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Yusuf Soner Baskaya
Julian di Giovanni
Sebnem Kalemli-Ozcan
Mehmet Fatih Ulu

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International Spillovers and Local Credit Cycles

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ABSTRACT

We study the transmission of global financial uncertainty to an emerging market economy, Turkey, using data on the universe of corporate loan transactions over 2003{2013. International arbitrage implies that a decline in global uncertainty reduces country risk, which narrows the deviation from uncovered interest parity, and pushes capital flows into Turkey, allowing domestic banks to lend to firms at lower interest rates. This leads to a domestic credit expansion since local currency borrowing becomes cheaper. Our estimates explain 43% of observed credit growth, where bank heterogeneity in access to international markets explains 94% of this aggregate impact. We show that collateral-based borrowing constraints do not relax during capital flow surges, while borrowing becomes cheaper for all firms on average. We rule out various alternative mechanisms such as exchange rate appreciation driven balance-sheet effects. Our results highlight a new international spillover mechanism, which we call the “interest rate channel.”

Yusuf Soner Baskaya
Central Bank of Turkey
Research Department
Istiklal Cad. No.10 Kat.15
Ulus/Ankara
Turkey
Soner.baskaya@bilkent.edu.tr

Sebnem Kalemli-Ozcan
Department of Economics
University of Maryland
Tydings Hall 4118D
College Park, MD 20742-7211
and CEPR
and also NBER
kalemli@econ.umd.edu

Julian di Giovanni
ICREA
Department of Economics and Business
Universitat Pompeu Fabra
Ramon Trias Fargas 25-27
08005 Barcelona
Spain
and Barcelona GSE, CREI, CEPR
julian.digiovanni@upf.edu

Mehmet Fatih Ulu
Central Bank of the Republic of Turkey
Fener Kalamis cad.
Atlihan Sok. No:30/A
Fenerbahce Kadikoy Istanbul
Turkey
fatih.ulu@tcmb.gov.tr

1 Introduction

The past decade has witnessed a surge in capital inflows to emerging market economies (EMEs). A key driver of this phenomenon that has been highlighted is the expansionary monetary policy taken by advanced economies in the wake of the global financial crisis, which has led to investors searching for higher returns regardless of country risk. In turn, these inflows have raised concerns for emerging market policy makers given potential excessive credit growth and unwanted exchange rate appreciations. Future normalization of advanced economies’ monetary policy has also raised the risk of capital flow reversals and potential sudden stops in EMEs. Thus, understanding the channels through which capital flows impact emerging markets’ domestic financial stability is of first-order importance.

We analyze how a decrease in global financial uncertainty pushes capital inflows into an EME and impacts domestic credit market conditions. Our empirical methodology exploits data on every loan transaction, including loan-level interest rates, between banks and firms for a large EME, Turkey, over 2003–2013, combined with firm and bank balance sheet information. By exploiting these granular data, we trace out the effects that these capital flows have on lending patterns between banks and firms, and quantify their aggregate impact on domestic credit growth.

Our paper makes three main contributions. First, we provide evidence on the causal effects of capital flows on borrowing costs and credit growth at both the individual (bank-firm) and aggregate levels. Second, our results provide evidence on a new international transmission mechanism, which we dub “the interest rate channel,” where capital inflows allow internationally-exposed domestic banks access to cheaper funding (given a fall in the country risk premium), which they pass-on to domestic firms via lower real borrowing costs. Third, we provide evidence that this channel implies a relaxation of firm-level borrowing constraints, but the mechanism is different than the one highlighted in the theoretical literature.¹ In particular, using loan-level data, we show that the collateral required to obtain a loan of a given size does not change with capital inflows, but instead real borrowing rates fall for the given collateral constraint.²

¹A large literature on capital outflows and sudden stops regards credit frictions as the central transmission mechanism. See, for example, Calvo (1998); Caballero and Krishnamurthy (2001); Gopinath (2004); Mendoza (2010). Korinek and Sandri (2016) study how capital inflows relax these frictions during boom episodes. This literature mimics the closed-economy literature, started by Kiyotaki and Moore (1997), in modeling collateral constraints as a limit in total debt not exceeding a fraction of the *market value* of the physical capital, which serves as collateral. When capital flows in and out of the banking sector, as opposed to the stock market, such fluctuations in firms’ collateral values might be absent as is the case in our data.

²For example, a 100,000 lira loan still requires 10% of the firm’s capital stock as collateral, but due to capital inflows such a loan can now be financed at 3% instead of 8%, where firm’s capital’s value does not change.

A key assumption underlying our empirical approach is that an important component of capital inflows are exogenous to Turkish fundamentals, since they are driven by changes in global uncertainty, which affect risk premia faced by emerging markets.³ Given a fall in risk premium, capital flows into the country, mostly via the banking sector as domestic banks' international funding costs decline. These lower costs are then passed on to firms via lower borrowing rates. Two key factors underlying this narrative are a failure of uncovered interest parity (UIP), that is existence of international arbitrage, and heterogeneous reactions of banks in terms of loan pricing. On the first factor, we provide evidence that foreign currency borrowing by firms from domestic banks is cheaper than local currency borrowing on average throughout our sample, which is consistent with a UIP failure involving country/currency risk and hence a higher interest rate on local currency loan. Interestingly, during a surge in capital flows driven by low global uncertainty, local currency borrowing becomes cheaper. This result is consistent with an improvement in the UIP relation, which delivers a local currency credit boom.⁴ On the second factor, we show that banks that are more exposed to international financing due to their liability structure charge relatively lower interest rates.

Our argument that country risk falls because of declining global uncertainty needs scrutiny since country risk can also go down due to good domestic policies and improved country fundamentals, which will also trigger capital inflows. An econometrician observing aggregate data on capital flows will not be able to identify an aggregate demand shock from an external shock due to an observational equivalence. In both cases, if the shock is favorable, capital will flow into the emerging market.⁵ Hence, demand and supply factors (global shocks) that drive capital flows need to be separated.

To achieve this goal, we combine our unique administrative firm-bank-loan-month-level dataset with quarterly capital flows and macro variables for Turkey for the period 2003–2013. We then pursue a two-pronged identification strategy. First, to separate demand- and supply-driven capital

³See [Rogers et al. \(2016\)](#) and [Jordà et al. \(2017\)](#).

⁴We also run a standard UIP regression of the Turkish-U.S. interest rate differential on the expected depreciation of Turkish lira (measured from a survey of forecasters), and find that the regression has low explanatory power, whereas residuals from this regression are highly correlated with exogenous capital inflows.

⁵In standard open-economy models, capital inflows are an endogenous response to some domestic or external shock that affects domestic consumption or investment. A temporary fall in the world nominal interest rate, for example, induces a consumption/investment boom, which is in turn financed by capital inflows as a response. These models cannot account for exogenous capital inflows into a country as a result of changing global financial conditions and/or foreign investor sentiments, since there is no role for such factors when UIP holds. As argued by [Blanchard et al. \(2015\)](#), exogenous capital inflows leading to an expansion in output and credit is a phenomenon that cannot be explained by the standard Mundell-Fleming model since capital inflows will lead to a currency appreciation which will cause a decline in net exports and hence a decline in output and investment.

flows and to gauge the average effect of supply-side capital inflows on the domestic credit market, we instrument capital inflows into Turkey by a measure of global uncertainty, the VIX, and run a two-stage instrumental variables regression.⁶ The intuition for why VIX is a valid instrument for capital inflows lies in the relationship between country risk and capital inflows. During low levels of global uncertainty, risk-aversion and volatility are low and investors are more willing to tolerate higher levels of country risk associated with investing in emerging markets. Put differently, if country risk has a global component and a country-specific component, the exogenous part of country risk will go down as a result of a decrease in global uncertainty (a fall in VIX). This will constitute a time-varying exogenous shock to the country risk premium which underlies the deviation from UIP.

For VIX to be a valid instrument, it is not enough that movements in VIX are exogenous to domestic fundamentals in Turkey and that VIX is a strong predictor of capital inflows, as shown by our first stage regression. We also need VIX to be excludable from the second-stage regression; i.e., that it affects domestic credit growth and borrowing costs in Turkey only via capital inflows. This assumption might be violated if movements in VIX are related to U.S monetary policy and if Turkish monetary policy responds to U.S policy.⁷ In such a case, firms' expectations of future economic conditions will be correlated with VIX through Turkish monetary policy and this will affect their credit demand.

We follow two approaches to resolve this issue, one theoretical and one empirical. On the theory side, we make use of the fact that we have data on both price and the quantity of borrowing. The standard theory of loanable funds market predicts an increase in the credit volume with a positive shock regardless this is a supply or demand shock to credit. However, the lending rate will go down if and only if the positive supply shock dominates the positive demand shock. Hence, we validate our identifying assumption by observing the sign on firm-level borrowing costs in our regressions. Our regressions further control for domestic monetary policy and all domestic fundamentals, such as GDP, the exchange rate, inflation, expectations of these variables. We also include firm \times year fixed effects which control for firm-level confounders, such as firm-level demand or credit riskiness,

⁶VIX is a forward-looking volatility index constructed by the Chicago Board Options Exchange. It measures the market's expectation of 30-day volatility, and is constructed using the implied volatilities of a wide range of S&P 500 index options. See [Forbes and Warnock \(2012\)](#), [Cerutti et al. \(2015\)](#), [Fratzschler et al. \(2016\)](#), and [Miranda-Agrippino and Rey \(2015\)](#) who show that low VIX is associated with capital inflows into emerging markets. See [Cerutti et al. \(2017\)](#) who challenges these findings and argue that VIX has low explanatory power for capital inflows into EMEs. In their country by country analysis, Turkey is a country where VIX can explain a large fraction of capital inflows.

⁷See [Rey \(2013\)](#), [Rey \(2016\)](#) and [Miranda-Agrippino and Rey \(2018\)](#) for studies that are trying to understand the link between the U.S. monetary policy and the VIX.

which move at the yearly level.

The second approach to identification addresses the potential that there are remaining firm-level confounders correlated with capital inflows and vary at the quarterly level. In particular, we can control for these unobserved time-varying firm-level factors by including firm \times quarter fixed effects, which will absorb the direct effect of VIX and capital flows but still allow us to identify the role of bank and firm heterogeneity in transmitting global uncertainty to credit growth and borrowing costs. As is common in the literature, firm \times quarter fixed effects allow us to identify our results for firms borrowing from multiple banks.⁸ We further control for bank \times quarter effects when exploring the interaction between banks' international exposure and firms' riskiness measures. Finally, to guard against the possibility of firms switching banks as a response to capital flows, we go one step further and identify from within firm-bank variation by including firm \times bank \times month fixed effects and identify from the changes in loan amounts and loan pricing from month-to-month variation in new loan issuances for the *same* firm-bank pair.

Let us detail our results for each of our contributions listed above. First, we show that a fall in VIX pushes capital flows into Turkey, which lead to a fall in nominal and real borrowing costs for domestic firms and an associated credit boom. These results can also be interpreted as showing that when global uncertainty is high, capital inflows fall, borrowing costs increase and domestic credit contracts. Importantly, the elasticity of the interest rate with respect to capital inflows is twice as large for the VIX-instrumented capital inflows regression compared to the OLS estimate, which is what one would expect based on our theoretical validation of our identifying assumption. Since demand- and supply-driven capital flows have opposite effects on borrowing rates, this biases the OLS coefficient on these rates towards zero and the IV coefficient capturing only the supply shock is larger in absolute value. Furthermore, by leaving out the global crisis episode of 2008, we are careful to show that our results are not solely identified from the large spike in VIX during the global financial crisis, and thus that our results are primarily driven by quarter-to-quarter changes of VIX over the whole sample period.⁹

These results are economically significant. We find a baseline micro estimate of the elasticity of domestic loan growth with respect to changes in VIX equal to -0.067 . In turn, this *micro* estimate

⁸For example, see Khwaja and Mian (2008); Chodorow-Reich (2014); Jiménez et al. (2014), among others.

⁹By beginning the sample in 2003 rather than after the 2008 crisis, we aim to help address the hypothesis put forth by advanced economies' central bankers that capital flows to emerging markets are primarily demand-driven, since they began prior to the global financial crisis. Our identification methodology separates demand and supply driven capital flows relying on observations before and after the global financial crisis and does not solely rely on the "shock event" of the 2007–2008 crisis. See Ammer et al. (2016).

implies that we can explain, on average, 43% of the observed cyclical loan growth of the *aggregate* corporate sector over the sample period.¹⁰ The elasticity of the real interest rate with respect to VIX in our core specification is 0.017, implying a 1 percentage point fall in the average real borrowing rate for an increase in global uncertainty equal to the interquartile range of $\log(\text{VIX})$ over the sample period.

Our second contribution is on the role of heterogeneity in banks' pricing of loans. We ask, what is the micro-channel through which certain banks are able to decrease their lending rates in response to a fall in global funding costs. Our previous work (Baskaya et al., 2017) shows that capital inflows lead to larger loan volumes when credit is supplied by domestic banks with higher non-core funding. The non-core funding encompasses everything but domestic deposits and hence is mostly raised in the international capital markets.¹¹ We conjecture that these banks' *lending rates* will differ when capital flows are *only* supply driven. We find evidence supporting our hypothesis: during low VIX episodes domestic banks with higher non-core funding reduces their lending rates more, which propels an increase in loan growth for firms borrowing from these banks. These regressions are identified from the *same* firms borrowing from multiple banks through the use of firm \times quarter fixed effects and given our data on each banks' loan share, we provide an aggregation exercise which shows that the estimated coefficients on borrowing costs and loan supply for bank heterogeneity in terms non-core funding can account for 94% of the overall 43% explanatory power of VIX on credit growth. Our interpretation of this result is that banks' funding costs decrease during episodes of low global uncertainty, and banks pass these improved financing conditions to firms by lowering local borrowing costs.

Our third contribution comes from digging deeper into this transmission channel, that is the "interest rate channel," in order to identify how capital inflows relax firms' credit constraints. We do so by asking not only how high non-core banks' lending rates varies but we also ask how these rates varies across firms with different *ex-ante* credit constraints (proxied by firms' net worth).¹² We find that low net worth firms face a larger decline in their borrowing costs from high non-core banks during periods of low VIX. Interestingly, we find loan volume results that are inconsistent with the results on rates. We do not find any difference in the changes in loan volumes provided

¹⁰We provide details of this calculation below, where using the loan shares from each bank, we aggregate the average impact of changes in VIX on loan growth.

¹¹See Akdogan and Yildirim (2014) for a discussion of Turkish banks' non-core liabilities and their relation to international funding.

¹²We focus on these measures given the importance of the interaction between the banks' credit supply and firms' credit constraints (e.g., see Holmstrom and Tirole, 1997).

by banks with high non-core funding to firms with different credit constraints. Therefore, while banks provide more credit at lower rates on average to *all* firms, it appears that they do not provide more credit to *risky* firms, although they offer these risky (low net-worth) firms lower lending rates. These contradictory patterns provide a puzzle as to how exactly firm credit constraints are relaxed over capital flow episodes.

To better understand the mechanism at work, we run regressions using data at the loan-month level for *new loan issuances* only. These loan-level regressions are identified from *within*-loan changes for the *same* firm-bank pair. The estimates show a strong positive relationship between the collateral-to-loan ratio and loan amounts, which suggests that there are loan-level collateral constraints that bind on average. This positive relation does not change with the fluctuations in VIX, suggesting that constraints still bind during supply-driven capital inflow episodes. Therefore, the results suggest that some firms remain constrained when they are borrowing large amounts even though they face a decline in their borrowing costs. These results are important findings in terms of separating two alternative margins of adjustment in the domestic credit market given fluctuations in capital inflows: it is possible for firms to borrow at lower rates on average, while their “hard” collateral constraints do not change over the cycle since capital that serves as collateral does not get over-valued with capital inflows into the banking sector.¹³ Thus, “risky” firms are allowed to borrow only some fraction of their capital stock, and this fraction does not change in spite of the lower real rates driven by exogenous capital inflows.¹⁴

Our paper is related to several strands of the literature but with key differences. Our results relate and differ from the closed-economy macro-finance literature, which shows that given financial frictions, expansionary monetary policy leads to an increase in net-worth of borrowers via higher asset prices, whereas our results does not work via higher asset prices driven relaxation of frictions. Furthermore, this lending/credit channel of monetary policy works via smaller banks rather than larger ones,¹⁵ which play a key role in our international setting, since large banks are the ones with better access to international funding. Other papers argue that leverage constraints of financial

¹³Our loan-collateral regressions explicitly control higher asset prices driven valuation effects since we observe collateral only once at its market value at the time of the new loan issuance.

¹⁴See [Fostel and Geanakoplos \(2015\)](#) for a model of endogenous leverage that provides a rationalization for our findings. They show an equilibrium relationship between interest rate and collateral-to-loan ratio given the equilibrium price level of collateral. In this framework a higher loan-to-value ratio is associated with higher interest rates. Hence if capital inflows do not affect the collateral valuation directly, as in our data, but in equilibrium affect supply of loans then the interest rate gets lower. This means for a given level of collateral value/price, firms can borrow more at lower interest rate.

¹⁵See [Bernanke and Gertler \(1995\)](#) and [Gertler and Kiyotaki \(2010\)](#). See [Kashyap and Stein \(2000\)](#) for the role of small banks in the data.

intermediaries relax due to lower funding costs of banks.¹⁶ An appreciating exchange rate as a result of capital inflows may also allow banks and firms with foreign currency debt to take on more leverage, again resulting in a credit boom.¹⁷ We investigate the role of these alternative mechanisms. We find that highly leveraged banks do not lend more to low net worth firms and/or do not reduce their lending rates during capital inflows episodes, but they do lend more to firms who have a balance sheet mismatch in terms of the currency composition of their liabilities and assets, when the exchange rate appreciates.¹⁸ However the estimated coefficients from these regressions cannot account for our aggregate estimates.

Our results are not driven by foreign banks' lending directly to domestic corporates.¹⁹ Recent work, using data on syndicated loans by global banks, shows that an easing in U.S. monetary policy is associated with more cross-border loans by global banks to emerging markets, while QE policies in general are shown to be associated with more lending by foreign banks in Mexico.²⁰ The new channel that we propose is complementary to these papers, and is able to explain a large part of aggregate credit growth since the large domestic banks are the main financial intermediaries that generate procyclicality in the domestic economy as a result of low global uncertainty driven capital flows.

[Section 2](#) presents our theoretical framework, and the identification methodology. [Section 3](#) describes the data. [Section 4](#) describes the empirical results and presents robustness, and [Section 5](#) concludes.

2 Empirical Strategy

2.1 Conceptual Framework

We start with the deviation from the standard no-arbitrage condition for a foreign lender to Turkey implied by uncovered interest rate parity (UIP) with country risk:

$$i_{c,t} = i_t^* + \mathbb{E}_t \Delta e_{t+1} + \gamma_{c,t}, \quad (1)$$

¹⁶See [Coimbra and Rey \(2017\)](#).

¹⁷See [Bruno and Shin \(2015a\)](#).

¹⁸See also [Aoki et al. \(2015\)](#) and [Farhi and Werning \(2016\)](#).

¹⁹See, for example, [Peek and Rosengren \(2000\)](#); [Cetorelli and Goldberg \(2011\)](#); [Schnabl \(2012\)](#); [Ongena et al. \(2015\)](#) who show that global banks transmit financial crises in general.

²⁰See [Bräuning and Ivashina \(2017\)](#) on the role of global banks' syndicated loans, and [Morais et al. \(2015\)](#) on the role of foreign banks in Mexico.

where $i_{c,t}$ and i_t^* are the nominal interest rates in Turkey and the U.S. (or the world), respectively; $\mathbb{E}_t \Delta e_{t+1}$ is the expected log exchange rate change between t and $t + 1$, and $\gamma_{c,t}$ is a country risk premium. The Turkish interest rate should exceed i_t^* by the amount of an expected depreciation of the Turkish lira relative to the USD (i.e., $\mathbb{E}_t \Delta e_{t+1} > 0$), and by the country risk premium $\gamma_{c,t}$, which captures both exchange rate and default risks. Therefore, a fall in interest rates in a small-open economy can result from a decline in exchange rate and default risks, which will also facilitate capital mobility.

Assuming that purchasing power parity (PPP) holds, changes in the exchange rate can be written in real terms as the inflation differential between Turkey and the U.S.: $\Delta e_{t+1} = \pi_{t+1} - \pi_{t+1}^*$, and noting that the real interest rates in the two countries are $r_{c,t} \equiv i_{c,t} - \mathbb{E}_t \pi_{t+1}$ and $r_t^* \equiv i_t^* - \mathbb{E}_t \pi_{t+1}^*$, respectively, we can re-write condition (1) in real terms as:

$$r_{c,t} = r_t^* + \gamma_{c,t}. \quad (2)$$

Therefore, if Turkish nominal and real interest rates are higher than those of the U.S., say due to higher country risk, a fall in this risk premium attracts capital flows, leads to a decline in both nominal and real interest rates and also to an appreciation of the Turkish lira viz. the USD. Crucially, any change in the risk premium will affect the real interest rate differential and hence real borrowing costs, and a lower country risk premium will imply lower real borrowing costs. Increased risk appetite of investors worldwide, and the accompanying fall in VIX, can then be thought of as an exogenous factor that leads to a fall in a country's risk premium, given the lower weight that investors place on country risk. That is, we can think of $\gamma_{c,t}$ as being composed of two different risks: global and country. We therefore write $\gamma_{c,t}$ as

$$\gamma_{c,t} \equiv \omega \text{VIX}_t + \alpha_{c,t}, \quad (3)$$

where VIX represents global uncertainty, ω needs not equal to one, and $\alpha_{c,t}$ is country-specific risk.

This framework is consistent with the literature that shows that UIP deviations are related to a time-varying risk premium, which is related to country/political risk.²¹ [Appendix A](#) details standard country-level UIP regressions that we run, where we show that UIP fails for Turkey over

²¹See among others [Chinn and Frankel \(2002\)](#); [Frankel and Poonawala \(2010\)](#). The recent work by [Salomao and Verala \(2016\)](#) models the optimal choice of foreign currency borrowing by firms, where foreign currency borrowing is more attractive under a UIP violation due to country risk, while [Hassan \(2013\)](#) and [Gopinath and Stein \(2017\)](#) model failures of UIP in a general equilibrium setting.

the sample period, and that the residuals, which capture a time-varying risk premium, are strongly correlated with movements in VIX.²²

Next, assume that the risk premium for a given firm f by bank b is linear in firm-specific risk:

$$\gamma_{f,b,t} \equiv \alpha_{f,t}, \quad (4)$$

where $\alpha_{f,t}$ represent time-varying firm risk. Then, we can write the nominal interest rate at the firm-bank level as a linear function of the country interest rate (1) and the risk premium (4), and apply the definition of the country risk factor (3):

$$\begin{aligned} i_{f,b,t} &= i_{c,t} + \gamma_{f,b,t} \\ &= i_t^* + \mathbb{E}_t(\Delta e_{t+1}) + \gamma_{c,t} + \gamma_{f,b,t} \\ &= i_t^* + \mathbb{E}_t(\Delta e_{t+1}) + \omega \text{VIX}_t + \alpha_{c,t} + \alpha_{f,t}, \end{aligned} \quad (5)$$

where the nominal interest rate at the firm level is now a function of the foreign interest rate, expected exchange rate changes, global and country risk factors, in addition to time-varying firm risk. Using (2), we can apply the same logic to derive a firm-bank level real interest rate as a function of risk factors and the foreign real interest rate:

$$r_{f,b,t} = r_t^* + \omega \text{VIX}_t + \alpha_{c,t} + \alpha_{f,t}. \quad (6)$$

Therefore, conditional on U.S. interest rates, country risk, and firm-time varying factors including idiosyncratic risk, real borrowing costs at the firm level will be a function of global uncertainty, proxied by VIX.

We take this simple framework to the data by using an estimation equation for the firm-bank level interest rate at the quarterly level that maps into (6).²³ We detail our identification strategy in the following section.

²²Below, when we present our benchmark results, we show that UIP fails at the firm-bank-level, whereby expected exchange rate changes cannot overturn the large differential in returns to borrowing in different currencies. See [Maggiori et al. \(2017\)](#) who show, using transaction level data from Morningstar, that emerging market firms only borrow in foreign currency from mutual fund investors.

²³The direct effect of r_t^* , separate from VIX_t , is hard to estimate given the limited quarterly variation for r_t^* , measured as the U.S. interest rates.

2.2 Identification Strategy

We begin with “macro regressions,” which regress (i) the loan principal outstanding (‘Loan’), and (ii) the real interest rate (‘ r ’) or nominal interest rate (‘ i ’) on Turkish capital inflows. Loans are deflated by the Turkish CPI, while the real interest rate is constructed using Turkish survey data on year-on-year inflation expectations.²⁴

Our transaction-level loan data that cover the universe of loans, report a loan’s origination date and we observe the same loan throughout its maturity. We collapse the data at the firm (f)-bank (b)-currency denomination (d)-quarter (q) level (see [Section 3.1](#) details on the credit register data). The main reason for aggregating at the quarterly level is to be consistent with capital flows data which are only reported at the quarterly level.²⁵ Further, the interest rate is a weighted-sum of individual real rates on loans between bank and firms, where the weights are based on a given loan’s share relative to total loans. All explanatory variables are in real terms or in ratios. We run regressions in log-log, so that we can interpret the coefficients on VIX and capital inflows as elasticities. We then run “interaction” regressions to exploit the rich heterogeneity in the data. These regressions will take into consideration the role of bank characteristics, as well as triple interactions that examine firm characteristics and the currency denomination of the loan. We provide substantial details on data construction in [Section 3](#). Regressions are weighted-least squares, where weights are the natural logarithm of the loan value. The standard errors are double clustered at the firm and time levels.²⁶

2.2.1 Macro Regressions

To examine the impact of capital inflows on credit in terms of either loan volume or interest rates, we begin with the following regression:

$$\begin{aligned} \log Y_{f,b,d,q} = & \alpha_{f,b} + \lambda \text{Trend}_q + \beta \log \text{Capital inflows}_{q-1} + \delta \text{FX}_{f,b,d,q} \\ & + \Theta_1 \mathbf{Bank}_{b,q-1} + \Theta_2 \mathbf{Macro}_{q-1} + \varepsilon_{f,b,d,q}, \end{aligned} \quad (7)$$

where $Y_{f,b,d,q}$ is either (i) $\text{Loans}_{f,b,d,q}$, (ii) one plus the nominal interest rate $(1+i_{f,b,d,q})$, or (iii) one plus the real interest rate $(1+r_{f,b,d,q})$, for a given firm-bank (f, b) pair in a given currency

²⁴[Section 3.4](#) describes the inflation expectations data.

²⁵We run loan-level regressions at the monthly level below.

²⁶[Petersen \(2009\)](#) shows that the best practice is to cluster at both levels, or if the number of clusters is small in one dimension, then use a fixed effect for that dimension and cluster on the other dimension, where more clusters are available.

denomination (d) and quarter (q). ‘Capital inflows’ is gross Turkish capital inflows in 2003 Turkish liras. Further, $\alpha_{f,b}$ is a firm \times bank fixed effect, which controls for unobserved firm and bank level time-invariant heterogeneity; Trend_q is a linear trend variable to make sure the data are stationary. FX is a dummy variable that is equal to 1 if the loan is in foreign currency, and 0 if it is in Turkish lira. **Bank** is a set of bank characteristics that control for heterogeneity, including $\log(\text{assets})$, capital ratio, liquidity ratio, non-core liabilities ratio, and return on total assets (ROA). These variables are standard in the literature and importantly include the inverse of banks’ leverage (i.e., the capital ratio), which has been highlighted as responding to global financial conditions and wealth effects arising from exchange rate and asset price changes (e.g., Bruno and Shin, 2015a,b), thus allowing banks to expand their lending.

Macro is a set of macro controls, including Turkish quarterly real GDP growth, inflation, and the Turkish lira/USD quarterly exchange rate change.²⁷ These variables account for macro pull factors, and are the standard variables in central banks reaction functions. These variables will capture how the Turkish economy reacts to world economic conditions. We further augment regression (7) with the lag of CBRT policy rate to directly control for domestic monetary policy.²⁸ Finally, for robustness, we move one step further by augmenting (7) with *firm* \times *year* effects, which capture the time-varying unobserved heterogeneity for firms from year to year, while still allowing us to estimate the impact of capital inflows and other variables at the quarterly level. These fixed effects map into a low-frequency version of $\alpha_{f,t}$ in (6), which control for unobserved firm time-varying characteristics at the annual level.

Figure 1 plots the CBRT policy rate, that is the overnight rate, together with VIX, and the weighted average of the nominal interest rates on TL and FX loans in our sample. As the figure clearly shows, nominal interest rates, especially for TL loans, show a time series pattern that closely follows VIX, although at times the policy rate deviates from VIX. Next, Figure 2 plots the average time series pattern of loan rates after purging all bank and firm characteristics from the nominal and real rates at the loan level. To plot the interest rates’ time effects in this figure, we regress these rates on bank \times firm fixed effects, month fixed effects, and several time-varying loan characteristics such a loan’s collateral-to-principal ratio, maturity, currency denomination and riskiness. We then plot the estimated month fixed effects. As in Figure 1, there is a close connection between VIX

²⁷In the regressions where we use real interest rate as the dependent variable, we still control for the quarter-on-quarter actual inflation since we used year-on-year expected inflation to calculate the real interest rates.

²⁸We proxy the CBRT policy rate with the CBRT overnight (O/N) lending rate. See Section 3.4 for a description of the changes in Turkish monetary policy over the sample period that underlie the choice of the O/N lending rate as the policy rate.

and the borrowing costs in Turkey, and especially during the unconventional monetary policy (QE) period.

2.2.2 Exogenous Capital Inflows

Capital inflows might be determined by firm and aggregate demand, and hence it is hard to identify the causal impact of supply-driven capital inflows on domestic credit conditions in (7). Studying both loan volumes and borrowing rates at the micro level and their relationship to capital flows helps tease out the relative importance of supply versus demand shocks, which would otherwise be difficult to do using aggregate data.

To provide some intuition on the relative impact of supply and demand shocks on the estimated coefficients in estimating regression (7) for loans and interest rates, Figure 3 presents two figures plotting out comparative statics arising from different sets of shocks. Figure 3a shows what happens for purely supply-driven changes in credit. In this case, the net effect on loan volumes will be positive, along with an unambiguous fall in borrowing costs, as the economy moves along the demand curve from point A to point B. Figure 3b considers an increase in the supply of lending, along with several different possible demand shocks. First, assume that the increase in demand (D_0 to D_1) is greater than the increase in supply (S_0 to S_1), which implies that while credit volume increases, the interest rate also rises (point B: $r_B > r_A$). Second, demand and supply are assumed to increase symmetrically (i.e., S_0 to S_2), so that new equilibrium is now at point C. Here, loan volumes increase even more relative to the initial equilibrium at point A, while the interest rate remains the same as in the initial equilibrium (i.e., $r_C = r_A$). Finally, the increase in supply to S_3 is greater than the shock to the demand for loans, so that the interest rate now falls relative to the pre-shock equilibrium ($r_D < r_A$). Again, loan volume increases.

To be able to make use of this framework, where demand and supply shocks will have opposing effects on the interest rates, we need to instrument capital inflows so that we isolate these shocks. To achieve this goal, we turn to the conceptual framework outlined in Section 2.1 to motivate using VIX as an instrument for capital inflows.²⁹ In particular, the first-stage regression instruments for $\log(\text{Capital inflows})$ by $\log(\text{VIX})$ in (7), which yields an IV estimate of β .³⁰

We can compare the OLS and IV estimates of β for the real interest rate regressions, β_r^{OLS} and β_r^{IV} to pin down the relevant shock. If capital inflows are driven both by demand and supply

²⁹There is a tight relationship between Turkish capital inflows and VIX during our sample period, where the two series (in logs) have a correlation of -0.68 .

³⁰See Appendix B.1 for details on the two-stage estimation strategy.

effects, and VIX is picking up the exogenous supply effect for a small open economy like Turkey, we would expect that $|\beta_r^{IV}| > |\beta_r^{OLS}|$. This case will hold true as long as our identifying assumption is valid – that is changes in VIX affect Turkish loan growth through the supply-side capital inflows and hence VIX is an excludable instrument.

2.2.3 Reduced-Form Regressions

We further examine the impact of VIX directly on loans and interest rates in a reduced-form setting, by running a regression analogous to (7), but replacing capital inflows with VIX directly:

$$\begin{aligned} \log Y_{f,b,d,q} = & \tilde{\alpha}_{f,b} + \tilde{\lambda}\text{Trend}_q + \tilde{\beta} \log \text{VIX}_{q-1} + \tilde{\delta}\text{FX}_{f,b,d,q} \\ & + \tilde{\Theta}_1\mathbf{Bank}_{b,q-1} + \tilde{\Theta}_2\mathbf{Macro}_{q-1} + \xi_{f,b,d,q}. \end{aligned} \quad (8)$$

This reduced-form approach not only provides a direct estimate of the elasticity of credit conditions in Turkey vis-à-vis VIX (i.e., $\tilde{\beta}$), but it also sets a benchmark for the heterogeneity regressions below, where we interact VIX with different loan, firm, and bank characteristics, thus avoiding the need for a two-stage approach in exploring heterogeneity.

2.2.4 Banks’ External Funding, Firm-Level Financial Constraints, and the Currency Denomination of Lending

To study how changes in global financing conditions spillover into the domestic credit market via banks’ exposure to international financial markets, we focus on how the difference in banks’ reliance on financing via non-traditional (or wholesale) funding impacts their behavior over the global financial cycle. This type of funding is dubbed as non-core liabilities (Hahm et al., 2013). We therefore construct a ‘Noncore’ ratio, which is non-core liabilities divided by total liabilities.³¹

In exploring these heterogeneous effects of the global financial cycle, we use VIX as a reduced-form measure of supply-driven capital flows, and we further saturate our regressions with time-varying fixed effects at the firm level. This fixed-effect methodology follows in the tradition of papers that use credit register data by exploiting the fact that firms borrow from multiple banks over time in order to identify heterogeneous effects. This literature almost exclusively focuses on the amount of domestic loan provisions by banks (e.g., see, Khwaja and Mian, 2008; Chodorow-

³¹Noncore liabilities = Payables to money market + Payables to securities + Payables to banks + Funds from Repo + Securities issued (net). Baskaya et al. (2017) find that the lending volume of banks which are more reliant on non-core financing is more responsive to movements in capital inflows, without identifying what drives capital inflows.

Reich, 2014; Jiménez et al., 2014). Our contribution is to focus on both loan volume and pricing of those loans jointly, and how this pricing changes with firm and bank heterogeneity. The use of firm \times quarter fixed effects also controls for unobserved time-varying firm characteristics such as firm productivity, quality, or credit worthiness, which may change with the global financial cycle.³² The regression specification is,

$$\log Y_{f,b,d,q} = \alpha_{f,b} + \alpha_{f,q} + \zeta(\text{Noncore}_b \times \log \text{VIX}_{q-1}) + \delta_1 \text{FX}_{f,b,d,q} + \epsilon_{f,b,d,q}, \quad (9)$$

where $\alpha_{f,q}$ is a firm \times quarter fixed effect. ‘Noncore $_b$ ’ is a time-invariant dummy variable, for whether a bank is has a high non-core liabilities ratio or not, where a bank is assigned a 1 for “high” if its average non-core ratio over time is larger than the median of all banks’ non-core over the sample; otherwise, it receives a zero for a “low” non-core bank .

Analyzing which banks play the largest role in passing through the global financial conditions to the domestic firms is only part of the story. The macroeconomic impact of the interaction between firms’ financial constraints and capital inflows has been highlighted in the international macroeconomics literature, and particularly since the Global Financial Crisis.³³ Given the rich heterogeneity of our dataset, we investigate how the effect of capital flows on domestic loan provision is impacted by firm characteristics. In particular, we investigate the interaction between movements in the VIX, banks’ non-core positions and firm financial constraints, which we proxy by firm net worth.³⁴ In order to focus on the difference-in-difference estimation across firm characteristics, we create time-invariant firm-level dummy variables that split firms into two groups based on net worth

We define firm’s net worth as $\log(\text{Assets} - \text{Liabilities})$, as is standard in the literature.³⁵ We define a time invariant dummy for firms’ net worth, ‘NetWorth $_f$ ’, by comparing a firm’s average net worth to the sample’s median value. A value of one indicates a “high” net worth firm. The key reason why we use time-invariant dummy variables to proxy for bank-level characteristics and firm-

³²We also experiment with first-difference specifications obtaining same qualitative results.

³³See, for example, Caballero and Simsek (2016); Farhi and Werning (2016); Gopinath et al. (2017).

³⁴We also ran regression for firms’ financial constraints proxied by firm size, as measured by $\log(\text{assets})$ and standard in the finance literature, and found the same qualitative results as when using groups based on net worth. Berger and Udell (1998) show that firms which are smaller have less capital, and hence smaller net worth. They argue that small firms have informational opaqueness and high default risk, so size and net worth can be proxies for financial frictions. Arellano et al. (2012) and Gopinath et al. (2017) document a positive cross-sectional relationship between firm leverage and size using AMADEUS data for several European countries.

³⁵This definition normally eliminates negative net worth firms, but this is not a constraint in our data sample, since firms always have positive net worth.

level financial constraints is that these balance sheet variables will be endogenous to loan outcomes over time. Notice that by using time-invariant dummies for balance sheet characteristics and also including firm and bank fixed effects that vary over quarters, we solve this problem. The regression specifications with the triple interaction can then be written as

$$\begin{aligned} \log Y_{f,b,d,q} = & \alpha_{f,b} + \alpha_{b,q} + \alpha_{f,q} + \kappa(\text{Noncore}_b \times \text{NetWorth}_f \\ & \times \log \text{VIX}_{q-1}) + \delta_2 \text{FX}_{f,b,d,q} + \vartheta_{f,b,d,q}, \end{aligned} \quad (10)$$

where $\alpha_{b,q}$ is a bank \times quarter fixed effect. We include these fixed effects since we want to focus on the supply of credit by banks with higher non-core liabilities to firms who are low net-worth, instead of the average supply of credit.

The potential for balance sheet currency mismatches has been investigated in numerous studies,³⁶ and the potential for these to build up during credit booms is particularly acute. To study the role of banks with higher non-core liabilities on potential differentials in the FX composition of loan provision and borrowing rates, we interact the Noncore_b measure with the FX dummy for the currency denomination; that is,

$$\begin{aligned} \log Y_{f,b,d,q} = & \alpha_{f,b} + \alpha_{b,q} + \alpha_{f,q} + \rho(\text{Noncore}_b \times \text{FX}_{f,b,d,q} \times \log \text{VIX}_{q-1}) \\ & + \delta_3 \text{FX}_{f,b,d,q} + u_{f,b,d,q}, \end{aligned} \quad (11)$$

where we include the same set of fixed effects as in (10).

2.2.5 Financial Constraints at the Loan-Level

We next estimate a loan-level version of our previous estimation equations using monthly data on new loans at the date of origination, exploiting data on the collateral of each loan as a proxy for financial constraints, and interact it with VIX and the non-core ratio; that is the regression specification is

$$\begin{aligned} \log Y_{f,b,l,m} = & \omega_{f,b,m} + \beta_1 \text{Collateral}_{f,b,l,m} + \beta_2 (\text{Collateral}_{f,b,l,m} \times \log \text{VIX}_{m-1}) \\ & + \beta_3 (\text{Noncore}_b \times \text{Collateral}_{f,b,l,m}) \\ & + \beta_4 (\text{Noncore}_b \times \text{Collateral}_{f,b,l,m} \times \log \text{VIX}_{m-1}) + \beta_5 \text{FX}_{f,b,l,m} + e_{f,b,l,m}, \end{aligned} \quad (12)$$

³⁶See, for example, [Aguiar \(2005\)](#); [Kalemli-Özcan et al. \(2016\)](#).

where we change the q subscript to m for variables that vary at a monthly level, and focus on both loan volume and the real interest rate as the endogenous variables for a give loan l . Collateral $_{f,b,l,m}$ measures the collateral-to-loan ratio at the initiation of the loan, and $\omega_{f,b,m}$ is a firm \times bank \times month effect that captures time-varying firm and bank level unobserved factors at the monthly level. Notice that with these fixed effects, we solely identify from changes in the amount of new loans and their interest rates for a given firm-bank pair. Hence we do not allow firms to switch banks and vice versa for banks.

The advantage of moving to the loan-level regression is threefold. First, given a smaller sample of data for the firm balance sheet variables (see [Section 3.3](#)), we do not have measures of financial constraints at the firm-level (i.e., net worth) for the whole population of firms in the credit register. Second, by drilling down to the loan level, we are able to control for potential time-varying selection effects at the bank-firm level. Finally, these regressions will help us to link our results to the theoretical literature on firm heterogeneity and collateral constraints, which we discuss after we present the results.

3 Data

To identify the impact of capital flows on the domestic credit cycle, we merge three large micro-level panel datasets together. All data are obtained from the CBRT. Specifically, we merge bank- and firm-level characteristics with individual loan-level data between banks and firms using unique bank and firm identifiers. We further augment this dataset with Turkish and world macroeconomic and financial data. The final dataset is at the quarterly frequency, except for the firm data, which are annual. We transform all loan, bank, and firm variables to real values, using 2003 as the base year for inflation adjustment. We further clean and winsorize the data in order to eliminate the impact of outliers.³⁷ We discuss the characteristics of each dataset in this section.

3.1 Credit Register

Our detailed monthly loan transaction-level data are collected by the Banking Regulation and Supervision Agency (BRSA), and provided to us by the CBRT. Banks have to report outstanding loans at the level of firms and individuals monthly to the BRSA at the transaction level.³⁸ For

³⁷We winsorize 1% of the data for the loan and bank variables, but need to winsorize 2% for the firm balance sheet variables given fatter tails.

³⁸There is a cutoff under which banks do not have to report the individual transactions to the authorities, which is 500 TL.

instance, if a firm has five loans with different maturities and interest rates at the branch of a bank and two other loans at another branch of the same bank, the bank then has to report all seven loans separately as long as each of the loans' outstanding amounts are above the bank-specific reporting cutoff level. If a loan's outstanding amount is below the bank's reporting cutoff then the bank may aggregate such small loans at the branch-level and report the aggregated amounts. This dataset provides the same information as found in credit register data in other countries, but contains a more comprehensive list of variables. In particular, besides providing the amount of a loan outstanding between a given individual (household, firm, government) and a bank, the dataset also provides several other key pieces of information, such as the (i) interest rate; (ii) maturity date as well as extended maturity dates if relevant; (iii) collateral provided; (iv) credit limit (only beginning in 2007); (v) currency of loan; (vi) detailed industry codes for the activity classification for which the loan is borrowed for, as well as the breakdown of consumer usage of loan (e.g., credit card, mortgage); (vii) bank-determined risk measures of the loans.

The data are cleaned at the loan level before we aggregate up to the firm-bank level for our regression analysis. The data cleaning is extensive and there are certain unique features of the Turkish data which must be tackled and which we describe in brief next. First, we use cash loans in terms of outstanding principal, since credit limit data are not available for the full sample period. Moreover, these loans naturally map into the data used to measure aggregate credit growth. Second, a significant component of lending in Turkey takes place in foreign currency (FX).³⁹ We clean the data to deal with exchange rate issues as follows. There are two types of FX loans, which banks report differently in terms of Turkish lira (TL) each month. The first type of FX loan is one that is indexed to exchange rate movements. This type of loan is reported based on its initial TL value each period, and thus is not adjusted by banks for exchange rate movements (of course, the value of these types of loans may still change if borrowers pay back some of the loan, for example). The second type of FX loan is issued in the foreign currency. The TL value of this type of loan is adjusted each period to account for exchange rate movements. This naturally creates a *valuation effect*, which we need to correct for in order to not under/overstate the value of the TL loan in the period following the initial loan issuance. For example, imagine that over a month period there are no new loans issued and no repayments made. A depreciation of the TL against the USD would appear to increase total loans outstanding for all existing FX loans issued in dollars. This valuation effect would in turn manifest itself as an expansion of credit when measured in TL,

³⁹Generally USD or euro.

but this expansion would solely have been due to a currency depreciation, rather than issues of new loans. We adjust for this valuation effect using official end-of-period exchange rates, before summing the data over firm-bank pairs for FX and TL loans, where we sum all FX loans (expressed in TL).

We then adjust the individual loans for inflation before summing across firm-bank pairs. The baseline regressions pool loans regardless of their maturity. Roughly half of the loans have maturities less than or equal to one year. We therefore also run regressions splitting the sample at the one-year mark for short and long maturities.

We use end-of-quarter data for a given firm-bank pair. The key reason for doing so is that capital flows and other macro/global variables are at the quarterly level. The final cleaned dataset, before aggregation to the bank-firm level for a given quarter, contains roughly 53 million loan records over the December 2003–December 2013 period. [Figure A1](#) compares the growth rate of the aggregated loans in our dataset (‘Firms’) to aggregate credit growth for the whole economy (‘Firms + Non-Firms’). The two series track each other very closely, with a correlation of 0.86. Of the whole sample of corporate loans, roughly one half of the loans are in TL, and the remaining FX. [Table A2](#) reports some key statistics on the coverage of the credit register data based on end-of-year data, both for all firm loans (Panel A), as well as for loans of the firms with matched firm balance sheet data (Panel B). We report the FX share of loans based on value within the respective firm datasets in Panels A and B. On average, this number is 50 and 67% for all firms and the firm sub-sample with matched balance sheet data, respectively. Therefore, foreign currency loans make up an important part of our sample in terms of value. The last two columns, columns (2) and (3), break this ratio up into loans that are issued in foreign currency (‘FX Loan’) and those that are issued in TL, but indexed to the exchange rate (‘Indexed Loan’). The FX loans make up the majority of total foreign currency loans, though indexed loans having been rising in importance over last few years.

[Table A3](#) reports summary statistics on banks, firms, and firm-bank pairs in the register for the end of year. As column (1) shows, the number of banks increase somewhat over the sample due to data collection for “participation” banks starting later. Similarly, the number of firms borrowing also increases, as reflected in the second column. The total number of firm-bank-quarter pairs in the full sample data is roughly 5.4 million (Panel A, sum of columns (3) and (4)). Firms with multiple bank relationships make up approximately 50% of total loans in terms of loan count (column 5), and 75-88% as a share of total loan value (column (6)). In Panel B, the proportion of multiple

bank relationships is even larger in terms of count, while the loan value share is comparable to that in Panel A. Finally, the average number of banking relationships a given firm has over the sample is between 2.8 and 4.3 (column (7)) for the whole sample and the matched sample, respectively.

Table A4 presents summary statistics for the credit register data for loans aggregated at the firm-bank pair each quarter. The table pools all the loans, regardless of currency of denomination in Panel A, while Panels B and C present statistics on TL and FX loans separately (i.e., the unit of observation is firm-bank-denomination). The table reports summary statistics for (i) loans outstanding in thousands of 2003 TL, (ii) the nominal interest rate, (iii) the real interest rate, and (iv) the remaining maturity (in months) of a loan. Furthermore, we do this for each currency type of loan. These are the data that form the basis for our regression samples.⁴⁰ As one can see, there is a lot of heterogeneity in the size of loans, as well as borrowing rates. In comparing Panels A and B, one also sees that FX loans are on average larger and cheaper than TL loans.

Since we are aggregating over several potential loans between a given bank and firm pair in a given time period, we need to take into account the size of the individual loans in calculating an “effective” interest rate and maturity for the firm-bank pair. We do this by creating weighted averages based on a loan’s share in total loans between each firm-bank pair in a given period. We allow the weights to vary depending on the unit of analysis we consider, and they also vary over time. Larger loans’ interest rates get a bigger weight.⁴¹ We want the weights to be time-varying to capture the time variation in the interest rates of the loan portfolio of a given bank-firm pair. Therefore, in Panel A, when we pool the TL and FX loans, the weight’s numerator is simply the loan value of an individual loan, while it’s denominator is the sum of all TL and FX loans between a firm-bank pair in a given period. In Panels B and C, the weight’s numerator is again the individual loan value, while the denominator is total TL loans in Panel B, and in Panel C the denominator is total FX loans.⁴² The loan variable is the sum of all loans between firm-bank pair, while the collateral ratio is simply the sum of collateral divided by the sum of loans between banks and firms in a given quarter. We always pool the data for FX and TL loans and do not sum these loans.

⁴⁰The min-max values are similar across panels due to winsorization.

⁴¹We follow the same strategy in calculating weighted averages across different maturities.

⁴²Formally, for a loan i between bank b and firm f in time t and denomination type $d = \{ALL, TL, FX\}$, in Panel A: $w_{i,f,b,t}^{ALL} = Loan_{i,f,b,t} / \sum_{i \in I_{f,b,t}^{ALL}} Loan_{i,f,b,t}$; Panel B: $w_{i,f,b,t}^{TL} = Loan_{i,f,b,t} / \sum_{i \in I_{f,b,t}^{TL}} Loan_{i,f,b,t}$; Panel C: $w_{i,f,b,t}^{FX} = Loan_{i,f,b,t} / \sum_{i \in I_{f,b,t}^{FX}} Loan_{i,f,b,t}$, where $I_{i,f,b,t}^d$ is the set of loans based on currency types between the firm-bank pair in a given quarter.

3.2 Bank-Level Data

Turkey, like many major emerging markets, has a bank dominated financial sector: in 2014, banks held 86% of the country’s financial assets and roughly 90% of total financial liabilities. The past decade has witnessed a doubling of bank deposits and assets, while loans have increased five-fold. As [Table A5](#) shows, by 2013 the banking sector’s assets represented more than 100 percent of GDP, and loans roughly 70 percent. This growth has been driven by a skewed banking sector, where the largest five banks hold between 50 to 60 percent of assets, deposits and loans over the sample period, while the largest ten banks’ shares are between 80 to 90 percent.

Our baseline analysis uses quarterly bank balance sheet data from Turkey for the 2003–2013 period. The data are collected at the monthly level, and we simply use March, June, September, and December reports. All banks operating within Turkey are required to report their balance sheets as well as extra items to the regulatory and supervisory authorities – such as the CBRT and the Banking Regulation and Supervision Agency (BRSA) – by the end of the month.

Over the 2003–13 period there are 47 banks, of which 28 are commercial, 14 are investment and development, and 5 are branches of foreign banks.⁴³ Our sample of banks varies from between 35 and 45 throughout the period since we focus on banks that are active in the corporate loan market and this number changes from period to period.⁴⁴ [Table A6](#) presents summary statistics for our final sample of banks, based on end-of-quarter data pooled over the sample period. These variables, like others used in the paper, are winsorized at the one-percent level. There is quite a bit of variation in bank size, as measured by total assets as noted above. Similarly, there is variation in the capital ratio, the non-core ratio, liquidity, and return on assets (ROA) across banks and over time.

3.3 Firm-Level Data

Firm balance sheet and income statement data come from a supervisory dataset that is collected by the CBRT annually, and date back to 1988. The data are collected to monitor the credit risk of firms. The CBRT sends the survey to the two groups of firms. The first group contains firms that have more than 10,000 TL credit and have appeared in the CBRT’s database in previous years. The second group includes the firms that have more than 1,000,000 TL credit, but have not appeared in

⁴³Note that in the aftermath of the 2001 crisis, the weak capital structure of the Turkish banks resulted in a number of takeovers. As a result, in 2000–2004 period, a total of 25 banks were taken over by Deposit-Insurance Fund, SDIF. Our sample begins at the end of this period, where the majority of takeovers were completed.

⁴⁴We also drop four participation banks that make up only a very small fraction of the loan market.

the CBRT’s database before. Although an important fraction of the firms have continuously existed over the sample period, the firm sample has been changing over time due to real entry and exit of firms and also entry and exit arising from the Central Bank’s size thresholds. The data are not drawn from the census, and tend to be dominated by manufacturing firms. We therefore compare our dataset to data collected by the Turkish Statistical Institute (Turkstat) for a much broader set of firms and industries. The aim of this dataset (Annual Industry and Service Statistics) is to produce information based on enterprises for all sectors. The firms that are sampled in Turkstat are the universe of enterprises with more than 20 employees, as well as a representative subset of smaller firms. We also drop financial firms and state owned enterprises from our own CBRT firm database and these sectors are also not included in the Turkstat database.

Table A7 shows that our dataset’s sample of firms represents on average approximately 50% of Turkey’s economic activity, as measured by total gross sales (Gross Output).⁴⁵ Next, **Table A8** compares the firm coverage of gross sales in our dataset relative to Turkstat across different firm-size strata, which are defined based on employment. Overall, our dataset does a relatively good job in terms of representing medium-sized firms (20-249 employees) for both all sectors of the economy, as well as the manufacturing sector. However, the firm data that are collected by the CBRT under represent small firms (1-19 employees), and thus over represent very large firms (250+ employees), though this difference in sampling is less dramatic in the manufacturing sector (Panel B).

We clean the firm-level data and winsorize variables at the 2 percent level to eliminate the impact of potential outliers. Furthermore, we deflate all nominal values to 2003 TL values. **Table A9** presents summary statistics for all firms in the sample. Panel A presents data for all firms, excluding the financial and government sectors, while Panel B restricts the data to only firms in the manufacturing sector. We present all measures in levels (in thousands of 2003 TL), ratios and growth rates. It is worth noting that in terms of counts, manufacturing firms make up slightly less than 50% of the sample. There is substantial variation in all variables across firms and over time. Moreover, in comparing Panels A and B, manufacturing firms tend to be slightly larger and have higher net worth on average.

Firms’ direct external borrowing is very limited in Turkey and hence banks are the key intermediary of capital flows. As **Figure 4** shows, the external corporate bond issuance is negligible as percent of GDP, whereas banks’ external borrowing is as high as 40 percent of GDP at the end of

⁴⁵Note that Turkstat has not released 2013 data yet, so we cannot compare the last year of our sample. Furthermore, our sample’s balance sheet coverage also improves in later years, where there is also a large increase in loans in the Turkish economy.

our sample period.

3.4 Macro-Level Data

Figure 5 plots Turkey’s credit growth (Loans/GDP Growth) and current account position (CA/GDP) against $\log(\text{VIX})$ and Turkish capital inflows on top and bottom panels respectively. Movements in the VIX tend to be negatively correlated with Turkey’s credit growth, and positively correlated with the current account balance (a fall in the current account implies an *increase* in net capital inflows). Loan-to-GDP growth fluctuates between 5 to 10 percent quarterly during our sample. Looking at a more direct measure of capital flows to Turkey, we see that this measure is positively correlated to Turkey’s credit growth, while negatively correlated with its current account. These correlations are consistent with the story as described for VIX. Plotting the level of loans to GDP in Figure A2, we show that there is a five-fold increase in the loan-to-GDP ratio during our sample period. This is driven by a six-fold increase in domestic currency loans and a tripling of FX loans, both as a ratio to GDP, over this period.⁴⁶

Next, Table A10 presents summary statistics for the quarterly Turkish and global macroeconomic and financial variables that we use as controls in our regressions, as well as measures of global financial conditions. All real variables are deflated using 2003 as the base year. The Turkish macroeconomic data are taken from the CBRT. VIX and the Turkish overnight rate are quarterly averages. There is substantial quarterly variation in all these variables, over the sample period, which is crucial for our identification strategy.

Our choice of using the overnight rate for the policy rate reflects the change in the definition of the policy rate and the monetary policy framework during our sample. The official policy rate is either the O/N borrowing rate of the CBRT (before 2010) or the CBRT 1-week repo rate (after 2010) where CBRT lends to banks through weekly repo. While central banks implement the monetary policy via a single policy rate, the CBRT deviated from this standard policy by using an asymmetric and wide interest rate corridor since 2010 in order to incorporate financial stability into the monetary policy framework. The upper bound of the corridor is the CBRT O/N lending rate to banks and the lower bound is CBRT borrowing rate. The CBRT provided liquidity mainly through two distinct channels (i.e., the O/N lending and 1-week repo lending rates) and hence at two different interest rates since 2010, during a period where the CBRT acted as a net lender. The CBRT announces the amount of funds allocated for weekly repo and distributes them among

⁴⁶The figure plots the aggregated loans from bank balance sheet data.

bidding banks in proportion to their size. When only part of the liquidity is provided through weekly repo, banks have to borrow overnight at the O/N lending rate for their remaining liquidity needs. By using the O/N lending rate as the policy rate, we are therefore using the upper bound for the cost of borrowing from the CBRT for banks.

Inflation expectations data are from the “Survey of Expectations,” which has been conducted by the Central Bank of the Republic of Turkey (CBRT) monthly since August 2001. It is the most widely followed survey by the CBRT and financial market participants on expectations about key macroeconomic variables in Turkey. The survey is sent to approximately 120 forecasters from the financial and real sectors and academia, and asks for their consumer price inflation expectations at various horizons (current month, end of year, 12-months ahead and 24-month ahead) as well as their expectations about interest rates, the current account balance and GDP growth rate. We use the 12-months ahead expectation to construct the real interest rate. Using model-predicted inflation expectations based on an AR(1) process based on year-on-year inflation rather than using actual survey data on inflation expectations at the annual frequency yields similar results.

4 Empirical Results

4.1 Macro Regressions

Table 1 presents the results for the capital inflows regressions (7) for loan volumes, and nominal and real interest rates. The regression for the real rates maps to equation (6) in our theoretical framework.⁴⁷ Given the inclusion of the firm×bank fixed effects, we use the within firm-bank variation over the sample period to estimate the coefficients of interest. Hence, we only identify from quarterly changes in aggregate loans and average interest rates as a function of quarterly changes in capital flows for a given firm-bank pair, relative to another pair. This strategy addresses potential time-invariant selection effects due to different types of bank and firm relationships, as well as controls for time-invariant firm and bank characteristics.

Columns (1), (3), and (5) of Panel A present the OLS estimates for log (Loans), the nominal interest rate, and the real interest rate, respectively. Across all columns, capital inflows to Turkey are associated with higher volume of loans as well as lower interest rates, both in nominal and real terms. Furthermore, the coefficient on the FX dummy shows that loans denominated in foreign

⁴⁷In a robustness table, we show results with firm×year fixed effects which corresponds to $\alpha_{f,t}$ in equation (6), where we use “year” for the t dimension in order not to absorb the direct effect of quarterly VIX.

currency are larger in value (twice the size of TL loans), and have lower interest rates on average relative to TL loans. In fact, there is a large price differential between FX and TL loans, where FX loans are 8 percentage points cheaper on average in real terms. Controlling expected exchange rate changes in this regression did not overturn this large differential and hence provide evidence for the failure of UIP at the micro-level.⁴⁸ This result is consistent with existing findings in the international macro literature on deviations from UIP at the macro-level, as cited above. These deviations make foreign currency borrowing cheaper. We control for the domestic monetary policy rate in all specifications, and find that this policy variable has a significant impact on nominal interest rates, but not on loan volumes nor real interest rates.

Columns (2), (4), and (6) present the IV estimates, which instrument capital inflows with VIX using 2SLS regressions. Recall from the discussion of the identifying assumptions in [Section 2.2.2](#), that if the supply side factors play an important role in local credit cycles, we would expect the interest rates' elasticities with respect to capital inflows obtained from the IV framework to be higher than their OLS counterparts in [Table 1](#).

Comparing the estimated OLS and IV coefficients on capital inflows for the loan volume regressions in column (1) and (2) of Panel A in [Table 1](#), there is almost no difference in the IV estimated elasticity (0.041) and its OLS counterpart (0.040). However, comparing the estimated IV and OLS elasticities for the nominal and real interest rates in columns (3)-(6), we see that $|\beta^{IV}| > |\beta^{OLS}|$ for both the real and nominal interest rates regressions, which points to VIX-driven capital inflows capturing an important supply-side effect. To quantify the difference in the OLS and IV estimates, we calculate the effect of an increase in the log of capital inflows equivalent to its interquartile range. The OLS estimate implies that the average real cost of borrowing will fall by 0.37 percentage point, while the IV estimate implies a drop of 0.73 percentage points as a response to such an increase in capital inflows.

This downward bias in the estimated OLS coefficient for the interest rates is what one would expect to find since, as we have noted, an increase in the demand for loans puts upward pressure on the interest rate, and if this demand also corresponds to increased demand for foreign capital, the estimated relationship between capital inflows and lending rates would be attenuated. Therefore, by using VIX to isolate the supply effect, the IV estimates deliver a larger negative relationship between capital inflows and interest rates, since now the estimated coefficients are free of demand

⁴⁸This coefficient on the expected exchange rate change is very similar to the one shown in macro-level UIP regression in [Appendix A](#).

effects.⁴⁹ Panel B shows the first-stage regression, which indicates the strong correlation between VIX and capital inflows, as also been found in the literature as cited in introduction. It should also be noted that the first-stage F-statistic is larger than 10, indicating that there is no weak instruments problem (Staiger and Stock, 1997; Stock et al., 2002).

4.1.1 Reduced-Form Regressions

Table 2 next presents the reduced-form results, where we directly use VIX rather than instrumented capital inflows as the key exogenous variable. These specifications also control for the firm×bank fixed effects, the macroeconomic factors and linear trends as well as the bank characteristics, as in the OLS and 2SLS regressions for capital inflows. The reduced-form regressions are useful to look at because we use VIX directly in reduced-form regressions to estimate heterogeneous effects across banks, firms, and the currency denomination of loans. First, however, we use the estimated VIX coefficients in the macro regressions to quantify the effect of movements in VIX on aggregate credit growth.

Appendix B.3 provides an aggregation equation, which shows how to use the micro estimates to draw implications for *aggregate* credit growth over the cycle. Our results are economically significant. The baseline micro estimates of the elasticity of domestic loan growth with respect to changes in VIX is -0.067 . In turn, applying (B.5), this *micro* estimate implies that we can explain on average 43 percent of observed cyclical *aggregate* loan growth to the corporate sector.⁵⁰ The estimated coefficient for the effect of VIX on the real interest rate (0.017) implies a one percentage point fall in the average borrowing rate resulting from an increase in global liquidity equal to the interquartile range of $\log(\text{VIX})$ over the sample period.

4.1.2 Regressions by Bank Type and Robustness Checks

Table 3 presents the real interest rate regressions for different bank samples, such as commercial and state banks, or domestic vs. foreign banks. First, the estimated VIX coefficient for the commercial-only sample in columns (1) is somewhat larger than the pooled estimated in column (3) of Table 2. However, when we expand the sample to also include state banks in column (2), the coefficient is of the same magnitude of the baseline result.

⁴⁹See Appendix B.2 for discussion on the potential that the IV estimates capture a local average treatment effect.

⁵⁰We apply (B.5) using $\hat{\beta} = -0.067$ and the observed change in $\log(\text{VIX})$ to obtain predicted aggregate loan growth. We then divide this series by the linearly detrended series of *actual* aggregate credit growth, and take the average of this ratio to arrive at 43 percent.

More interestingly, we next turn to the split of the sample between domestic (column (3)) and foreign (column (4)) banks. The elasticity of the real interest rate with respect to VIX for domestic banks is more than double that of foreign banks, and is strongly significant. This results is novel in the international transmission literature and points to the relative importance of domestic banks in transmitting the global financial cycle to the Turkish domestic credit market. Typically, papers in this literature as cited earlier focus on the importance of global banks' lending to the domestic corporate sector. In the case of Turkey, we show the importance of a new channel arising from the role of domestic banks as intermediaries of capital inflows. The importance of this channel is further highlighted by the fact that corporates' direct financing from global banks via syndicated loans and firms direct bond issuance abroad are extremely small compared to the domestic banks' external liabilities, as shown in [Figure 4](#).

Finally, [Appendix B.4](#) and [Table A11](#) present results on numerous robustness checks for the interest rate regressions. We include firm \times year effects; use only a sub-component of VIX that represents risk aversion, which is computed following [Bekaert et al. \(2013\)](#);⁵¹ include only firms that borrow from multiple banks; and split the sample by maturity of loans, as well as pre-/post-crisis periods. Results are robust to all checks.

4.2 Global Financial Conditions and Financial Constraints

We next explore how the effect of global financial conditions on loan volume and borrowing costs differ with respect to banks' relative non-core funding, and how these interact with firm credit constraints and the currency composition of lending based on specifications (9)-(11). Given the inclusion of firm \times quarter effects, the sample size drops as the regressions eliminate all firms that borrow from only one bank in a given quarter.⁵² The advantage of this specification is that we are able to control for time-varying firm credit worthiness, changes in firms direct borrowing from abroad, and other firm-level characteristics that may move with capital inflows.

[Table 4](#) first presents only the interaction between VIX and the dummy variable for banks' non-core liabilities, where the sample is split between high (= 1) and low (= 0) non-core banks. This dummy is based on the share of non-core liabilities to total liabilities, where a high non-core bank has a larger exposure to non-domestic deposit funding, typically raised externally. We also

⁵¹We would like to thank Marie Horoeva for providing us with an updated series.

⁵²Note that firms that borrow in both FX and TL from only one bank in a given quarter will not be eliminated from these regressions. However, these cases are rare, and the total number of additional observations gained relative to the 'multi-linked' firms of column (2) in [Table A11](#) is only about one hundred thousand, or 1% more than the multi-linked sample.

run regressions allowing for the slope on the trend variable to be heterogeneous across groups. The estimated coefficients for the interaction variables in these regressions are similar to the ones reported in [Table 4](#) with homogenous trends.

Column (1) shows that banks with higher non-core liabilities respond more to movements in VIX in their loan issuances compared to the low non-core banks. This result has similarities to the one in [Baskaya et al. \(2017\)](#), who study the differential impact of capital inflows on loans for large and high non-core banks vis-à-vis small/low non-core ones, but without discriminating between the different currency composition of loans as we do here, and also without isolating the supply side of capital inflows. Next, column (4) provides a novel result on the differential impact of VIX on the interest rate for banks with a higher non-core ratio. We find these banks to be more responsive to changes in VIX, such that their lending rates are more procyclical – that is, during periods of low global uncertainty (i.e., low VIX), high non-core banks decrease their borrowing rates more in real terms (this result also holds when looking at nominal rather than real rates).

The estimated coefficient on the interaction between VIX and the non-core dummy is 0.015, which is almost as large as the estimated elasticity of 0.017 between the real interest rate and VIX in the macro regression ([Table 2](#), column (3)). Therefore, the relative differential in changes in interest rates for high non-core banks given movement in global uncertainty is economically large, and high non-core banks are responsible for a significant part of the aggregate effect. We further run the interaction regression including VIX on its own without firm \times quarter effect in order to recover the VIX-only coefficient. In this case, the estimated coefficient on VIX is slightly lower (0.013) than the one in the macro regressions, while the coefficient on the interaction between the non-core dummy and VIX is almost the same (0.014) as in the regression with firm \times quarter effects. Given this regression, the estimated real interest rate-VIX elasticity for high non-core banks is double ($0.013 + 0.014 = 0.027$) that of low non-core banks (0.013). We can use the estimated coefficients for the loan volume regressions and the aggregation accounting exercise as described in [Appendix B.3](#) to gauge the importance of high non-core banks in explaining aggregate credit growth over the sample period. Specifically, we take the ratio of the calculated average aggregate loan growth using the coefficients for VIX and interacted non-core coefficient for high non-core banks to the the average aggregate loan growth calculated for all banks, and find this ratio to be 94 percent. Therefore, internationally exposed banks (as proxied by the non-core ratio) plays a dominant role in explaining our overall aggregate results in [Section 4.1.1](#).

Next, columns (2) and (5) explore the interaction between banks' relative non-core positions

and firm credit constraints by presenting results of regression (10) using the net worth dummy variable, where these regressions now also include bank \times quarter effects. First, we find no statistical significance on the triple interaction term for loans in column (2), implying there is no differential in the supply of loans from high non-core banks to low and high net worth firms as VIX varies. Interestingly, turning to the real interest rate regression in column (5), we find a negative and significant coefficient on the triple interaction. Given the positive coefficient on the non-core interaction on its own in the real interest rate regression of column (4), this negative coefficient on the triple interaction in column (5) implies that in periods of low global uncertainty, high non-core banks lower rates relatively more for low net worth firms. Section 4.3 uses loan-level data to further explore the differing findings for the loan volume and real interest regressions, and the possibility that collateral constraints at the loan level may bind for low net worth firms.

Combining the coefficient on the double and triple interactions for the real interest rate in columns (4) and (5), 0.015 and -0.005 , respectively, the elasticity of the real interest rate vis-à-vis VIX is approximately 0.01 when high non-core banks lend to high net worth firms, versus a value of 0.015 if high non-core banks lend to low net worth firms. In other words, the elasticity is roughly 50% larger for high non-core banks lending to low net worth firms relative to if they lend to high net worth firms.⁵³

Finally, to gauge the importance of FX-denominated loans, columns (3) and (6) present the results studying the potential heterogeneous effects of global uncertainty on the foreign currency denomination of loans and interest rates. First, as column (3) shows, there appears to be no differential in the volume of FX and TL loans issued by high non-core banks over the cycle. It is interesting to note this fact since the conventional wisdom is that internationally borrowing banks extend more foreign currency loans domestically, and firms who are in the tradeable sector demand such loans more, during booms. Recall that we control for time-varying firm effects to control for such effects of an increase in FX loans during boom periods, since exporters might be more likely to demand such loans.

However, turning to the interest rate regression of column (6), we find a differential in the relative interest rates in spite of controlling for both bank and firm time varying factors. In particular, high

⁵³As a further check, we run the triple interaction regression without firm \times quarter and bank \times quarter effects in order to recover the coefficient on VIX on its own, as well as the interaction with both VIX and the non-core and net worth dummies. In this regression, the coefficient on the interaction between non-core and VIX is 0.011, and the coefficient on the triple interaction is -0.004 . These coefficients are comparable to those reported in Table 4 with the fixed effects, and imply that the real interest rate elasticity vis-à-vis VIX is roughly 57% larger for high non-core banks lending to low net worth firms relative to if they lend to high net worth firms.

non-core banks tend to lower the TL borrowing rate relatively more than the FX ones when VIX is low. This result is novel and is in line with our theoretical framework where the differential between FX and TL rates goes down (TL borrowing becomes relatively cheaper) as a result of a decrease in country risk premium, which is triggered by a fall in VIX.

4.3 Loan-Level Evidence for Financial Constraints

We next investigate the possibility that collateral constraints may play a role in the estimated relationships between banks' non-core positions, firms' financial constraints, and movements in VIX. To do so, we exploit data on *new* loan issuances and run the regression specification (12).

Since we use data on *new* loan issuances to run these regressions, we only see each loan once and thus exploit changes in rates and volume of each new loan from month to month to identify the impact of loan riskiness/collateral, conditional on all other time-varying firm and bank factors.⁵⁴

Table 5 presents results for regression (12) for specifications that examine the impact of VIX on the loan volume and real borrowing costs at the loan-level instead of at the firm-bank level, as we were doing so far, where we aggregated all the loans between a given pair. The regressions use different sets of fixed effects for identification: (i) month fixed effects only, (ii) firm \times month effects, and finally (iii) firm \times bank \times month effects, in moving from left to right for the loan and real interest rate regressions. These last set of fixed effects keep the firm-bank pair fixed and identify from loan changes from month to month for a given pair. Therefore, these regressions control for time-varying matching/selection between firms and banks.⁵⁵

The results for loans in columns (1)-(3) show that the collateral-to-loan ratio is positive and significant, indicating collateral constraints exist at the loan level. Importantly, this result remains significant in column (3), which includes the most stringent set of fixed effects that capture all the factors such as the interaction between banks' non-core and firms net worth positions and identifies from new loans within a given bank-firm pair over time since this column uses firm \times bank \times month fixed effects. Therefore, the collateral ratio is significant regardless of which fixed effects are used, implying that loan-level collateral constraints exist and they are independent of firm and bank

⁵⁴Note that the collateral-to-loan ratio can be greater than one for several reasons. First, banks may ask for more collateral than the loan value, since the collateral may also include liquidation costs or legal costs, or other risks attached to the collateral. Second, depending on the type of collateral posted, such as residential property, banks require collateral up to 200% of the loan value. Third, firms must post collateral for the whole credit line (or multiple credit lines) requested, even if the initial loan withdrawal is less than amount. We therefore winsorize the collateral-to-loan ratio at the 5% level. Also note that book and market value of the collateral is the same since we observe each loan and collateral posted only once in a given month given our focus on new issuances.

⁵⁵Note that there may not be a new loan every month and by construction these regressions will only identify from the months when there is a new loan.

characteristics. In terms of the magnitudes, the effect is sizeable. We demean both the collateral ratio and the VIX. At the mean value of the VIX, the total effect of collateral ratio on loan amount is 0.091 in column (3) and similar in other columns. This coefficient implies that an increase in the collateral ratio for new loans that is equivalent to its interquartile range of 0.95, increases the new loan by 8.6 percentage points.

Next, turning to the interaction between the collateral ratio and VIX, again focusing on columns (1)-(3), the coefficient is positive and significant in all specifications. This indicates that loan-level collateral constraints get stronger during episodes of increased global uncertainty. By the same token, the constraints get weaker when VIX goes down. Notice that these results hold regardless of controlling for unobserved time-varying firm and bank heterogeneity, most importantly within bank-firm pairs as implied by the estimation in column (3) that include $\text{firm} \times \text{bank} \times \text{month}$ fixed effects.

To quantify the relative impact of collateral constraints in periods of low global uncertainty, we take the derivative of (12) with respect to the collateral ratio, and evaluate it at the minimum value of $\log(\text{VIX})$.⁵⁶ This yields a total effect of the collateral ratio on the new loan amount of 0.074 based on the parameter estimates in column (3). Therefore, when VIX moves from its mean to its minimum level in the sample, the loan-level collateral constraint relaxes very little from 0.091 to 0.074, an amount of 0.017. So now an increase in the collateral ratio equivalent to its interquartile range of the collateral ratio of new loans implies that during low VIX periods the response of new loan volumes is 7.0 percentage points. This is a very small relaxation in the loan-level collateral constraint as a response to exogenous capital flows; a mere 1.6 percentage points.⁵⁷

Columns (5)-(7) present consistent results for the real interest rate regression. Like the loan volume regressions, the collateral ratio coefficient is significant and has the expected negative sign in columns (5)-(7); that is, there is a negative relationship between the collateral ratio and the price of a loan. During low VIX periods this relationship weakens (and during high VIX periods the relationship strengthens), implying that firms can obtain a lower interest rate, without posting as high a collateral during periods of low VIX, as shown in column (5). However, this effect is very small and becomes insignificant when including $\text{firm} \times \text{month}$ and $\text{firm} \times \text{bank} \times \text{month}$ fixed effects, in columns (6) and (7). In other words, once we control for the unobserved time-varying firm

⁵⁶The mean of $\log(\text{VIX})$ is 2.93 and minimum of $\log(\text{VIX})$ is 2.38 for the monthly data series.

⁵⁷Recall that the elasticity of loan amount with respect to VIX is 0.067 in our macro regressions. Although 0.067 is an elasticity and here we move VIX from its mean to its minimum value, the difference in the overall impact on loan growth between two sets of estimates is sizeable, where the macro regression estimate implies a much larger impact of VIX.

characteristics, such as time-varying firm risk, the relation between loan-level interest rates and collateral does not respond to global uncertainty.

Finally, turning to the triple interactions with the non-core liability ratio indicator for banks as we used before, in columns (4) and (8), we find that the coefficient is significant for both loan volumes and the interest rate. We have calculated the total effect of the collateral ratio on loan volumes during low VIX periods and this effect on the new loans supplied by high non-core banks is 0.158 and on the interest rate is -0.024 . This means that during low VIX periods collateral constraints at the loan level is stronger when new loans are supplied by high non-core banks relative to the effects we find earlier for an average bank. Note further that on average there is no differential between low and high non-core banks, as the double interaction is insignificant. These results are consistent with our previous results at the firm-bank level where loan supply from high and low non-core banks did not differ during low VIX periods. Similarly, in column (8), a total effect of -0.024 implies that high non-core banks require a higher collateral to offer a lower interest rate during periods of low VIX. This result again confirms our prior based on the previous results at the firm-bank level that high non-core ratio banks do decrease the borrowing costs more, but this behavior leads to higher credit supply only for firms who are not collateral constrained.⁵⁸ All our results in this table are robust to splitting new loans by maturity and also by currency as shown in [Table A12](#) and [Table A13](#).⁵⁹

Overall, we interpret these findings as additional evidence for the importance of the interest rate channel relative to the collateral constraint (relaxation) channel. During times of low global uncertainty, where global liquidity is presumably high, banks obtain cheap funding and they pass this on to firms as lower borrowing costs. Since firm-level borrowing costs include firm-level risk, during periods of low global uncertainty, banks might assign lower risk to some of the risky (low net worth) firms and offer them lower interest rates. However, collateral constraints at the loan level still prevent some of these firms from further borrowing even when they can finance their borrowing at a lower cost.⁶⁰

⁵⁸The flip side of this result means that low non-core banks require less collateral to offer a lower interest rate during periods of low VIX. However, the differential that these banks offer in terms of the interest rate response to the collateral ratio is very tiny, at 0.08 percentage points.

⁵⁹In fact for long term borrowing, as shown in column (2) of [Table A13](#), loan level collateral constraints get stronger during periods of low VIX.

⁶⁰Note that regression results are robust to restricting the sample to the set of firms used in the previous firm-bank level regressions where firm-level net worth data are available.

4.4 Exchange Rate Changes and Risk-Taking Channel

Finally, we explore the possibility for an alternative channel driving our main findings. Recent work has pointed to the role of global financial intermediaries in driving credit cycles of domestic economies via the “risk-taking channel,” whereby fluctuations in the exchange rate affect the net worth of borrowers and relax the leverage constraint of lenders (e.g., [Bruno and Shin, 2015a](#)). In particular, an appreciation of the domestic currency vis-à-vis the USD improves domestic firms’ balance sheets, allowing lenders to lend more to these borrowers.

The mechanism is relevant for domestic firms who have debt in U.S. dollars since the shock is on the nominal exchange rate. We control for exchange rate fluctuations in our regressions, but there might still be an interaction effect where such fluctuations affect certain banks and firms as envisioned by the models. Although these models have firms directly borrowing from global banks, we can still test for this possible channel in our set up where firms borrow from domestic banks, who in turn borrow from international markets, since firms can also borrow in foreign currency from domestic banks.⁶¹

We run a triple interaction specification, which interacts the logarithm of the Turkish lira-U.S. dollar exchange rate and $\log(\text{VIX})$ with a dummy variable indicating whether a bank is either a low or a high leverage bank on average throughout the sample, and also with a measure of the FX share of a firm’s liabilities. This type of heterogeneity in risk taking as a function of heterogeneity in bank leverage is a feature of [Coimbra and Rey \(2017\)](#), who model the mechanism in a closed-economy setting. Since the firm-level balance sheet data are not broken down by currency, we construct a proxy for the FX share using the currency composition of firms’ loans in the credit register. In particular, we calculate the FX share of loans for each firm over the sample, and divide firms into low and high FX share bins, based on the median in the whole sample of firms. Therefore, a firm with an average FX share of loans higher than the sample median is assigned a one, while firms with a lower share is assigned a zero.

[Table 6](#) presents results for these regressions using quarterly data, where we use aggregate loans for a given firm-bank pair in a quarter as in our benchmark regressions. We present specifications that control for both firm \times quarter and bank \times quarter effects, mimicking our previous triple interaction specifications with firm net worth and bank non-core liabilities. First, the coefficient on the VIX interaction with bank leverage and firm FX exposure dummies is insignificant both for the loan

⁶¹As discussed above, Turkish corporate borrowing from foreign banks inside or outside the country and firms’ direct external bond issuance are minimal.

volume and the interest rate in columns (1) and (3). This means that our previous result where we showed banks with higher non-core funding lowering nominal and real rates and extending more credit during low VIX periods cannot be explained by the alternative risk-taking channel. The result may not be surprising given the negative correlation (-0.2) between high leverage banks and high non-core funded banks. Since both these types of banks are large banks, a negative correlation implies that domestic large banks who are leveraged fund themselves more in the domestic market. This result highlights the importance of funding costs for banks.

The specifications in columns (1) and (3) may not be the right ones to test the risk-taking channel since this channel should operate via movements in the exchange rate. Hence, columns (2) and (4) interact dummies for high leverage bank and high FX exposure firm with the changes in the log exchange rate. Again, the risk-taking channel cannot explain the reduction in borrowing costs given the insignificant coefficient in column (4). However, this channel has the potential to explain changes in credit volume given the significant coefficient in column (2). This column shows that an appreciation of the Turkish lira against the USD (i.e., $\log(\text{XR})$ falls) leads to leveraged banks lending more to firms with higher FX exposure relative to firms with lower exposure borrowing from banks with lower leverage. This result resonates with [Bruno and Shin \(2015a\)](#), who argue that the risk-taking channel might work better via quantities rather than prices. The magnitude of this effect is sizeable. For an increase equivalent to the interquartile range of $\log(\text{XR})$, which is 0.18, the estimated coefficient of -0.392 implies highly leveraged banks increase the loan amount by 7 percentage points to high-FX exposure firms. Notice that we condition on time-varying firm and bank characteristics in all these regressions as we did before when investigating the effect of the interest rate channel.

In order to better gauge the size of this estimate in terms of the aggregate impact and hence its potential to explain our *macro* estimates, we revisit our macro regressions, where we also include the logarithm of the exchange rate ($\log(\text{XR})$) directly in the regression. Since VIX is a proxy for exogenous capital flows and the nominal exchange rate is a function of inflows, we begin by omitting $\log(\text{VIX})$ and regress loan volumes on the $\log(\text{XR})$ alone. As can be seen in column (1) [Table A14](#), $\log(\text{XR})$ is insignificant on its own in the reduced-form macro regression for loan volume. Furthermore, $\log(\text{XR})$ remains insignificant in column (2) when including $\log(\text{VIX})$, which is still significant. Finally, as seen in columns (3)-(6), $\log(\text{XR})$ remains insignificant in all but one specifications for the real interest rate regressions regardless of controlling for VIX. Hence, an exchange rate driven risk-taking channel cannot explain our macro estimates, but this channel has

an impact on the credit supply of highly leveraged banks to a particular set of firms who borrow in FX.

Finally, to understand the partial effect of this channel, we run a set of regressions mimicking columns (1) and (4) of [Table 4](#), where we include the interaction of $\log(\text{VIX})$ with the non-core dummy together with the interaction of $\log(\text{XR})$ and the leverage dummy. The estimated coefficient on the $\log(\text{VIX})$ -non-core interaction variable is similar to what we report in column (4) of [Table 4](#) for the interest rate regression, while the coefficient on the interaction of $\log(\text{XR})$ and the leverage dummy is insignificant. For the loan outcome, we also obtain a very similar coefficient on the interaction of $\log(\text{VIX})$ and the non-core dummy (-0.035) with similar significance as in column (1) of [Table 4](#). Recall that these coefficients for loan and interest rate outcomes are similar to macro estimates, which highlights the important role played by high non-core funded banks in *aggregate* credit expansion. The coefficient on the interaction of $\log(\text{XR})$ and the leverage dummy (0.354) for the loan outcome is significant but has the wrong sign. This implies that when exchange rate appreciates, high leveraged banks supply less credit on average and they supply more credit *only to high FX-exposed* firms.

5 Conclusion

We show that fall in global financial uncertainty drives capital inflows in a major EME, and that these inflows substantially impacts domestic credit conditions. Capital inflows transfer global conditions to the emerging market by lower real borrowing costs given a failure of UIP, a new mechanism that we call the “interest rate channel.” Domestic banks intermediate these inflows, and differences in banks access to international capital markets impact the pricing of loans, playing an important role in the aggregate impact of capital inflows on local credit cycles. We further show that while borrowing costs fall for all firms on average, there is no relaxation of their “hard” credit constraint, as measured by a loan’s collateral-to-loan ratio as global uncertainty falls.

The results in this paper have important policy implications both at the microeconomic and macroeconomic levels. The results on bank and firm level heterogeneity point to important transmission mechanisms for regulators to consider when designing prudential policy. Meanwhile, the results on the aggregate impact of capital inflows hold when controlling for changes in the domestic monetary policy and the exchange rate. Thus, in spite of the response of monetary policy and the exchange rate, domestic credit and real borrowing costs respond significantly to global factors.

Our results suggest the existence of a “financial trilemma”: that is the task of achieving financial stability is hard under national financial regulation, free capital flows, and a global financial cycle, regardless of the exchange rate regime (Obstfeld, 2015; Mishra and Rajan, 2016).

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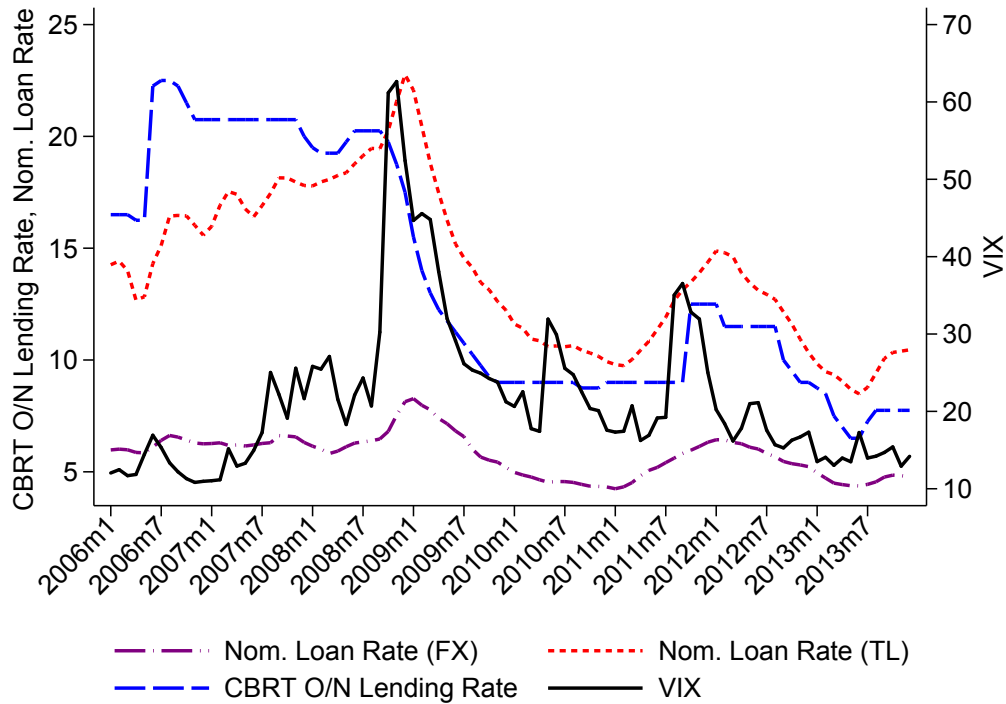
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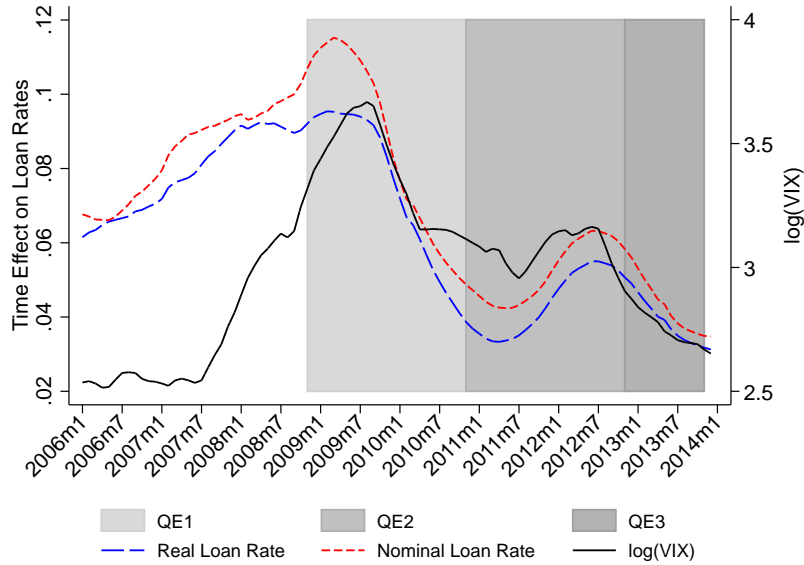
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Figure 1. Central Bank Policy Rates, Borrowing Costs and VIX, 2006–13



Notes: This figure plots nominal interest rates in Turkey (in percentage terms) along with VIX over 2003–13 at a monthly level. ‘CBRT O/N Lending Rate’ is the nominal interest rate at which the CBRT lends at overnight maturity to the banks who are in liquidity-need. ‘Nom. Loan Rate (TL)’ is the weighted average value of nominal interest rates on the TL-denominated loans in our loan data. ‘Nom. Loan Rate (FX)’ is the weighted average value of nominal interest rates on the FX-denominated loans in our loan data. ‘VIX’ is the end-of-month VIX. Source: CBRT.

Figure 2. Real and Nominal Borrowing Costs' Time Effects and VIX, 2006–13



Notes: This figure plots time effects on nominal and real loan rates in Turkey along with VIX over 2003–13 at a monthly level. The time (month) effects are obtained from a regression of loan level rates on bank×firm and month fixed effects controlling several time-varying loan characteristics such as collateral, maturity, currency and riskiness. We normalize the time effects by adding the absolute value of the minimum of the series to all value in the series. Source: CBRT.

Figure 3. Supply and Demand Shocks to Credit Market: Relative impacts

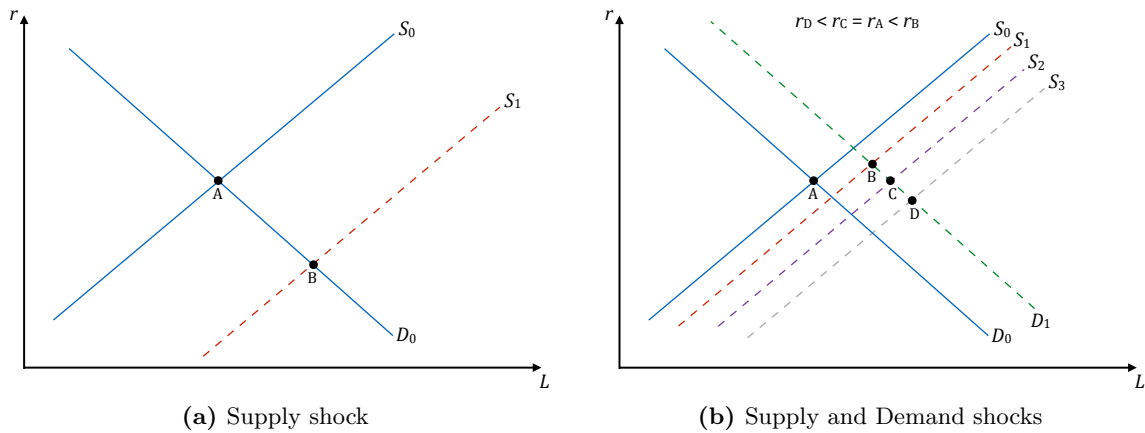
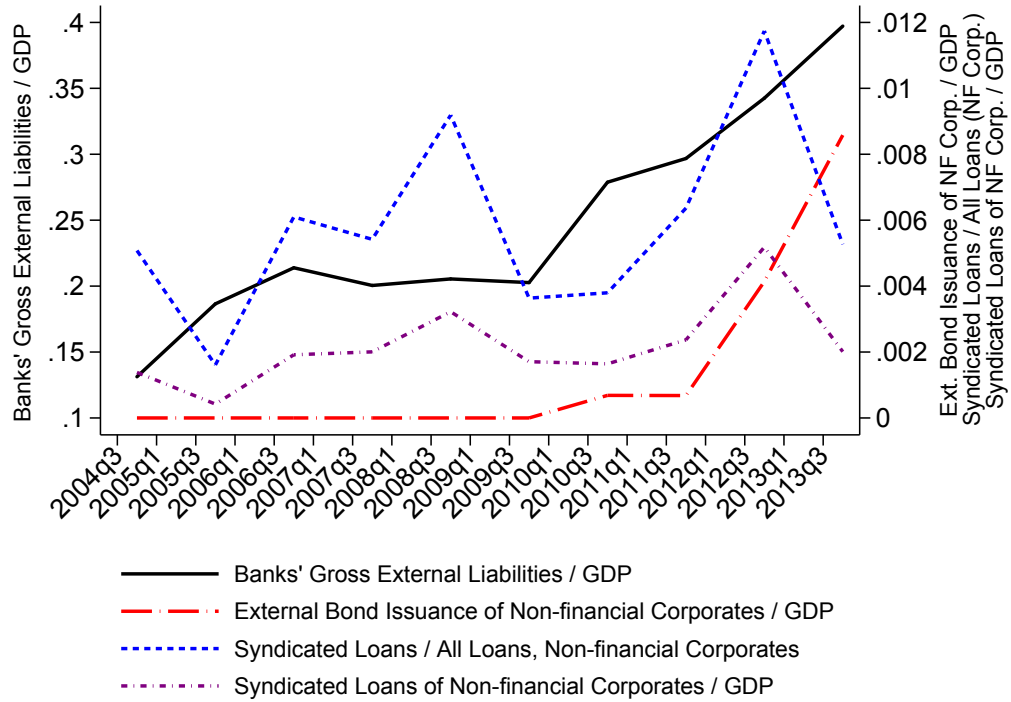
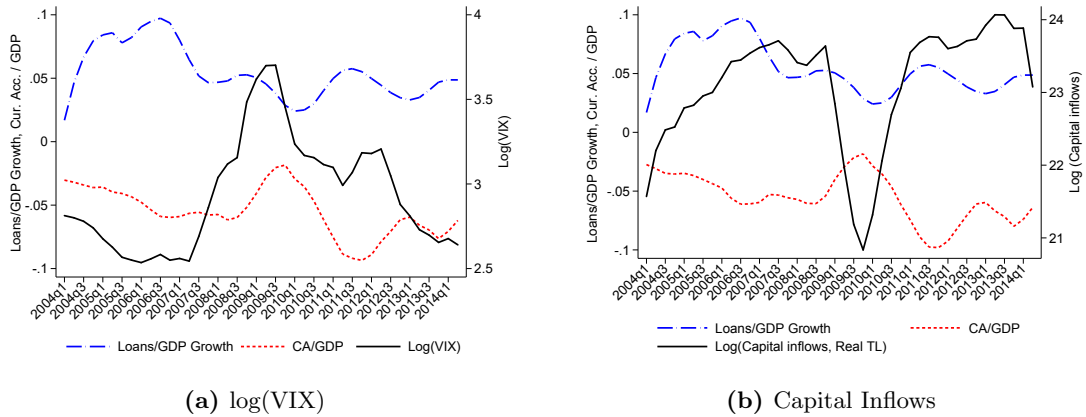


Figure 4. Banks and Firms External Borrowing, 2005–13



Notes: This figure plots the external liabilities of banks and external corporate bond issuance as a ratio to GDP. Source: CBRT.

Figure 5. Capital Flows, VIX, and Credit Growth in Turkey, 2004–13



Notes: These figures plot Turkey's Loans/GDP and CA/GDP ratios over time with (a) log(VIX) and (b) Turkish capital inflows. Turkey's Loans/GDP, CA/GDP, and Capital inflows are sourced from the CBRT, and VIX is the period average. Four-quarter moving averages are plotted.

Table 1. Impact of Capital Flows on Loan Volume and Borrowing Costs

Panel A. OLS and Second-stage of IV						
	log(Loans _q)		log(1+i _q)		log(1+r _q)	
	OLS (1)	IV (2)	OLS (3)	IV (4)	OLS (5)	IV (6)
log(K Inflows _{q-1})	0.040 ^a (0.006)	0.041 ^b (0.017)	-0.005 ^a (0.001)	-0.011 ^a (0.002)	-0.005 ^b (0.002)	-0.010 ^a (0.003)
FX	0.645 ^a (0.012)	0.645 ^a (0.012)	-0.070 ^a (0.003)	-0.070 ^a (0.003)	-0.078 ^a (0.003)	-0.078 ^a (0.003)
Policy rate _{q-1}	-0.078 (0.262)	0.171 (0.325)	0.231 ^a (0.022)	0.192 ^a (0.023)	0.046 (0.059)	0.009 (0.053)
Observations	19,982,267	19,982,267	19,982,267	19,982,267	19,982,267	19,982,267
R-squared	0.850	0.850	0.791	0.793	0.778	0.779
Bank×firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls & trend	Yes	Yes	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel B. First-stage of IV: log(K inflows _q) Regression				
	log(VIX _{q-1})	Observations	R-squared	F-stat
	-1.667 ^a (0.427)	1,685	0.5625	15.28

Notes: This table presents results for the OLS and IV regressions for (7) using quarterly data for all loans in Panel A. Columns (1) and (2) use the natural logarithm of total loans between a firm-bank as the dependent variable; columns (3) and (4) use the natural logarithm of one plus the weighted-average of nominal interest rates for loans between a firm-bank as the dependent variable, and columns (5) and (6) use the natural logarithm of the weighted average of the real interest rates for loans between a firm-bank as the dependent variable. The ‘K Inflows’ variable is real quarterly gross capital inflows into Turkey, the policy rate is the quarterly average overnight rate, and FX is a 0/1 dummy indicating whether a loan is in foreign currency (= 1) or domestic (= 0). Lagged Turkish real GDP growth, inflation, Turkish lira/USD exchange rate change, and a linear time trend are included (not shown) as regressors. Furthermore, the following lagged values of the following bank-level characteristics are also controlled for (not reported): log(assets), capital ratio, liquidity ratio, non-core liabilities ratio, and return on total assets (ROA). Regressions are all weighted-least square, where weights are equal to the loan share, and standard errors are double clustered at the firm and quarter levels.

Panel B presents the first-stage regression for the IV, which is run at the bank×quarter level for the whole sample period. The first-stage regression includes all time-varying controls appearing in the second stage, as well as bank fixed effects, and standard errors are double clustered at the bank and quarter levels.

‘a’ indicates significance at the 1% level, ‘b’ at the 5% level, and ‘c’ at the 10% level.

Table 2. Impact of VIX’s Spillovers on Loan Volume and Borrowing Costs

	$\log(\text{Loans}_q)$	$\log(1+i_q)$	$\log(1+r_q)$
	(1)	(2)	(3)
$\log(\text{VIX}_{q-1})$	-0.067 ^b (0.029)	0.019 ^a (0.003)	0.017 ^a (0.004)
FX	0.645 ^a (0.012)	-0.070 ^a (0.003)	-0.078 ^a (0.003)
Policy rate _{q-1}	0.127 (0.323)	0.204 ^a (0.024)	0.021 (0.053)
Observations	19,982,267	19,982,267	19,982,267
R-squared	0.850	0.793	0.779
Bank × firm F.E.	Yes	Yes	Yes
Macro controls & trend	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes

Notes: This table presents results for the regressions (8) using quarterly data for all loans. Column (1) use the natural logarithm of total loans between a firm-bank as the dependent variable, and columns (2) and (3) use the natural logarithm of the weighted average of the nominal and real interest rates, respectively, for loans between a firm-bank as the dependent variable. VIX and the policy rate are quarterly averages, and the same other controls as Table 1 are included. Regressions are all weighted-least square, where weights are equal to the loan share. Standard errors are double clustered at the firm and quarter levels, and ‘a’ indicates significance at the 1%, level ‘b’ at the 5% level, and ‘c’ at the 10% level.

Table 3. Impact of VIX’s Spillovers on Real Borrowing Costs by Bank Type

	<i>Bank Type</i>			
	Commercial (1)	Comm. + State (2)	Domestic (3)	Foreign (4)
$\log(\text{VIX}_{q-1})$	0.023 ^a (0.004)	0.017 ^a (0.004)	0.019 ^a (0.005)	0.009 ^b (0.004)
Observations	13,376,195	19,922,760	14,514,150	5,440,975
R-squared	0.784	0.779	0.706	0.857

Notes: This table presents results by bank-type groups for the regressions (8) using quarterly data for all loans. All columns use the natural logarithm of the weighted average of the real interest rates for loans between a firm-bank as the dependent variable. VIX is the quarterly average, and the same other controls as Table 1 are included. The sample broken down by bank groups across columns: (1) Commercial, (2) Commercial + State, (3) Domestic, and (4) Foreign banks. Regressions are all weighted-least square, where weights are equal to the loan share. Standard errors are double clustered at the firm and quarter levels, and ‘a’ indicates significance at the 1% level, ‘b’ at the 5% level, and ‘c’ at the 10% level.

Table 4. Impact of VIX's Spillovers on Loan Volume Real Borrowing Costs via Banks, Firms, and Currency Denomination

	log(Loans _q)			log(1+r _q)		
	(1)	(2)	(3)	(4)	(5)	(6)
Noncore _b ×log(VIX _{q-1})	-0.035 ^b (0.017)			0.015 ^a (0.004)		
Noncore _b ×NetWorth _f ×log(VIX _{q-1})		-0.004 (0.020)			-0.005 ^a (0.001)	
Noncore _b ×FX×log(VIX _{q-1})			-0.007 (0.018)			-0.012 ^a (0.004)
FX	0.690 ^a (0.013)	0.802 ^a (0.019)	0.745 ^a (0.095)	-0.079 ^a (0.003)	-0.078 ^a (0.004)	-0.042 ^c (0.021)
Observations	9,280,825	1,281,369	9,280,825	9,280,825	1,281,369	9,280,825
R-squared	0.876	0.764	0.877	0.852	0.814	0.877
Bank×firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Bank controls	Yes	No	No	Yes	No	No
Firm×quarter F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Bank×quarter F.E.	No	Yes	Yes	No	Yes	Yes

Notes: This table presents results for the regressions (9), (10), and (11) using quarterly data for all loans. Columns (1)-(4) use the natural logarithm of total loans between a firm-bank as the dependent variable, and columns (5)-(8) use the natural logarithm of the weighted average of the and real interest rates for loans between a firm-bank as the dependent variable. Columns (1) and (4) present the double interaction from regression (9); column (2), (3) and (5), (6) the triple interaction from regression (10), and columns (4) and (8) the triple interaction from regression (11). Noncore_b is a 0/1 dummy variable indicating whether a bank has a high (= 1) or low (= 0) non-core liabilities ratio; NetWorth_f is a 0/1 dummy variable indicating whether a firm is a high (= 1) or low (= 0) net worth firm; FX is a 0/1 dummy indicating whether a loan is in foreign currency (= 1) or domestic (= 0). The lagged values of the following bank-level characteristics are also controlled for in columns (1) and (4) (not reported). Regressions are all weighted-least square, where weights are equal to the loan share. Standard errors are double clustered at the firm and quarter levels, and 'a' indicates significance at the 1% level, 'b' at the 5% level, and 'c' at the 10% level.

Table 5. Loan-Level Evidence on Credit Constraints and Impact of VIX's Spillover via Banks: New Loans at Origination Date

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	log(Loans _{<i>m</i>})				log(1+r _{<i>m</i>})			
Collateral/Loan	0.106 ^a (0.005)	0.089 ^a (0.010)	0.091 ^a (0.011)	0.090 ^a (0.004)	-0.002 ^a (0.001)	-0.004 ^a (0.001)	-0.004 ^a (0.001)	-0.0003 (0.0003)
Collateral/Loan×log(VIX _{<i>m-1</i>})	0.019 ^c (0.010)	0.025 ^c (0.013)	0.030 ^b (0.015)	0.056 ^a (0.008)	-0.004 ^a (0.001)	-0.0002 (0.001)	0.002 (0.002)	-0.002 ^a (0.001)
Noncore _{<i>ep</i>} ×Collateral/Loan				-0.013 (0.038)				-0.014 ^a (0.003)
Noncore _{<i>ep</i>} ×Collateral/Loan×log(VIX _{<i>m-1</i>})				-0.204 ^a (0.030)				0.015 ^a (0.003)
FX	0.441 ^a (0.019)	0.488 ^a (0.038)	0.560 ^a (0.048)	0.560 ^a (0.048)	-0.082 ^a (0.002)	-0.080 ^a (0.003)	-0.082 ^a (0.004)	-0.082 ^a (0.004)
Observations	16,578,790	11,618,529	10,096,917	10,096,917	16,578,790	11,618,529	10,096,917	10,096,917
R-squared	0.738	0.840	0.851	0.851	0.657	0.844	0.861	0.863
Bank×firm F.E.	Yes	Yes	No	No	Yes	Yes	No	No
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Risk F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Maturity F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month F.E.	Yes	No	No	No	Yes	No	No	No
Firm×month F.E.	No	Yes	No	No	No	Yes	No	No
Bank×firm×month F.E.	No	No	Yes	Yes	No	No	Yes	Yes

Notes: This table presents results for regressions using monthly data at the loan level at the origination date. All variables are measured at the loan level, where 'Collateral/Loan' ratio is the collateral-to-loan ratio; Noncore_{*ep*} is a 0/1 dummy variable indicating whether a bank has a high (= 1) or low (= 0) non-core liabilities ratio; FX is a 0/1 dummy indicating whether a loan is in foreign currency (= 1) or domestic (= 0). The regressions further include (i) bank defined risk weights, (ii) sectoral activity of loan, and (iii) maturity levels. Columns (1)-(4) present results for the natural logarithm of loan value, and columns (5)-(8) for the real interest rate. Columns (1)-(3) and (5)-(7) study the impact of VIX on collateral constraint, irrespective of type of bank, where columns (1) and (5) control for month fixed effects; columns (2) and (6) control for firm×month fixed effects; and columns (3) and (7) control for firm×bank×month fixed effects. Columns (4) and (8) include the non-core interaction, and control for firm×bank×month fixed effects. Standard errors are double clustered at the firm and month levels, and 'a' indicates significance at the 1% level, 'b' at the 5% level, and 'c' at the 10% level.

Table 6. Impact of VIX and the Exchange Rate on Bank and Firm Risk-Taking: Loan Volume and Borrowing Cost Evidence

	log(Loans _q)		log(1+r _q)	
	(1)	(2)	(3)	(4)
Leverage _b × FXshare _f × log(VIX _{q-1})	0.041 (0.032)		-0.003 (0.002)	
Leverage _b × FXshare _f × log(XR _{q-1})		-0.392 ^a (0.107)		-0.006 (0.006)
FX	0.688 ^a (0.013)	0.688 ^a (0.013)	-0.079 ^a (0.003)	-0.079 ^a (0.003)
Observations	9,280,825	9,280,825	9,280,825	9,280,825
R-squared	0.877	0.877	0.877	0.877
Bank × firm F.E.	Yes	Yes	Yes	Yes
Firm × quarter F.E.	Yes	Yes	Yes	Yes
Bank × quarter F.E.	Yes	Yes	Yes	Yes

Notes: This table presents results for the risk-taking channel regressions using quarterly data for all loans. Columns (1)-(2) use the natural logarithm of total loans between a firm-bank as the dependent variable, and columns (3)-(4) use the natural logarithm of the weighted average of the and real interest rates for loans between a firm-bank as the dependent variable. Columns (1) and (3) present the triple interaction with log(VIX); column (2) and (4) the triple interaction using the logarithm of the TL/USD nominal exchange rate. Leverage_b is a 0/1 dummy variable indicating whether a bank has a high (= 1) or low (= 0) leverage bank; FXshare_f is a 0/1 dummy variable indicating whether a firm has a high (= 1) or low (= 0) share of loans in foreign currency denomination; FX is a 0/1 dummy indicating whether a loan is in foreign currency (= 1) or domestic (= 0). Standard errors are double clustered at the firm and quarter levels, and ‘a’ indicates significance at the 1% level, ‘b’ at the 5% level, and ‘c’ at the 10% level.

Appendix A UIP Regressions

To assess the validity of uncovered interest parity (UIP) in the context of Turkey, we run a standard UIP regression, with and without time trend:

$$i_t - i_t^* = \alpha + \lambda_t + \beta \mathbb{E}_t \Delta e_{TL/USD,t+1} + \epsilon_t, \quad (\text{A.1})$$

where i and i^* denote the (annualized) quarterly-average Turkish policy rate and U.S. federal funds rate at time t respectively. Exchange rate expectations are based on data from a survey of forecasters of the one-year ahead expected Turkish lira-U.S. dollar, which are collected at the monthly frequency. The expected quarterly (t to $t + 1$) exchange rate change, $\mathbb{E}_t \Delta e_{TL/USD,t+1}$, is calculated by taking the difference of the quarterly average of the monthly expectations. These data run from 2006Q3 to 2013Q4. λ_t denotes the time trend. Before we run the regressions, we perform an augmented DickeyFuller unit-root test, which shows that the included variables are stationary.

Table A1 reports the estimates for (A.1). It also shows the correlation of regression residuals with VIX. As can be seen, the coefficients on the expected changes in the exchange rate are always significantly different from one, and there is a high correlation of the regression residuals with $\log(\text{VIX})$. That is, with low VIX country risk goes down and vice versa. The correlation between the residuals and VIX is 68 percent if we do not include a time trend (column (1)) and 48 percent if we include a time trend (column (2)). Note that since the domestic rate, i_t is not a pure risk-free rate, since the Turkish policy rate may embed some country risk, these correlations of VIX and residuals are potentially underestimated.

Appendix B Regression Details

B.1 Instrumental Variables' Two-Stage Regression Strategy

We estimate the instrumental regression for (7) in two-stages, where we instrument with VIX in our baseline regression. Given that all controls are either at the country or bank level, and vary over time, we run the first-stage regression for capital flows at the {bank, quarter} level, which allows us to exploit all data included in the second-stage, while maintaining a balanced panel at the bank level. Furthermore, we include bank fixed effects in order to exploit the within time variation, which is equivalent to the second-stage approach in estimating (7) with bank×firm fixed effects.

The first-stage estimation equation for quarter q is then:

$$\log \text{Capital inflows}_{b,q} = \alpha_b + b_1 \log \text{VIX}_q + b_2 \text{Trend}_q + \mathbf{B}_1 \mathbf{Bank}_{b,q} + \mathbf{B}_2 \mathbf{Macro}_q + w_{b,q}, \quad (\text{B.1})$$

where we use the predicted values for capital inflows at $q - 1$ in the second-stage of (7). Note that there is a small difference in notation however, where given the inclusion of the exogenous bank variables in (B.1), the predicted capital inflows measure may differ due to the cross-sectional difference of the bank variables at time q .⁶² In particular, the capital inflows measure is repeated for each bank b in a given quarter q .

B.2 LATE in Instrumental Variable Regressions

Although we believe that the key reason for having higher IV coefficients is the demand effect as we explained above, it is also possible that we estimate a local average treatment effect (Imbens and Angrist, 1994) In particular, the regression estimates based on VIX-driven capital inflows may differ for small versus large loans and their interest rates because the effect of capital inflows differs for large versus small banks' credit supply (and hence the loans they provide), which is relevant given the observed heterogeneity of bank size in our data. We outline our interpretation of this case as follows. Assume that there are two equally large groups of banks, which are differentially impacted by capital inflows. For banks (b) belonging to group j ($j = 1, 2$), the impact of VIX on capital inflows, Kf, (in logs) is $\log \text{Kf}_{b,t}^j = d_j \log \text{VIX}_{b,t}^j + v_{b,t}^j$. Banks in group 1, where d_1 is large, are banks which are more likely to receive more capital inflows. Under regularity conditions in large samples, the first-stage WLS estimate from a regression using the combined sample is $\Delta \log \text{Kf} = \frac{d_1 + d_2}{2} \Delta \log \text{VIX}$. Consider also that the impact of capital inflows differs between groups for the interest rate: $\log(1 + i_{b,t}) = \beta_j \log \text{Kf}_{b,t}^j + e_{b,t}$. An IV regression of $\log(1 + i)$ on $\log \text{Kf}$, using our instrument VIX, gives, in large samples, the coefficient $\frac{d_1 \beta_1 + d_2 \beta_2}{d_1 + d_2}$; that is, a weighted average of β_1 and β_2 . Relatively larger coefficients d_1 and β_1 imply that the IV estimate is larger than the OLS estimate, which gives equal weight to β_1 and β_2 . As we show in Baskaya et al. (2017), it is indeed the case that larger banks are more procyclical during capital inflow episodes by providing more loans at cheaper rates during episodes of high capital inflows.

⁶²Omitting the FX dummy in (B.1) does nothing. Including it would imply needing to double the number of observations, but the inclusion of the bank fixed effect then makes the FX dummy redundant in the panel, so no additional information is gained in the regression and the estimated coefficients for other variables are identical.

B.3 Aggregate Implications of Reduced-Form Regressions

There is a natural aggregation exercise to undertake in order to examine the economic significance of our micro estimates on overall credit growth. In particular, ignoring the other control variables and intercept coefficients (i.e., fixed effects), we can write the VIX-predicted Loan variable from estimating (8) as

$$\log(\widehat{\text{Loan}}_{f,b,d,q}) = \widehat{\beta} \log(\text{VIX}_{q-1}), \quad (\text{B.2})$$

where $\widehat{\beta}$ is the estimated coefficient. First, differentiate both sides of (B.2), and then multiply this equation by $w_{f,b,d,q-1}$, which is a firm-bank-denomination loan share viz. total loans in a given lagged quarter, such that $\sum w_{f,b,d,q-1} = 1$ by definition. These manipulations yield

$$w_{f,b,d,q-1} d \log(\widehat{\text{Loan}}_{f,b,d,q}) = w_{f,b,d,q-1} \widehat{\beta} d \log(\text{VIX}_{q-1}), \quad (\text{B.3})$$

so,

$$w_{f,b,d,q-1} \left(\frac{\Delta \widehat{\text{Loan}}}{\widehat{\text{Loan}}} \right)_{f,b,d,q} = w_{f,b,d,q-1} \widehat{\beta} \left(\frac{\Delta \text{VIX}}{\text{VIX}} \right)_{q-1}, \quad (\text{B.4})$$

where (B.4) comes from rewriting the change in logs from (B.3) as a growth rate, and $\left(\frac{\Delta \widehat{\text{Loan}}}{\widehat{\text{Loan}}} \right)_{f,b,d,q}$ is the predicted growth rate in Loan between quarter $q-1$ and q , while $\left(\frac{\Delta \text{VIX}}{\text{VIX}} \right)_{q-1}$ is the growth in Global between quarter $q-2$ and $q-1$. Next, summing (B.4) over $\{f, b, d\}$ in a given quarter q , we have:

$$\left(\frac{\Delta \widehat{\text{Agg. Loan}}}{\widehat{\text{Agg. Loan}}} \right)_q = \widehat{\beta} \left(\frac{\Delta \text{VIX}}{\text{VIX}} \right)_{q-1}, \quad (\text{B.5})$$

which yields a relationship between aggregate credit growth (Agg. Loan), the growth rate of the VIX variable and the estimated micro estimate $\widehat{\beta}$.

B.4 Reduced-Form Regressions: Robustness

We present several robustness tests for our benchmark reduced-form regression studying the impact of VIX on real interest rates in Table A11.⁶³ Column (1) includes firm \times year effects. Since our regressions are at the quarterly level, any quarter fixed effect will absorb the direct effect of VIX, but time dummies at the yearly level will not absorb VIX's effect. Hence, we employ firm \times year fixed effects to control for slow moving firm-level unobserved heterogeneity. Column (2) shows that results are robust when using a sub-component of VIX that represents risk aversion, and which is

⁶³Results for the loan and nominal interest rate regressions are similar, and available from the authors upon request.

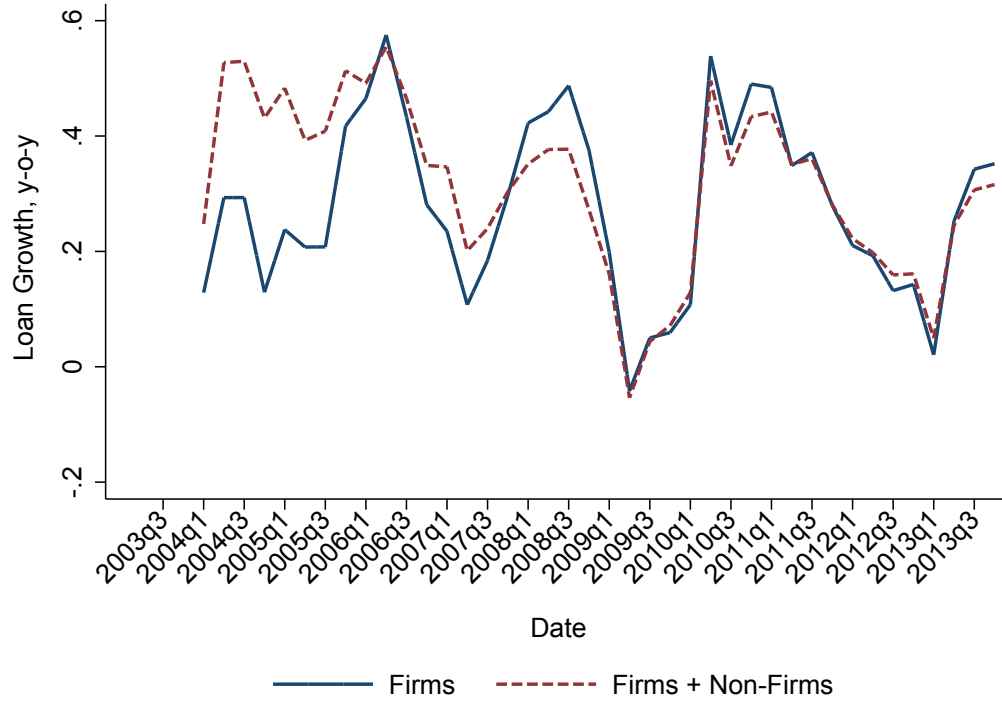
computed following [Bekaert et al. \(2013\)](#),⁶⁴ rather than total VIX. Column (3) uses a subset of the data that only includes firms that borrow from multiple banks in a given quarter. Results are identical in these columns and very close to the benchmark result of [Table 2](#).

Next, columns (4) and (5) split the sample of loans by maturity, where short-term loans are the ones that mature during a year, and long-term loans have maturities over a year. We use remaining maturity in a given quarter and not the maturity at origination. Results are again similar to our benchmark elasticity of 0.017, which is the average of the two elasticities in columns (4) and (5), 0.014 and 0.023, respectively.

In columns (6)-(9), we look at the pre-/post-crisis period for real and nominal rates. We define the pre-crisis as the period from 2003q1 to 2008q4 and post-crisis period as 2009q3 to 2013q4. With this definition, we leave out the observations where VIX registers a big spike. The reason we study both nominal and real rates for pre- and post-crisis periods is the difference in results. There is no effect of VIX on real rates during the pre-crisis period, but during the post-crisis period VIX has a similar effect both on nominal and real rates. Meanwhile, during the pre-crisis period VIX only affects nominal rates. Our hypothesis for the difference in results for the pre/post-crisis periods for the effect of VIX on the real interest rate is that the first three years of pre-crisis period saw Turkey taming actual and expectation inflation, which fell dramatically and faster than nominal interest rates. Therefore, this period witnessed increased real rates on average, and their period-on-period changes due to the disinflation effect swamped the effect of changes in VIX, which still show up with the expected sign for the pre-crisis movements in nominal borrowing rates. Although we control for lagged quarter-on-quarter inflation, this variable does not pick up the full effect of the faster decline in expected inflation relative to nominal rates on real rates during the disinflation period.

⁶⁴We would like to thank Marie Horoeva for providing us with an updated series.

Figure A1. Loan Growth Comparison of Corporate Sector and Whole Economy, 2003–13



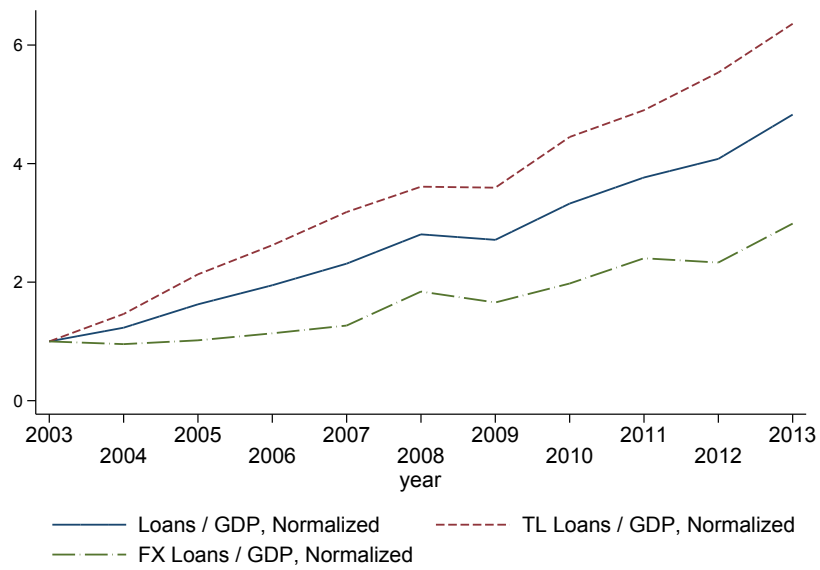
Notes: This figure plots the year-on-year loan growth rate each quarter of our sample of firms ('Firms') with that of for the whole economy ('Firms + Non-Firms'). All values are nominal. Source: authors' calculations based on official credit register data, CBRT.

Table A1. UIP Regressions for Turkish-U.S. Interest Rates, 2005–13

	(1)	(2)
$\Delta e_{TL/USD,t}$	-0.005 (0.083)	0.122 ^b (0.045)
Time trend		-0.002 ^a (0.000)
Constant	0.084 ^a (0.006)	0.336 ^a (0.026)
Observations	30	30
R-squared	0.010	0.780
Correlation of residuals and VIX	0.685	0.487

Notes: This table presents UIP regressions from (A.1) using quarterly data between 2005–13. The interest rate differential, $i_t - i_t^*$, is calculated using the Turkish overnight policy rate and the U.S. Fed Funds rate, while the expected exchange rate change is calculate using survey data as described in Appendix A. Column (1) presents the regression without a time trend, and column (2) includes a linear trend. Robust standard errors are used, and 'a' indicates significance at the 1% level, and 'b' at the 5% level.

Figure A2. Loan Growth, 2003–13



Notes: This figure plots the end of year ratio of total outstanding loans reported in balance sheets of Turkish banks to Turkish GDP, where each year's ratio is normalized with the ratio for the first year of sample, 2003. 'Loans/GDP' is for total loans, while 'TL Loans/GDP' and 'FX Loans/GDP' are ratios for loans denominated in Turkish lira and foreign currency, respectively. Source: CBRT.

Table A2. Credit Register FX Breakdown, 2003–13

Panel A. Universe of Corporate Loans			
	(1)	(2)	(3)
	<i>Share of FX Loans in All Loans</i>		
	Overall	In FX	FX-Indexed
2003	0.557	0.537	0.020
2004	0.469	0.445	0.024
2005	0.512	0.434	0.077
2006	0.534	0.453	0.081
2007	0.506	0.405	0.100
2008	0.558	0.471	0.087
2009	0.504	0.430	0.074
2010	0.480	0.409	0.071
2011	0.512	0.440	0.071
2012	0.446	0.376	0.070
2013	0.473	0.399	0.074

Panel B. Sample with Matched Firm Balance Sheet Data			
	(1)	(2)	(3)
	<i>Share of FX Loans in All Loans</i>		
	Overall	In FX	FX-Indexed
2003	0.742	0.719	0.023
2004	0.718	0.694	0.024
2005	0.688	0.619	0.069
2006	0.658	0.591	0.067
2007	0.654	0.565	0.089
2008	0.695	0.626	0.069
2009	0.661	0.595	0.066
2010	0.645	0.551	0.093
2011	0.680	0.584	0.096
2012	0.641	0.541	0.100
2013	0.671	0.569	0.102

Notes: This table presents annual summary statistics of the credit register coverage of loans, over the 2003–13 period, using end-of-year data. Panel A presents summaries for all loans in the dataset, while Panel B presents statistics based on loans for the sample that includes loans for firm-bank pairs where the firms also have usable balance sheet data (i.e., for the matched credit register and firm-level datasets). Columns (1)-(3) present the FX share of loans within the data sample: column (1) presents the overall share, while columns (2) and (3) break down the share between loans issued in a foreign currency ('In FX') and those that are indexed to foreign currency ('FX-Indexed').

Table A3. Credit Register Sample Coverage of Firm-Bank Relationships, 2003–13

Panel A: All Firms							
(1)	(2)	(3)	(4)	(5)	(6)	(7)	
Banks	Firms	<i>Bank-Firm Relationships</i>		<i>Multiple</i>	<i>Bank-Firm Share</i>		Av. No. Rel.
		Single	Multiple	Number	Value	per Firm	
2003	39	31,837	26,411	14,479	0.354	0.681	2.668
2004	36	60,963	48,576	33,341	0.407	0.723	2.692
2005	37	94,884	75,649	51,520	0.405	0.695	2.678
2006	35	124,861	95,682	83,521	0.466	0.735	2.862
2007	37	251,862	195,596	159,611	0.449	0.731	2.837
2008	37	297,574	232,034	185,242	0.444	0.746	2.826
2009	37	338,051	267,107	191,469	0.418	0.746	2.699
2010	40	448,978	352,644	275,220	0.438	0.763	2.857
2011	42	604,522	462,782	409,097	0.469	0.776	2.886
2012	42	641,935	494,449	437,781	0.470	0.814	2.968
2013	43	776,257	595,999	518,645	0.465	0.812	2.877

Panel B: Matched Firms							
(1)	(2)	(3)	(4)	(5)	(6)	(7)	
Banks	Firms	<i>Bank-Firm Relationships</i>		<i>Multiple</i>	<i>Bank-Firm Share</i>		Av. No. Rel.
		Single	Multiple	Number	Value	per Firm	
2003	34	3,718	1,882	5,677	0.751	0.798	3.092
2004	34	4,439	1,795	8,918	0.832	0.847	3.373
2005	34	5,151	1,858	11,489	0.861	0.862	3.489
2006	36	5,296	1,459	15,348	0.913	0.89	4.000
2007	35	6,248	1,627	19,883	0.924	0.88	4.303
2008	35	7,631	2,061	23,419	0.919	0.882	4.204
2009	34	8,512	2,362	24,992	0.914	0.886	4.064
2010	38	10,614	2,430	38,239	0.940	0.906	4.672
2011	40	11,382	2,399	45,748	0.950	0.915	5.093
2012	39	10,999	2,096	47,534	0.958	0.919	5.339
2013	41	9,458	1,763	41,897	0.960	0.918	5.445

Notes: This table presents annual summary statistics on the frequency of different types of firm-bank relationships within the credit register using end-of-year data. Panel A presents summaries for all loans in the dataset, while Panel B presents statistics based on loans for the sample that includes loans for firm-bank pairs where the firms also have usable balance sheet data (i.e., for the matched credit register and firm-level datasets). Columns (1) and (2) list the number of banks and firms, respectively; column (3) lists the number of observations where a firm has a unique banking relationship; column (4) lists the number of observations where a firm has multiple banking relationships. Columns (5) and (6) presents the share of loans (relative to total) from firms with multiple bank relationships, in terms of loan number and loan value, respectively; and column (7) presents the average number of multiple banking relationships a firm has in a given year.

Table A4. Credit Register Quarterly Summary Statistics, Firm-Bank Level, All Loans, 2003–13

Panel A. All Loans						
	Obs.	Mean	Median	Std. Dev.	Min.	Max.
Loan	19,982,267	136.9	36.243	387.8	0.996	3,478
Interest Rate	19,982,267	0.147	0.131	0.100	0.001	0.54
Real Interest Rate	19,982,267	0.065	0.056	0.083	-0.081	0.37
Maturity	19,982,267	18.322	12.000	16.785	0.000	82.69
Panel B. Turkish Lira Loans						
	Obs.	Mean	Median	Std. Dev.	Min.	Max.
Loan	18,714,102	96.34	33.65	261.9	0.996	3,478
Interest Rate	18,714,102	0.153	0.137	0.100	0.001	0.540
Real Interest Rate	18,714,102	0.070	0.061	0.083	-0.081	0.365
Maturity	18,714,102	18.58	12.43	16.77	0.000	82.69
Panel C. FX Loans						
	Obs.	Mean	Median	Std. Dev.	Min.	Max.
Loan	1,268,165	735.9	268.0	987.1	0.996	3,478
Interest Rate	1,268,165	0.060	0.060	0.029	0.001	0.540
Real Interest Rate	1,268,165	-0.014	-0.011	0.029	-0.081	0.365
Maturity	1,268,165	14.47	8.000	16.56	0.000	82.69

Notes: This table presents summary statistics using quarterly data for aggregate firm-bank transactions over the 2003–13 period. The sample includes loans for all firm-bank pairs reported in the dataset. Panel A presents data based on pooling all FX and TL transactions at the firm-bank×quarter level; Panel B considers only Turkish lira loans, and Panel C considers only FX loans (expressed in Turkish liras). ‘Loan’ is the end-of-quarter total outstanding principal for all loans between a firm-bank pair, in thousands of Turkish lira and adjusted for inflation; ‘Interest Rate’ and ‘Real Interest Rate’ are the weighted average of the nominal and real borrowing rates, respectively, reported for loans between a firm-bank pair, where the weights are constructed based on loan shares between a firm-bank pair in a given quarter, and are based on either all, TL, or FX loans for Panels A-C, respectively; ‘Maturity’ is the weighted average of the initial time to repayment reported for loans of a firm-bank pair, which is measured in months, and where the weights are constructed based on loan shares between a firm-bank pair in a given quarter, and are based on either all, TL, or FX loans for Panels A-C, respectively.

Table A5. Banking Sector Growth, Based on Official Aggregate Data, 2003–13

	Assets/GDP	Loans/GDP	Deposit/GDP
2003	0.54	0.14	0.33
2004	0.55	0.18	0.34
2005	0.6	0.23	0.37
2006	0.64	0.28	0.39
2007	0.67	0.32	0.41
2008	0.74	0.37	0.46
2009	0.84	0.39	0.51
2010	0.92	0.48	0.56
2011	0.94	0.53	0.54
2012	0.97	0.56	0.54
2013	1.11	0.67	0.60

Notes: This tables shows the banking sector’s assets, loans, and liabilities relative to GDP. The banking sector variables are created by aggregating the official bank balance sheet data for the end of year. GDP data are also sourced from the CBRT.

Table A6. Bank-Level Quarterly Summary Statistics, Based on Official Bank-Level Balance Sheet Data, 2003–13

	Obs.	Mean	Median	Std. Dev	Min.	Max.
Log (Total Real Assets)	1,685	14.40	14.47	2.230	8.387	18.31
Capital Ratio	1,685	0.145	0.138	0.044	0.064	0.198
Leverage Ratio	1,685	7.684	7.254	2.756	5.041	15.68
Liquidity Ratio	1,685	0.400	0.335	0.217	0.018	0.960
Noncore Ratio	1,685	0.298	0.227	0.224	0.000	0.907
ROA	1,685	0.012	0.010	0.010	0.000	0.033

Notes: This table presents summary statistics using quarterly data pooled over the 2003–13. ‘Total Assets’ are in nominal terms. The ‘Capital Ratio’ is equity over total assets; the ‘Liquidity Ratio’ is liquid assets over total assets; the ‘Noncore Ratio’ is non-core liabilities over total liabilities; and ‘ROA’ is return on total assets. Noncore liabilities = Payables to money market + Payables to securities + Payables to banks + Funds from Repo + Securities issued (net).

Table A7. Firm Database Coverage, 2003–12

Year	Gross Output
2003	0.45
2004	0.33
2005	0.34
2006	0.38
2007	0.40
2008	0.47
2009	0.50
2010	0.50
2011	0.49
2012	0.45

Notes: This table compares our cleaned sample with the Annual Industry and Service Statistics collected by the Turkish Statistical Institute (Turkstat) over the 2003-12 period. The column ‘Gross Output’ measures the total of the sales of goods and services invoiced by the observation unit during the reference period in our dataset relative to the same number reported in Turkstat for a broader and representative set of firms.

Table A8. Firm Database Coverage: Breakdown by Firm Employee-Size Distribution, 2012

	Strata	Gross Output	
		All Sectors	Mfg. Sector
Sample	1-19 employees	0.053	0.013
	20-249 employees	0.304	0.235
	250+ employees	0.642	0.752
TurkStat	1-19 employees	0.270	0.095
	20-249 employees	0.364	0.361
	250+ employees	0.367	0.544

Notes: This table compares our cleaned sample with the Annual Industry and Service Statistics collected by the Turkish Statistical Institute (Turkstat) broken down by firm size (employees) for 2012. The column ‘Gross Output’ measures the total of the sales of goods and services invoiced by the observation unit during the reference period in our dataset relative to the same number reported in Turkstat for a broader and a representative set of firms.

Table A9. Firm-Level Annual Summary Statistics, All Firms, 2003–13

Panel A. All Sectors excluding Finance and Government						
	Obs.	Mean	Median	Std. Dev.	Min.	Max.
Log(Assets)	71,034	4.518	4.430	1.513	-5.612	12.01
Net Worth	71,034	3.761	3.737	1.728	-5.992	11.77

Panel B. Manufacturing Sector						
	Obs.	Mean	Median	Std. Dev.	Min.	Max.
Log(Assets)	33,346	4.667	4.557	1.472	-3.055	11.15
Net Worth	33,346	4.022	3.974	1.701	-4.402	10.94

Notes: This table presents summary statistics using firm balance sheet and income statement data are sourced from a supervisory dataset that is collected by the CBRT annually. Panel A presents statistics for firms in all sectors of the economy, excluding the financial and governmental sectors; Panel B presents statistics for only firms in the manufacturing sectors. All levels are in real thousands of TL, and the base year is 2003.

Table A10. Turkish and World Macroeconomic and Financial Quarterly Summary Statistics, 2003–13

	Obs.	Mean	Median	Std. Dev	IQR	Min.	Max.
Real GDP Growth (q-o-q)	44	0.012	0.012	0.017	0.022	-0.059	0.048
Inflation (q-o-q, annualized)	44	0.089	0.069	0.066	0.073	-0.013	0.322
$\Delta \log(\text{TL}/\text{US\$})$ (q-o-q)	44	0.006	0.001	0.066	0.058	-0.104	0.271
CBRT overnight rate	44	0.188	0.182	0.113	0.118	0.067	0.517
Expected annual inflation (y-on-y)	44	0.088	0.07	0.049	0.017	0.055	0.264
CA/GDP	44	-5.144	-5.379	3.63	2.227	-9.803	-1.303
$\log(\text{Capital inflows})$	44	18.25	18.61	0.926	0.730	15.92	19.22
$\log(\text{VIX})$	44	2.957	2.913	0.368	0.567	2.401	4.071

Notes: This table presents summary statistics for quarterly Turkish and world macroeconomic and financial data. All real variables are deflated using 2003 as the base year. Turkish macroeconomic data are sourced from the CBRT. Turkish real GDP growth, inflation, and exchange rate change viz. the USD are all quarter-on-quarter; while expected inflation, which is used to calculate real rates, is year-on-year. The VIX and the CBRT overnight rate are quarterly averages. ‘IQR’ stands for the interquartile range. Turkish capital inflows are in real Turkish lira. ‘CA/GDP’ variables measure the quarterly Turkish current account relative to GDP, while ‘ $\log(\text{Capital inflows})$ ’ is the natural logarithm of gross real capital inflows into Turkey.

Table A11. Impact of VIX’s Spillovers on Borrowing Costs: Robustness Checks

	<i>Whole Sample</i>		<i>Multi-Bank</i>	<i>Maturity</i>	
	Firm×year F.E. $\log(1+r_q)$ (1)	Risk Aversion $\log(1+r_q)$ (2)	<i>Links</i> $\log(1+r_q)$ (3)	Short $\log(1+r_q)$ (4)	Long $\log(1+r_q)$ (5)
$\log(\text{VIX}_{q-1})$	0.018 ^a (0.003)	0.007 ^b (0.003)	0.018 ^a (0.004)	0.014 ^a (0.004)	0.023 ^a (0.005)
Observations	19,173,132	19,982,267	9,176,769	9,891,414	9,758,665
R-squared	0.874	0.778	0.750	0.798	0.836
	<i>Crisis Period</i>				
	Pre $\log(1+r_q)$ (6)	Post $\log(1+r_q)$ (7)	Pre $\log(1+i_q)$ (8)	Post $\log(1+i_q)$ (9)	
$\log(\text{VIX}_{q-1})$	-0.003 (0.005)	0.025 ^a (0.005)	0.039 ^a (0.008)	0.022 ^a (0.004)	
Observations	4,293,517	14,626,000	4,293,517	14,626,000	
R-squared	0.771	0.858	0.773	0.868	

Notes: This table presents robustness results for the regressions (8) using quarterly data for all loans. Columns (1)-(7) use the natural logarithm of the weighted average of the real interest rates for loans between a firm-bank as the dependent variable, and columns (8) and (9) use the natural logarithm of the weighted average of the nominal interest rates for loans between a firm-bank as the dependent variable. VIX is the quarterly average, and the same other controls as Table 1 are included. Column (1) includes firm×year effects for the the whole sample; column (2) uses the “risk aversion” component of VIX (rather than total VIX), which is extracted following Bekaert et al. (2013); column (3) only includes firms that borrow from multiple banks in a given quarter; columns (4) and (5) split the sample by maturity type; columns (6)-(9) look at the pre-/post-crisis period for real and nominal rates. Regressions are all weighted-least square, where weights are equal to the loan share. Standard errors are double clustered at the firm and quarter levels, and ‘a’ indicates significance at the 1% level, ‘b’ at the 5% level, and ‘c’ at the 10% level.

Table A12. Loan-Level Evidence on Credit Constraints and Impact of VIX's Spillover: New Loans at Origination Data. Loan Maturity and Currency Denomination Sample Split

	log(Loans _m)				log(1+r _m)			
	Maturity Short (1)	Long (2)	Currency TL (3)	FX (4)	Maturity Short (5)	Long (6)	Currency TL (7)	FX (8)
Collateral/Loan	0.080 ^a (0.009)	0.089 ^a (0.018)	0.094 ^a (0.012)	0.034 ^a (0.005)	-0.001 ^b (0.001)	-0.005 ^a (0.002)	-0.004 ^a (0.001)	-7.24e-05 (0.0001)
Collateral/Loan×log(VIX _{m-1})	0.072 ^a (0.012)	-0.057 ^b (0.028)	0.025 ^c (0.015)	0.046 ^a (0.011)	-0.0009 (0.001)	0.010 ^b (0.004)	0.002 (0.002)	-0.0007 ^a (0.0002)
FX	0.451 ^a (0.040)	0.704 ^a (0.079)			-0.090 ^a (0.005)	-0.055 ^a (0.004)		
Observations	7,149,616	2,109,050	9,095,253	903,322	7,149,616	2,109,050	9,095,253	903,322
R-squared	0.878	0.772	0.823	0.878	0.885	0.870	0.847	0.940
Bank×firm×month F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Risk F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Maturity F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents results for regressions using monthly data at the loan level at the origination date broken down by maturity and currency denomination of loans. All variables are measured at the loan level, where 'Collateral/Loan' ratio is the collateral-to-loan ratio; FX is a 0/1 dummy indicating whether a loan is in foreign currency (= 1) or domestic (= 0). The regressions further include (i) bank defined risk weights, (ii) sectoral activity of loan, and (iii) maturity levels. Columns (1)-(4) present results for the natural logarithm of loan value, and columns (5)-(8) for the real interest rate. 'Short' includes all loans with a maturity of less than or equal to one year, and 'Long' includes all loans with a maturity greater than one year. 'TL' includes all loans denominated in Turkish lira, and 'FX' denotes all loans denominated in a foreign currency. All specifications control for firm×bank×month fixed effects. Standard errors are double clustered at the firm and month levels, and 'a' indicates significance at the 1% level, 'b' at the 5% level, and 'c' at the 10% level.

Table A13. Loan-Level Evidence on Credit Constraints and Impact of VIX's Spillover vis Banks: New Loans at Origination Data. Loan Maturity and Currency Denomination Sample Split

	log(Loans _m)				log(1+r _m)			
	Maturity		Currency		Maturity		Currency	
	Short (1)	Long (2)	TL (3)	FX (4)	Short (5)	Long (6)	TL (7)	FX (8)
Collateral/Loan	0.105 ^a (0.006)	0.0361 ^a (0.006)	0.091 ^a (0.005)	0.064 ^a (0.005)	-8.61e-06 (0.0002)	0.004 ^a (0.001)	-0.0003 (0.0003)	-0.0001 (0.0001)
Collateral/Loan×log(VIX _{m-1})	0.082 ^a (0.012)	0.023 ^a (0.008)	0.053 ^a (0.008)	0.037 ^a (0.009)	-0.003 ^a (0.0004)	0.002 (0.001)	-0.002 ^a (0.001)	-0.0009 ^a (0.0002)
Noncore _b ×Collateral/Loan	-0.165 ^a (0.025)	0.122 ^a (0.013)	-0.004 (0.036)	-0.181 ^a (0.011)	-0.009 ^a (0.003)	-0.023 ^a (0.001)	-0.015 ^a (0.003)	0.0005 ^c (0.000)
Noncore _b ×Collateral/Loan×log(VIX _{m-1})	-0.182 ^a (0.033)	-0.170 ^a (0.037)	-0.213 ^a (0.029)	-0.122 ^a (0.027)	0.013 ^a (0.004)	0.003 (0.003)	0.016 ^a (0.003)	0.002 ^c (0.001)
FX	0.450 ^a (0.040)	0.706 ^a (0.079)			-0.090 ^a (0.005)	-0.056 ^a (0.004)		
Observations	7,149,616	2,109,050	9,095,253	903,322	7,149,616	2,109,050	9,095,253	903,322
R-squared	0.879	0.773	0.823	0.878	0.885	0.881	0.848	0.940
Bank×firm×month F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Risk F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Maturity F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents results for regressions using monthly data at the loan level at the origination date broken down by maturity and currency denomination of loans. All variables are measured at the loan level, where 'Collateral/Loan' ratio is the collateral-to-loan ratio; Noncore_b is a 0/1 dummy variable indicating whether a bank has a high (= 1) or low (= 0) non-core liabilities ratio; FX is a 0/1 dummy indicating whether a loan is in foreign currency (= 1) or domestic (= 0). The regressions further include (i) bank defined risk weights, (ii) sectoral activity of loan, and (iii) maturity levels. Columns (1)-(4) present results for the natural logarithm of loan value, and columns (5)-(8) for the real interest rate. 'Short' includes all loans with a maturity of less than or equal to one year, and 'Long' includes all loans with a maturity greater than one year. 'TL' includes all loans denominated in Turkish lira, and 'FX' denotes all loans denominated in a foreign currency. All specifications control for firm×bank×month fixed effects. Standard errors are double clustered at the firm and month levels, and 'a' indicates significance at the 1% level, 'b' at the 5% level, and 'c' at the 10% level.

Table A14. Impact of the Nominal Exchange Rate on Loan Volume and Borrowing Costs

	log(Loans _q)		log(1+i _q)		log(1+r _q)	
	(1)	(2)	(3)	(4)	(5)	(6)
log(XR _{q-1})	-0.205 (0.144)	-0.181 (0.142)	-0.01 (0.012)	-0.017 ^b (0.008)	-0.019 (0.023)	-0.024 (0.019)
log(VIX _{q-1})		-0.058 ^b (0.023)		0.016 ^a (0.003)		0.012 ^a (0.005)
FX	0.645 ^a (0.012)	0.645 ^a (0.012)	-0.070 ^a (0.003)	-0.070 ^a (0.003)	-0.079 ^a (0.003)	-0.078 ^a (0.003)
Overnight rate _{q-1}	0.177 (0.327)	0.134 (0.330)	0.211 ^a (0.027)	0.222 ^a (0.024)	0.0409 (0.052)	0.0501 (0.050)
Observations	19,982,267	19,982,267	19,982,267	19,982,267	19,982,267	19,982,267
R-squared	0.850	0.850	0.789	0.792	0.777	0.778
Bank×firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls & trend	Yes	Yes	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents results for the regressions (8) using quarterly data for all loans. Columns (1) and (2) use the natural logarithm of total loans between a firm-bank as the dependent variable, and columns (3)-(4) and (5)-(6) use the natural logarithm of the weighted average of the nominal and real interest rates, respectively, for loans between a firm-bank as the dependent variable. The exchange rate, VIX and the policy rate are quarterly averages, and the same other controls as Table 2 are included, except for the quarterly change in the exchange rate, which is omitted. Regressions are all weighted-least square, where weights are equal to the loan share. Standard errors are double clustered at the firm and quarter levels, and ‘a’ indicates significance at the 1%, level ‘b’ at the 5% level, and ‘c’ at the 10% level.