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ABSTRACT

Using credit-registry data for Spain and Peru, we document that four main types of commercial credit—asset-based loans, cash-flow loans, trade finance and leasing—are easily identifiable and represent the bulk of corporate credit. We show that credit dynamics and bank lending channels vary across these loan types. Moreover, aggregate credit supply shocks previously identified in the literature appear to be driven by individual loan types. The effects of monetary policy and the effects of the financial crisis propagating through banks' balance sheets are primarily driven by cash-flow loans, whereas asset-based credit is mostly insensitive to these types of effects.

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Worldwide, much of commercial credit consists of four distinct types of loans: (i) asset-based loans, (ii) cash flow loans, (iii) trade finance agreements, and (iv) leases.[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). This separation of commercial credit is widely acknowledged in practice, but has only been partially recognized in academic research. In particular, to date, the work relying on the use of credit registry does not make this distinction, treating all credit of the same firm as directly comparable. 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. Although some of these differences are not due to intrinsic characteristics of the physical asset used as a collateral, but 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). Leasing is an arrangement where the creditor finances an asset and the firm uses it in exchange for fixed rental payments. From a collateral perspective, asset-based loans 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.

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[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 receivable, 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 consists of 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 asset-based loans 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 asset-based loans, the borrower pledges specific physical assets to secure the loan. In the case of cash flow 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 loans differs from asset-based loans and leases 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., computers and office furniture). Indeed, a typical credit agreement for a cash flow loan does not have a comprehensive list of what represents 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 asset-based loan), 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 contract for delivery of goods. Amiti and Weinstein (2011)

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[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. This has a direct parallel to person credit: it is common for an individual to have a separate mortgage, car loan, and a student loan.

[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.

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 agreements are 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 trade finance agreements, 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.

As we will show—precisely because of its ubiquity—accounting for loan type using representative credit registry data appears to be straightforward. Moreover, accounting for the loan type is pivotal for several 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 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

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[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.

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.)

Second, the caveat of the KM methodology, which relied on borrowers with multiple lenders at a given point in time, is that it discards a significant fraction of the borrowers in the economy (the single lender borrowers).[7] Thus, the generalizability of the conclusions emerging from such identification, as well as the policy implications, are dependent on the broader distribution of credit. Indeed, we show that 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. Moreover, the type of loans used by these firms tends to be extremely persistent. Note that just because a borrower has a relationship with one lender does not mean that it relies on one loan type. However, we find that the overlap, at a given point in time, between the sample of borrowers that rely on one lender and the sample of borrowers that rely on one loan is substantial: about 79% of single-lender borrowers are also single-loan type for Spain; this number is 69% for Peru.

Finally, there is a large body of literature that shows that bank credit shocks affect economic activity. The focus of more recent literature has not been on whether such connections exist, but on the measurement of the sensitivity of real output to bank funding shocks, and the economic mechanisms underlying this connection. Thus, recognizing that these sensitivities vary by the type of credit is an important advance

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[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 asset-based loan 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 and Peydró (2015) find that 46% of borrowers in Bolivia have only one lender at a given point in time. Bolton et al. (2016) 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.

in both of these directions. Specifically, because the differences between the types of commercial credit are rooted in the nature of collateral, it would likely affect young and old firms differentially, as well as firms in different industries. Although this implication of our findings is outside of the scope of this paper, it could lead to a better understanding of the sources of financial constraints in the cross-section of firms, and over a firm's lifecycle.

Our empirical analysis is based on the credit registry data from Spain and Peru. We start by showing that in both countries the bulk of bank commercial credit can be grouped into four main types: asset-based loans, cash flow loans, trade finance agreements, and leases. 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 the volume 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.

Thus, the first contribution of our paper is to give a comprehensive insight into the prevalence of different loan types in representative economies, and provide a transparent methodology for identifying loan-type in a credit registry data. The second contribution is to show that what we know about the magnitude of the credit supply effects is driven by specific loan-types. To do so, we reexamine several notable studies, zooming in on individual loan types.

Applying the methodology proposed by Amiti and Weinstein (2018), we find that aggregate credit supply shocks constructed using their methodology differ substantially across loan types. In particular, in the Spanish data, we find that aggregate 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 re-estimate the baseline specifications in Jiménez, Ongena, Peydró and Saurina (2012), Paravisini, Rappoport, Schnabel and Wolfenzon (2015) and

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Bentolila, Jansen and Jiménez (2018) separately for different loan types.[8] Jiménez et al. (2012) uses Spanish data to assess how variation in bank capital interacts with changes in monetary policy rates to influence credit growth. Consistent with a risk-taking channel of monetary policy, they find that lower interest rates spur loan growth especially at lowly capitalized banks. Paravisini et al. (2015) and Bentolila et al. (2018) build on the KM methodology using shocks to banks' liquidity following the 2007-2008 global financial crisis, in Peru and Spain, respectively. Using variation in bank exposure they quantify relative effects of the credit channel. We find that the results in all of these papers are sensitive to the type of loan considered. Moreover, they appear to be driven mainly by cash flow loans, while asset-based loans exhibit a different pattern in the estimates.

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 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 cash flow loans appear to be driving contraction in credit supply during the financial crisis.

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, Stein and Wilcox (1993), Bernanke and Gertler (1995), Kashyap and Stein (2000), Ivashina and Scharfstein (2010) and the set of papers that trace the impact of credit market disruptions on real

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[8] Note that these are cross-sectional estimates, whereas Amiti and Weinstein (2018) focus on the time-series behavior of the credit shocks. We will elaborate on the assumptions and methodological differences in these papers later on.

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 the empirical approach in Khwaja and Mian (2008) and use loan-level data to measure effects of credit shocks and their transmission. As already mentioned, we will specifically replicate Jiménez et al. (2012), Paravisini et al. (2015) and Bentolila et al. (2018). Perhaps closest to our research are recent papers by Paravisini, Rappoport and Schnabl (2017), which considers lender specialization, and Jiménez, Mian, Peydró and Saurina (2019), which incorporates firm-level general equilibrium adjustments. Both studies refine the KM methodology. We contribute to this literature by considering the importance of loan types. We show that this differentiation is grounded in actual lending practices of banks and that credit growth dynamics and bank lending channels vary across loan types.

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. In Section 3, we present results of estimating effects of credit supply accounting for loan heterogeneity. Section 4 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 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

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[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*.

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 Jiménez et al. (2012). Because several of the results will build on Jiménez et al. (2012), we restrict the Spanish sample to the 2002-2010 period. However, the descriptive statistics by loan type generalize to a longer sample.

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 asset-based loans, and as cash flow loans otherwise.

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

[11] For full details, we refer to *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.

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 Spanish sample, and confirm that firms with a higher share of fixed assets over total assets rely more on asset-based lending. In particular, asset tangibility has a strong economic and statistical power in explaining borrower's reliance on asset-based loans, 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, which 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* (savings banks).[14] Microcredit institutions are excluded from the sample.

We assign loans into four basic types using the 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 loan types: *garantía hipotecaria*, *garantías preferidas*, *garantías preferidas autoliquidables*, *garantías preferidas de muy rápida realización*, and *otras garantías*. That is, we treat loans with the following collateral as asset-based loans: real estate, other collateral with stand-alone title, deposits and other liquid financial securities, and other collateral. The values of *Cuenta* that are assigned to cash flow-based lending include: *líneas de crédito* (revolving lines) and

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[13] Peruvian data has a structural break in 2010:Q2, at which point the Credit Registry applied a new size 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 savings banks. Their origin and stated main objective is different than that of commercial banks; however, they often act as traditional lenders.

préstamos (loans). *Créditos-comercio exterior* (loans for international trade) are 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. For Peru, we only capture international trade, whereas for Spain we capture all types of credit to firms. As such, the behavior of trade financing is not directly comparable across the two countries.

2. Use of Different Types 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. Asset-based loans correspond to about 40% of lending volume in Spain, but only about a quarter of all outstanding loans; whereas in Peru, asset-based loans in the past ten years had represented about 50% of the lending volume and close to 40% of all loans.

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	39.1%	43.7%	41.8%	14.7%	17.9%	26.5%
Cash flow	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	1st %	99th %
Asset-based	1,001.93	5,977.96	171.00	9.00	15,000.00
Cash flow	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

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	43.5%	52.8%	51.7%	35.0%	42.7%	32.6%
Cash flow	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	6,436.4	60,712.7	437.5	0.02	88,014.8
Cash flow	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

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 asset-based lending. The average size of asset-based loans doubled during the boom, but it was then adjusted. Also, the increase in total credit was fourfold during the boom for asset-based loans while it was three- and two-fold for leasing and cash-flow lending, respectively. Similarly, the rise in asset-based lending seems to be at the heart for the credit expansion experienced in Peru.[15] Consistent with the weaker creditor protection that we expect for an emerging market, leasing (often a direct alternative to asset-based loans) plays a substantial role as well.

FIGURE 1. CREDIT EVOLUTION BY LOAN TYPE

Panel A. Spain

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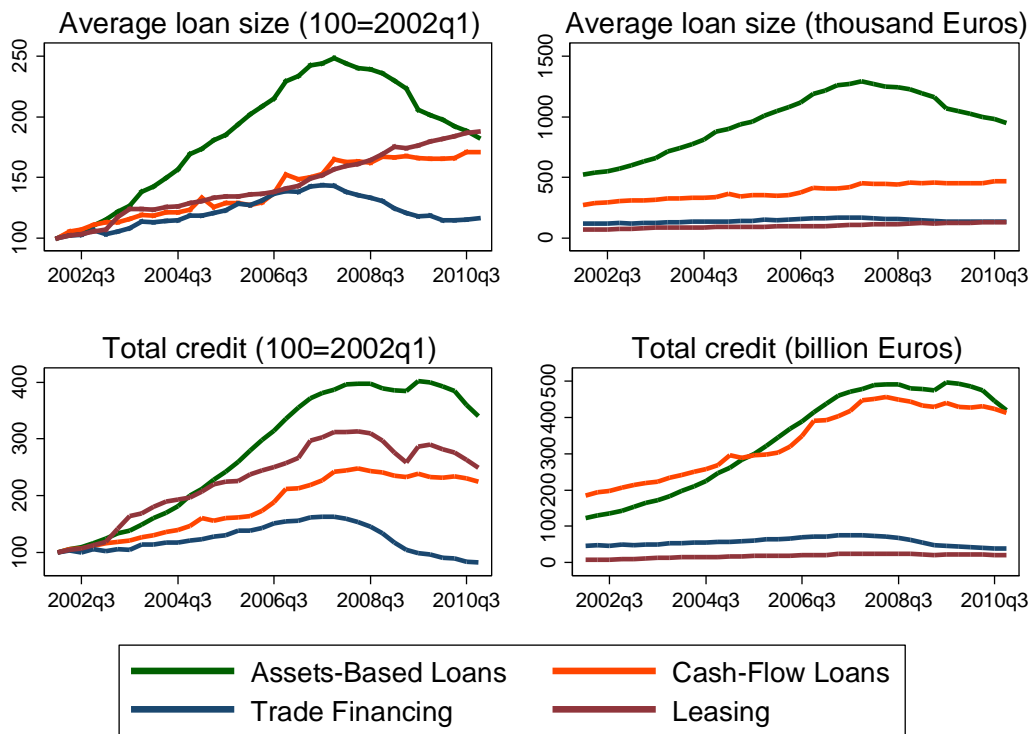
[15] As mentioned earlier, in 2010 Peru has reclassified corporate loans. Figure 1 only includes borrowers that appear in the credit registry after the reclassification. This softens the structural break in the data, but it can still be seen. The focus on the growth of leasing and asset-based loans however is unaffected by the methodology for constructing this graph, and is clearly there even in the raw sample.

Panel B. Peru
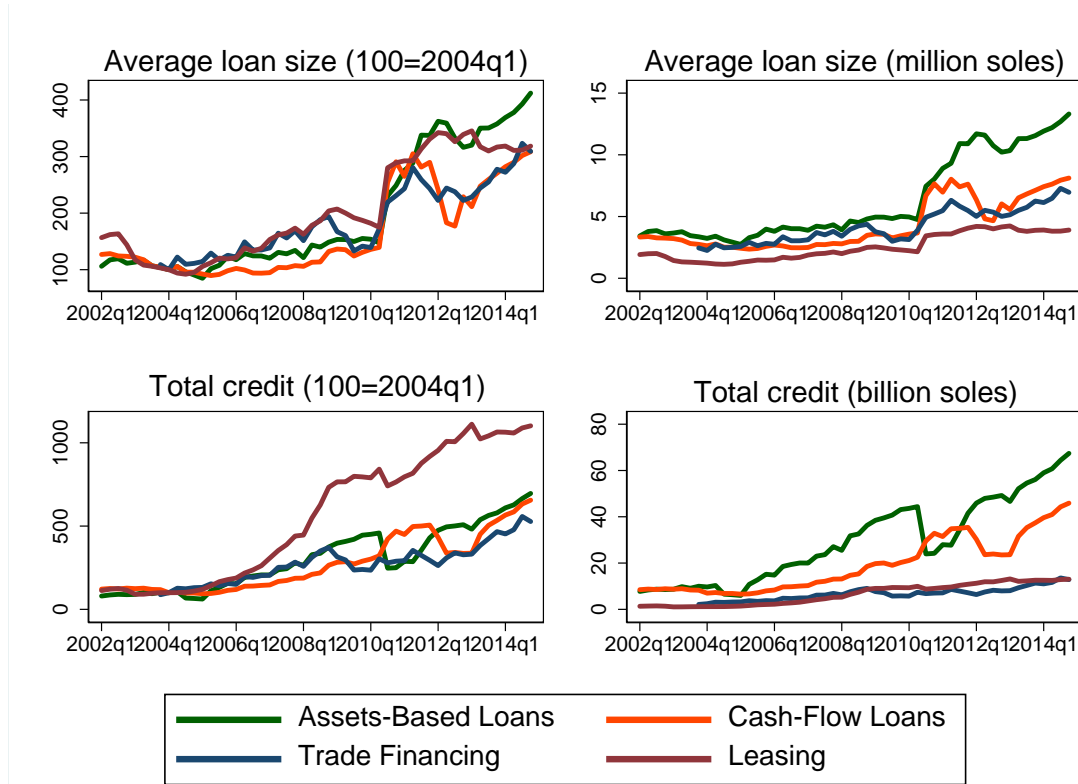
In order to account for loan-specific heterogeneity when revisiting the bank lending channel literature, we need to condition the sample not only on borrowers with multiple lending relationships in a given quarter, but also require that there are multiple relationships within the same loan type. Note 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 asset-based loan 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

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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—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 Soles. On average for the sample, $1 USD = S/. 3.13.

Panel A: Spain

	Number of unique borrowers	Number of lenders per borrower			Obs.	Average loan size
		Mean	Median	99th %		
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	132,860	3.0	2	12	4,158,440	1,655.90
Cash flow	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	99th %		
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	9,576	3.5	3	8	359,160	7,298.8
Cash flow	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

FIGURE 2—USE OF DIFFERENT LOAN TYPES

This figure illustrates the fraction of firms that use different loan types. We exclude loans not classified as asset-based loans, cash flow loans, trade financing, or leasing. The maximum number of loan types 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
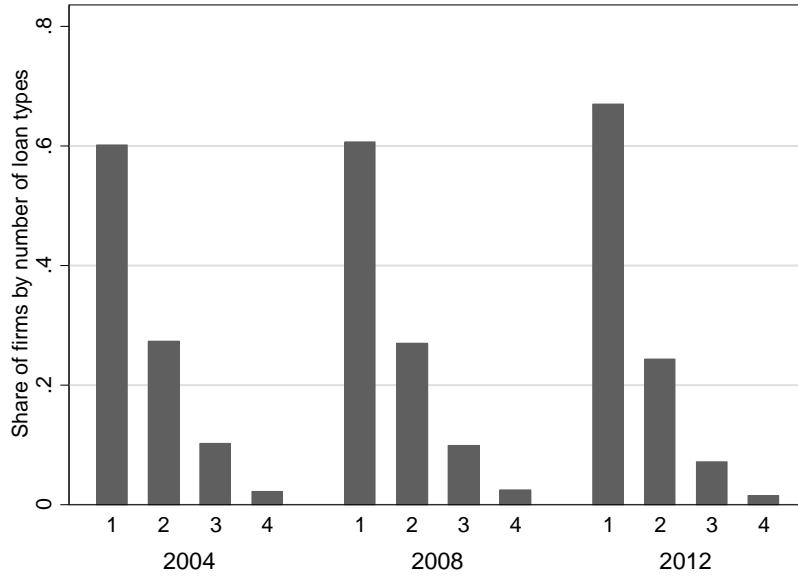
Panel B. Peru
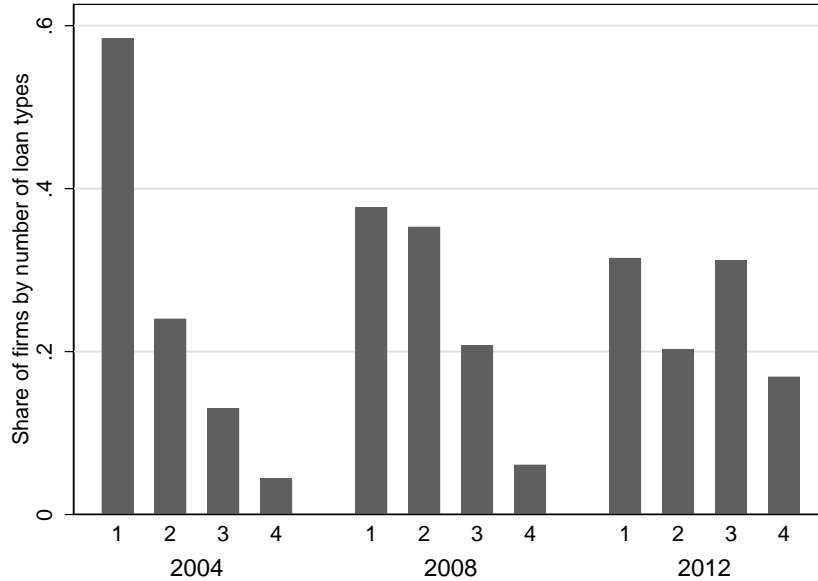
To emphasize the importance of accounting for loan type for the generalizability of results out of sample, in Figure 2, we show the fraction of firms that use different loan types. This figure is constructed using the four loan types for the last quarter of 2004, 2008, and 2012. The sample corresponds 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 the "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%.[16] [17]

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. 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 a 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 loans 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

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[16] These differences in the use of one or more loan types 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.

[17] "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.

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—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 rather 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

Initial loan type:	Loan type in the following period:			
	Asset-based	Cash flow	Trade financing	Leasing
Full sample, 1-year later				
Asset-based	95.1%	8.5%	2.8%	3.1%
Cash flow	5.3%	95.6%	4.1%	3.9%
Trade financing	5.9%	9.8%	85.2%	5.7%
Leasing	6.5%	8.1%	5.4%	82.2%
2007-2009, 1-year later				
Asset-based	95.8%	4.9%	2.1%	1.7%
Cash flow	4.9%	94.9%	2.8%	2.2%
Trade financing	6.5%	4.6%	82.0%	2.8%
Leasing	6.7%	4.9%	4.2%	78.1%
Full sample, 3-years later				
Asset-based	90.8%	14.4%	3.4%	5.7%
Cash flow	11.2%	91.1%	5.4%	7.1%
Trade financing	12.8%	16.3%	74.1%	10.1%
Leasing	14.1%	13.7%	6.8%	55.1%

Panel B: Peru

Initial loan type:	Asset-based	Cash flow	Trade financing	Leasing
	Full sample, 1-year later			
Asset-based	94.9%	17.3%	2.0%	4.6%
Cash flow	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	84.8%	28.0%	1.4%	6.6%
Cash flow	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	86.3%	36.3%	4.6%	14.0%
Cash flow	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%

The header above the data reads: "Loan type in the following period:" spanning Asset-based, Cash flow, Trade financing, Leasing.

3. Credit Supply Shocks and Loan Heterogeneity

In what follows, we incorporate loan types into the existing studies of the shocks to credit supply that use micro-data. Specifically, we will replicate core results in three prominent papers that isolate the effects of credit supply: Amiti and Weinstein (2018), Jiménez et al. (2012), and Paravisini et al. (2015). Conveniently, Jiménez et al. (2012) look at the Spanish markets, and Paravisini et al. (2015) look at the Peruvian market, which is the data that we have, and it will help us confirm that our results are not driven by sample differences. However, a more profound reason for selecting these three studies is that they use related but different methodologies: they deviate in the strength of the assumptions required for identification of credit supply and, consequently, the generality of their insight. Amiti and Weinstein (2018) present an empirical methodology for constructing *time-series* of *aggregate* supply and demand shocks. As the authors themselves emphasize, their shortcoming is that shocks to supply are identified from the data using a stringent structure for the behavior of supply and demand. (We present a detailed discussion of the identifying assumptions in the Appendix.) On the other side of the spectrum are studies that use a direct exogenous shock that impacts the balance sheet of the banks: an anticipated nuclear test in Pakistan that led to the collapse of the dollar deposit funding

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(Khwaja and Mian, 2008), or shortages in foreign funding to Peruvian banks following the Lehman collapse (Paravisini et al., 2015). These studies rely on differential exposure of banks to such shocks; they "cleanly" identify marginal effects in the cross-section, but do not provide a path for measuring an aggregate impact.

We want to stress that it is not our intention to opine on the usefulness or validity of these different methodological approaches. We take these studies as a state of empirical literature on the credit channel. Our core insight is that— regardless of the approach—the credit channel operates differentially for separate loan types.

3.1 Credit Supply Shocks in the Time-Series

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 bank loan supply in determining aggregate variables such as investments and employment is. The AW methodology builds on the following specification:

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

where $\Delta ln L_{fbt}$ 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 and Peruvian credit registry, we estimate equation (1) with the AW methodology and recover a sequence of bank-year and

firm-year fixed effects that can be 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: asset-based loans (ABL), cash flow loans (CF), trade finance loans (TF), and leasing loans (LEA) shocks.

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.
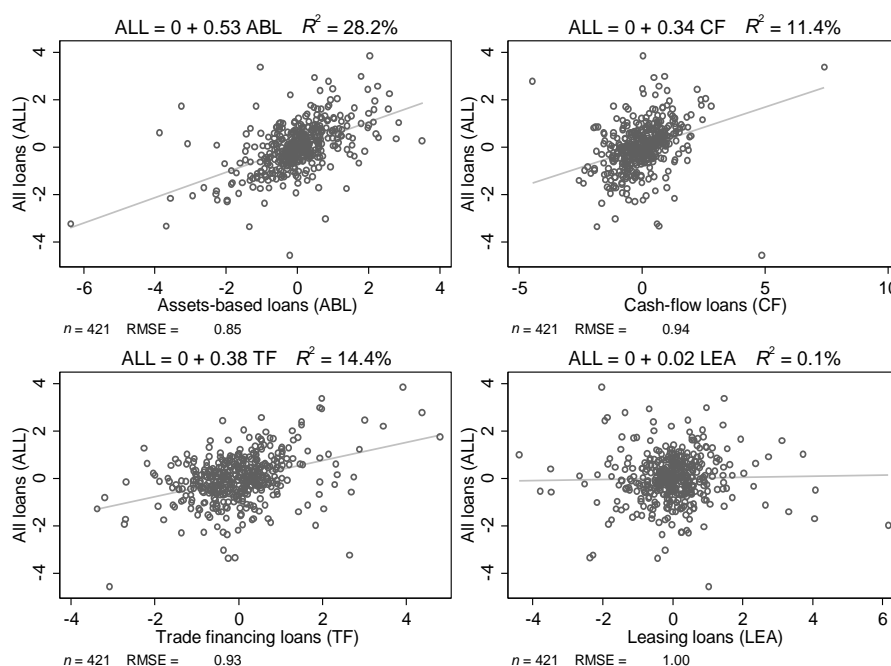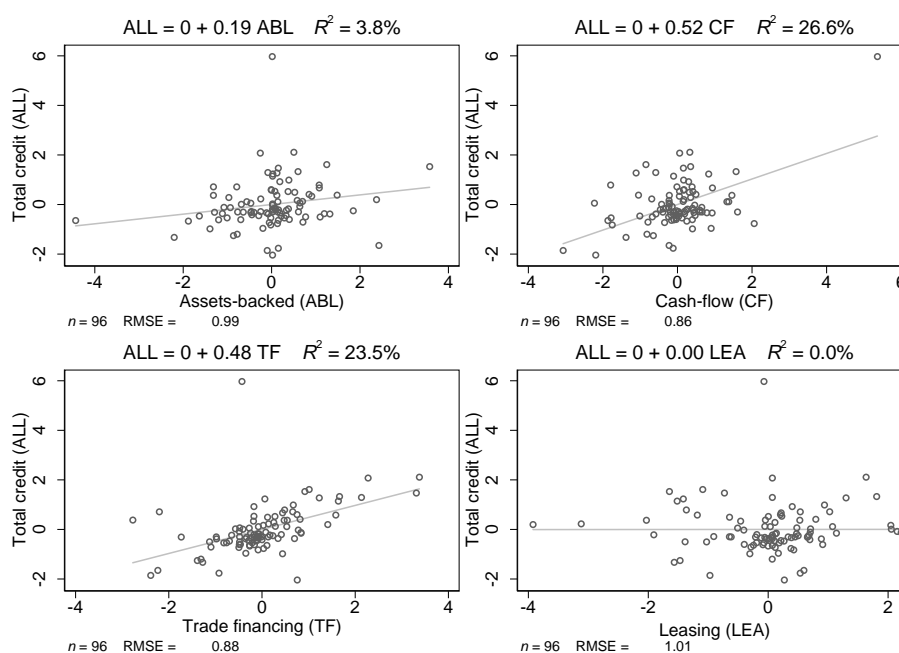
Panel A. Spain

Panel B. Peru

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, while Panel B corresponds to Peru. The takeaway is that the correlation is positive but relatively small. For Spain, the *R*-squared ranges from 0.001 in the case of leasing to 0.282 for asset-based loans. For Peru, the range is from 0.001 to 0.266; the lowest and highest numbers correspond to leasing and cash-flow lending. It is striking that—with the exception of "trade finance" category, which captures different things for the two countries—the range of the magnitudes of errors resulting from omission of accounting for loan type are very similar for the two 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.

Table 4 presents correlations of AW credit supply shocks across different loan types. 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—VIS-À-VIS COMPARISON OF LOAN-SPECIFIC BANK SHOCKS

This table presents regression coefficients of regressing Amiti and Weinstein (2018) bank shocks estimated by loan type on each other. The R-squared is reported in parentheses. For example, regressing bank shocks estimated using Spanish data for asset-based loans on bank shocks estimated for cash flow loans produces a slope of -0.05 and an R-squared of 0.003.

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	0.12 (1.7%)	--	--
Trade	0.07 (0.4%)	0.17 (2.4%)	--
Leasing	-0.10 (1.5%)	0.13 (2.0%)	-0.00 (0.0%)

Finally, in unreported results, we also estimated equation (1) considering two alternative 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.

Overall, in line with the evidence in Figure 1, the AW methodology reveals stark differences in behavior of bank credit shocks for different loan types over our sample period.

3.2 Bank Lending Channel of Monetary Policy

In this section, we re-estimate the baseline specifications in Jiménez et al. (2012), which uses Spanish data. This study gets closer to the Khwaja and Mian (2008) setting, in that it relies on within-borrower differential response of lenders to monetary policy. One potential critique of this study, however, is that it does not have a clean exogenous credit supply shock, but instead looks at the ECB's changes in interest rates for the euro area.

As before, our idea is to incorporate loan-type into the analysis and to see if credit supply substantially differs across core loan types. Our identification is thus based on differences across banks within the same firm *and* loan type pair. Intuitively, we compare the same firm which has cash flow loans from two (or more) banks that are differentially exposed to changes in monetary policy.

The complete replication exercise follows the following econometric 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 × loan type × quarter) fixed effects. Even though a large fraction of the borrowers relies on one loan type, many borrowers use more than one lender by loan type, which is what ultimately allows us to do the replication exercise. We consider two alternative dependent variables, namely, credit growth for the intensive margin and issuance of new loans for the extensive margin. Credit growth is based on annual log differences winsorized at -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. ΔIR_t is the annual change in a 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 Jiménez 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 months), 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 Jiménez 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 replicating the results in Jiménez et al. (2012) using credit registry data. Regressions in columns (5) through (8) control for (firm × loan type × quarter) fixed effects and are the results of interest.

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 ones 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 Jiménez et al. (2012). Indeed, cash flow loans represent around 53% of the total number of loans (about 11 million out of 21 million observations). Interestingly, asset-based loans, which were central to the Spanish credit boom, present a different pattern in the estimates.

TABLE 5—LOAN GRANTING AND MONETARY CONDITIONS

Results in columns (1) through (4) replicate results in Jiménez et al. (2012), and are directly comparable to the results reported in their paper with the exception that we use credit register data. All regressions include the same control variables as in Jimenez et al. (2012). The 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). In columns (5) through (8) we add (firm × loan type × quarter) fixed effects. Standard errors are reported in parentheses.

Dependent	Firm-quarter FE				Firm-loan type quarter FE			
	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)
Firm FE	yes	--	yes	--	--	--	--	--
Firm-quarter FE	--	yes	--	yes	--	--	--	--
Firm-loan-quarter	--	--	--	--	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— LOAN GRANTING AND MONETARY CONDITIONS BY LOAN TYPE

This table reports the estimated coefficients from re-running specifications (1) through (4) in Table 5 by loan type. For example, regressions (2.a) though (2.d) that appear in Panel B correspond to Table 5, specification (2). The four columns correspond to four key loan types. As in Table 5, the 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 observations and bank-quarter clusters; these are reported at the end of Panel B. Standard errors are reported in parentheses.

Panel A: Only macro variables

Dependent	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
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

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TABLE 6—CONT.

Panel B: Bank characteristics

Dependent	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

3.3 The Global Financial Crisis and the Bank Lending Channel

As mentioned earlier, the "gold standard" of measurement of credit supply in the cross-section requires a credible exogenous shock to banks balance sheet to instrument for the supply of credit. In that sense, some might argue that earlier results that built on Amiti and Weinstein (2018) and Jiménez et al. (2012) reflect a violation of identification assumptions in those studies. So, for completeness, we look at Paravisini et al. (2015) which uses Peruvian data. As in their study, we combine three data sets: bank-level data on Peruvian banks; loan-level data on credit in the domestic banking sector; and customs data for Peruvian firms containing record of exports at the 4-digit product level. There is only one difference between our data and the data used in Paravisini et al. (2015): our sample excludes the smallest companies. The average loan size to an exporting firm in our sample is \$2.37 million, as opposed to \$1.01 in their sample. Our data was obtained several years apart, and, in the most recent years, the Peruvian financial regulator prohibited access to the information on the smallest firms for purposes of external research. That said, on many dimensions our sample seems to match reasonably close. For example, their sample includes 41 lenders whereas ours has 40 lenders. So, put simply, any differences in estimates in our paper should be attributed to any differences between small and large companies.

We use the same filters in our analysis: (i) the sample is constrained to July 2007-June 2009, with July 2007-June 2008 corresponding to the period prior to the foreign capital flow reversal caused by the 2008 crisis (the credit supply instrument in their study); (ii) we only include banks and *cajas* (i.e., savings banks); (iii) we only look at firms with non-zero credit in the pre-crisis period; (iv) by construction, we only look at the universe of exporters; and (v) we look at the volume of exports measured in kilograms.

We focus on two key results in Paravisini et al. (2015). The central insight of their paper can be already seen in the cross-sectional analysis that they report in their Table 3. The explanatory variables are the share of lenders' assets funded with foreign debt, and an indicator variable of whether that share exceeds 10% (which is the sample mean for commercial banks for that time period.) The results are reported in Table 7. The estimates in column (1) closely match the results in Paravisini et al. (2015). Overall, this result shows that a banks' foreign funding

was negatively correlated with its change in supply of credit following the financial crisis. This insight is the core building block of their study.

TABLE 7—TRANSMISSION OF CREDIT SHOCKS BY BANKS AND BY LOAN TYPE

Column (1) replicates the result in Table 3 in Paravisini et al. (2015). Columns (2)-(5) re-estimate this equation for different loan types. FD_b is the share of foreign funding of bank b. $D(FD_b > 10\%)$ is a dummy that signals whether foreign funding of bank b is above 10%, the mean among the commercial banks (as in Paravisini et al. 2015). Standard errors are clustered at the bank level and are reported in parentheses.

Dependent variable:	Credit growth				
	All	Asset-based	Cash flow	Trade	Leasing
	(1)	(2)	(3)	(4)	(5)
$D(FD_b > 10\%)$	-0.207	-0.156	-0.292	-0.337	-1.122
	(0.092)	(0.130)	(0.167)	(0.178)	(0.083)
Firm FE	yes	yes	yes	yes	yes
Observations	5,643	3,366	2,257	1,618	1,137
R-squared	0.348	0.325	0.436	0.447	0.416

As before, our goal is to illustrate that this aggregate result is limited to some, though not all loan types. The rest of Table 7 reports the same regression, but estimated within a sample of individual loan types. Once again, what seems to emerge is that cash-flow appears to be behind the core underlying mechanism. Asset-backed loans display a sharp difference compared to other types of credit; the statistical significance of the aggregate result comes from the loan types other than asset-based loans. Overall, the structure of this empirical model substantially reduces the number of observations for individual loan types, which likely also impacts the statistical significance of the results.[18]

Table 8 instead uses a firm-product-destination level panel of export volumes to estimate intensive margin elasticity of exports to credit shocks. Credit supply is instrumented using banks reliance of foreign funding. Paravisini et al. (2015) emphasize that their empirical strategy relies on accounting for shocks to export demand and input cost which they achieve by looking at variation within product-destination. As with Table 7, our estimates are higher than in the original paper, but reasonably close. Separation of the result by loan-type indicates that the

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[18] Inclusion of (firm × loan type) fixed effects preserves the signs, but reduces the economic and statistical significance of the results.

aggregate result does not generalize to leasing or international trade, although in this result, contraction in asset-backed loans does lead to substantial contraction in exports. As before, cash-flow loans continue to play a significant role in economic terms.

TABLE 8— ELASTICITY OF INTENSIVE MARGIN OF EXPORTS TO CREDIT SHOCKS BY LOAN TYPE

Columns (1) and (2) replicate the results in Table 5 in Paravisini et al. (2015). Columns (3)-(6) re-estimate this equation for different loan types. Columns (2)-(6) are estimated using instrumental variables. In the IV regressions, the change in (log of) credit of firm i, ΔlnC_i, is instrumented with the measure of lender's exposure to foreign funding which is a weighted average of $D(FD_b >10\%)$, a dummy that signals whether foreign funding of bank b is above 10%, the mean among the commercial banks (as in Paravisini et al. 2015). Standard errors are clustered at the product-destination level and are reported in parentheses.

Dependent variable:	$\Delta \ln Exports_{ipd}$					
	OLS		IV			
	All	All	Asset-based	Cash flow	Trade	Leasing
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \ln C_i$	0.026	0.455	0.431	0.294	0.009	-1.508
	(0.020)	(0.239)	(0.167)	(0.982)	(0.332)	(1.263)
Product-destination FE	yes	yes	yes	yes	yes	yes
Observations	3,715	3,715	3,254	2,751	2,456	2,340
R-squared	0.283	0.284	0.283	0.299	0.301	0.295

As a final insight, we look at another study that is also focused on the financial crisis as a source of a shock to banks liquidity, but uses Spanish data, that is Bentolila et al. (2018). This paper exploits differences across banks that were bailed out by the Spanish government ("weak banks") versus the rest ("healthy banks"). Following Khwaja and Mian (2008), 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. We re-estimate the first-stage regression in Bentolila et al. (2018) at the bank-firm-loan type level. More formally:

$$Y_{fbl} = \pi Weak\ bank_b + \gamma Z_{fb} + Bank_b'\lambda + \eta_{fl} + \varepsilon_{flb} \qquad (3)$$

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. Z is the log of (one plus) the length of the bank-firm relationship, measured in months. *Bank* is a vector of bank controls, namely, log total assets, doubtful assets ratio, return on assets, capital ratio, and liquidity ratio. In the first specification of equation (3) we include firm fixed effects, as in Bentolila et al. (2018). All other specifications include firm-loan type fixed effects.

TABLE 9—WEAK BANK ATTACHMENT AND CREDIT GROWTH BY LOAN TYPE

Column (1) replicates the results in Table 3 of Bentolila et al. (2018) using loan-level data. Column (2) includes firm-loan fixed effects. Columns (3) to (6) re-estimate this equation for different loan types. The dependent variable is credit growth between 2006:Q4-2010:Q4. The estimated coefficients are obtained from linear probability models estimated using least squares. *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). Standard errors clustered at the bank-quarter level are reported in parentheses.

	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)
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

The results are reported in Table 9. 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 the other loan types together.

4. Conclusions

Practitioners commonly refer to four distinct loan types: asset-based 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 focusing 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-registry data from two largely unrelated countries—Spain and Peru—to show that four loan types are easily identifiable in the data. We show that these four loan types represent the bulk of commercial credit in both economies, and, importantly, that the bank lending channel varies by loan type.

An important contribution of this paper is that we use the micro data to gain insight into what type of data drives the existing findings on credit supply by replicating several notable studies that tackle different questions and use different methodologies. Using the approach in Amiti and Weinstein (2018), we show that the time-series of aggregate credit supply shocks is driven by individual loan types. In the Spanish data, the aggregate credit supply shocks are most strongly correlated with supply shocks in asset-based loans, while the correlation is weaker for other types of credit including cash flow loans (one of the two most prominent types of credit). Instead, in Peru, aggregate bank shocks are mainly associated with cash flows loans and international trade credit behavior. Replication of studies looking into cross-sectional variation reveals that much of what we know from these studies is attributable to cash flow loans, and not to asset-based loans. Overall, 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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Consider the following regression model of loan growth typically used in studies that build on methodology in Khwaja and Mian (2008):

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

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: $E[\varepsilon_{fbt}] = 0$. 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 were 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:

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

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).

In the existing literature, there exist three approaches to identifying credit supply using loan level data. These approaches vary in the strength of the assumptions required for identification of credit supply and in the generality of their application. In this Appendix, we set out the assumptions of each method, starting with the method that is the most general but also requires the strongest set of assumptions.

The first approach is introduced by Amiti and Weinstein (2018) and it estimates the following model of credit growth:

$$\Delta \ln L_{fbt} = \alpha_{bt} + \eta_{ft} + \varepsilon_{fbt} \qquad \text{(B1)}$$

where ΔL_{fbt} refers to loan growth by firm f from bank b in time t, α_{bt} refers to a bank-specific shock, and η_{ft} refers to a firm-specific shock. The authors interpret α_{bt} as a (bank-specific) supply shock and η_{ft} as a (firm-specific) demand shock.

The key assumptions underlying the identification in AW are: (i) credit demand is firm-specific, not bank-specific; and (ii) credit supply is bank-specific, not firm-specific. Any shock that leads banks to lend more to some firms than others will result in supply being misinterpreted as demand. Such firm-specific supply of credit by banks could originate from lender specialization, differences in market power, or the value of bank relationships. Similarly, any shift in firm's credit demand from some banks relative to others may lead to credit demand being misinterpreted as supply. Such bank-specific demand by firms could originate from borrower specialization in certain type of credit products, differences in the type of collateral used for credit, or the existence of different loan types more generally.

The approach proposed by Khwaja and Mian (2008) instead estimates the following model of credit growth:

$$\Delta \ln L_{fbt} = \beta X_{bt} + \eta_{ft} + \varepsilon_{fbt}. \qquad \text{(B2)}$$

The difference is in X_{bt} which denotes a bank-specific shock (typically a liquidity shock of some sort). Focusing on an exogenous bank shock imposes more structure on the model and potentially allows for stronger identification – to the extent that βX_{bt} relates to bank-specific shocks – at the loss of generality. The

key assumptions underlying KM are: (i) credit demand is firm-specific, not bank-specific; (ii) the time variation in X_{bt} is not correlated with shifts in credit demand; and (iii) the coefficient β is constant across banks and firms.

The first assumption is identical in both approaches. Any shift in firm demand for loans from some banks relative to others (e.g. originating from differences in type of credit) may lead to demand being misinterpreted as supply, rendering this assumption invalid. The second and third assumptions are strictly weaker than the first assumption in AW. If there is lender specialization and firm demand is bank-specific, then these two assumptions are not met. This would be the case, for instance, if in response to a demand shock, firms demand more credit from banks that specialize in the type of credit that the firms demand (e.g. export credit).

Paravisini et al. (2017) extends the KM approach by estimating:

$$\Delta \ln L_{fbt} = \beta X_{bt} + \eta_{ft} + \gamma D_{fbt} + \varepsilon_{fbt}. \qquad \text{(B3)}$$

The new element, D_{fbt}, denotes a demand shock that varies by firm and bank. Paravisini et al. (2017) interpret D_{fbt} as a source of variation related to credit demand that varies with lender specialization. In their study, they look at banks specializing in specific export markets. This approach allows for stronger identification to the extent that γD_{fbt} relates to bank-specific firm demand.

The key additional assumption in Paravisini et al. (2017) is that the coefficient γ is constant across banks and firms. This assumption is not met if the relationship between bank-specific firm demand and credit growth is not stable over time. For instance, this could be due to changes over time in the type of firms that banks specialize in or shifts in bank market power that cause disproportionate shifts in the demand for certain type of loans. In the application of Paravisini et al. (2017) this would be the case if the type of banks operating in the firm's export markets suddenly changes (for instance, due to regulation or firm entry). In that case, the term γD_{fbt} may capture bank-specific supply shocks that will be misinterpreted as demand. However, to the extent that lender specialization is stable over time, the assumption underlying the approach in Paravisini et al. (2017) is likely to be met. This approach, therefore, requires the weakest identifying assumption of the three methods considered. Its application is, however, also more limited given the additional structure imposed on the model and the need to find suitable proxies for D_{fbt}.

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FIGURE A1: DISTRIBUTION OF LOAN TYPES FOR FIRMS INCLUDED AND EXCLUDED FROM KHWAJA AND MIAN (2008)-STYLE 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.
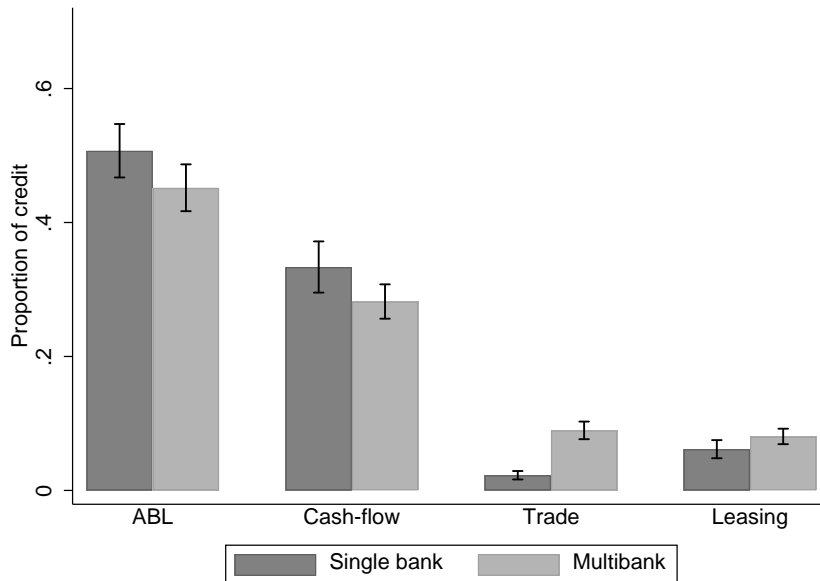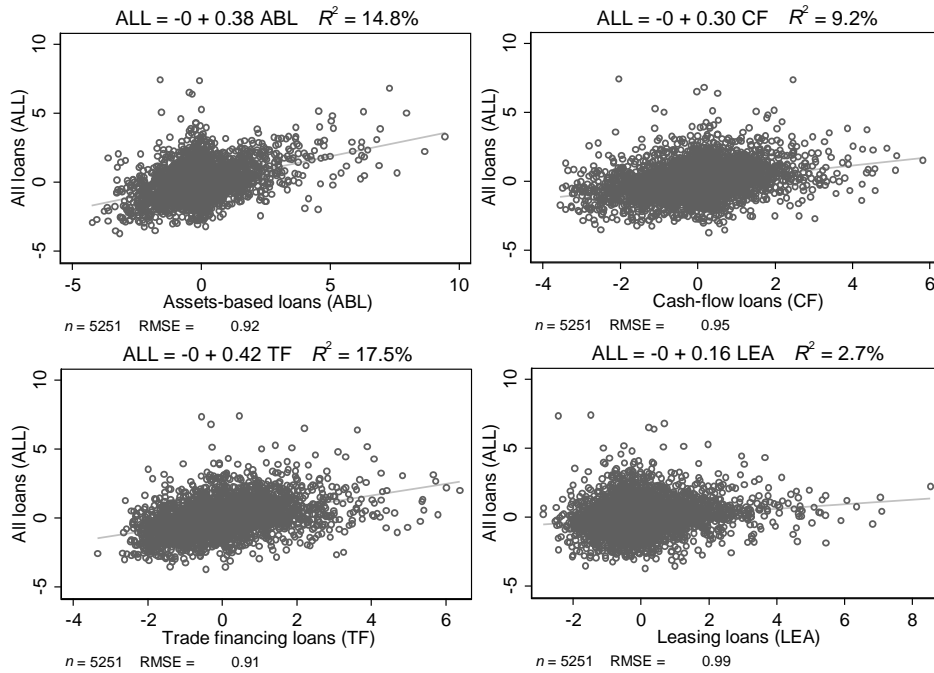
Panel A. Spain
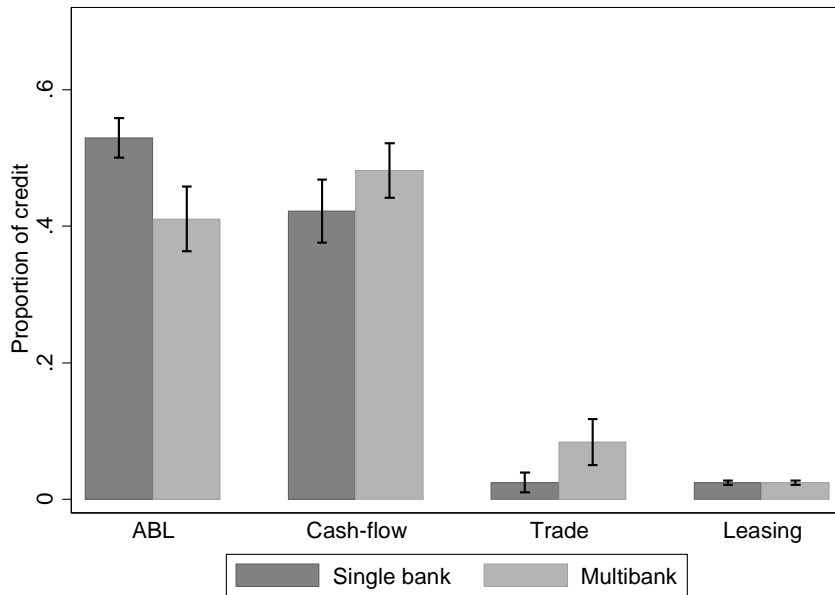
Panel B. Peru

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.
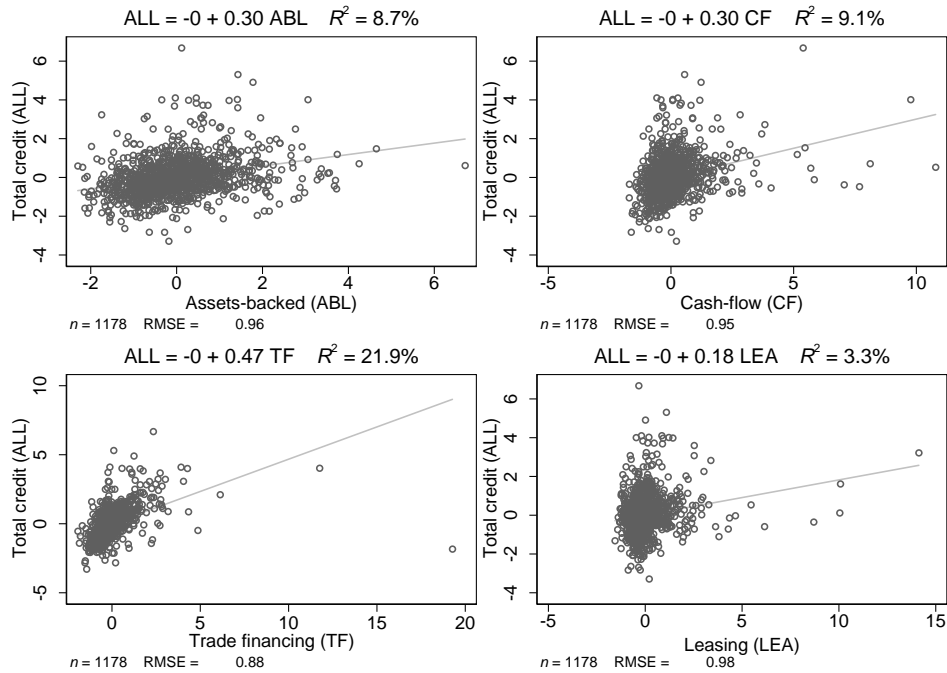
Panel A. Spain

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 loans, trade financing, and leasing, respectively. 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 and are reported in parentheses.

	(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