International Financial Flows and Misallocation

Federico Cingano*, Fadi Hassan†

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Abstract

We study the impact of international financial flows on misallocation. Using detailed bank-firm matched data, we identify the patterns of credit allocation by banks with different exposure to a boom of capital inflows in Italy. We find that exposed banks expand credit to high productivity firms, even if likely to be credit constrained. The results hold using alternative measures of firm characteristics or bank exposure to inflows, and are not driven by concurrent changes in bank funding or by sorting between borrowers and lenders. The patterns of credit allocation induced by capital inflows have a positive impact on aggregate TFP.

*Bank of Italy, federico.cingano@bancaditalia.it

†Bank of Italy and CEP, fadi.hassan@bancaditalia.it

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1 Introduction

The impact of international financial flows on the real economy is one of the key questions in international economics. Early work looked at the aggregate performance of countries experiencing episodes of financial account liberalization (Gourinchas and Jeanne, 2006; Prasad et al., 2007; Bonfiglioli, 2008; Rodrik and Subramanian, 2009). More recently, the attention shifted to the relevance of financial frictions for aggregate productivity through their impact on the allocation of resources across heterogenous firms. Some works emphasize that capital inflows yield to significant misallocation, both between and within sectors, lowering aggregate productivity (Reis, 2013; Benigno et al., 2015; Gopinath et al., 2017); others associate capital inflows to higher investments, especially in manufacturing, and higher productivity (Buera et al., 2011; Buera and Shin, 2017; Varela, 2018). These opposing outcomes largely depend on the assumptions on the structure and stringency of borrowing constraints in the economy. While in many countries experiencing foreign capital inflows, the relevant constraints would be those prevailing in domestic credit markets, the role of bank lending decisions for resource allocation has received little attention in this literature.

In this paper we study empirically the link between foreign capital flows, the allocation of bank credit, and productivity. We leverage on detailed micro data on banks, credit, and firms to isolate credit supply shocks induced by bank exposure to international flows. This allows identifying which type of firms benefit the most from these inflows, assessing the relative importance of productivity and firm collateral in lending decisions. Finally, we provide an assessment of the consequences of credit allocation on aggregate productivity.

We find evidence that international financial flows do not contribute to increase misallocation through bank credit supply. Banks exposed to capital inflows increase lending to high productivity industries and, within industries, to high productivity firms. While collateral matters for credit allocation, constrained but high productivity firms do benefit from the credit supply shock induced by foreign capital flows. These results hold looking at the intensive margin of credit, exploiting within firm variation in credit allocation for continuing bank-firm relationships, at the entry and exit margin, and at the aggregate level combining both margins. Aggregating our firm-level results following the approach of Sraer and Thesmar (2018), shows that foreign flows helped improve aggregate TFP.

To the best of our knowledge, this is the first paper estimating the impact of international capital flows on misallocation matching them to banks and firms' characteristics at granular level. Previous works linking capital flows to banks and their customers through credit registry data cannot observe firm-level characteristics (Baskaya et al., 2017; di Giovanni et al., 2017). By contrast, Gopinath et al. (2017) and Varela (2018) use firm-level data, but cannot directly link firms to banks and capital inflows. Matching credit registry data with balance sheet information on all banks operating in Italy and the universe of incorporated firms allows us to identify the impact of international financial flows on misallocation.

Our study exploits the boom of international cross-border flows of the early 2000s, which was driven by favorable global financial conditions, and that involved greatly countries in the European Monetary Union (EMU), especially the more peripheral ones (Lane and Milesi-Ferretti, 2007*b*, 2008; Kalemli-Ozcan et al., 2010; Lane, 2013; Hale and Obstfeld, 2016). The Italian banking system benefitted largely from these inflows. Between 2002 and 2008 the net international investment position of banks went from -5.5% to -25.5% of GDP, mostly driven by an increase of liability flows. This is a large shift, which is similar to the one experienced by Spain even if the starting point of the two countries was different (from -19% to -42% of GDP).[1] Amiti et al. (2017) decompose the raise of capital inflows into country-specific demand and supply factors, and common global factors. They find that, especially for Italy global push factors represent the bulk of the raise of capital inflows, which makes Italy a natural setting to study the impact of international financial flows.

The initial step of our identification strategy is grounded on the intuition that capital inflows would benefit disproportionately banks already relying on funding from foreign markets. We rely on variation in ex-ante banks' foreign liability ratio (foreign liabilities relative to total liabilities) as a measure of their exposure to the inflows, which is similar to the approach of Paravisini et al. (2015). In the data bank's foreign liability ratio is highly correlated to its share of total inflows during the boom. Exploiting banks' heterogeneity along this dimension, we first estimate wether bank exposure affects the supply of credit to firms, and second whether the allocation of such credit is consistent with an increase in misallocation.[2]

In quantifying the impact of foreign capital flows on credit, we first use the Khwaja and Mian (2008) within-estimator to isolate credit supply from demand factors. Following the surge in capital inflows, high exposure banks increase credit supply relatively

[1] A decrease of banks' NIIP of 20% of GDP over six years, is very large also from an international perspective; looking at international data of both developed and developing countries, such changes are in the top 10% of the distribution.

[2] As robustness, we will use two alternative measures that aim to isolate the push component of international capital flows: one is a shift-share measure exploiting bank-level information about the country of origin of foreign funding; the other uses a time varying measure following Cesa-Bianchi et al. (2018).

more than less exposed banks lending to the same firm. Our baseline specification indicate that a 10 p.p. increase in exposure raise credit supply by 4.0%. Importantly, bank exposure does not affect credit supply in normal times. Finally, foreign capital inflows are positively associated to lending also in aggregate regressions, where a firm's exposure to the shock is computed as the credit-weighted average of its lenders' exposure. A 10 p.p. increase in firm exposure is associated to a 2.4% increase in total credit due to capital inflows. This suggests that the patterns of entry and exit in credit relationships were not able to undo the consequences of banks' exposure to the shock on lending.

We then analyze the effect of capital inflows on misallocation asking, first, which sectors benefit the most from the credit shock. Our results show that exposed banks increase lending to firms in manufacturing industries, but not those in services or construction. Hence, bank lending does not seem to contribute to misallocation along the sectoral dimension. Moreover, we do not find a significant impact of capital inflows on household credit.

Next, we investigate the patterns of credit supply according to firms' ex-ante productivity, measured by marginal revenue product of capital (MRPK) and total factor revenue productivity (TFPR), and accounting for the degree of credit constraint, proxied by firms' fixed assets as a measure of collateral. Exposed banks disproportionally lending to low-productivity firms would be important evidence that the surge in foreign capital flows induces a rise in resource misallocation.

However, we do not find that this is the case. The strength of the credit supply shock associated to capital inflows is greater for firms with ex-ante above-average productivity. Exposed banks also increase credit to firms with higher fixed assets, which is consistent with the existence of borrowing constraints. However, our results show the tightness of such constraints is not independent of productivity. Constrained but high productivity firms do benefit from the credit-supply shock, by an amount that is comparable to that of unconstrained but low-productivity firms. Only the worse borrowers (i.e. those with both low productivity and low collateral) see no increase in credit from exposed banks. These results suggest that when banks benefit from a positive funding shock, they ease credit conditions not only depending on firm size, but also on productivity.

In order to infer the implications of the above findings on aggregate TFP, we rely on both the Hsieh and Klenow (2009) framework and on the aggregation approach of Sraer and Thesmar (2018). Despite the several caveats emphasized by recent literature[3], the

[3]See Asker et al. (2014), De Loecker and Goldberg (2014), Haltiwanger (2016), Bils et al. (2018), Haltiwanger et al. (2018), David and Venkateswaran (2019) for discussions about the limitations of the HK approach.

Hsieh and Klenow (2009) framework (HK) represents an important benchmark to link misallocation, as measured by the dispersion of firm level productivity, to aggregate TFP. On the other hand, the Sraer and Thesmar (2018) approach (ST) provides sufficient statistics to aggregate the results of firm-level "treatments" by taking into account general equilibrium effects. These two approaches deliver similar results. We estimate that, absent the credit supply shock induced by international flows, aggregate TFP in Italy would have been 0.4% and 0.3% lower according to the HK and the ST framework, respectively. While not a striking figure, this result corroborates the finding that international financial flows did not curb aggregate productivity.

Our core findings are robust to alternative definitions of bank exposure, changing the timing of the shock, controlling for bank characteristics and variation in other sources of funding, and withstand a host of specification checks. We also investigate the possibility of *indirect* effects of capital inflows on misallocation. For one thing, banks exposed to foreign flows can increase the liquidity of other banks through interbank lending, bonds and equity acquisition, which in turn might favor a higher flow of credit to less productive firms. We do not find evidence of spillover effects from exposed to non-exposed banks, however. For instance, interbank lending did not increase across banking groups and there was no surge in bonds or equity financing from exposed to non-exposed banks. Moreover, we do not find a significant effect on the share of deposits to less exposed banks, which could have been associated to capital inflows feeding into changes of banks' retail policy. We also test whether capital inflows made banks more fragile after 2008, as the boom stopped and foreign funding began to decline rapidly. We do not find that this was the case: despite the increase in lending in the previous period, exposed banks did not suffer from higher NPLs once the global financial crisis erupted.

The paper contributes to the literature about the impact of international financial flows on productivity in presence of financial frictions and heterogenous firms such as Buera et al. (2011), Reis (2013), Moll (2014), Benigno et al. (2015), Buera and Shin (2017), Gopinath et al. (2017), Varela (2018), Bau and Matray (2020), and Saffie et al. (2020). These papers have different theoretical predictions about the impact of capital inflows, resource allocation and aggregate TFP. They differ in the type of shock they consider, e.g. some focus on the transitional dynamics following a decline in the real interest rate (Gopinath et al., 2017; Reis, 2013) and others on a financial liberalization episodes (Buera and Shin, 2017; Varela, 2018). Crucially, they differ in the way they model firms' borrowing constraint, which is key for delivering different predictions. For instance Gopinath et al. (2017) assume a size-dependent borrowing constraint, implying that capital inflows disproportionately favor debt accumulation by firms with higher net-worth, irrespective of their productivity level. Because these tend to have lower marginal product of capital, capital inflows end up having a negative effect on aggregate productivity. However, our results show that the borrowing constraint is not independent of productivity. High productivity firms endowed with scarce assets do benefit from the credit shock, by an amount that is comparable to that of high-fixed asset, but low-productivity firms. Our main finding is that foreign capital inflows induce an increase of the relative supply of credit towards the more productive firms and that the resulting credit allocation increases aggregate productivity. This is consistent with the findings of, among others, Buera et al. (2011), Moll (2014), and Buera and Shin (2017), Varela (2018), Bau and Matray (2020) and Saffie et al. (2020) where an increased availability of financial resources, spurred by the supply of foreign funding, favors firms and sectors with higher productivity. Relative to this literature we are able to directly identify the effects of capital flows to firms through the banks they borrow from.

The paper contributes also to the literature on the effects of capital inflows in Southern Europe on productivity and misallocation (Reis, 2013; Benigno and Fornaro, 2014; Benigno et al., 2015; Gopinath et al., 2017; Castillo-Martínez, 2019). Benigno and Fornaro (2014) and Benigno et al. (2015) show that foreign capital flows trigger a consumption boom and the shift of productive resources toward the non-tradable sector at the expenses of the tradable one generating stagnant productivity growth. A similar story is proposed by Reis (2013), who argues that abundant capital flows in Portugal were misallocated causing a slump due to the expansion of the unproductive non-tradable sector. These papers look at the aggregate macro trends of productivity and capital inflows and then build models that can link the two patterns in the data. Our contribution is to test empirically the link between capital inflows and firms through bank intermediation.

More broadly our paper contributes to the literature on the effects of foreign capital flows on the real economy such as Gourinchas and Jeanne (2006), Prasad et al. (2007), Bonfiglioli (2008), Rodrik and Subramanian (2009), Levchenko et al. (2009), Bekaert et al. (2011); Chari et al. (2012), Gourinchas and Jeanne (2013), Broner and Ventura (2016), Baskaya et al. (2017), di Giovanni et al. (2017), Sander (2019). These papers typically look at episodes of financial account liberalization across emerging countries at the macro level. Baskaya et al. (2017), di Giovanni et al. (2017) are a notable exception. They use micro data on banks and credit in Turkey to look at the impact of capital inflows on bank lending exploiting exogenous fluctuations in the global financial cycle. Relative to them, we also observe firm characteristics, which allow us to focus on the link between credit allocation and aggregate productivity.

Finally, the paper speaks to the literature analyzing capital flows and the EMU such as, Lane and Milesi-Ferretti (2007*a*); Spiegel (2009); Kalemli-Ozcan et al. (2010); Giavazzi and Spaventa (2011), Lane (2013); and Hale and Obstfeld (2016). Our contribution is to look into the effect of these flows on local banking and productivity. This is a different source of shock to bank fundings than those analyized by an extensive literature on the so-called bank lending channel as in Khwaja and Mian (2008), Paravisini (2008), Amiti and Weinstein (2011), Schnabl (2012), Jiménez et al. (2014), Chodorow-Reich (2014), Paravisini et al. (2015), Cingano et al. (2016), Mian et al. (2017), Amiti and Weinstein (2018).

The paper is structured as following: Section 2 describes the historical context of our setting; Section 3 presents the data; Section 4 discusses the empirical strategy; Section 5 presents the results; Section 6 looks at the aggregate implication on TFP; Section 7 analyzes the robustness of our results along several dimensions; and Section 8 concludes.

2 The early 2000s boom of cross-border flows

The acceleration of capital inflows from 2002 to 2007 in Southern European countries has been documented by an extensive set of research. The extent to which these flows involved banks is exemplified in Figure 1 plotting the dynamics of gross foreign liabilities and claims of banks in Italy between 1998 and 2008. Until 2002 foreign liabilities remained stable, but then increased by almost four folds up to the global financial crisis. The increase was not matched by a raise of foreign assets, and thus translated into more funding available in the domestic economy. The majority of the foreign funding took the form of loans denominated in euro, i.e. with no currency risk relative to assets, and had an average maturity around 12 months. The aggregate trends are similar to those experienced by other European countries, as Spain, and underpin the idea of foreign capital-induced misallocation.

Lane and Milesi-Ferretti (2007*b*) and Lane (2013) show that the increase in cross-border flows was part of a general international pattern associated to global factors such as the surge of securitisation, that increased banks' liquidity for further lending, and the decline in global uncertainty, as exemplified by the decline of the VIX in that period. In the Euro area the rise of cross border flows was particularly remarkable as the common currency stimulated international financial integration (Kalemli-Ozcan et al., 2010) and European banks were frontrunners in the surge of securitization (Lane and Milesi-Ferretti, 2008). More specifically, Hale and Obstfeld (2016) documented how, leveraging on foreign funds, banks from core Eurozone countries increased their lending to the banks of peripheral countries in the Euro area.

Despite the substantial increase in its banking sector foreign liabilities, in Italy the overall current account imbalance was mild compared to other Southern European countries. Some of these countries, as Portugal and Greece, experienced large sovereign inflows, in others such as Spain, domestic pull factors added steam to capital inflows. Amiti et al. (2017) decompose the growth of foreign bank inflows to several countries into i) global shocks, ii) idiosyncratic demand shocks, and iii) idiosyncratic supply shocks. Their analysis shows that, in the case of Italy, the surge in foreign capital inflows was largely driven by global factors (see Figure 2). This is not the case of Spain, where idiosyncratic demand factors played a prominent role.

The distinction between capital inflows driven by global push- vs. domestic pull-factors has relevant policy implications. Finding evidence that capital inflows cause misallocation when driven by push-factors would provide a rationale for capital controls. Whereas if misallocation is associated to domestic pull-factors, it would rather point to the need to strengthen macro-prudential policies. The distinction is also useful for identification purposes: capital flows being mainly driven by global factors, as in Italy, reduces the potential contamination of the estimated impact of cross-border flows by domestic endogenous drivers.

3 Data

Our analysis is based on a matched loan-bank-firm dataset containing information on bank credit for a large sample of Italian companies. The final dataset is obtained by combining three sources: credit register; banks' balance sheets data; firms' balance sheets data.

The first source is the Italian Credit Register administered by the Bank of Italy, which contains a monthly panel of the outstanding debt of every borrower (firms or individuals) with loans above EUR 75,000 with each bank operating in Italy. We focus on non-financial corporations and build an annual bank-firm panel, where loans are measured as the outstanding credit granted at the end of a given year. As banks use the credit register in order to assess the creditworthiness of their current or prospective borrowers, its data quality is very high.

Banks' balance sheet data are from the Bank of Italy Supervisory reports, which provide detailed data on banks' assets and liabilities, including details about banks' foreign funding. Whenever a bank ceases to exist, due to either bankruptcy or merger, firms will cease reporting that bank as a source of loans. Firms' balance sheet data (including variables such as revenues, investment, employment, wage bill) are taken from the CERVED database, which covers the universe of incorporated firms in Italy. We match the bank-firm loan data to banks' and firms' balance sheet data using unique bank and firm identifiers, respectively.

Lending and funding policies of banks are typically decided at the banking group level, so we consolidate banks' balance sheet at the group level, as this is the relevant unit of observation to analyze the dynamics of credit supply. This implies that if a firm borrows from two banks of the same group, we consider this as a single relationship given by the sum of the two loans. We also keep track of mergers and acquisition among banks. If a firm is borrowing from a bank, and the bank disappears because it is acquired or merged, we track if there is a new relationship with the newly formed bank, or with the acquirer, in which case we consider the relationship as still existing. This ensures that we do not have any gaps associated with mergers.

Table 1 shows the summary statistics of banks and firms characteristics in our sample. The unit of observation in our empirical analysis is at the bank-firm-year level. The dataset includes, on average, about 500 banks and 86 thousand manufacturing firms per year. The simple average of the share of banks' foreign liability is 3.7% and the standard deviation 13.1%. The distribution of banks' foreign funding shows that many banks, mostly the small ones, are not exposed to international financial markets; hence, as a robustness, we drop banks with no-exposure or exposure below 2% and the results go through. Finally, it is important to notice that multiple banking is very common in Italy, also among small firms. About 75% of firms in our sample borrow from multiple banks, which is an essential feature of our identification strategy, and the average number of banking relations per firm is 3.4.

4 Empirical strategy

4.1 Lender-level exposure to foreign capital

Financial institutions rely on a number of sources of financing when originating loans. The literature suggests that there are relevant distinctions between banks that rely on core deposits versus non-core liabilities. Hahm et al. (2013) show that non-core financing is associated with greater risk taking in the banking sector. Hanson et al. (2015) and Drechsler et al. (2017) argue that financial institutions that rely more heavily on core deposits are less prone to runs and costs shocks due to monetary policy.

Our empirical approach rests on the idea that the surge of international capital flows between 2002 and 2007 offered greater funding opportunities to banks featuring a higher liability share of foreign funding before the shock.[4] A relevant underlying assumption of this approach is that there is some stickiness in the liability structure of banks.

Figure 3 shows that there is a strong correlation between how much a bank used to fund itself from abroad (foreign liability ratio in 1998-2000, horizzontal axis) and how much it actually benefitted from capital inflows (bank's share of total inflows after 2002, vertical axis). Panel A looks at this relation unconditionally, whereas Panel B controls for key bank characteristics measured in the first period.[5] In both cases we observe a positive and significant correlation between the two variables. This suggests that the intensity of foreign financing in the years pre-capital inflows boom is a good proxy to measure banks' exposure to the raise in international flows in the years 2002-2007. Table 2 provides further support for this approach with cross-sectional bank level regressions. Column 1 reports the regression coefficient plotted in Figure 3-B. The second column confirms the significant positive correlation between ex-ante foreign liability ratio and exposure to capital inflows using a different dependent variable, the growth of the foreign liability ratio between the pre- and post-2002 periods. Column 3 finally checks the stickiness of the liability structure of banks looking at the persistence of banks' ranking by foreign liability ratio: a regression of the ranking as of 1998-2000 on the ranking as of 2002-2007 delivers a coefficient of 0.75. There are potentially several causes of such persistence, e.g. fixed costs to engage foreign funding, but it is reassuring that the share of foreign liabilities ex-ante captures well the heterogeneity of exposure to capital flows ex-post.

While our baseline approach relies on existing evidence as to the drivers and dating of the surge of foreign capital flows to Italy, we look at alternative approaches allowing for more flexibility in both dimensions. First, we employ a shift-share measure of exposure exploiting bank-level information on the country of origin of foreign funding. This allows predicting the exposure of an Italian bank as a weighted average of how much foreign countries are exporting capital in general (the "shift"), with weights that come from the initial bank composition of inflow by country of origin (the "shares"). Second, we construct a time varying measure of bank exposure isolating a shock of capital inflows induced by push factors as in Cesa-Bianchi et al. (2018) (see Section 7 for details). Our

[4] The source of variation that we exploit is similar to that of Paravisini et al. (2015), di Giovanni et al. (2017), and Mian and Sufi (2018). The former looks at the effects of capital flows reversal in Peru and measure bank exposure to capital outflows as the share of foreign liability before the global financial crisis. The second, analyzes the transmission of the Global Financial Cycle to the local credit market in Turkey and measures banks exposure as the share of non-deposit liabilities. Finally, the latter exploits the fact that US lenders which relied on non-core deposits in their liability structure pre-2002 are the ones that benefited more from the global rise of shadow banking and private label securitisation post-2003.

[5] These include log-assets, as a proxy for bank size; the share of core liabilities, to capture the relevance of deposit funding in the liability structure; capital ratio, as a proxy for leverage; and the share of NPLs, to control for bank vulnerability.

results are confirmed using these alternative measures.

Identification also rests on the assumption that bank exposure to capital inflows does not correlates with unobserved determinants of credit supply. Table 3 looks at the balancing of observable characteristic of banks (i.e. their size or balance sheet composition) and of their borrower (for example, in terms of productivity) between high-exposure and low-exposure banks (Imbens and Wooldridge, 2008). The characteristics of the average borrower across the two groups show a high degree of overlap, which suggests that sorting between banks and firms is unlikely to drive our results. While normalized differences lay within the commonly accepted 0.25 threshold, the degree of overlap is less satisfactory in the case of some banks characteristics. To account for their potential concurring effect in the estimation of the lending channel from capital inflows, our baseline specification will allow for a differential impact of each such variable on credit.

4.2 Foreign capital flows and credit supply

Our empirical approach firstly relies on the Khwaja and Mian (2008) within estimator allowing to isolate demand and supply of credit. The estimator exploits the fact that the vast majority of firms (about 75% of firms in our sample) borrow from multiple banks, which allows comparing the dynamic of credit granted by banks with different exposures to the *same* firm:

$$\ln C_{ibt} = \beta_1 \; Exposure_b \times Post_t + \beta_2 \; Spec_{ibt} + \boldsymbol{X_b'}\boldsymbol{\delta} \times Post_t + \alpha_{it} + \gamma_{ib} + \epsilon_{ibt} \qquad (1)$$

The dependent variable is the log of outstanding credit granted by bank b to firm i at the end of year t. The variable $Exposure_b$ measures the ex-ante share of foreign funding in bank's liability over the 1998-2000 period, and it is interacted with a dummy equal to one for the years after the boom in capital inflows (2002-2007), and zero for the earlier years ($Post_t$). The specification includes a full set of firm-year fixed-effects (α_{it}) which control for any firm-specific shock potentially affecting credit demand (expected to be common across all banks). Because demand shocks may not be equally distributed across banks (Paravisini et al., 2017), the specification also includes $Spec_{ibt}$, a dummy equal to 1 if a firm operates in a sector where a bank is specialized into.[6] We also control for potential non-random matching between firms and banks by including a set of firm-bank fixed effects (γ_{ib}). These fixed effects capture all time-invariant factors that may affect credit for any bank-firm pair such as relational banking and time invariant drivers of sorting

[6]A bank is considered to be specialized in one sector if its share of loans in that sector is above the interquartile range of all the other banks in the economy.

between banks and firms. Finally, the specification accounts for potentially confounding determinants of changes in credit supply, interacting a set of bank characteristics with the post dummy.[7] Given that our source of variation is at the bank level and that firms' demand for specific banks can vary according to the sector of specialization of the bank, we cluster the standard errors at the bank-sector (2 digits) level.[8]

The coefficient of interest is β_1, which captures the marginal effect of bank exposure on credit supply, following the surge in capital inflows. Given the presence of firm-year fixed effects, our source of identification relies on within firm variation of credit across multiple lenders with different degree of exposure. The firm-year fixed effects, combined with the bank-specialization dummy, absorb firm level shocks that affect the demand of credit, so β_1 represents a credit supply shock due to bank's exposure to capital inflows.

To assess the relevance of pre-trends across banks that could be associated to different bank characteristics and drive our results, we also estimate a dynamic diff-in-diff. This allows us to look into the full dynamics of credit supply between 1998 and 2007, and to show in a transparent way how this varies for the years before and after the boom in capital inflows.[9]

One concern is that Equation 1 only captures the *intensive* margin of credit, as it only accounts for bank-firm relations that exist before and after the boom of capital inflows. However, we are also interested in the effects on the *extensive* margin. For this reason we run the following specification:

$$Entry_{ib\tau}\ (Exit_{ib\tau}) = \beta_1\ Exposure_b * \times Post_\tau + \beta_2\ Spec_{ib\tau} + \boldsymbol{X_b'}\boldsymbol{\delta} \times Post_\tau + \alpha_{i\tau} + \gamma_b + \epsilon_{ib\tau} \quad (2)$$

where the dependent variable takes the value of one if bank b and firm i starts (exit) a lending relation after the boom of capital inflows. This is a two-period panel, $\tau = 1, 2$ refers to the years pre- and post-2002. The coefficient of interest β_1 captures the marginal effect of bank's exposure to foreign capital on the probability that the bank starts (ends) a credit relation with firm i after the shock. The specification controls for whether the

[7]These include log-assets as a proxy of bank size; the share of NPLs, to captures bank performance and management; bank core liabilities, which control for the funding structure of the bank; and the capital ratio, which controls for the degree of bank leverage. All variables are average values (1998-2000).

[8]As a robustness, we run specification 1 using a balanced panel only and results are confirmed (see Table A1 in the Appendix). We also compute Equation (1) in first difference by taking the average of the pre- and post- period for the variables of interest, as in the original paper of Khwaja and Mian (2008). This makes the standard errors robust to possible concerns of auto-correlation as highlighted by Bertrand et al. (2004). Specifically, we run: $\Delta \ln C_{ib} = \beta_1\ Exposure_b + \beta_2\ \Delta Spec_{ib} + \boldsymbol{X_b'}\boldsymbol{\delta} + \alpha_i + \epsilon_{ib}$. Results are confirmed, see Table A2 in the Appendix for details.

[9]Specifically, we run $\ln C_{ibt} = \sum_{q=1998}^{2007} \beta_q\ Exposure_b \times \mathbb{1}_{t=q} + \beta_2\ Spec_{ibt} + \sum_{q=1998}^{2007} \boldsymbol{X_b'}\boldsymbol{\delta_q} \times \mathbb{1}_{t=q} + \alpha_{it} + \gamma_{ib} + \epsilon_{ibt}$, where β_q capture the year-by-year effect of bank exposure.

bank is specialized in the sector the firm operates, for bank's pre-characteristics, and for firm-time fixed effects, and for bank fixed effects; errors are clustered at the bank-sector (2-digits) level.

Another concern is that a raise in credit supply from more exposed banks could be compensated by a decline of credit from less exposed ones, so there may not be an effect on the aggregate amount of credit that a firm receives. In order to investigate this possibility, we compute the exposure of firms to the bank lending channel of international financial flows, as the weighted average of the exposure of all the banks a firm:

$$Exposure\ Firm_i = \sum_b Exposure_b\ \frac{Credit_{ib}}{Total\ Credit_i} \tag{3}$$

With this measure in hand, we look at the effect of firm exposure on the aggregate credit of a firm by running:

$$\ln C_{ist} = \beta_1\ Exposure\ Firm_i \times Post_t + \boldsymbol{X_i'\delta} \times Post_t + \hat{\alpha_{it}} + \gamma_i + \delta_{st} + \epsilon_{ist} \tag{4}$$

the overall amount of loans received by firm i at year t is regressed on firm fixed effects, sector-time fixed effects, X_i, which is a weighted average of firm lenders' characteristics measured in 1998-2000. The coefficient of interest β captures the interaction between firm exposure to capital inflows, through the banks it borrows from, and the post-2002 dummy. This specification includes also the firm-time fixed effects estimated in Equation 1, as a proxy of credit demand by firms.

The set of specifications presented in this section should give us a complete picture of the credit effect of a trade shock. Equation 1 allows us to distinguish neatly between supply and demand effects; Equation 2 accounts for the extensive margin of credit; and Equation 4 looks into the effect on the aggregate credit that a firm receives. In the following sections we also look into the effect of the trade shock on the total credit that a firm receives and its effect misallocation.

4.3 Credit supply and misallocation

We next investigate whether the patterns of credit supply induced by foreign capital inflows are compatible with an increase in resource misallocation either across or within sectors. Specifically, we ask whether exposed banks tilted the composition of their credit portfolio towards low productivity firms or towards services and construction. We also explore the role of borrowing constraints, the main mechanism preventing an optimal allocation of resources toward high productivity firms in the literature linking financial friction to misallocation.[10]

A simple way to nest the insights of these papers into our framework is to assume that a bank's supply shock varies with borrowers' characteristics. One natural firm dimension to look at in our context is productivity: finding that exposed banks passed along the shock more to low productivity firms would confirm that foreign capital inflows contributed to dampen aggregate efficiency in Italy through bank lending. We look at firm productivity using alternative measures (TFPR, MRPK, or value added per worker) computed before the shock, and group our sample according to whether the firms have productivity above or below their 3-digit industry average (high and low productivity borrowers).[11] We allow for heterogeneity in the strength of credit supply shocks simply writing our baseline specification as:

$$\ln C_{ibt} = \sum_{d=H,L} \beta_d \, D_i^d \, (Exposure_b \times Post_t) + \beta_2 \, Spec_{ibt} + \boldsymbol{X_b'\delta} \times Post_t + \alpha_{it} + \gamma_{ib} + \epsilon_{ibt} \quad (5)$$

where D_i^d is an indicator distinguishing high productivity borrowers from low productivity borrowers.[12] This specification captures credit misallocation along the intensive margin, but we run similar specifications for Equations 2 and 4 to look also at the extensive margin and aggregate credit respectively. Estimating $\beta_L > \beta_H$ would reveal that exposed banks disproportionately allocated funds to relatively less productive firms following the shock.[13] This would be consistent with the idea that capital inflows ended up dampening aggregate TFP through credit misallocation.

To study the relevance of credit constraints we exploit the idea that they should be less stringent, on average, for firms with high collateral availability. We therefore also explore the relevance of borrowers' pledgeable (fixed) assets in banks credit allocation decisions. Our simple framework is illustrated in Figure 4 where the set of borrowers is now split into four groups along the productivity and collateral dimensions, and we

[10]The role of financial frictions on aggregate productivity is well developed by, among others, Banerjee and Duflo (2005); Buera et al. (2011); Reis (2013); Midrigan and Xu (2014); Moll (2014); Buera and Moll (2015); Buera and Shin (2017); Gopinath et al. (2017); Varela (2018); David and Venkateswaran (2019); Saffie et al. (2020).

[11]Using the overall mean in the sample to distinguish firms with different productivity does not affect our findings. We thank Simone Lenzu and Francesco Manaresi for sharing their data on TFPR and MRPK on the CERVED sample. TFPR is computed following the methodology of Levinsohn and Petrin (2003) and Wooldridge (2009) and MRPK is estimated following De Loecker and Warzynski (2012). See Lenzu and Manaresi (2018) for further details.

[12]As a robustness we use also a continuous measure of ex-ante firm-level productivity interacted with bank exposure and the results are confirmed (see Section A.2)

[13]Because the lending activity of banks is forward looking, we also considered a classification based on firms' realized productivity at the end of our sample period (see the robustness section).

allow credit supply shocks to vary for each group. Our main set of variables therefore becomes $\sum_{d} \beta_d D_i^d$ with $d = HH, LH, LL, HL$ (for the two dimensions of productivity and collateral, respectively).[14]

In a simple world in which credit is optimally allocated across projects accounting for the risk-return trade-off, an increase in the funding available to banks should favour the financing of projects by high-productive and high-collateral (low risk) firms (1st quadrant). Banks pursuing a balanced expansion of their portfolios should also pass along their shocks to high-collateral but low-productivity firms, and to low-collateral high-productivity firms ($\beta_{L,H} \cong \beta_{H,L}$). However, if lending is severely constrained by the availability of collateral, it would be large firms in the 3rd quadrant to disproportionately benefit from the easing of credit conditions ($\beta_{L,H} > \beta_{H,L}$). Such pattern should be particularly evident if credit allocation is subject to size-dependent borrowing constraints (as in Gopinath et al. (2017)) so that a firm's ability to borrow disproportionately increases in its size. Finally, the credit expansion should not (or only to a limited extent) concern low-productive constrained firms ($\beta_{L,L} \approx 0$).

5 Results

5.1 Capital inflows and credit supply

Table 4 reports our baseline results on the intensive margin of credit supply. The five columns refers to alternative a specifications of the within-firm regression 1, testing whether banks exposed to foreign capital inflows increased their lending relative to less exposed banks when looking at the same firm. Column 1 shows that this is the case in the baseline specification, when exposure is measured by a bank's ratio of foreign liabilities before the shock. The estimated coefficient implies that a 10 percentage point increase in this ratio leads to a 4% increase in lending between the pre- and post-years. In columns (2) and (3) banks' exposure is captured by a an indicator variable for banks with a share of foreign liabilities above 10% and 15% respectively; this is meant to account for potential non-linearities of the effects of foreign funding. In both cases, the treated banks increase credit supply by 7% relative to control banks. In column (4) we check for the relevance of the large number of small banks with limited access to foreign capital flows in our sample, restricting the analysis to those with exposure larger than a minimum threshold

[14] There is not much overlap between these firm level characteristics. For instance the correlation between marginal product of capital and total fixed assets is -0.27, which is sufficiently low to ensure that firms with a high MRPK ex-ante are not also the ones with low collateral to start with. Similarly, the correlation between MRPK and other measures of risk, such as credit score, is -0.05, which is very low.

(here, 2%). Finally, in column (5) we check the relevance of firm size, weighting the least square estimates by firm revenues. In either case, the results are unaffected.

Figure 5 plots the marginal effect of bank exposure on credit supply estimated every year between 1998 and 2007. While the differential supply of credit between exposed and non-exposed banks shows no clear pattern until 2002, it displays a positive trend following the surge in foreign capital inflows.

We next look at the effects of foreign capital inflows on the extensive margin of credit, estimating the effects of bank exposure on the probability to terminate an existing credit relation and on the probability to start a new relation. The results in Table 5 show that exposed banks are less likely to terminate a credit relation (columns 1 and 2) and more likely to enter a new relation with an existing firm (columns 3 and 4). Both results hold using the linear and the dummy variable exposure measures. The estimated coefficients imply that a 10 p.p. increase in exposure is associated to 1.1% lower probability to stop lending to a given firm and a 1.9% higher probability to start a new credit relation.

In Table 6 we extend our analysis to estimate the impact of firm exposure to foreign capital (the weighted average of bank exposure computed across the firm's lenders) on total credit (Equation 4). If clients of low exposure banks were able to promptly switch to lenders who benefit from the shock then there would be little or no dependence between aggregate credit and initial firm exposure. The results in Table 6 suggest this is not the case: a 10 p.p. increase in firm exposure before the shock is associated to a 2.4% increase in credit afterwards (column 1). The other columns replicate the specification changes of Table 4 confirming the baseline finding. The estimates being smaller than those of the firm-bank level specification in Table 4 suggests some credit substitution, which is however unable to undo the transmission of the shock to borrowers.

5.2 Capital inflows and misallocation

We first look at the between-industry dimension emphasized in the literature, testing whether the credit supply shock associated to foreign capital was stronger in relatively less productive industries. Table 7 reports the results obtained running the baseline within firm specification in Equation 1 for each macro industry. Our evidence suggests that exposed banks increase their lending to manufacturing firms relative to other banks (column 1), but not to firms in construction or services (columns 2 and 3). This result is consistent for instance with Gopinath et al. (2017) who focus their analysis on capital flows and misallocation within manufacturing. These findings are confirmed when looking at the extensive margin (Table 8). While high exposure banks reduce the exit rates of their existing relationships, the effect is significantly larger for firms in manufacturing (column 5), than in services and construction (columns 6 and 7). The former also benefit from a higher probability of starting a credit relation (column 1). The fact that capital inflows translate into more credit for firms in the manufacturing sector, but not for those in services and construction is confirmed in Table 9, where we analyze the effect of firms exposure to the bank lending channel on the aggregate credit.

We next analyze the allocation of credit across firms. The results in Table 10 refer to the specification in Equation 5, which allows for heterogeneous credit supply shocks across firms with different productivity and credit constraint. Columns 1 and 2 show that loans by exposed banks are, if anything, disproportionally allocated to firms with above industry level of MRPK and TFPR: a 10 p.p. increase of bank exposure translates into a raise in credit by 4.4% for high-MRPK (4.6%, high-TFPR) and by 3.4% for low-MRPK (2.6%, low-TFPR). In both cases the difference between the two groups is statistically significant at conventional thresholds. These results, which are confirmed using simpler measures of firm performance such as sales per capita or returns on assets, are not compatible with capital inflows increasing misallocation through the bank-lending channel.

We also find that the supply shock is significantly stronger for firms with high collateral (column 3), which is consistent with the size dependent borrowing constraint emphasised by Gopinath et al. (2017). However, when decomposing our sample accounting for both productivity and collateral constraint, we do not find evidence that collateral availability is a necessary condition for being granted more credit. The results in columns 4 and 5 show that, in fact, low-collateral but productive firms see their credit supply increase, suggesting that the size dependent borrowing constraint is not state invariant. Interestingly, the strength of the shock is statistically equal to that experienced by unconstrained (high collateral) low productive firms, suggesting an allocation policy balancing risk and returns in the portfolio. Accordingly, exposed banks do not increase lending to risky and low productive firms, while credit increase the most for unconstrained high-productivity borrowers.

In Table 11 we look at the extensive margin of credit. On the exit side, the results show that banks more exposed to capital inflows have a lower probability to terminate a relationship with more productive firms, even if these have low-collateral (columns 1-3); so, this channel is unlikely to have contributed to higher misallocation. The results are more mixed when we look at firms' entry (columns 4-7).

We find that exposed banks are more likely to start a credit relation with more productive but also to more risky firms (column 2). In this case a 10 p.p. increase in bank exposure raises the probability of entry, over a 5 year horizon, by 3.6%. However, given that the unconditional probability of entry in the post post period is 30%, this is not a very large increase. Moreover, the size of the new loans granted to less productive firms is smaller than that of productive firms.[15] Finally, if we look at the effects in terms of net-entry (probability of entry minus probability of exit), the results are not different across type of firms. Taken together these results suggest that it is unlikely that foreign capital flows increased misallocation in any substantial way through the extensive margin of credit.

Next, to combine both the intensive and the extensive margin, we look at the aggregate effect on credit. In Table 12 we analyze the impact of capital inflows on misallocation on the aggregate credit of firms. The results account for both the intensive and extensive margin and confirm that the more productive and more collateralised firms are the ones that benefited more for the higher supply of credit by exposed banks. This supports the evidence that there is no direct link between foreign capital inflows and credit misallocation by banks.

5.3 A focus on household lending

Foreign capital may also induce higher lending to households, especially through mortgages. To test whether this is the case in our setting, we use an empirical approach similar to that of Greenstone et al. (2014) and Gilchrist et al. (2017); because households rarely borrow from two or more banks, identification exploits bank lending across multiple provinces:

$$\ln C^H_{pbt} = \beta_1 \; Exposure_b \times Post_t + \boldsymbol{X_b'}\boldsymbol{\delta} \times Post_t + \alpha_{pt} + \gamma_{pb} + \epsilon_{pbt} \tag{6}$$

The dependent variable is the log of outstanding credit from bank b to households in province p in year t. The specification include province-time fixed effects to control for local shocks to credit demand, and province-bank fixed effects accounting for the sorting of banks in specific provinces. The vector $\boldsymbol{X_b}$ contains the same set of pre-2002 bank controls used in the previous specifications with banks' characteristics and β_1 is our coefficient of interest, estimated with weighted least-squares (WLS).[16]

[15] Results available upon request.

[16] We estimate eq.6 using the geometric average of two different sets of weights. The first captures the importance of a particular bank in a given province: $b_{pbt} = C^H_{pbt} / \sum_b C^H_{pbt}$, the second captures the importance of a particular province in a bank's household loan portfolio: $c_{pbt} = C^H_{pbt} / \sum_p C^H_{pbt}$. A high b-weight implies that the market share of home mortgage lending of bank b in province p is high, so it is useful to capture the impact of bank-specific credit supply shocks. Observations with relatively high c-weights are useful in identifying the county-specific credit demand effects.

The results reported in Table 13 show that exposed banks do not significantly increase household credit supply relative to other banks (column 1). The result holds also looking at the dummy variable definition of exposure, capturing non linearities of capital inflows exposure, which if anything would lead to the opposite conclusion (column 2 and 3). Hence, while Italy did see a considerable expansion in household lending after 2002, based on our results, this was not associated to the boom in foreign capital inflows.

6 Implications on aggregate misallocation and TFP

In this section we provide evidence of the aggregate effects of capital inflows on misallocation and TFP in Italy. We proceed in three steps. First, we run a reduced form estimation to check if exposure to capital inflows lead to convergence or divergence of the marginal product of capital across firms. Then, we follow the approach of Hsieh and Klenow (2009), an important benchmark in the misallocation literature, to infer the aggregate TFP gain/loss implied by financial flows. Finally, we cast the previous estimate in the framework of Sraer and Thesmar (2018), allowing to account for general equilibrium effects.

If international financial flows are associated to an increase in misallocation, we should observe divergence in the distribution of marginal product of capital across firms: MRPK should decrease (increase) at firms with low (high) initial returns. We check the impact of firm exposure to capital flows on MRPK in a specification similar to regression 4 (see Table 14). In the full sample, the estimated effect of bank exposure on productivity is negative, albeit not statistically significant (column 1). However, this aggregate result masks important heterogeneity across firms. Those with above median MRPK before the shock see their marginal revenue product of capital decrease when borrowing from exposed banks (column 2). For low ex-ante MRPK firms, the estimated coefficient is negative and non-statistically significant. These findings are consistent with the idea that capital inflows contributed to decrease MRPK dispersion across Italian firms.

To gauge the aggregate consequences of international financial flows through resource allocation we first rely on the Hsieh and Klenow (2009) (HK) framework. There, one can express aggregate TFP gains or losses as a function of changes in the dispersion of productivity across firms, which is interpreted as a measure of resource misallocation.[17]

[17] There are several caveats associated to the HK measure of misallocation. Asker et al. (2014) argue that, in the presence of adjustment costs in investment, transitory idiosyncratic TFP shocks across firms naturally generate dispersion in productivity without this implying inefficiency. De Loecker and Goldberg (2014) and Haltiwanger (2016) argue that much of the variation in revenue-based TFP reflects demand shifts and market power rather than allocative inefficiency. Bils et al. (2018) stress the role of mismeasurement of

We implement their method in a simple exercise comparing the actual dispersion of TFPR ($var(\ln TFPR_i)$) during the boom of capital inflows with the counterfactual dispersion of firm-level productivity without the credit shock ($var(\ln \widehat{TFPR}_i$, see Appendix A.3 for details).[18] With these quantities, TFP gains can be expressed as:

$$TFP\ Gain = \ln \widehat{TFP} - \ln TFP = \frac{\sigma}{2}[var(\ln \widehat{TFPR}_i) - var(\ln TFPR_i)] \tag{7}$$

Our estimates imply that foreign capital inflows decrease the dispersion of TFPR, translating in an aggregate TFP gain of 0.4% in the post-2002 period. To weigh the magnitude of this effect, using the HK framework Calligaris et al. (2018) find that the increase of aggregate misallocation in the Italian economy led to a 1% TFP loss in the same period.

The HK framework does not take into account general equilibrium effects, which typically dampen firm-level responses. For instance, the fact that high-MRPK firms receive more credit, may lead to an increase in labor demand by these firms, raise the equilibrium wage, and therefore mitigate the potential expansion of such firms. In this respect the previous results would be an upper bound of the aggregate effect on TFP.

Sraer and Thesmar (2018) propose a framework to aggregate firm level responses to a shock accounting for general equilibrium effects. Their framework features heterogenous firms subject to generic capital frictions such as adjustment costs, taxes and financing constraints, which are altered by a policy shock. In our setting, the shock is induced by capital inflows that relax firms' credit constraints depending on the exposure of banks they borrow from (the firm level exposure in Equation 3). Sraer and Thesmar (2018) show that the effects of such shock on aggregate TFP can be expressed as a function of three sufficient statistics of MRPK and TFPR:

$$TFP\ Gain = F\left(\mathbf{\Lambda}, \widehat{\Delta\mu_{mrpk}}, \widehat{\Delta\sigma^2_{mrpk}}, \widehat{\Delta\sigma_{mrpk,tfpr}}\right) \tag{8}$$

In other words, the general equilibrium impact of capital inflows on aggregate TFP can can be expressed as a function of the effects of the shock on the mean and the variance of MRPK ($\widehat{\Delta\mu_{mrpk}}$ and $\widehat{\Delta\sigma^2_{mrpk}}$, respectively), and on the covariance between MRPK and

factors' marginal product in the calculation of misallocation. Finally, Haltiwanger et al. (2018) show that the HK model can map observed production behaviors to inefficient wedges/distortions only under strict theoretical assumptions that may not hold in all cases. David and Venkateswaran (2019) show that for the US firms' adjustment costs could explain only a small fraction of dispersion in productivities and that markups could account for about 28% of the overall productivity dispersion.

[18] In practice, we computed $\ln \widehat{TFPR}_{ist} = \ln TFPR_{ist} - \hat{\beta}_1\ Exposure\ Firm_i$, where β_1 is the estimated productivity effect of bank exposure $\ln TFPR_{ist} = \beta_1\ Exposure\ Firm_i \times Post_t + \boldsymbol{X_i'\delta} \times Post_t + \gamma_i + \delta_{st} + \epsilon_{ist}$. The moment $var(\ln \widehat{TFPR}_i)$ is computed for the post-2002 period.

TFPR ($\Delta\widehat{\sigma_{mrpk,tfpr}}$), as well as the parameters of the model ($\mathbf{\Lambda}$).[19]

Following their methodology, we find that firm exposure to international financial flows increased aggregate TFP by 0.3% in the post period, which is very similar, although smaller, to that obtained in the HK framework. The fact that different approaches deliver close results is comforting about the robustness of the finding, and confirms that capital flows did not contribute to misallocation through the bank lending channel.

7 Robustness

We run an extensive set of robustness checks with alternative specifications, measures of banks' exposure, and firms' classification. In the Appendix we report our main results using alternative econometric specifications. In Table A1 we estimate the baseline specification in Equation 5 using a balanced panel. In Table A2 we estimate Equation 5 as a first difference transformation, which makes the standard errors robust to possible concerns of auto-correlation as highlighted by Bertrand et al. (2004). Then, in Table A3 we look at credit allocation by firm characteristics no-longer splitting the sample between e.g. high- and low-productivity firms, but using a continuous measure of productivity and collateral interacted with bank exposure. Next, in Table A4 we look at credit allocation by firm-characteristics measured in the post-2002 period. Finally, in Table A5 we add bank-time fixed effects to specification 5, which allows to control for any other shock that can hit a bank in a given year. The results of the paper hold across these alternative specifications.

In this section we discuss more in details our robustness analysis on five further issues. First we look at threat to identification coming from confounding factors. Then, we explore alternative measures of bank exposure to international financial flows. Next, we check robustness to different proxies of firm-level productivity and credit constraint typically used in the literature. Further, we investigate whether spillover across banks can affect our results. Finally, we analyse if banks more exposed to international financial flows turn to be more fragile after the global financial crisis.

7.1 Omitted variable bias and confounding factors

Potential threats to identification stem from simultaneous shocks correlated with bank exposure to foreign capital flows. We are particularly concerned about i) the raise of

[19]See Appendix A.4 for more details on the approach, and on the estimates involved to compute the TFP gain in our case.

securitisation in the early 2000s; ii) a sharp decrease of GDP growth in 2002-03; and iii) banks' exposure to the China shock. Table A6 reports the results obtained accounting for these potential confounds, augmenting the baseline specification (col.1) with indexes of banks' exposure to these alternative drivers of credit supply decisions (cols. 2 to 4).

In column 2 we allow banks propensity to securitization before the shock (the average share of securitized lending in 2001) to affect credit supply after 2002. Because securitization affects available liquidity it might also spur an increase in credit supply, which would bias our estimates if securitization is correlated to reliance on foreign funding. Column 3 accounts for bank exposure to the slowdown, measured by the share of outstanding loans to the sectors that were most affected by the GDP slowdown, identified by taking industry level changes in revenues in 2002-03 relative to 2000-01. Finally, column 4 accounts for banks' exposure to the industries that most suffered the trade shock following China entrance in the WTO as in Federico et al. (2020).

The results in Table A6 show that our core finding on the impact of bank exposure to capital inflows on credit supply is robust to these potential confounding factors.

7.2 Alternative measures of bank exposure to capital flows

We experiment with two other measures of the shock to banks' balance sheet induced by the surge in foreign capital inflows. The first is a shift-share Bartik instrument combining (i) the bank composition of foreign liabilities by sourcing country before the shock with (ii) data on changes in capital outflows from those countries to the rest of the world after the shock. We focus on the top 15 sourcing countries that account for more than 90% of foreign liabilities, and we measure their change in capital outflows towards the rest of the world (excluding Italy) between the period 1998-2001 and 2002-2007. As an illustrative example, Figure 6 in the Appendix plots the patterns of foreign claims of banks in Germany and Luxembourg. These were similar in the 1980s and in the 1990s but diverged starting in 2002, when cross-border lending from Germany sharply increased. The new bank-level exposure indicator would then capture that Italian banks borrowing from Germany before 2002 are disproportionally more exposed to financial flows than banks borrowing from Luxembourg.[20] Table A7 shows that our core results on misallocation are unaffected using this alternative exposure measure.

The second measure aims at isolating the supply side component of capital flows and exploit the time-series dimension of the data. We first project the log-change of Italian

[20] Here bank exposure is computed as: $Exposure_b^{Geo} = \sum_c \omega_{bc} \, \Delta World\ Outflows_c^{post-pre}$, where ω_{bc} is the share of foreign liability that bank b sources from country c in 1998-2000, and $\Delta World\ Outflows_c^{post-pre}$ is the increase in lending of country c to the rest of the world.

banks' foreign liabilities on their world counterpart over the 1998-2007 period, as in Cesa-Bianchi et al. (2018), using BIS data on changes of outstanding cross-border liabilities:

$$\Delta \ln KF_t^{IT} = \lambda_0 + \lambda_1 \Delta \ln KF_t^{World} + \epsilon_t^{IT} \tag{9}$$

where KF_t^{IT} are the outstanding foreign liabilities of the Italian banking sector in year t and KF_t^{World} are the foreign outstanding liabilities of the other countries in the world, excluding Italy. If country-specific pull shocks to Italy do not affect world capital flows, the fitted values $\hat{\lambda}_1 \Delta \ln KF_t^{World}$ can be interpreted as the supply side component of capital inflows into the Italian banking sector. With this measure in hand we estimate:

$$\ln C_{ibt} = \sum_{d=1}^{4} \beta_d \, D_{di} \times Exposure_b \times \hat{\lambda}_1 \Delta \ln \; KF_t^{World} + \beta_2 \, Spec_{ibt} + \boldsymbol{X_b'\delta} \times Post_t + \alpha_{it} + \gamma_{ib} + \epsilon_{ibt} \tag{10}$$

where the strength of credit supply shocks is obtained comparing the patterns of lending by banks with different exposure induced by yearly changes in push determinants of foreign capital flows. The results in Table A8 confirm that while exposed banks increase credit supply as global flows gain strength, the allocation of such credit is not consistent with an increase in misallocation.

7.3 Additional and time-varying firm level characteristics

We extend our analysis looking at alternative definitions of firm productivity and credit constraint. First, we focus on firms' credit rating, an index computed by CERVED as an Altman score that accounts, among other things, for firms' profitability, assets, and credit history. The credit score takes values between 1 and 9; firms with a credit score above 6 are considered to have a high risk of default (Rodano et al., 2018). The first two columns of Table A9 show that our core findings on misallocation are unaltered if grouping firms based on productivity and the credit score. In particular, high productivity but risky firms benefitted from the increase in lending by exposed banks as much as low-productivity but low-risk firms, irrespective of the productivity measure. Then, in the third column, we look at value added per worker as an alternative measure of productivity and we can confirm the previous results of the paper.

The firm-level measures of productivity and credit constraint are defined according to ex-ante characteristics, but we check the robustness of results to allowing them to vary. For example, due to firms' life cycle or to idiosyncratic shock, some ex-ante high productivity firm might become unproductive, and viceversa. The time-varying measures of firm productivity and credit constraint are taken at $t-1$, so that the the grouping of firms can vary year by year. Because firm characteristics might also vary in response to credit supply allocation, the results can only be taken as indicative, but they confirm our baseline findings (Table A10).[21]

7.4 Potential spillovers across banks

The possibility of spillovers from exposed to non-exposed banks is a relevant threat to our identification strategy. Non-exposed banks could in principle benefit from international capital inflows indirectly through interbank linkages or through market effects, such as bond or equity purchases. Moreover, exposed banks may change their retail policy, by either focusing less on, or bidding more aggressively for deposits. In all these cases, capital inflows would end up affecting the funds available to non-exposed banks. We therefore check for the relevance of these indirect effects.

In principle, interbank lending is of particular concern for identification, as transactions grew disproportionately in Italy around the same time as the surge in capital inflows. In practice, however, we do not expect spillovers through that market to be a relevant confounding factor in our case. The reason is that the upward trend in interbank transaction was driven by intra-group lending, that is loans between banks belonging to the same banking group (Figure 7). As explained in Section 3 our analysis refers to banking groups so that intra-group lending is consolidated in the data. As the figure shows, lending across groups, and therefore exposed vs non exposed banks, remains flat over the period. We test for this more formally by running the following specification at the bank level:

$$Y_{bt} = \beta_1 \; Exp_b \times Post_t + \boldsymbol{X_b'\delta} \times Post_t + \gamma_b + \alpha_t + \epsilon_{bt} \tag{11}$$

where Y_{bt} is alternatively i) interbank lending of bank b in year t; ii) holding of bonds and equity of financial institutions; iii) share of deposit on banks' liabilities; iv) bank's b share of the total deposit taking in the economy. The coefficient β_1 captures how these variables change after 2002 for banks more exposed to capital inflows, controlling for our standard vector of bank characteristics pre-2002, banks fixed effects, and year dummies; errors are clustered at the bank level.

The results, reported in table A11, show that bank exposure is uncorrelated with bonds or equity holdings, as well as with the share of deposits. Moreover, interbank lending by exposed banks slightly decreased after 2002. These results imply that potential indirect

[21] An alternative way to look at the same issue is to define firms' characteristics as an average of the ex-post years and our results hold using also that approach (Table A4).

effects of capital inflows are unlikely to weaken the results on misallocation discussed in Section 5.2.

7.5 Fragility of exposed banks after the global financial crisis

Our baseline analysis focuses on the boom in capital inflows during the run up to the global financial crisis. In 2008 the Italian economy suffered the consequences of the Great recession, which was followed by a second severe downturn in 2011 with the sovereign debt crisis erupted; as a result, its banking system experienced a disproportionate increase in non-performing loans (NPLs).

In this context, it is relevant to ask whether reliance on foreign funds made banks more vulnerable, implying a higher incidence of NPLs during the following double-dip recession. The global financial crisis also implied a reversal of international financial flows, which begs the questions whether borrowers of exposed banks were made more vulnerable by a credit contraction.

We check for these possibilities extending our time window to 2013, and evaluating the differential impact of bank exposure across three subperiods (1998-2001; 2002-2007; 2008-2013).[22] We focus on i) the effect of exposure on the patterns of NPL ratios at the bank-level, and ii) the effects on the intensive margin of credit supply in the bank-firm level regressions.

Our findings in Table A12 suggest that the higher credit supply of exposed banks during the boom of capital inflows did not imply a higher incidence of loans in or near default in the subsequent years (columns 1 and 2). Moreover, we find no evidence of a decline in credit supply from exposed banks in the post-2008 period (columns 3 an 4).

The many concurring shocks to banks' and firms' financial conditions during the crisis and double dip recession period, however, suggest the results of this analysis should be interpreted with caution.

8 Concluding remarks: remaining puzzles and further research

To the best of our knowledge, this is the first paper that is able to link international financial flows and misallocation at the bank-firm level. Looking at the boom of cross-border

[22] We consolidate the data based on groups' composition in 2013 and we recompute all bank-specific variables accordingly.

flows of the early 2000s, we find that increased capital flows did not lead to higher misallocation nor lowered aggregate productivity in Italy. These findings are somehow unexpected and leave open the question of what explains the rise of misallocation in Italy and, possibly, other Southern European countries. We discuss a few potential avenues for future research seeking to investigate further the impact of cross-border flows on productivity.

For one thing, international financial flows may distort resource allocation not through the bank lending channel but through the government, or households. In Italy, government borrowing accounted for a small, but non-negligible, fraction of the decrease of the net international investment position (around 20% of the total decline). To the extent that these funds induced an increase of e.g. public procurement, the government channel could explain part of the raise of misallocation in Italy. Similarly, capital inflows could trigger a reallocation of households' investments towards less productive firms or towards banks that then increase credit to firms with lower productivity. These alternative channels deserve further investigation.

Second, capital inflows may have different consequences when driven by domestic pull-factors rather than by push-factors external to the country, as was largely the case for Italy. Establishing whether such difference exists would be important in terms of policy implications. If international financial flows distort resource allocation when driven by global factors, then capital controls should be called for to mitigate this negative effect. However, if capital flows have a negative effect only when driven by domestic pull-factors, then macro-prudential tools would be more appropriate.

Third, our findings suggest that the liability structure of banks may matter for credit allocation and aggregate productivity. International financial flows seem to have a disciplining effect on credit allocation that traditional deposits may not have. This could be associated to the higher rollover risk that characterizes international interbank lending, but it can reflect also stronger monitoring, as most foreign funding is unsecured. This poses the question of whether the funding structure of banks matters for a country's productivity and, more generally, to what extent credit intermediation can account for the observed trends of aggregate misallocation. Hopefully, the findings of the paper can stimulate further research along these dimensions.

References

Amiti, M., McGuire, P. and Weinstein, D. E. (2017), Supply- and Demand-side Factors in Global Banking, Nber working papers, National Bureau of Economic Research, Inc.

Amiti, M. and Weinstein, D. E. (2011), 'Exports and Financial Shocks', *The Quarterly Journal of Economics* **126**(4), 1841–1877.

Amiti, M. and Weinstein, D. E. (2018), 'How Much Do Idiosyncratic Bank Shocks Affect Investment? Evidence from Matched Bank-Firm Loan Data', *Journal of Political Economy* **126**(2), 525–587.

Asker, J., Collard-Wexler, A. and Loecker, J. D. (2014), 'Dynamic Inputs and Resource (Mis)Allocation', *Journal of Political Economy* **122**(5), 1013–1063.

Banerjee, A. V. and Duflo, E. (2005), Growth Theory through the Lens of Development Economics, *in* P. Aghion and S. Durlauf, eds, 'Handbook of Economic Growth', Vol. 1 of *Handbook of Economic Growth*, Elsevier, chapter 7, pp. 473–552.

Baskaya, Y. S., di Giovanni, J., Kalemli-zcan, S., Peydro, J.-L. and Ulu, M. F. (2017), 'Capital flows and the international credit channel', *Journal of International Economics* **108**(S1), 15–22.

Bau, N. and Matray, A. (2020), Misallocation and capital market integration: Evidence from india.

Bekaert, G., Harvey, C. R. and Lundblad, C. (2011), 'Financial Openness and Productivity', *World Development* **39**(1), 1–19.

Benigno, G., Converse, N. and Fornaro, L. (2015), 'Large capital inflows, sectoral allocation, and economic performance', *Journal of International Money and Finance* **55**(C), 60–87.

Benigno, G. and Fornaro, L. (2014), 'The Financial Resource Curse', *Scandinavian Journal of Economics* **116**(1), 58–86.

Bertrand, M., Duflo, E. and Mullainathan, S. (2004), 'How much should we trust differences-in-differences estimates?', *Quarterly Journal of Economics* **119**(1), 249–275.

Bils, M., Klenow, P. J. and Ruane, C. (2018), Misallocation or Mismeasurement? , mimeo stanford university, mimeo Stanford University.

Bonfiglioli, A. (2008), 'Financial integration, productivity and capital accumulation', *Journal of International Economics* **76**(2), 337–355.

Broner, F. and Ventura, J. (2016), 'Rethinking the Effects of Financial Globalization', *The Quarterly Journal of Economics* **131**(3), 1497–1542.

Buera, F. J., Kaboski, J. P. and Shin, Y. (2011), 'Finance and Development: A Tale of Two Sectors', *American Economic Review* **101**(5), 1964–2002.

Buera, F. J. and Moll, B. (2015), 'Aggregate Implications of a Credit Crunch: The Importance of Heterogeneity', *American Economic Journal: Macroeconomics* **7**(3), 1–42.

Buera, F. J. and Shin, Y. (2017), 'Productivity Growth and Capital Flows: The Dynamics of Reforms', *American Economic Journal: Macroeconomics* **9**(3), 147–185.

Calligaris, S., Gatto, M. D., Hassan, F., Ottaviano, G. I. P. and Schivardi, F. (2018), 'The productivity puzzle and misallocation: an Italian perspective', *Economic Policy* **33**(96), 635–684.

Castillo-Martínez, L. (2019), Sudden stops, productivity, and the exchange rate.

Cesa-Bianchi, A., Ferrero, A. and Rebucci, A. (2018), 'International credit supply shocks', *Journal of International Economics* **112**(C), 219–237.

Chari, A., Henry, P. B. and Sasson, D. (2012), 'Capital market integration and wages', *American Economic Journal: Macroeconomics* **4**(2), 102–32.

Chodorow-Reich, G. (2014), 'The Employment Effects of Credit Market Disruptions: Firm-level Evidence from the 2008-9 Financial Crisis', *The Quarterly Journal of Economics* **129**(1), 1–59.

Cingano, F., Manaresi, F. and Sette, E. (2016), 'Does Credit Crunch Investment Down? New Evidence on the Real Effects of the Bank-Lending Channel', *Review of Financial Studies* **29**(10), 2737–2773.

David, J. M. and Venkateswaran, V. (2019), 'The sources of capital misallocation', *American Economic Review* **109**(7), 2531–67.

De Loecker, J. and Goldberg, P. K. (2014), 'Firm Performance in a Global Market', *Annual Review of Economics* **6**(1), 201–227.

De Loecker, J. and Warzynski, F. (2012), 'Markups and firm-level export status', *American Economic Review* **102**(6), 2437–71.

di Giovanni, J., Kalemli-Ozcan, S., Ulu, M. F. and Baskaya, Y. S. (2017), International Spillovers and Local Credit Cycles, Nber working papers, National Bureau of Economic Research, Inc.

Drechsler, I., Savov, A. and Schnabl, P. (2017), 'The Deposits Channel of Monetary Policy', *The Quarterly Journal of Economics* **132**(4), 1819–1876.

Federico, S., Hassan, F. and Rappoport, V. (2020), Trade shocks and credit reallocation, CEPR Discussion Papers dp14792, Centre for Economic Policy Research.

Giavazzi, F. and Spaventa, L. (2011), Why the current account may matter in a monetary union: lessons from the financial crisis in the euro area, *in* M. Beblavy, D. Cobham and L. Odor, eds, 'The Euro Area and the Financial Crisis', Cambridge University Press, Cambridge, p. 199–221.

Gilchrist, S., Siemer, M. and Zakrajsek, E. (2017), The Real Effects of Credit Booms and Busts: A County-Level Analysis, mimeo boston university, mimeo Boston University.

Gopinath, G., Kalemli-zcan, S., Karabarbounis, L. and Villegas-Sanchez, C. (2017), 'Capital Allocation and Productivity in South Europe', *The Quarterly Journal of Economics* **132**(4), 1915–1967.

Gourinchas, P.-O. and Jeanne, O. (2006), 'The Elusive Gains from International Financial Integration', *Review of Economic Studies* **73**(3), 715–741.

Gourinchas, P.-O. and Jeanne, O. (2013), 'Capital Flows to Developing Countries: The Allocation Puzzle', *Review of Economic Studies* **80**(4), 1484–1515.

Greenstone, M., Mas, A. and Nguyen, H.-L. (2014), Do Credit Market Shocks affect the Real Economy? Quasi-Experimental Evidence from the Great Recession and 'Normal' Economic Times, Nber working papers, National Bureau of Economic Research, Inc.

Hahm, J., Shin, H. S. and Shin, K. (2013), 'Noncore Bank Liabilities and Financial Vulnerability', *Journal of Money, Credit and Banking* **45**, 3–36.

Hale, G. and Obstfeld, M. (2016), 'The Euro And The Geography Of International Debt Flows', *Journal of the European Economic Association* **14**(1), 115–144.

Haltiwanger, J. (2016), 'Firm Dynamics and Productivity: TFPQ, TFPR, and Demand Side Factors', *Economía Journal* **17**(Fall 2016), 3–26.

Haltiwanger, J., Kulick, R. and Syverson, C. (2018), Misallocation measures: The distortion that ate the residual, Working Paper 24199, National Bureau of Economic Research.

Hanson, S. G., Shleifer, A., Stein, J. C. and Vishny, R. W. (2015), 'Banks as patient fixed-income investors', *Journal of Financial Economics* **117**(3), 449–469.

Hsieh, C.-T. and Klenow, P. J. (2009), 'Misallocation and Manufacturing TFP in China and India', *The Quarterly Journal of Economics* **124**(4), 1403–1448.

Imbens, G. and Wooldridge, J. M. (2008), 'Recent Developments in the Econometrics of Program Evaluation', *Journal of Economic Literature* **47**(1), 5–86.

Jiménez, G., Ongena, S., Peydró, J. L. and Saurina, J. (2014), 'Hazardous Times for Monetary Policy: What Do Twenty?Three Million Bank Loans Say About the Effects of Monetary Policy on Credit Risk Taking?', *Econometrica* **82**(2), 463–505.

Kalemli-Ozcan, S., Papaioannou, E. and Peydro, J.-L. (2010), 'What lies beneath the euro's effect on financial integration? Currency risk, legal harmonization, or trade?', *Journal of International Economics* **81**(1), 75–88.

Khwaja, A. I. and Mian, A. (2008), 'Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market', *American Economic Review* **98**(4), 1413–1442.

Lane, P. R. (2013), Capital Flows in the Euro Area, Cepr discussion papers, C.E.P.R. Discussion Papers.

Lane, P. R. and Milesi-Ferretti, G. M. (2007*a*), 'Europe and global imbalances', *Economic Policy* **22**, 519–573.

Lane, P. R. and Milesi-Ferretti, G. M. (2007*b*), 'The external wealth of nations mark II: Revised and extended estimates of foreign assets and liabilities, 1970-2004', *Journal of International Economics* **73**(2), 223–250.

Lane, P. R. and Milesi-Ferretti, G. M. (2008), 'The Drivers of Financial Globalization', *American Economic Review* **98**(2), 327–332.

Lenzu, S. and Manaresi, F. (2018), Sources and implications of resource misallocation: new evidence from firm-level marginal products and user costs.

Levchenko, A. A., Rancière, R. and Thoenig, M. (2009), 'Growth and risk at the industry level: The real effects of financial liberalization', *Journal of Development Economics* **89**(2), 210–222.

Levinsohn, J. and Petrin, A. (2003), 'Estimating production functions using inputs to control for unobservables', *Review of Economic Studies* **70**(2), 317–341.

Mian, A. and Sufi, A. (2018), Credit Supply and Housing Speculation, Nber working papers, National Bureau of Economic Research, Inc.

Mian, A., Sufi, A. and Verner, E. (2017), How do Credit Supply Shocks Affect the Real Economy? Evidence from the United States in the 1980s, Nber working papers, National Bureau of Economic Research, Inc.

Midrigan, V. and Xu, D. Y. (2014), 'Finance and Misallocation: Evidence from Plant-Level Data', *American Economic Review* **104**(2), 422–458.

Moll, B. (2014), 'Productivity losses from financial frictions: Can self-financing undo capital misallocation?', *American Economic Review* **104**(10), 3186–3221.

Paravisini, D. (2008), 'Local bank financial constraints and firm access to external finance', *The Journal of Finance* **63**(5), 2161–2193.

Paravisini, D., Rappoport, V. and Schnabl, P. (2017), Specialization in bank lending: Evidence from exporting firms.

Paravisini, D., Rappoport, V., Schnabl, P. and Wolfenzon, D. (2015), 'Dissecting the Effect of Credit Supply on Trade: Evidence from Matched Credit-Export Data', *Review of Economic Studies* **82**(1), 333–359.

Prasad, E. S., Rajan, R. G. and Subramanian, A. (2007), 'Foreign Capital and Economic Growth', *Brookings Papers on Economic Activity* **38**(1), 153–230.

Reis, R. (2013), 'The Portugese Slump and Crash and the Euro Crisis', *Brookings Papers on Economic Activity* **44**(1 (Spring), 143–210.

Rodano, G., Serrano-Velarde, N. and Tarantino, E. (2018), 'Lending standards over the credit cycle', *Review of Financial Studies* **31**(8), 2943–2982.

Rodrik, D. and Subramanian, A. (2009), 'Why Did Financial Globalization Disappoint?', *IMF Staff Papers* **56**(1), 112–138.

Saffie, F., Varela, L. and Yi, K.-M. (2020), The micro and macro dynamics of capital flows, Working Paper 27371, National Bureau of Economic Research.

Sander, N. (2019), Causal effects of capital inflows.

Schnabl, P. (2012), 'The international transmission of bank liquidity shocks: Evidence from an emerging market', *The Journal of Finance* **67**(3), 897–932.

Spiegel, M. M. (2009), 'Monetary and Financial Integration in the EMU: Push or Pull?', *Review of International Economics* **17**(4), 751–776.

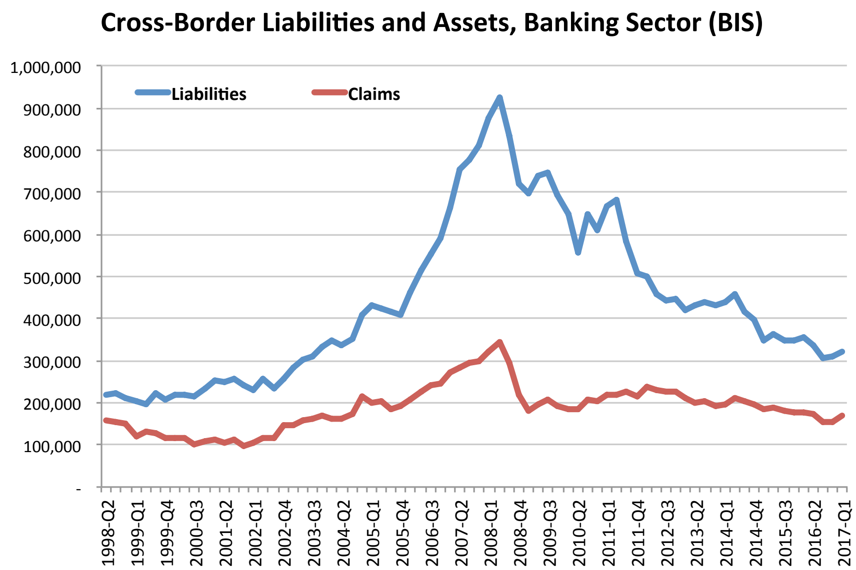
Sraer, D. and Thesmar, D. (2018), A sufficient statistics approach for aggregating firm-level experiments, Working Paper 24208, National Bureau of Economic Research.

Varela, L. (2018), 'Reallocation, Competition, and Productivity: Evidence from a Financial Liberalization Episode', *Review of Economic Studies* **85**(2), 1279–1313.

Wooldridge, J. M. (2009), 'On estimating firm-level production functions using proxy variables to control for unobservables', *Economics Letters* **104**(3), 112–114.

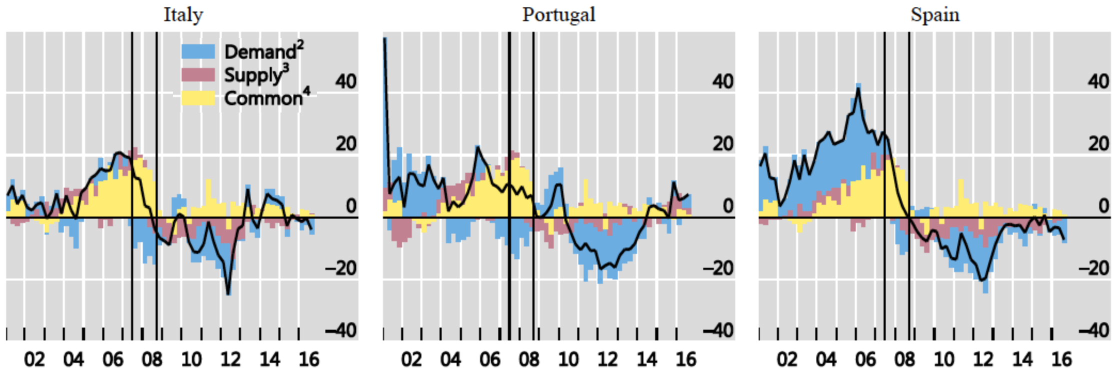
Figures

Figure 1: Foreign liabilities and claims of banks operating in Italy



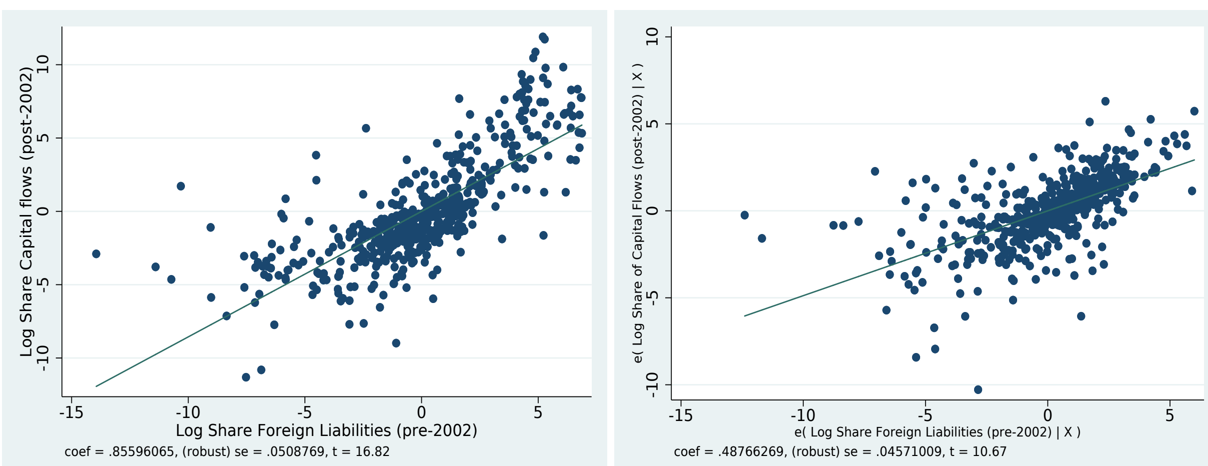
Source: BIS. Foreign liabilities (claims) of Italian banks are defined by taking the total cross-border claims (liabilities) of all countries and all sectors to Italian banks (nominal USD).

Figure 2: Capital inflows to the banks operating in selected Euro area countries, decomposition of drivers



Source: Amiti et al. (2017). Year-on-year growth in foreign claims of all reporting internationally active banks on the country listed in the panel title, adjusted for breaks in series and exchange rate movements. 2: Estimated demand shocks to unique to the borrower country listed in the panel title. 3: Estimated net supply shocks to the constellation of banking systems that have outstanding foreign claims on the borrower country listed in the panel title. 4: Estimated shocks that are common to all banking systems and borrower countries.

Figure 3: Share of foreign liabilities and capital inflows received by bank



(a) Without bank controls

(b) With bank characteristics

For each bank we look at the average share of capital flows that it received relative to the overall flows in the economy in the post-2002 period (vertical axis) and at the average foreign liabilities ratio - foreign liabilities relative to overall liabilities - pre-2002 (horizontal axis). In Panel A we look at the unconditional correlation between the two variables and in Panel B we control for bank characteristics such as log-assets, share of non-core liabilities, share of NPLs, and capital share (pre-2002 average).

Figure 4: Portfolio allocation by productivity and credit constraint

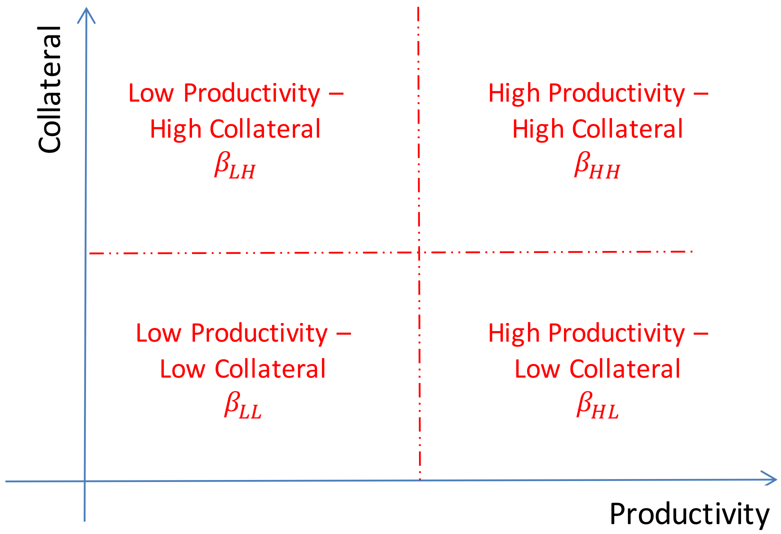
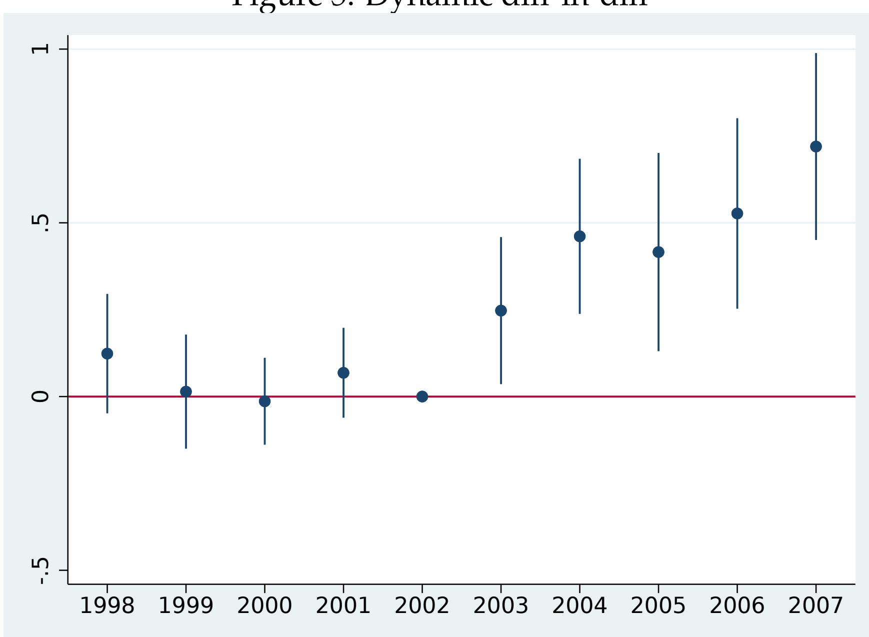


Figure 5: Dynamic diff-in-diff



The Figure reports the coefficients β_q, with 99% confidence interval, of the dynamic diff-in-diff in the following specification, where we take the year 2002 as baseline:

$$\ln C_{ibt} = \sum_{q=1998}^{2007} \beta_q \, Exposure_b \times \mathbb{1}_{t=q} + \beta_2 \, Spec_{ibt} + \sum_{q=1998}^{2007} \boldsymbol{X_b'\delta_q} \times \mathbb{1}_{t=q} + \alpha_{it} + \gamma_{ib} + \epsilon_{ibt}.$$

Tables

Table 1: Summary statistics

	Unit	Mean	S.D.	p25	p50	p75
Bank characteristics						
Total Assets	€Millions	3,230	27,800	79	176	442
Liquid Assets	% Assets	3,605	5,230	626	1,473	3,841
Nonperforming Loans	% Assets	2.6	3.3	0.8	1.7	3.3
Core capital	% Assets	1.8	8.2	0.01	0.2	1.5
Deposits	% Liabilities	54.5	19.1	45	54	68
Foreign Funding	% Liabilities	3.7	13.1	0.003	0.01	0.06
Firm characteristics						
Bank Credit	€Thousands	1,642	15,700	155	395	1083
Revenues	€Thousands	4,173	5,673	743	1,751	4,708
Fixed Assets	€Thousands	2,327	72,301	70	240	819
Gross operating margin	% Revenues	6	52	3.3	7.6	13
Credit Score	Units	5.2	1.9	4	5	7

Note: The table reports relevant statistics (1998-2007, average) of banks and firms in the firm-bank matched sample. Bank balance sheet data are from the Supervisory Reports submitted by banks to the Bank of Italy. Credit data are from the Italian Credit Register. Firm balance sheet data are from CERVED. Liquid assets include cash, interbank deposits, and bond holdings. Firms' credit score is computed by CERVED based on past defaults and firms' balance sheet information.

Table 2: High Foreign Liability Ratio Predicts Exposure to Capital Inflows

	Share of total inflows (02-07) (1)	Growth of foreign liabilities (post vs. pre) (2)	Rank foreign liability ratio (02-07) (3)
Foreign liability ratio (98-00)	0.54***	0.51***	
	(0.03)	(0.04)	
Rank foreign liability ratio (98-00)			0.75***
			(0.03)
Bank Controls	✓	✓	✓
Observations	494	494	494
$Adj.R^2$	0.80	0.63	0.71

Note: Cross-sectional bank-level regressions. Column 1 reports the elasticity of the average share of the aggregate capital inflows that bank b gets in the period 2002-2007 ($ForeignLiab_b^{02-08} / \sum_b ForeignLiab_b^{02-08}$) on the foreign liability ratio of the bank measured 1998-2000 ($ForeignLiab_b^{98-00}/TotLiab_b^{98-00}$). Column 2 reports the elasticity of the growth in foreign funding (pre-vs.post) relative to the total liabilities in the pre-period ($\Delta ForeignLiab_b/TotLiab_b^{98-00}$) on the foreign liability ratio of the bank ($ForeignLiab_b^{98-00}/TotLiab_b^{98-00}$). Column 3 regress the ranking of banks by the foreign liability ratio in the 2002-07 period relative to the ranking in 1998-2000. All regressions include bank controls measured in the 1998-2000 period such as log-assets, NPL ratio, capital ration and core funding ratio. Standard errors are clustered at the bank level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 3: Balancing tests

	Unit	*High exposed Banks* Mean	*Low exposed banks* Mean	Normalized difference
Bank characteristics				
Total Assets	€Millions	5,780	1,800	0.23
Nonperforming Loans	% Assets	2.4	3.4	-0.25
Domestic interbank	% Liability	8	13.1	0.21
Core capital	%Liabilities	3.7	3.9	0.007
Borrower characteristics				
Fixed Assets	€Thousands	2,990	1,095	0.02
Gross operating margin	% Revenues	8.4	8.7	-0.04
Credit Score	Units	5.3	5.4	0.04
Productivity	log-TFPR	5.2	4.9	0.12
Age	years	15	13	0.19

Note: The table reports relevant balance sheet characteristics of banks and of their average borrower (1998-2000 average), dividing the sample between high- and low-exposed banks. High-exposed (low-exposed) banks have a share of foreign liabilities above (below) 10% over the period 1998-2000. The last column shows the normalized difference between the two groups as specified in Imbens and Wooldridge (2008); an absolute value above 0.25 indicates an imbalance between the two groups.

Table 4: Capital inflows and credit supply, intensive margin

	Dependent variable: ln $Credit_{ibt}$				
$Bank\ Exposure$:	Continuous (1)	Dummy 10% (2)	Dummy 15% (3)	Exposure above 2% (4)	WLS (5)
$Exposure_b \times Post_t$	0.40***	0.069***	0.070***	0.40***	0.40***
	(0.06)	(0.004)	(0.004)	(0.05)	(0.06)
Firm-time F.E.	✓	✓	✓	✓	✓
Firm-bank F.E.	✓	✓	✓	✓	✓
Specialization	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓
Observations	4,141,748	4,141,748	4,141,748	3,407,129	4,110,749
$Adj.R^2$	0.82	0.82	0.82	0.82	0.82

Note: The table reports the coefficients of the baseline specification in Equation 1. The dependent variable, $\ln C_{ibt}$, is the log of outstanding credit between bank b and firm i in year t. $Exposure_b$ captures bank exposure to foreign capital flows, defined as the foreign liability ratio over the period 1998-2000. Specialization is a time-varying dummy that captures if a firm operates in a sector in which the bank specializes its lending activities. Bank controls include bank characteristics measure in 1998-2000 interacted with a post-2002 dummy: log-assets, share of NPLs, core-funding ratio, and the capital ratio. All regressions include firm-year fixed effects and firm-bank dummies. Standard errors are clustered at the bank-sector (2-digit) level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 5: Capital inflows and bank-firm relation, extensive margin

	Dependent variable:			
	$Exit_{ib\tau}$		$Entry_{ib\tau}$	
$Bank\ Exposure$:	Continuous (1)	Dummy 15% (2)	Continuous (3)	Dummy 15% (4)
$Exposure_b * Post_\tau$	-0.11***	-0.009***	0.19***	0.03***
	(0.024)	(0.002)	(0.03)	(0.004)
Firm-period F.E.	✓	✓	✓	✓
Bank F.E.	✓	✓	✓	✓
Specialization	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓
Observations	1,030,013	1,030,013	1,030,013	1,030,013
$Adj.R^2$	0.55	0.55	0.45	0.48

Note: The table reports the coefficients of the extensive margin specification in Equation 2. The dependent variable is a dummy that takes the value of 1 if firm i starts (entry) or ends (exit) a credit relation with bank b in period τ=1998-2002, 2002-07. $Exposure_b$ captures bank exposure to foreign capital flows, defined as the foreign liability ratio over the period 1998-2000. Specialization is a time-varying dummy that captures if a firm operates in a sector in which the bank specializes its lending activities. Other bank controls include bank characteristics measured in 1998-2000 interacted with a post-2002 dummy: log-assets, share of NPLs, core-funding ratio, and the capital ratio. All regressions include firm-period fixed effects and bank dummies. Standard errors are clustered at the bank-sector (2-digit) level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 6: Capital inflows and credit supply, aggregate credit

	Dependent variable: ln $Credit_{it}$				
$Bank\ Exposure$:	Continuous (1)	Dummy 10% (2)	Dummy 15% (3)	Exposure above 2% (4)	WLS (5)
$Exposure_i \times Post_t$	0.24***	0.031***	0.032***	0.40***	0.216***
	(0.06)	(0.006)	(0.005)	(0.05)	(0.04)
Estimated firm-time F.E.	✓	✓	✓	✓	✓
Firm F.E.	✓	✓	✓	✓	✓
Sector-time F.E.	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓
Observations	4,141,748	4,141,748	4,141,748	3,407,129	4,110,749
$Adj.R^2$	0.82	0.82	0.82	0.82	0.82

Note: The table reports the coefficients of the baseline specification in Equation 4. The dependent variable, $\ln C_{it}$, is the log of outstanding credit of firm i in year t. The variable $Exposure_i$ is the weighted average of exposure to foreign capital inflows of firm's i lenders in the period 1998-2000, as defined in Equation 3. Bank controls are a weighted average of firm's i lenders' characteristics measured in 1998-2000, interacted with a post-2002 dummy, these are log-assets, share of NPLs, core-funding ratio, and the capital ratio. All regressions include sector-year fixed effects and firm dummies, and the firm-time fixed effects computed in the intensive margin regression. Standard errors are bootstrapped with clusters at the sector-main bank level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 7: Capital inflows and credit allocation by industry, intensive margin

	Dependent variable: ln $Credit_{ibt}$			
	Manufacturing (1)	Construction (2)	Trade Service (3)	Other (4)
$Exposure_b \times Post_t$	0.57***	0.14	0.18	0.34***
	(0.06)	(0.19)	(0.16)	(0.10)
Firm-time F.E.	✓	✓	✓	✓
Firm-bank F.E.	✓	✓	✓	✓
Specialization	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓
Observations	1,922,581	427,477	1,101,423	690,267
$Adj.R^2$	0.90	0.87	0.91	0.91

Note: The table reports the coefficients of the baseline specification in Equation 1, where we divide the sample by firms' macro sectors. The dependent variable, $\ln C_{ibt}$, is the log of outstanding credit between bank b and firm i in year t. The variable $Exposure_b$ captures bank exposure to foreign capital flows, defined as the foreign liability ratio over the period 1998-2000. Specialization is a time-varying dummy that captures if a firm operates in a sector in which the bank specializes its lending activities. Bank controls include bank characteristics measure in 1998-2000 interacted with a post-2002 dummy: log-assets, share of NPLs, core-funding ratio, and the capital ratio. Specialization is a dummy that captures if a firm operates in a sector in which the bank specializes its lending activities. All regressions include firm-year fixed effects and firm-bank dummies. Standard errors are clustered at the bank-sector (2-digit) level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level

Table 8: Capital inflows and firm-bank relations by industry, extensive margin

	Dependent variable:							
	$Entry_{ib\tau}$				$Exit_{ib\tau}$			
	Manuf. (1)	Constr. (2)	Trade Service (3)	Other (4)	Manuf. (5)	Constr. (6)	Trade Service (7)	Other (8)
$Exposure_b * Post_\tau$	0.0548*	-0.0793	0.0321	-0.0191	-0.260***	-0.134**	-0.190***	-0.188***
	(0.0322)	(0.108)	(0.0865)	(0.0330)	(0.0252)	(0.0592)	(0.0471)	(0.0308)
Firm-period F.E.	✓	✓	✓	✓	✓	✓	✓	✓
Bank F.E.	✓	✓	✓	✓	✓	✓	✓	✓
Specialization	✓	✓	✓	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	358,591	115,188	234,597	188,242	358,591	115,188	234,597	188,242
$Adj.R^2$	0.337	0.316	0.328	0.328	0.340	0.354	0.345	0.357

Note: The table reports the coefficients of the extensive margin specification in Equation 2, where we divide the sample by firms' macro sectors. The dependent variable is a dummy that takes the value of 1 if firm i starts (entry) or ends (exit) a credit relation with bank b in period τ=1998-2002, 2002-07. The variable $Exposure_b$ captures bank exposure to foreign capital flows, defined as the foreign liability ratio over the period 1998-2000. Specialization is a time-varying dummy that captures if a firm operates in a sector in which the bank specializes its lending activities. Bank controls include bank characteristics measured in 1998-2000 interacted with a post-2002 dummy: log-assets, share of NPLs, core-funding ratio, and the capital ratio. Standard errors are clustered at the bank-sector (2-digit) level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 9: Capital inflows and credit allocation by industry, aggregate effect

	Dependent variable: ln $Credit_{it}$			
	Manufacturing (1)	Construction (2)	Trade Service (3)	Other (4)
$Exposure_b \times Post_t$	0.24***	0.11	0.05	0.42***
	(0.07)	(0.15)	(0.09)	(0.11)
Estimated firm-time F.E.	✓	✓	✓	✓
Firm F.E.	✓	✓	✓	✓
Sector-time F.E.	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓
Observations	504,261	129,812	317,217	218,134
$Adj.R^2$	0.90	0.87	0.91	0.91

Note: The table reports the coefficients of the baseline specification in Equation 1, where we divide the sample by firms' macro sectors. The dependent variable, $\ln C_{it}$, is the log of outstanding credit of firm i in year t. The variable $Exposure_i$ is the weighted average of exposure to foreign capital inflows of firm's i lenders in the period 1998-2000 as defined in Equation 3. Specialization is a time-varying dummy that captures if a firm operates in a sector in which the bank specializes its lending activities. Bank controls are a weighted average of firm's i lenders' characteristics measured in 1998-2000, interacted with a post-2002 dummy: log-assets, share of NPLs, core-funding ratio, and the capital ratio. All regressions include sector-year fixed effects and firm dummies, and the firm-time fixed effects computed in the intensive margin regression. Standard errors are bootstrapped with clusters at the sector-main bank level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level. .

Table 10: Capital inflows and credit allocation by firm characteristics, intensive margin

	Dependent variable: ln $Credit_{ibt}$				
Firm characteristic D_i:	MRPK	TFPR	Fixed Assets	MRPK / Fixed Assets	TFPR / Fixed Assets
Ind. var.: $Exposure_b * Post_t * D_i$	(1)	(2)	(3)	(4)	(5)
High	0.436***	0.460***	0.448***		
	(0.077)	(0.067)	(0.065)		
Low	0.343***	0.262***	0.253***		
	(0.065)	(0.066)	(0.067)		
High P - High FA				0.524***	0.478***
				(0.084)	(0.068)
Low P - High FA				0.358***	0.334***
				(0.066)	(0.07)
High P - Low FA				0.240***	0.352***
				(0.076)	(0.086)
Low P - Low FA				0.113	0.122
				(0.081)	(0.074)
Firm-time F.E.	✓	✓	✓	✓	✓
Firm-bank F.E.	✓	✓	✓	✓	✓
Specialization	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓
Observations	2,689,020	3,183,909	3,183,909	2,689,020	3,183,909
$Adj.R^2$	0.90	0.90	0.90	0.90	0.90

Note: The dependent variable is the log of outstanding credit between bank b and firm i in year t, , $\ln C_{ibt}$,. The variable $Exposure_b$ captures bank exposure to foreign capital flows, defined as the foreign liability ratio over the period 1998-2000. Specialization is a time-varying dummy that captures if a firm operates in a sector in which the bank specializes its lending activities. Bank controls include bank characteristics measured in 1998-2000 interacted with a post-2002 dummy: log-assets, share of NPLs, core-funding ratio, and the capital ratio. Standard errors are clustered at the bank-sector (2-digit) level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 11: Capital inflows and bank-firm relation by firm characteristics, extensive margin

	Dependent variable:					
	$Exit_{ib\tau}$			$Entry_{ib\tau}$		
Firm characteristic D_i:	MRPK	Fixed Assets	MRPK/ Fixed Assets	MRPK	Fixed Assets	MRPK / Fixed Assets
$Exposure_b * Post_\tau * D_i$	(1)	(2)	(3)	(4)	(5)	(6)
High	-0.14***	-0.162***		0.221***	0.125***	
	(0.028)	(0.030)		(0.035)	(0.029)	
Low	-0.070***	0.026		0.162***	0.365***	
	(0.028)	(0.027)		(0.033)	(0.037)	
High P - High FA			-0.223***			0.100***
			(0.030)			(0.035)
Low P - High FA			-0.100***			0.136***
			(0.029)			(0.034)
High P - Low FA			0.00			0.368***
			(0.033)			(0.043)
Low P - Low FA			0.113***			0.345***
			(0.040)			(0.049)
Firm-period F.E.	✓	✓	✓	✓	✓	✓
Bank F.E.	✓	✓	✓	✓	✓	✓
Specialization	✓	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓	✓
Observations	766,654	841,324	766,654	766,654	841,324	766,654
$Adj.R^2$	0.55	0.55	0.55	0.45	0.46	0.46

Note: The table reports the coefficients of the specification on misallocation on the extensive margin in the context of specification in Equation 2. The dependent variable is a dummy that takes the value of 1 if firm i starts (entry) or ends (exit) a credit relation with bank b in period τ=1998-2002, 2002-07. We show the results of bank exposure to foreign capital flows by firm types, where firms are divided along a productivity dimension (above and below the sectoral average) and credit constraint (fixed assets above and below the sectoral average). Specialization is a time-varying dummy that captures if a firm operates in a sector in which the bank specializes its lending activities. Bank controls include bank characteristics measured in 1998-2000 interacted with a post-2002 dummy: log-assets, share of NPLs, core-funding ratio, and the capital ratio. All regressions include firm-period fixed effects and bank dummies. Standard errors are clustered at the bank-sector (2-digit) level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 12: Capital inflows and credit allocation by firm characteristics, aggregate credit

	Dependent variable: $\ln\ Credit_{it}$				
Firm characteristic D_i:	MRPK	TFPR	Fixed Assets	MRPK / Fixed Assets	TFPR / Fixed Assets
Ind. var.: $Exposure_i * Post_t * D_i$	(1)	(2)	(3)	(4)	(5)
High	0.346***	0.293***	0.311***		
	(0.068)	(0.061)	(0.062)		
Low	0.220***	0.170***	0.155***		
	(0.061)	(0.062)	(0.061)		
High P - High FA				0.497***	0.340***
				(0.082)	(0.068)
Low P - High FA				0.223***	0.215***
				(0.075)	(0.073)
High P - Low FA				0.144**	0.260***
				(0.072)	(0.073)
Low P - Low FA				0.105	0.040
				(0.10)	(0.071)
Est. Firm-time F.E.	✓	✓	✓	✓	✓
Firm F.E.	✓	✓	✓	✓	✓
Sector-time F.E.	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓
Observations	743,522	886,227	886,227	743,522	886,227
$Adj.R^2$	0.92	0.92	0.92	0.92	0.92

Note: The table reports the coefficients of the specification on misallocation on aggregate credit. The dependent variable, $\ln C_{it}$, is the log of outstanding credit of firm i in year t. We show the results of firm exposure to foreign capital flows according to the exposure of the banks they are borrowing from, as defined in Equation 3. Firms are divided along a productivity dimension (above and below the sectoral average) and credit constraint (fixed assets above and below the sectoral average). Bank controls include bank characteristics pre-2001 interacted with a post-2001 dummy: log-assets, share of NPLs, core-funding ratio, and the capital ratio. All regressions include sector-year fixed effects and firm dummies, and the firm-time fixed effects estimated in the intensive margin regression. Standard errors are bootstrapped with clusters at the sector-main bank level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 13: Capital inflows and household lending

	Dependent variable: $\ln Household\ credit_{pbt}$		
$Exposure_b$:	Continuos (1)	Dummy 10% (2)	Dummy 15% (3)
$Exposure_b \times Post_t$	0.086	-0.043*	-0.013
	(0.068)	(0.024)	(0.021)
Province-Year F.E..	✓	✓	✓
Province-BankF.E.	✓	✓	✓
Bank Controls	✓	✓	✓
Observations	128,904	128,904	128,904
$Adj.R^2$	0.97	0.97	0.97

Note: The table reports the coefficients of the specification in Equation 6. The dependent variable is household lending by bank b in province p at time t. The variable $Exposure_b$ captures bank exposure to foreign capital flows, defined as the foreign liability ratio over the period 1998-2000. Bank controls include bank characteristics pre-2001 interacted with the post-dummies: log-assets, share of NPLs, core-funding ratio, and the capital ratio. All regressions include province-year fixed effects, bank-province fixed effects and bank controls. Standard errors are clustered at the province level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 14: Capital inflows and MRPK convergence

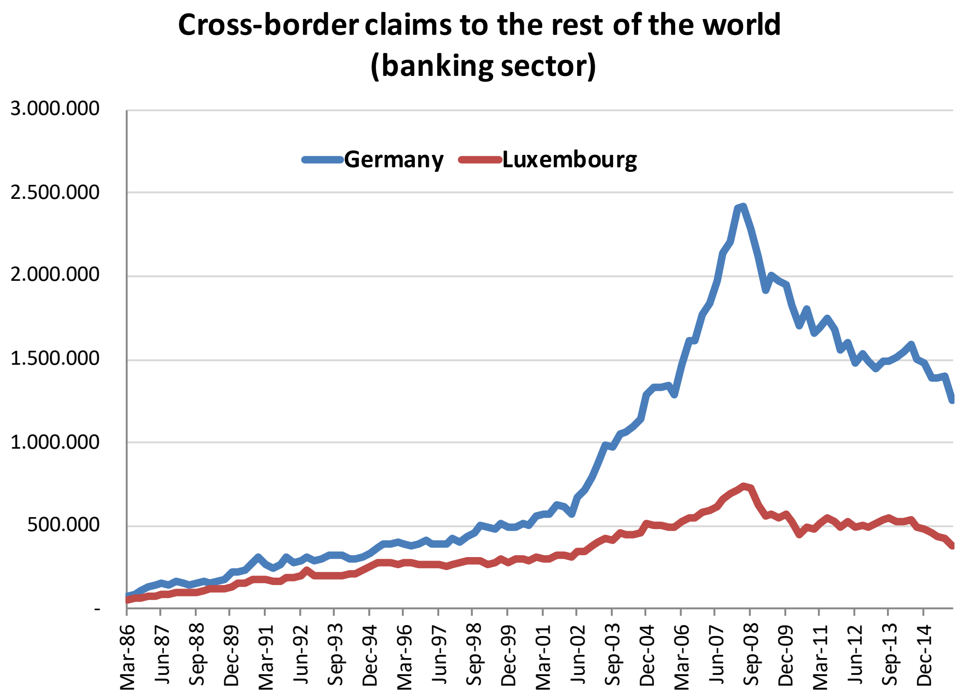
	Dependent variable: $\ln MRPK_{it}$		
	Full sample (1)	High MRPK-pre (2)	Low MRPK-pre (3)
$Exposure_i * Post_t$	-0.20 (.16)	-0.69** (0.33)	-0.01 (0.09)
Firm F.E.	✓	✓	✓
Sector-time F.E.	✓	✓	✓
Bank Controls	✓	✓	✓
Observations	683,136	357,865	325,271
$Adj.R^2$	0.72	0.73	0.41

Note: The table reports the coefficients of the specification $\ln MRPK_{ist} = \beta_1\ Exposure\ Firm_i \times Post_t + \boldsymbol{X_i'\delta} \times Post_t + \gamma_i + \delta_{st} + \epsilon_{ist}$. The dependent variable, $\ln MRPK_{it}$, is the log of the marginal product of firm i in year t. The variable $Exposure_i$ is the weighted average of exposure to foreign capital inflows of firm's i lenders in the period 1998-2000, as defined in Equation 3. X_i is a vector of the weighted average of the lender pre-2001 characaterstics: log-assets, share of NPLs, core-funding ratio, and the capital ratio. All regressions include sector-year fixed effects and firm dummies. Standard errors are clustered at the sector-main bank level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

For Online Publication - Appendix

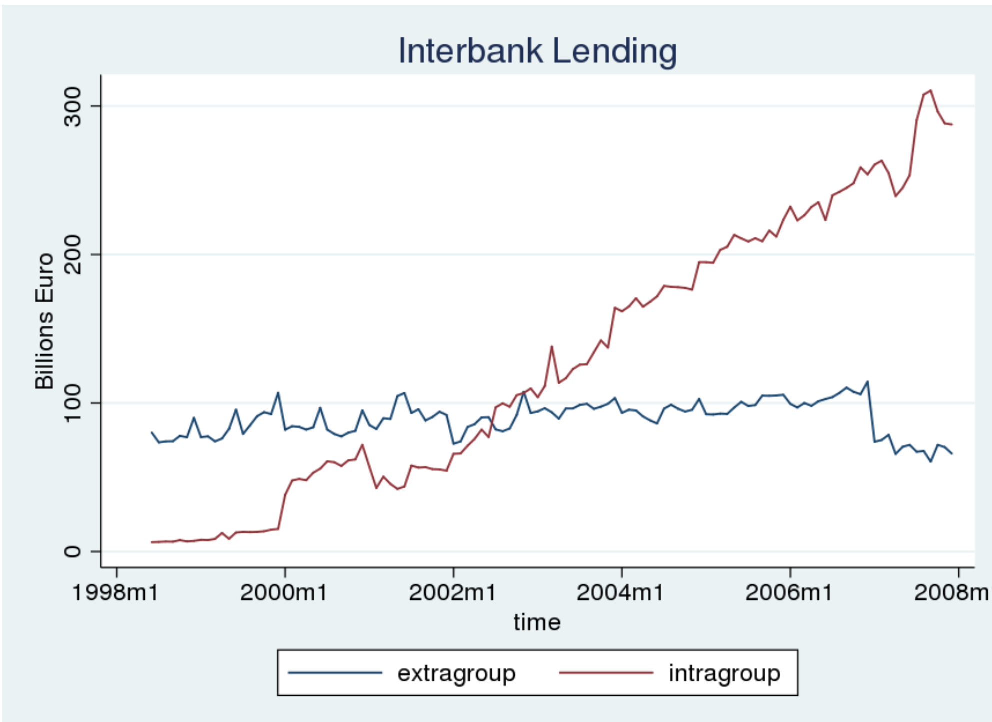
A.1 Additional figures

Figure 6: Capital outflows by banks operating in Germany and Luxembourg



Source: BIS. Foreign claims of banks located in Germany and Luxembourg to the banks located in the rest of the world (nominal USD).

Figure 7: Interbank lending between and within groups



The Figure reports the evolution of the interbank lending at monthly frequency between 1998 and 2007 across and within banking groups. It shows that interbank lending raised mainly within banking groups and not much across groups.

A.2 Robustness tables

In this section we report the robustness results discussed in Section 7. Below, we describe the specifications of Tables A1-A4, which were briefly introduced in Section 7. Whereas Sections 7.1-7.5 provide a detailed discussion of Tables A6-A12.

Table A1 reports the coefficients of the baseline specification in Equation 5 using a balanced panel of firm-bank relations.

Table A2 reports the coefficients of a first-difference transformation of the diff-in-diff specification in Equation 5: $\Delta \ \ln C_{ib} = \sum_{d=1}^{4} \beta_d \, D_{di} \times Exposure_b + \beta_2 \, \Delta \, Spec_{ib} + \boldsymbol{X_b'} \boldsymbol{\delta} + \alpha_i + \epsilon_{ib}$

Table A3 looks at credit allocation by firms' characteristics using a continuous measure of firm-level productivity and collateral (rather than an indicator variable if the firm is above or below median). We run the baseline specification in Equation 5 adding an interaction term between bank-level exposure and firm-level ex-ante characteristics.

Table A4 reports the coefficients of the baseline specification in Equation 5, but firms' characteristics are computed based on their 2002-2007 average.

Table A5 reports the coefficients of the baseline specification in Equation 5 with bank-time fixed effects: $\ln C_{ibt} = \sum_{d=1}^{3} \beta_d \, D_{di} \times Exposure_b \times Post_t + \beta_2 \, Spec_{ibt} + \alpha_{it} + \gamma_{ib} + \mu_{bt} + \epsilon_{ibt}$. Given the presence of bank-time fixed effects, we need to omit a category, which is low-productivity & low-collateral, so the coefficients should be interpreted as the marginal difference with respect to the excluded category. Moreover, we no longer have the ex-ante bank controls times the post dummy, as these are absorbed by the bank-year fixed effects.

Table A1: Capital inflows and credit allocation by firm characteristics, balanced panel

	Dependent variable: ln $Credit_{ibt}$				
Firm characteristic D_i:	MRPK	TFPR	Fixed Assets	MRPK / Fixed Assets	TFPR / Fixed Assets
Ind. var.: $Exposure_b * Post_t * D_i$	(1)	(2)	(3)	(4)	(5)
High	0.48***	0.48***	0.45***		
	(0.08)	(0.07)	(0.07)		
Low	0.37***	0.30***	0.29***		
	(0.07)	(0.08)	(0.08)		
High P - High FA				0.66***	0.48***
				(0.08)	(0.07)
Low P - High FA				0.40***	0.45***
				(0.08)	(0.08)
High P - Low FA				0.30***	0.37***
				(0.08)	(0.09)
Low P - Low FA				0.18*	0.11
				(0.10)	(0.09)
Firm-time F.E.	✓	✓	✓	✓	✓
Firm-bank F.E.	✓	✓	✓	✓	✓
Specialization	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓
Observations	1,307,788	1,491,312	1,491,312	1,307,788	1,491,312
$Adj.R^2$	0.83	0.83	0.83	0.83	0.83

Note: The table reports the coefficients of the specification in Equation 5 using a balanced panel of firm-bank relations. The dependent variable, $\ln C_{ibt}$, is the log of outstanding credit between bank b and firm i in year t. $Exposure_b$ captures bank exposure to foreign capital flows, defined as the foreign liability ratio over the period 1998-2000. Specialization is a time-varying dummy that captures if a firm operates in a sector in which the bank specializes its lending activities. Bank controls include bank characteristics measure in 1998-2000 interacted with a post-2002 dummy: log-assets, share of NPLs, core-funding ratio, and the capital ratio. All regressions include firm-year fixed effects and firm-bank dummies. Standard errors are clustered at the bank-sector (2-digit) level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A2: Capital inflows and credit allocation by firm characteristics, first difference

	Dependent variable: $\Delta \ln Credit_{ib}$				
Firm characteristic D_i:	MRPK	TFPR	Fixed Assets	MRPK / Fixed Assets	TFPR / Fixed Assets
Ind. var.: $Exposure_b * D_i$	(1)	(2)	(3)	(4)	(5)
High	0.055***	0.048***	0.043***		
	(0.007)	(0.009)	(0.008)		
Low	0.031***	0.015	0.017*		
	(0.007)	(0.009)	(0.009)		
High P - High FA				0.066***	0.051***
				(0.008)	(0.009)
Low P - High FA				0.034***	0.019*
				(0.007)	(0.01)
High P - Low FA				0.027***	0.030***
				(0.008)	(0.01)
Low P - Low FA				-0.007	0.003
				(0.01)	(0.01)
Firm-F.E.	✓	✓	✓	✓	✓
Specialization	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓
Observations	249,687	334,319	332,656	248,574	332,656
$Adj.R^2$	0.43	0.43	0.43	0.43	0.43

Note: The table reports the coefficients of Equation 5 estimated in first difference as $\Delta \ \ln C_{ib} = \sum_{d=1}^{4} \beta_d \, D_{di} \times Exposure_b + \beta_2 \, \Delta \, Spec_{ib} + \boldsymbol{X_b'\delta} + \alpha_i + \epsilon_{ib}$. The dependent variable $\Delta \ln C_{ib}$ is the difference between the post (2002-2007) and pre (1998-2001) period of the log of outstanding credit between bank b and firm i. We show the results of bank exposure to foreign capital flows by firm types, where firms are divided along a productivity dimension (above and below the sectoral average) and credit constraint (fixed assets above and below the sectoral average). $Exposure_b$ captures bank exposure to foreign capital flows, defined as the foreign liability ratio over the period 1998-2000. Specialization is a time-varying dummy that captures if a firm operates in a sector in which the bank specializes its lending activities. Bank controls include bank characteristics measure in 1998-2000 interacted with a post-2002 dummy: log-assets, share of NPLs, core-funding ratio, and the capital ratio. All regressions include firm-year fixed effects and firm-bank dummies. Standard errors are clustered at the bank-sector (2-digit) level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A3: Capital inflows and credit allocation by continuous measures of firm characteristics

	Dependent variable: $\ln Credit_{ibt}$				
Firm characteristic D_i:	MRPK (1)	TFPR (2)	Fixed Assets (3)	D_i: MRPK / F_i: Fixed Assets (4)	D_i: TFPR / F_i: Fixed Assets (5)
$Exposure_b * Post_t$:	0.37***	0.33***	0.03	-0.01	-0.19*
	(0.06)	(0.06)	(0.10)	(0.11)	(0.11)
$Exposure_b * Post_t * D_i$:	0.02**	0.06***	0.06***	0.05***	0.14***
	(0.009)	(0.008)	(0.01)	(0.01)	(0.03)
$Exposure_b * Post_t * F_i$				0.05***	0.08***
				(0.01)	(0.01)
$Exposure_b * Post_t * D_i * F_i$				-0.01**	-0.004
				(0.005)	(0.002)
Firm-time F.E.	✓	✓	✓	✓	✓
Firm-bank F.E.	✓	✓	✓	✓	✓
Specialization	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓
Observations	2,689,020	3,183,909	3,183,909	2,689,020	3,183,909
$Adj.R^2$	0.83	0.83	0.83	0.83	0.83

Note: The table reports the coefficients of the specification Equation 1 adding an interaction term with ex-ante firm-level characteristics (MRPK, TFPR, and fixed assets). The dependent variable, $\ln C_{ibt}$, is the log of outstanding credit between bank b and firm i in year t. $Exposure_b$ captures bank exposure to foreign capital flows, defined as the foreign liability ratio over the period 1998-2000. Specialization is a time-varying dummy that captures if a firm operates in a sector in which the bank specializes its lending activities. Bank controls include bank characteristics measure in 1998-2000 interacted with a post-2002 dummy: log-assets, share of NPLs, core-funding ratio, and the capital ratio. All regressions include firm-year fixed effects and firm-bank dummies. Standard errors are clustered at the bank-sector (2-digit) level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A4: Capital inflows and credit allocation by post-2002 firm characteristics

	Dependent variable: ln $Credit_{ibt}$				
Firm characteristic D_i^{02-07}:	MRPK	TFPR	Fixed Assets	MRPK / Fixed Assets	TFPR / Fixed Assets
Ind. var.: $Exposure_b * Post_t * D_i^{02-07}$	(1)	(2)	(3)	(4)	(5)
High$^{02-07}$	0.49***	0.50***	0.46***		
	(0.08)	(0.07)	(0.07)		
Low$^{02-07}$	0.37***	0.23***	0.19***		
	(0.06)	(0.07)	(0.06)		
High P - High FA $^{02-07}$				0.60***	0.52***
				(0.10)	(0.06)
Low P - High FA $^{02-07}$				0.42***	0.29***
				(0.06)	(0.07)
High P - Low FA $^{02-07}$				0.27***	0.28***
				(0.08)	(0.06)
Low P - Low FA $^{02-07}$				0.08	0.07
				(0.06)	(0.07)
Firm-time F.E.	✓	✓	✓	✓	✓
Firm-bank F.E.	✓	✓	✓	✓	✓
Specialization	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓
Observations	2,628,302	2,894,797	2,894,797	2,628,302	2,894,797
$Adj.R^2$	0.83	0.83	0.83	0.83	0.83

Note: The table reports the coefficients of the specification similar to Equation 5, where firms' are grouped according to their characteristics in the 2002-07 period. The dependent variable, $\ln C_{ibt}$, is the log of outstanding credit between bank b and firm i in year t. We show the results of bank exposure to foreign capital flows by firm types, where firms are divided along a productivity dimension (above and below the sectoral average) and credit constraint (fixed assets above and below the sectoral average). The variable $Exposure_b$ captures bank exposure to foreign capital flows, defined as the foreign liability ratio over the period 1998-2000. Specialization is a time-varying dummy that captures if a firm operates in a sector in which the bank specializes its lending activities. Bank controls include bank characteristics measure in 1998-2000 interacted with a post-2002 dummy: log-assets, share of NPLs, core-funding ratio, and the capital ratio. All regressions include firm-year fixed effects and firm-bank dummies. Standard errors are clustered at the bank-sector (2-digit) level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A5: Capital inflows and credit allocation by firm characteristics, adding bank-time fixed effects

	Dependent variable: ln $Credit_{ibt}$				
Firm characteristic D_i:	MRPK	TFPR	Fixed Assets	MRPK / Fixed Assets	TFPR / Fixed Assets
Ind. var.: $Exposure_b * Post_t * D_i$	(1)	(2)	(3)	(4)	(5)
High	0.135***	0.228***	0.236***		
	(0.04)	(0.04)	(0.04)		
Low	-	-	-		
High P - High FA				0.562***	0.381***
				(0.064)	(0.050)
Low P - High FA				0.366***	0.193***
				(0.062)	(0.51)
High P - Low FA				0.233***	0.197***
				(0.058)	(0.052)
Low P - Low FA				-	-
Firm-time F.E.	✓	✓	✓	✓	✓
Bank-time F.E.	✓	✓	✓	✓	✓
Firm-bank F.E.	✓	✓	✓	✓	✓
Specialization	✓	✓	✓	✓	✓
Observations	2,689,020	3,183,909	3,183,909	2,689,020	3,183,909
$Adj.R^2$	0.90	0.90	0.90	0.90	0.90

Note: The table reports the coefficients of the specification in Equation 5 with the addition of bank-time fixed effects. The dependent variable, $\ln C_{ibt}$, is the log of outstanding credit between bank b and firm i in year t. We show the results of bank exposure to foreign capital flows by firm types, where firms are divided along a productivity dimension (above and below the sectoral average) and credit constraint (fixed assets above and below the sectoral average), the Low-Productivity and Low-Collateral are the excluded categories. The variable $Exposure_b$ captures bank exposure to foreign capital flows, defined as the foreign liability ratio over the period 1998-2000. Specialization is a time-varying dummy that captures if a firm operates in a sector in which the bank specializes its lending activities. All regressions include firm-year fixed effects and firm-bank dummies. Standard errors are clustered at the bank-sector (2-digit) level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A6: Capital inflows and credit supply, potential confounding factors

	Dependent variable: ln $Credit_{ibt}$				
Confounding:	Baseline (1)	Securitization (2)	Recession (3)	China (4)	All (5)
$Exposure_b \times Post_t$	0.40***	0.383***	0.424***	0.397***	0.411***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
$Securitization\ Share_b \times Post_t$		-2.02***			-1.8***
		(0.30)			(0.32)
$Recession\ Share_b \times Post_t$			-0.427***		-0.379***
			(0.07)		(0.12)
$China\ Share_b \times Post_t$				-0.142***	-0.04
				(0.03)	(0.11)
Firm-time F.E.	✓	✓	✓	✓	✓
Firm-bank F.E.	✓	✓	✓	✓	✓
Specialization	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓
Observations	4,141,748	4,059,984	4,059,984	4,059,984	4,059,984
$Adj.R^2$	0.82	0.82	0.83	0.83	0.83

Note: The table reports the coefficients of the baseline specification in Equation 1 with additional controls for potential confounding factors. The dependent variable, $\ln C_{ibt}$, is the log of outstanding credit between bank b and firm i in year t. $Exposure_b$ captures bank exposure to foreign capital flows, defined as the foreign liability ratio over the period 1998-2000. Specialization is a time-varying dummy that captures if a firm operates in a sector in which the bank specializes its lending activities. Bank controls include bank characteristics measure in 1998-2000 interacted with a post-2002 dummy: log-assets, share of NPLs, core-funding ratio, and the capital ratio. All regressions include firm-year fixed effects and firm-bank dummies. Standard errors are clustered at the bank-sector (2-digit) level. Column 1 reports the baseline results; column 2 accounts for the share of securitized loans that banks made in 2001; column 3 controls for the share of loans in 1998-2000 to sectors that experienced a recession in 2001-02; column 4 controls for the share of loans in 1998-2000 to sectors that turned out to be more exposed to competition from China after its access in the WTO; column 5 includes all the robustness controls at the same time. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A7: Capital inflows and credit allocation by firm characteristics, shift-share measure of bank exposure

	Dependent variable: ln $Credit_{ibt}$				
Firm characteristic: D_i	MRPK	TFPR	Fixed Assets	MRPK / Fixed Assets	TFPR / Fixed Assets
Ind. var.: $Exposure_b^{Geo} * Post_t * D_i$	(1)	(2)	(3)	(4)	(5)
High	0.151***	0.142***	0.135***		
	(0.007)	(0.006)	(0.006)		
Low	0.112***	0.092***	0.099***		
	(0.007)	(0.007)	(0.007)		
High P - High FA				0.170***	0.145***
				(0.008)	(0.006)
Low P - High FA				0.122***	0.103***
				(0.008)	(0.008)
High P - Low FA				0.109***	0.123***
				(0.009)	(0.008)
Low P - Low FA				0.061***	0.074***
				(0.012)	(0.009)
Firm-time F.E.	✓	✓	✓	✓	✓
Firm-bank F.E.	✓	✓	✓	✓	✓
Specialization	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓
Observations	2,689,020	3,183,909	3,183,909	2,689,020	3,183,909
$Adj.R^2$	0.90	0.90	0.90	0.90	0.90

Note: The table reports the coefficients of the specification in Equation 5 with and alternative measure of bank exposure. The dependent variable, $\ln C_{ibt}$, is the log of outstanding credit between bank b and firm i in year t. We show the results of bank exposure to foreign capital flows by firm types, where firms are divided along a productivity dimension (above and below the sectoral average) and credit constraint (fixed assets above and below the sectoral average), the Low-Productivity and Low-Collateral are the excluded categories. Bank exposure is defined as $Exposure_b^{Geo} = \sum_c \omega_{bc}\, \Delta World\ Outflows_c^{post-pre}$, where $\Delta World\ Outflows_c^{post-pre}$ is the change of outstanding claims of the banks of country c towards the rest of the world, excluding Italy, in the period before and after 2002; ω_{bc} is the share of inflows of bank b from country c in the 1998-2000 period. Specialization is a time-varying dummy that captures if a firm operates in a sector in which the bank specializes its lending activities. Bank controls include bank characteristics measure in 1998-2000 interacted with a post-2002 dummy: log-assets, share of NPLs, core-funding ratio, and the capital ratio. All regressions include firm-year fixed effects and firm-bank dummies. Standard errors are clustered at the bank-sector (2-digit) level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A8: Capital inflows and credit allocation by firm characteristics, bank exposure to a time-varying measure capital inflows driven by push-factors

	Dependent variable: ln $Credit_{ibt}$				
Firm characteristic: D_i	MRPK	TFPR	Fixed Assets	MRPK / Fixed Assets	TFPR / Fixed Assets
Ind. var.: $Exposure_b * \hat{\lambda}_1 \Delta \ln KF_t^{World} * D_i$	(1)	(2)	(3)	(4)	(5)
High	0.400***	0.416***	0.393***		
	(.020)	(0.017)	(0.017)		
Low	0.310***	0.240***	0.260***		
	(0.022)	(0.022)	(0.023)		
High P - High FA				0.518***	0.433***
				(0.029)	(0.019)
Low P - High FA				0.356***	0.274***
				(0.023)	(0.029)
High P - Low FA				0.309***	0.334***
				(0.029)	(0.032)
Low P - Low FA				0.126***	0.185
				(0.046)	(0.031)
Firm-time F.E.	✓	✓	✓	✓	✓
Firm-bank F.E.	✓	✓	✓	✓	✓
Specialization	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓
Observations	2,689,020	3,183,909	3,183,909	2,689,020	3,183,909
$Adj.R^2$	0.90	0.90	0.90	0.90	0.90

Note: The table reports the coefficients of the specification in Equation 10 with an alternative measure of bank exposure. The dependent variable, $\ln C_{ibt}$, is the log of outstanding credit between bank b and firm i in year t. We show the results of bank exposure to foreign capital flows by firm types, where firms are divided along a productivity dimension (above and below the sectoral average) and credit constraint (fixed assets above and below the sectoral average). The variable $Exposure_b$ is the foreign liability ratio over the period 1998-2000 and it is interacted with a measure of capital inflows to Italy in year t driven by push-factors, as estimated in Equation 9. Specialization is a time-varying dummy that captures if a firm operates in a sector in which the bank specializes its lending activities. Bank controls include bank characteristics measure in 1998-2000 interacted with a post-2002 dummy: log-assets, share of NPLs, core-funding ratio, and the capital ratio. All regressions include firm-year fixed effects and firm-bank dummies. Standard errors are clustered at the bank-sector (2-digit) level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A9: Capital inflows and credit allocation by alternative measure of firm risk and productivity

	Dependent variable: ln $Credit_{ibt}$		
Firm characteristic: D_i	P: MRPK	P: TFPR	P: Labor prod.
Ind. var.: $Exposure_b * Post_t * D_i$	R: Credit score	R: Credit score	R: Fixed assets*
High P - Low R	0.51***	0.482***	0.513***
	(0.06)	(0.067)	(0.07)
Low P - Low R	0.38***	0.299***	0.279***
	(0.06)	(0.067)	(0.063)
High P - High R	0.35***	0.285***	0.299***
	(0.09)	(0.086)	(0.09)
Low P - High R	0.066	0.088	0.079
	(0.09)	(0.07)	(0.091)
Firm-time F.E.	✓	✓	✓
Firm-bank F.E.	✓	✓	✓
Specialization	✓	✓	✓
Bank Control	✓	✓	✓
Observations	2,689,020	3,183,909	3,151,375
$Adj.R^2$	0.90	0.90	0.90

Note: The table reports the coefficients of the specification in Equation 5 using alternative definitions of firm credit constraint and productivity. The dependent variable, $\ln C_{ibt}$, is the log of outstanding credit between bank b and firm i in year t. We show the results of bank exposure to foreign capital flows by firm characteristics (above or below their sectoral average), looking at productivity as MRPK (column 1), TFPR (column 2) and value added per worker (column 3), and credit constraint using credit score (columns 1 and 2) and fixed assets (column 3, where low R is associated with high fixed assets). The variable $Exposure_b$ captures bank exposure to foreign capital flows, defined as the foreign liability ratio over the period 1998-2000. Specialization is a time-varying dummy that captures if a firm operates in a sector in which the bank specializes its lending activities. Bank controls include bank characteristics measure in 1998-2000 interacted with a post-2002 dummy: log-assets, share of NPLs, core-funding ratio, and the capital ratio. All regressions include firm-year fixed effects and firm-bank dummies. Standard errors are clustered at the bank-sector (2-digit) level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A10: Capital inflows and credit allocation by lagged firm characteristics

	Dependent variable: ln $Credit_{ibt}$				
Firm characteristic D_i:	MRPK	TFPR	Fixed Assets	MRPK / Fixed Assets	TFPR / Fixed Assets
Ind. var.: $Exposure_b * Post_t * D_{it-1}$	(1)	(2)	(3)	(4)	(5)
High_{t-1}	0.492***	0.496***	0.462***		
	(.064)	(0.068)	(0.065)		
Low_{t-1}	0.339***	0.255***	0.237***		
	(0.062)	(0.069)	(0.063)		
High P - High FA_{t-1}				0.589***	0.528***
				(0.048)	(0.038)
Low P - High FA_{t-1}				0.369***	0.327***
				(0.047)	(0.044)
High P - Low FA_{t-1}				0.242***	0.337***
				(0.049)	(0.043)
Low P - Low FA_{t-1}				0.153***	0.115**
				(0.053)	(0.045)
Firm-time F.E.	✓	✓	✓	✓	✓
Firm-bank F.E.	✓	✓	✓	✓	✓
Specialization	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓
Observations	2,585,734	3,016,942	3,016,942	2,585,734	3,016,942
$Adj.R^2$	0.90	0.90	0.90	0.90	0.90

Note: The table reports the coefficients of the specification $\ln C_{ibt} = \sum_{d=1}^{4} \beta_d \, D_{dit-1} \times Exposure_b \times Post_t + \beta_2 \, Spec_{ibt} + \boldsymbol{X_b'\delta} \times Post_t + \alpha_{it} + \gamma_{ib} + \epsilon_{ibt}$. The dependent variable, $\ln C_{ibt}$, is the log of outstanding credit between bank b and firm i in year t. We show the results of bank exposure to foreign capital flows by firm types, where, for each $t-1$ year, firms are divided along a productivity dimension (above and below the sectoral average) and credit constraint (fixed assets above and below the sectoral average). The variable $Exposure_b$ captures bank exposure to foreign capital flows, defined as the foreign liability ratio over the period 1998-2000. Specialization is a time-varying dummy that captures if a firm operates in a sector in which the bank specializes its lending activities. Bank controls include bank characteristics measure in 1998-2000 interacted with a post-2002 dummy: log-assets, share of NPLs, core-funding ratio, and the capital ratio. All regressions include firm-year fixed effects and firm-bank dummies. Standard errors are clustered at the bank-sector (2-digit) level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A11: Spillover effects across banks, a balance sheet analysis

Dependent variable Y_{bt}:	Interbank lending (1)	Bonds & equity holdings (2)	Deposits (3)	Share of deposits (4)
$Exposure_b \times Post_t$	-1.92***	-0.36	0.21	-0.0003
	(0.45)	(1.07)	(0.40)	(0.0003)
Bank controls	✓	✓	✓	✓
Bank F.E.	✓	✓	✓	✓
Time F.E.	✓	✓	✓	✓
Observations	5,326	5,167	5,552	5,720
$Adj.R^2$	0.90	0.90	0.93	0.99

Note: The table reports the coefficients of the specification in Equation 11. The dependent variable is the log of domestic interbank-lending (column 1); the log of bonds and equity holdings of other financial institutions (column 2); the log of deposits (column 3); and the share of the total deposit in the economy (column 4). The variable $Exposure_b$ captures bank exposure to foreign capital flows, defined as the foreign liability ratio over the period 1998-2000. Bank controls include bank characteristics measured in 1998-2000 interacted with a post-2002 dummy. All regressions include bank fixed effects and year dummies. Standard errors are clustered at the bank level. ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A12: Bank exposure to capital inflows and post-2008 fragility

	Bank level regression		Bank-firm level regression	
Dependent variable:	*NPL ratio*$_{bt}$		*Credit*$_{ibt}$	
Bank Exposure:	Continuos	Dummy 15%	Continuos	Dummy 15%
	(1)	(2)	(3)	(4)
$Exposure_b \times Post_t^{2002}$	0.02	-0.001	0.23***	0.05***
	(0.02)	(0.004)	(0.06)	(0.004)
$Exposure_b \times Post_t^{2008}$	0.03	0.008	0.25***	0.04***
	(0.02)	(0.012)	(0.05)	(0.007)
Bank F.E.	✓	✓		
Year F.E.	✓	✓		
Firm-time F.E.			✓	✓
Firm-bank F.E.			✓	✓
Specialization			✓	✓
Bank Controls	✓	✓	✓	✓
Observations	5,846	5,846	7,494,518	7,494,518
$Adj.R^2$	0.62	0.62	0.84	0.84

Note: In columns 1 and 2 we report the results of the bank level regression $NPL\ Ratio_{bt} = \beta_1\ Exposure_b \times Post_t^{2002-07} + \beta_2\ Exp_b \times Post_t^{2008-13} + \boldsymbol{X_b'\delta} \times Post_t + \gamma_b + \alpha_t + \epsilon_{bt}$. In columns 3 and 4 we report the results of the bank-firm level regression $\ln C_{ibt} = \beta_1\ Exposure_b \times Post_t^{2002-07} + \beta_2\ Exposure_b \times Post_t^{2008-13} + \beta_3\ Spec_{ibt} + \boldsymbol{X_b'\delta} \times Post_t^{2002-07} + \boldsymbol{X_b'\delta} \times Post_t^{2008-13} + \alpha_{it} + \gamma_{ib} + \epsilon_{ibt}$. Standard errors are clustered at the bank level (columns 1 and 2) and at the bank-sector (2-digit) level (columns 3 and 4). ***significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

A.3 The Hsieh-Klenow framework to compute aggregate TFP gains

In Hsieh and Klenow (2009) misallocation and inefficiency are defined relative to a world where there are no frictions in product and factors markets, so that the value of the marginal product of each factor is equalized across firms. This is an equilibrium because firms have no incentive to change their production decisions. Moreover, it is a stable equilibrium as any exogenous shock that creates dispersion in factors' marginal product across firms would trigger a reallocation of that factor until its remuneration is again equalized across firms.

They use a standard model of monopolistic competition with heterogenous firms with different TFPQ levels A_i. Each firm combines capital and labor to produce a single good using a Cobb-Douglas technology. All firms face the same factor prices, but they are subject to firm-specific distortions. They assume that there are two types of distortions, one that affects output, which works like a tax or a subsidy, and another factor specific distortion that affects firms' capital-labor ratio. In this setting firm i's revenue-based productivity ($TFPR_i$) is proportional to the weighted geometric average of the marginal revenue product of capital and labor ($MRPK_i$ and $MRPL_i$), which in turn are proportional to the firm's distortions:

$$TFPR_i \propto (MRPK_i)^{\alpha}(MRPL_i)^{1-\alpha} \propto \frac{(1+\tau_i^K)^{\alpha}}{(1-\tau_i^Y)}$$

This implies that the cross-firm variability of $TFPR_i$ is not influenced by firm-level characteristics other than the distortions, so that the extent of misallocation can be studied by looking at the dispersion of the $TFPR_i$ distribution. Moreover, HK show that, assuming that TFPR and TFPQ are jointly log-normally distributed, the dispersion of $TFPR_i$ maps into the aggregate level TFP through the following expression:

$$\ln TFP = \frac{1}{\sigma-1}\ln\left(\sum_i A_i^{\sigma-1}\right) - \frac{\sigma}{2}var(\ln TFPR_i).$$

where σ is the elasticity of substitution across porducts. As this Equation highlights, a larger dispersion of $TFPR_i$ leads to lower aggregate productivity. We use this formula to provide some estimate of the impact of foreign capital flows on misallocation. We assume that the credit that more exposed firms get affects only firms' wedges and not their physical productivity A_{si}. The idea is that firm-specific financial constraints are part of the distortions that firms face and that a higher supply of credit relaxes such constraints. Therefore, we estimate the impact of firms' exposure to treated banks on $TFPR_i$ using a specification similar to regression 4 and we compute the variance of the predicted $TFPR_i$ resulting from the bank-lending channel. In this way, we can compute the aggregate TFP

gain/loss induced by capital inflows as:[23]

$$\ln TFP\ Gain = \ln\widehat{TFP} - \ln TFP = \frac{\sigma}{2}[var(\ln\widehat{TFPR}_i) - var(\ln TFPR_i)]$$

A.4 The Sraer-Thesmar approach to compute aggregate TFP gains

Sraer and Thesmar (2018) set up a steady-state general equilibrium model with heterogeneous firms that face stochastic productivity shocks and are subject to distortions such as adjustment costs, taxes, and financial frictions. They do not solve for the the model explicitly, but they derive sufficient statistics formulas that allow to aggregate the effects of firms' treatment. They provide conditions under which the estimated treatment effects on the joint ergodic distribution of output to MRPK and TFPR are independent of general equilibrium conditions, which allows to aggregate the treatment effects estimated in partial equilibrium.

These conditions relate on two key assumptions about technology and frictions. First, a change in general equilibrium, which affects firm size, will not affect distortions. This means that the sources of distortions are assumed to be homogeneous of degree one, so that frictions remain on average constant on a size-adjusted basis. Second, firm-level production technology is Cobb-Douglas, with either constant or decreasing returns to scale. They argue that these assumptions, even if could appear restrictive, are largely satisfied in the macro-finance literature. Moreover, they show that these conditions are valid also in the presence of persistent difference in productivity across firms, with heterogeneous treatment effects, and under alternative industry structures.

They obtain a formula for changes in steady-state aggregate TFP (and output) that combine parameters of the model (labor share, the elasticity of substitution of goods within an industry, labor supply elasticity) and three sufficient statistics that characterize the joint distribution of TFPR and MRPK. The first statistic is the effect of firm treatment on the average log MRPK, which measures the effect of firm exposure on the credit available to firms. The second statistic is the treatment effect on the variance of the log MRPK, which measures the effect of treatment on the allocation of capital across firms. The final statistic is the effect on the covariance of the log MRPK and log TFPR; if treatment reduces this covariance, it makes productive firms relatively less distorted, which favors aggregate output and TFP. Therefore, we group firms in percentiles j according to their degree of firm level exposure and then compute:

$$\widehat{\Delta\mu_{mrpk,j}} = \widehat{\beta}_1 Exposure_j + \widehat{\beta}_2 Exposure_j^2 \tag{1}$$

$$\widehat{\Delta\sigma^2_{mrpk,j}} = \widehat{\alpha_1} Exposure_j + \widehat{\alpha_2} Exposure_j^2 \tag{2}$$

$$\widehat{\Delta\sigma_{mrpk,tfpr;j}} = \widehat{\gamma_1} Exposure_j + \widehat{\gamma_2} Exposure_j^2 \tag{3}$$

[23]First, we estimate $\ln TFPR_{ist} = \beta_1\ Exposure\ Firm_i \times Post_t + \boldsymbol{X_i'\delta} \times Post_t + \gamma_i + \delta_{st} + \epsilon_{ist}$. Then we compute $\ln\widehat{TFPR}_{ist} = \ln TFPR_{ist} + \hat{\beta}_1\ Exposure\ Firm_i$. Finally, we estimate the $var(\ln\widehat{TFPR}_i)$ for the post-2002 period. Finally, we set the elasticity of substitution σ equal to 3.

Equation 1 captures the fitted value of the change of average MRPK for the j percentile between the post- and pre-2002 period, where the coefficients come from first-difference estimates of the treatment effect.[24] Similar estimates apply for the fitted change of the variance of MRPK and of the covariance between MRPK and TFPR in Equations 2 and 3. Then, Sraer and Thesmar (2018) prove that the effect on aggregate TFP is given by:

$$\begin{aligned}\Delta \ln TFP = & -\frac{\alpha}{2}\left(1+\frac{\alpha\theta}{1-\theta}\right)\sum_j \kappa_j \widehat{\Delta\sigma^2_{mrpk,j}} \\ & + \alpha\left(1+\frac{\alpha\theta}{1-\theta}\right)\sum_j(\kappa_j-\gamma_j)\left[-\widehat{\Delta\mu_{mrpk,j}}+\frac{1}{2}\left(\frac{\theta}{1-\theta}\right)\left(\alpha\widehat{\Delta\sigma^2_{mrpk,j}}-2\widehat{\Delta\sigma_{mrpk,tfpr;j}}\right)\right] \\ & + \frac{\alpha}{2}\left(1+\frac{\alpha\theta}{1-\theta}\right)\left[\left(\frac{\alpha\theta}{1-\theta}var_{\gamma_j}\left(\widehat{\Delta\mu_{mrpk,j}}\right)\right)-\left(\frac{\alpha\theta}{1-\theta}var_{\kappa_j}\left(\widehat{\Delta\mu_{mrpk,j}}\right)\right)\right]\end{aligned} \tag{4}$$

where α is the share of capital in the Cobb-Douglas production function, which we set at 0.33; θ is the elasticity of substitution of goods within an industry, which we set at 3; κ_j and γ_j are the capital and sales shares of groupup j in the pre-period; $var_{\kappa_j}\left(\widehat{\Delta\mu_{mrpk,j}}\right) = \sum_j \kappa_j\left(\widehat{\Delta\mu_{mrpk,j}}\right)^2-\left(\sum_j \kappa_j\widehat{\Delta\mu_{mrpk,j}}\right)^2$; and $var_{\gamma_j}\left(\widehat{\Delta\mu_{mrpk,j}}\right) = \sum_j \gamma_j\left(\widehat{\Delta\mu_{mrpk,j}}\right)^2-\left(\sum_j \gamma_j\widehat{\Delta\mu_{mrpk,j}}\right)^2$.

[24]Specifically, following Sraer and Thesmar (2018), we run $\Delta\mu_{mrpk,j} = \beta_1 Exposure_j + \beta_2 Exposure_j^2 + \epsilon_j$.