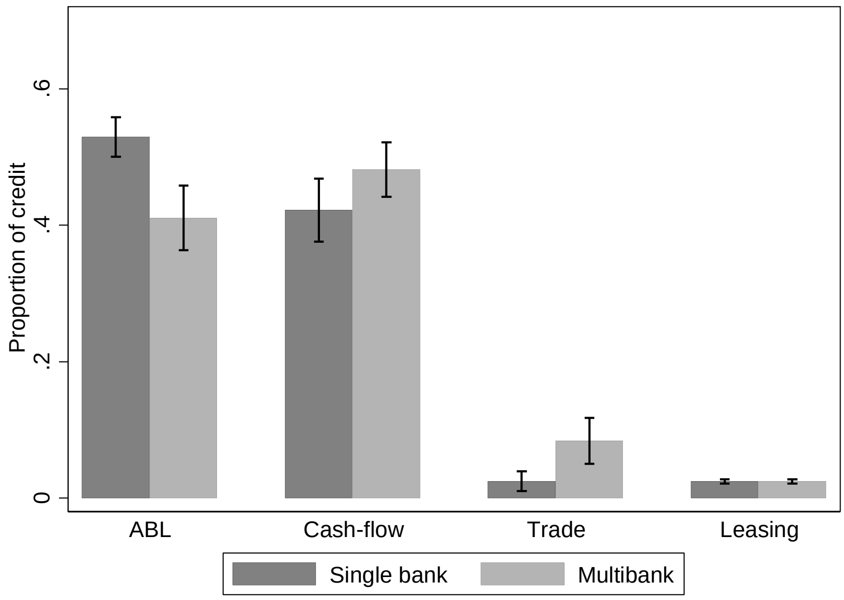
$$\Delta \ln L_{fbt} = \alpha_{bt} + \eta_{ft} + \varepsilon_{fbt} \tag{A5}$$

where ΔL_{fbt} refers to loan growth by firm *f* from bank *b* in time *t*, α_{bt} refers to the bank-lending channel (bank-specific supply shock), and η_{ft} refers to the firm-borrowing channel (firm-specific demand shock).

FIGURE A1: DISTRIBUTION OF LOAN TYPES FOR FIRMS INCLUDED AND EXCLUDED FROM KHWAJA AND MIAN (2008) ESTIMATION

This figure plots the distribution of loan type for borrowers with multiple lenders in a given quarter (KM sample) and for single lender borrowers. The idea is to understand whether the estimates in the KM-style approach are based on a sample with a similar distribution of loan types as in the sample of single lender borrowers. We first compute the distribution for each year in the sample, and then take the average across years.

Panel A. Spain



Panel B. Peru

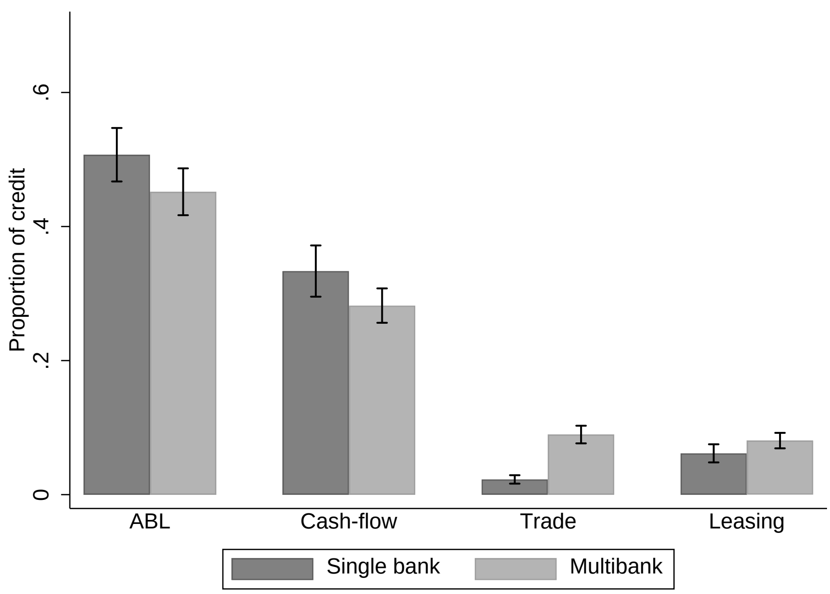
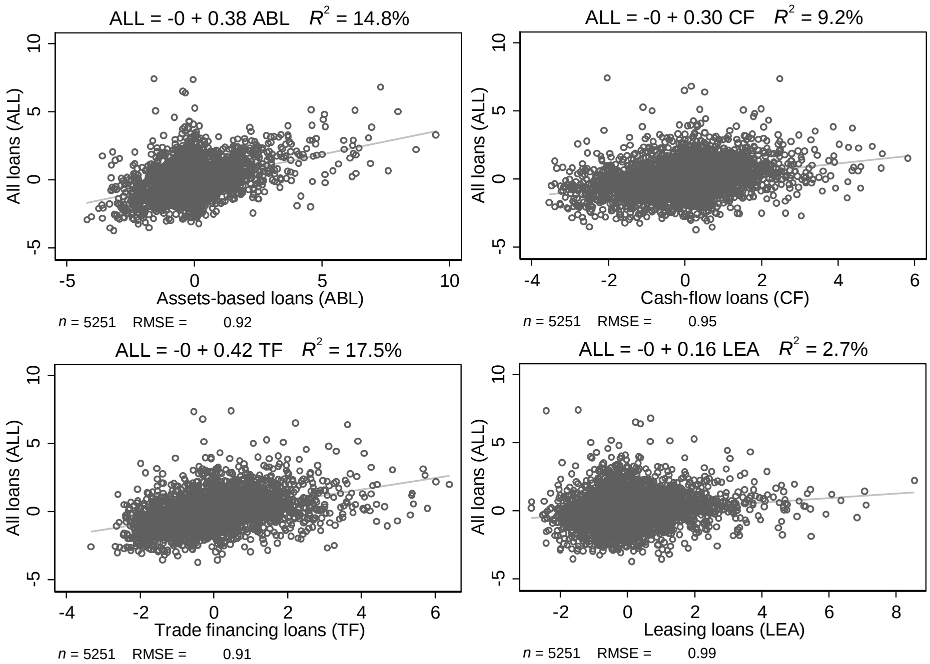


FIGURE A2: AMITI AND WEINSTEIN (2018) BANK SHOCKS BY LOAN TYPE

This figure plots Amiti and Weinstein (2018) firm shocks computed for the full sample against bank shocks computed by loan type. Panel A shows the results using data from Spain and panel B using data from Peru.

Panel A. Spain



Panel B. Peru

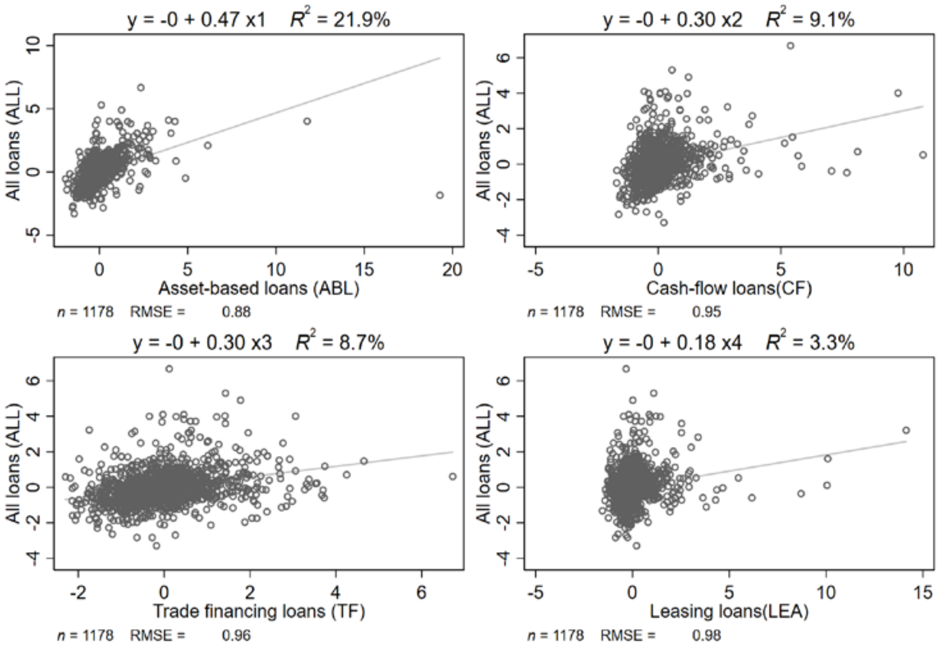


TABLE A1—ASSET TANGIBILITY AND LOAN TYPE

This table provides support for our loan classification. For Spanish firms, we have financial information from a source that is independent of the credit registry, taken from Almunia et al. (2018), for the period 2002:Q1-2010:Q4. Our focus is on assets' tangibility, measured as PPE/Total assets. Each observation in the sample is firm-quarter. The dependent variable is the share of credit of each loan type (Asset-based loans, Cash-flow based loans, Trade financing, Leasing). Controls include: firm age, total assets, leverage ratio, a set of industry-year dummies and year fixed effects. Standard errors are clustered at the firm level. Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) Asset-based Loans	(2) Cash-flow loans	(3) Trade financing	(4) Leasing
Asset tangibility	0.75***	-0.53***	-0.31***	0.09***
	(0.07)	(0.05)	(0.02)	(0.00)
Observations	2,753,435	2,753,435	2,753,435	2,753,435
R-squared	0.26	0.13	0.24	0.05
Controls	yes	yes	yes	yes
Clustering	yes	yes	yes	yes