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SPILLOVER EFFECTS IN FIRMS' BANK CHOICE

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Spillover effects in firms' bank choice *

(Spillover hatások a vállalatok bankválasztásában)

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Contents

Abstract

In this paper, we study firm-bank relationship formation. Combining domestic inter-firm network data from value-added tax declarations and credit registry for Hungary, we estimate the spillover effects in bank choice, identifying from variation on the bank level. Having at least one peer in the network who has an existing loan with a bank increases the probability that the firm will borrow a new loan from the same bank. We provide suggestive evidence that the estimated spillover effect is due to firm-to-firm information transmission about banks. According to our results, firms can learn about banking practices from their peers but they also point to financial stability concerns in the event of shocks to domestic supply chains.

JEL: G30, L14, D22.

Keywords: Bank choice, firm network, spillover effects.

Összefoglaló

Tanulmányunkban a vállalatok bankválasztását vizsgáljuk. Megbecsüljük a bankválasztásra ható vállalatok közötti spillover hatást, melyhez magyarországi vállalatok közötti általános forgalmi adó (ÁFA) bevallásokból származó kereskedelmi forgalom adatokat és hitelregisztert használunk, és a bankok közötti variációból identifikálunk. Azt találjuk, hogy ha a vállalat legalább egy olyan céggel kereskedik, amely adott bankkal kapcsolatban áll, akkor megnő annak a valószínűsége, hogy a vállalat ugyanattól a banktól vesz fel hitelt. Megmutatjuk, hogy a becsült spillover hatás a vállalatok közötti információ átadásnak tulajdonítható. Eredményeink szerint a vállalatok tanulhatnak egymástól a bankválasztásról, de rámutatnak lehetséges pénzügyi stabilitási kockázatokra is a hazai beszállítói láncot érő sokkok esetén.

1 Introduction

Banking relationships shape the financing decisions of firms. For many firms, borrowing from banks represents the only source of external finance. How do firms decide which bank to borrow from when they apply for a new loan? Existing theory (e.g. Rajan (1992)) describes how firms choose the amount of borrowing from different sources, suggesting that bank-firm relationships are strongly shaped by firm decisions. However, we know little about what drives firms' choice of specific banks.

In this paper, we provide evidence on peer effect in bank choice, pointing to a new mechanism explaining firm-bank relationship formation. Combining domestic production network data from value-added tax (VAT) declarations and corporate credit registry for Hungary, we estimate that having at least one peer in the network who has an existing loan with a bank increases the probability that the firm will borrow a new loan from the same bank by 0.36 percentage point. This spillover effect is large compared to the baseline probability of 0.55 percent of obtaining a new loan in our sample. As the estimated coefficients are similar for buyer and supplier links, the direction of trade does not matter in information diffusion about banks.

Next, we turn to the estimation of heterogeneous spillover effects by firm characteristics. Peer effects are stronger for smaller firms (in terms of employment and total assets) and they are increasing in traded value between firms. In addition, we show that spillover effects are stronger when firms obtain a bank loan compared to other types of borrowing.

We examine what mechanism can explain our result and provide suggestive evidence that the estimated spillover effect is due to firm-to-firm information transmission about banks. Firm-bank relationship formation could be explained by both supply and demand factors. On the supply side, banks might be able to see the transactions between firms and thus be able to identify interfirm connections or they could try to obtain this information from existing clients. Banks might use the network of firms to obtain soft information about potential clients and to target new clients. On the demand side, firms might have limited information and understanding about bank choice. Under such circumstances, peers might be a valuable source of information about borrowing from certain banks. Learning about bank specific borrowing opportunities is important when firms apply for new loans and such information might be discussed among buyer-supplier firms.

We provide suggestive evidence against the main alternative mechanism of bank information advantage. From the symmetric network effect for buyers and suppliers and from that the estimated effect is the strongest between small firms, we infer that it is rather the firm-to-firm information transmission mechanism explaining our results. The estimated spillover effect further increases when hubs are excluded, which we consider yet another suggestive evidence for this mechanism. In addition, we show that the effect is the strongest when peers have a relationship with only one bank, that is when the information signal about the recommended bank is univocal. Moreover we find a much stronger effect when we estimate the effect of peers on firm loan demand, and not realised borrowing.

We build a new firm-bank-quarter panel dataset for firms borrowing a new loan that combines several sources. First, the VAT declaration database allows us to observe buyer and supplier links for domestic firms. Second, firms' credit history, existing exposure with banks and new borrowing can be defined from the firm credit registry. Thus, for any firm borrowing a new loan we observe its credit history, its connections and connected firms' credit history, on the bank level. We complement this dataset with firm level characteristics from census data, firm headquarter and bank branch location data, and firm ownership data.

Our sample construction allows us to identify the effect of interest from bank variation, despite the difficulty of network effect estimation using observational data. First, by looking at peers' past experience with banks and by constructing a sample with firms who never had a bank loan from a given bank in the past, we overcome the problem of peers' and firm's behavior being jointly determined (reflection problem). Second, by exploiting variation on the bank level, we can overcome the selectivity problem in network formation, namely that certain types of firms trade with certain types of firms who might borrow from the same bank. Estimating our regression on a firm-bank-quarter level database allows us to include firm-quarter fixed effects, which mitigates this selectivity problem. Third, this specification allows us to control for any unobserved shock by including bank-quarter fixed effects. A main concern would be that there are changes in the supply of credit at certain banks, influencing the availability of credit for firms in a network. Bank-quarter fixed effects capture such changes in credit supply and it allows us to disregard any other bank level controls.

Given this specification, a remaining concern is that the source of variation in connected firms' bank choice is unknown, which could lead to omitted variable bias. For instance, some banks are present only in some regions, so that it is rather availability of credit through distance to a bank that determines bank choice. Our choice of banks for the estimation sample mitigates this bias. We focus on the eight main banks on the Hungarian market, which have a country-wide branch network, have similar corporate portfolio market shares, offer products with comparable conditions and are similar in terms of average characteristics of their corporate portfolio. Thus, we think that it is less likely that certain types of firms borrow from certain banks. Nevertheless, we complement our estimations with a wide set of robustness checks through which we rule out various alternative stories that could drive our results.

This paper contributes to a growing literature on the effect of networks on various firm level outcomes. In a randomized experiment, Cai and Szeidl (2018) find that the networking of owner-managers of young Chinese firms persistently increases firm revenue, profits, inputs, the number of partners, bank and informal borrowing and leads to improvements in management practices. In a similar setting, Fafchamps and Quinn (2018) show that meetings between experienced and aspiring entrepreneurs influence VAT registration and having a bank current account for firms in the manufacturing sector in Africa. In addition, Mion and Opromolla (2014) and Bisztray et al. (2018) document spillover effects in exporting and importing in firm networks. Compared to these papers, our work explicitly focuses on firm-bank level borrowing.

In terms of outcomes of interest, our paper is related to that of Khwaja et al. (2011) and Bao (2019). In the first paper, the authors show that for firms entering a network, borrowing increases both on the intensive and extensive margin and new relationships are more likely to be formed with banks that already have a lending relationship with one of the immediate giant-network neighbors of the firm which enters the network. Membership in the network also reduces the propensity to enter financial distress. Interfirm network is defined based on common directors in the study. In the second paper, the author shows that firms obtain lower loan rates when borrowing from banks that lent to their peers in the syndicated loan market in previous quarters, where peers are defined based on the proximity of products sold. We add to these papers by clearly defining interfirm connections from a production network, where we observe supplier-buyer links and by knowing the universe of bank-firm lending relationships for a country where bank lending is the main source of external finance.

Finally, our paper builds on a broader literature on bank-firm relationships. This literature (e.g. Degryse and Van Cayseele (2000), Ongena and Smith (2001), Bolton et al. (2016), Dass and Massa (2011), Santos and Farinha (2000), Cole (1998), Agarwal and Ann Elston (2001), Boot (2000)) focuses mostly on the informational advantage stemming from durable bank-firm relationships. Fewer papers have studied how firm-bank relationships actually form. Ongena et al. (2011) show that those firms which find bank reputation more important than costs when choosing a bank form fewer banking relationships and are less likely to end their relationship. By estimating a spillover effect in bank choice, we add to the understanding about how firms choose banks when applying for a new loan.

Our paper has two main contributions. As the literature above suggests, there is a diffusion in various firm level decisions among networked firms. By showing that there is a network effect in bank choice upon obtaining a new loan, our paper adds to the knowledge about firm behavior on credit markets. This helps us uncover a new channel of bank-firm relationship formation. Moreover, our results point to important aggregate effects stemming from firms' selective choice of banks due to network effects. Shocks to domestic supply chains can have an impact on corporate default (e.g. Jacobson and Schedvin (2015)) and loan repayment and, as a consequence, on bank profitability, raising financial stability concerns.

The remainder of the paper is structured as follows. In Section 2, we briefly describe the Hungarian market for corporate loans. Section 3 describes the data. Section 4 presents the empirical strategy. We present our results in Section 5. The mechanism behind our results is presented in Section 6. The results of an extensive set of robustness checks are summarized in Section 7. The last section concludes.

2 Bank lending in Hungary

In Hungary, the banking industry is dominated by eight large banks covering most of the corporate lending market. These banks, in comparison with smaller ones present on the market, have a wide territorial coverage. The eight main banks have at least 2 branches in a county.[1] Motivated by the fact that geographic distance matters for loan availability Degryse and Ongena (2002), we exclude smaller, area-specific lending institutions from our sample. We focus on the eight largest bank in terms of their corporate portfolio market share, which are present at least at the county level so that they are equally accessible for firms.

Beyond accessibility, the eight large banks chosen for our estimation sample are similar in their corporate portfolio and lending conditions. We refer to the main banks in Hungary as Bank1 through Bank8 and we present the main facts regarding corporate lending for these banks for the period 2015-2017 in Table 1. Bank9 refers to all other banks present in the Hungarian market. Column 1 shows that the top eight banks cover almost 75 percent of the corporate lending market, with individual shares varying between 5 and 13 percent. These banks have also the largest shares in terms of new corporate loans issued, with an aggregate market share of 73.6 percent in new lending. Compared to the rest of the banks, the eight main banks have large corporate portfolios, with shares between 35 and 76 percent. In terms of lending conditions, for the main banks, interest rates on new loans are in the range of 1.9 and 2.5 percent, whereas the weighted average for the rest of the banks is 2.9 percent. The interest rate spread on new lending varies between 1.4 and 2 percentage points for the top eight banks, with 2.3 percentage points for the banks representing the rest of the market.

Table 1
Bank characteristics and lending conditions

	Corporate lending market share %	New corporate lending market share %	Firm portfolio %	Interest rate on new loans %	Interest rate spread on new loans pp
Bank1	8.1	6.6	59.0	2.1	1.8
Bank2	8.2	2.0	60.1	1.9	1.9
Bank3	10.6	8.5	52.0	2.3	2.0
Bank4	5.0	5.3	53.2	2.3	2.0
Bank5	6.5	9.7	34.6	1.9	0.9
Bank6	10.7	13.4	67.4	2.5	1.6
Bank7	13.0	14.1	76.1	1.9	1.5
Bank8	12.0	14.1	58.9	2.2	1.4
Bank9	25.8	26.3	15.7	2.9	2.3

Notes: Descriptive statistics represent mean values for the period 2015-2017. Bank1 to Bank8 represent the eight largest banks in the Hungarian market. Bank9 refers to all the other banks present in the Hungarian market. Corporate lending market share gives the share of bank specific corporate lending in total corporate lending. New corporate lending market share is defined as the share of new bank specific corporate lending in total new corporate lending. Firm portfolio gives the bank specific share of corporate lending in total lending. Interest rates on new loans and interest rate spreads on new loans are loan volume weighted average interest rates. The interest rate spread can be calculated for HUF loans and it represents the spread over 3-month BUBOR. In this period, around 80 percent of new lending was denominated in HUF. For Bank9, representing the rest of the banking sector, values for firm portfolio, interest rate and interest rate spread on new loans are corporate market share weighted averages.

[1] Hungary is subdivided administratively into 19 counties and the capital city, Budapest. We assume that for most of the administration as well as banking, firms have to travel to the county seat, which is the main city within the county.

3 Data and summary statistics

We build a novel firm-bank-quarter level database by combining firm-to-firm sales data with credit registry, firm tax filings as well as various other sources of data. Below, we briefly describe our main sources of data, estimation sample construction and present descriptive statistics to justify our sample used for estimation.

3.1 DATA

Production network data We use domestic firm-to-firm sales data to construct our production network for Hungary for the period 2015-2017. The data originates from value added tax (VAT) filings submitted to the National Tax and Customs Administration (NAV).

The reporting rules for the VAT data are the following. By default, firms have to declare on a quarterly basis the value of their purchases/sales, the VAT claims/obligations stemming from transactions which imply a VAT due/claim of around above EUR 3000 and the identity of the transaction partner. Firms which generated a high tax value have the obligation to report monthly, while firms with a low tax liability report on a yearly basis. The cutoffs for declaration frequency are defined based on the difference between VAT payable and VAT deductible, two years prior to the fiscal year: if this difference (irrespective of sign) is below appr. EUR 750 for the year $t-2$, firms can report on a yearly basis. In addition, yearly reporting implies gross sales below EUR $145,000$. If tax liability was above EUR 3200 on a yearly basis two years before the current fiscal year, firms have the obligation to report monthly. [2]

We define our dataset on quarterly frequency.[3] We define two firms to be connected in the production network if the quarterly transaction of a given firm pair is positive. For some of our regressions, we will account for the direction of transactions as well as traded value.

Credit registry The corporate credit registry contains all loans granted to firms by all credit institutions on the contract level in Hungary. The dataset is available for the period 2012-2017 on a monthly frequency.[4] The credit registry offers information on the original amount, outstanding amount, date of origination, maturity, type of reimbursement, loan type, currency, delinquency, firm and bank identifier for each contract.

In our definition, a firm obtains a new loan from a given bank in a given quarter if that firm borrowed at least one new loan from that bank. The database also allows us to construct the credit history of the firm with a specific bank: we define a firm being connected to a bank if in a quarter it has exposure with that bank. Regarding loan types, we know whether the loan is short or long term borrowing and whether it enters the balance sheet of the bank. [5] We can differentiate between the following types of corporate borrowing: bank loan, bank guarantee, documentary letter of credit, credit line, financial leasing and loan guarantee.

Firm-level data Firm-level data originates from corporate tax filings to the National Tax and Customs Administration (NAV) and contains balance sheet and income statement entries for all double bookkeeping firms in Hungary. It contains information on

[2] Quarterly reporting implies the submission of the VAT filings up to 20 days after the last month of the quarter, monthly reporting implies the submission of the VAT filings up to 20 days after the end of the month, whereas yearly reporting implies the submission of the VAT filing until February 25 of the next year.

[3] Yearly tax declarations are accounted for in the fourth quarter of the year, while monthly declarations are aggregated to quarterly frequency. For example, in the raw dataset for 2017, 4 percent of firms report on a yearly frequency, 34 percent report on a quarterly frequency and 62 percent report on a monthly frequency.

[4] While credit registry data is available from 2005 for Hungary, data reporting has changed from 2012. We use the version of the credit registry starting in 2012.

[5] For example, unused credit line is not in the balance sheet of the bank, whereas if it has been drawn down, it enters the balance sheet of the bank.

capital, assets, sales, export sales, employment, payrolls, intermediate inputs, value added and industry of the firm. Using this dataset, we estimate firm level total factor productivity (TFP) using the Olley and Pakes (1996) method.

Bank query data The bank query shows the day on which a given bank queried a firm from the credit registry. In case of an existing bank-firm connection such as loan contract, the bank has the obligation to query the firm yearly. Banks also have the obligation to query a firm from the credit registry when they seriously consider giving a loan to a firm. Upon query, banks can see all the variables from the credit registry listed earlier, allowing them to track the credit history of a firm. This dataset is available starting from 2011.

Other datasets used We use several other data sources for our robustness checks. We add direct ownership data to our firm level and network data. Starting from 2012, this dataset shows the owner of the firm. We also use firm headquarter location data on the zip-code level and we have information on the address of each bank and its branches.

3.2 DATABASE CONSTRUCTION AND DESCRIPTIVE STATISTICS

For our estimations, we construct a database on the bank-firm-quarter level. As our production network data is available for the period 2015-2017, this will give the time dimension for our analysis. The production network data contains some VAT resident firms which do not have a Hungarian tax identification number. We discard those transaction pairs from our estimation sample, where at least one firm does not appear in the firm census database. These firms might be foreign ones or might not fall under double bookkeeping and we would not be able to add any other firm level characteristics to these observations. As detailed earlier, out of the banks and lending institutions which we observe in the credit registry, we focus on the lending and bank-firm connections of eight banks.[6] We obtain a sample of 5,619,238 firm-bank-quarter observations.

Throughout our estimations, we consider new loans which were obtained only from 8 banks. To ensure that no past bank connection of the firm has an influence on the bank choice in the present, we consider only those firm-bank-quarter observations in which the firm did not have a loan from that specific bank up until quarter q. With this sample construction we estimate the probability that a firm obtains a loan from a particular bank for the first time. Our credit registry allows us to trace back the history of borrowing until 2012. By considering peers' outstanding exposures with any of these 8 banks and by adding the network data with trading partners' banks to the database of new borrowers we define trading partners' bank connections.

After merging the databases we show that, on average, the firms connected to these banks are similar in terms of their size (employment and assets total), productivity, SME and exporter status and industry. Table 2 gives the bank-specific average value for various firm level outcomes for those firms, which have an existing exposure with banks, i.e. connected firms which obtained a new loan. Bank1 through Bank8 refer to the top eight banks in the Hungarian market in terms of their corporate loan portfolio, while Bank9 shows an average for the rest of the banks in the economy.

Table 3 presents descriptive statistics for the firms in our sample, in comparison with all firms in the economy, all firms in the network and firms in the network who have a new loan in the period 2015-2017. Comparing the first two columns shows that firms in the network relative to the firm in the economy are slightly older, are larger in terms of employment, sales and total assets. Firms in the network have a higher share of their sales from exports and they are more productive both in terms of value added and estimated TFP. These firms are also more likely to be in the manufacturing and construction sectors compared to the population of firms. Firms in the network who obtain a new loan (column 3) are even larger and more productive in comparison with all firms in the network. However, we do not see a large difference between the characteristics of firms in the network with new loans and those with new loans from the 8 banks chosen for our sample. While on average firms are larger in our database, 97 percent of our sample are small and medium sized enterprises.

Table 4 gives the number of peers in different networks. In the firm network (Column 1), most of the firms, 80 % have up to five links. The average number of peers is 6. Those firms in the network who obtained a new loan have more connections, 90 percent of the firms have up to 20 connections and on average these firms have 11 links. By comparing columns 2 and 3, again, we notice that firm with new loans from 8 banks in our sample are quite similar to firms in the network with new loans; 87 percent of the firms have up to 20 links and have on average 13 connections.

[6] In our robustness checks we rerun our main regression for various combinations of these 8 banks. Our results are unchanged.

Table 2
Firm characteristics by bank

	Employment (log)	Assets total (log)	Sales (log)	Value added (log)	Productivity (log)	SME (%)	Exporter (%)	Manufacturing (%)	Construction (%)	Services (%)
Bank1	3.5	13.9	14.3	12.4	8.4	66.8	27.3	20.3	9.7	59.1
Bank2	3.4	13.7	14.1	12.2	8.4	67.9	25.0	17.6	9.0	62.1
Bank3	3.6	14.0	14.5	12.5	8.4	64.8	29.7	21.3	8.6	57.1
Bank4	3.6	14.0	14.4	12.5	8.4	64.4	29.4	22.9	10.6	54.5
Bank5	3.6	14.0	14.4	12.6	8.5	64.7	27.1	20.5	9.6	56.9
Bank6	3.6	13.9	14.4	12.5	8.4	67.1	26.1	18.9	10.7	58.7
Bank7	3.6	13.9	14.3	12.5	8.5	68.7	28.0	21.9	9.6	58.9
Bank8	3.5	13.9	14.4	12.4	8.3	65.4	25.5	18.7	11.3	57.6
Bank9	3.3	14.0	14.2	12.3	8.5	64.5	23.3	14.4	7.5	61.6

Notes: The table shows average values for the period 2015-2017. Bank1 to Bank8 represent the eight largest banks in the Hungarian market. Bank9 is a market share weighted average for all the other banks in Hungary. Descriptive statistics refer to firms in the production network, which were connected to banks and which obtained a new loan. For these firms, bank specific firm-level average characteristics are calculated from the firm level database.

Table 3
Firm level characteritics

	All firms	Firms in the network	Firms in the network with new loan	Firms in the network with new loan from 8 banks
Number of firms	1,185,200	285,690	78,984	45,474
Age	10.7	11.2	12.7	13.23
	(7.6)	(7.9)	(7.5)	(7.6)
Nr of employees	9.1	22.3	34.9	43.9
	(115.9)	(201.4)	(318.5)	(399.1)
Log sales	9.6	11.6	12.3	12.6
	(2.2)	(1.6)	(1.6)	(1.5)
Log assets total	9.2	11.3	12	12.2
	(2.4)	(1.8)	(1.6)	(1.6)
Export sales share	0.05	0.07	0.08	0.09
	(7.3)	(0.3)	(0.2)	(0.212)
Log value added	8.5	10.1	10.7	10.9
	(2.0)	(1.8)	(1.6)	(1.6)
Log TFP	6.9	7.6	7.6	7.7
	(1.3)	(1.1)	(0.9)	(0.9)
Percentage SME	98	97	98	97
Share in:				
Manufacturing	8.4	12.9	17.0	17.9
Construction	8.7	12.6	14.2	14
Service	64.3	62.2	57.2	57.3

Notes: The table includes averages and shares by industry for firm-year observations for the period 2015-2017. The share of firms in other industries is not reported. Below the sample averages standard deviations are included in parantheses.

Table 5 shows link strength. On a quarterly basis, the average traded value in our database is HUF 53 million, while the median traded value is around HUF 13 million.

Table 4
Links

		Firm network	Firm network, new loan	Firm network, new loan from 8 banks
Network	up to 5 links	80.08 %	62.26 %	56.63 %
	up to 10 links	89.93 %	78.24 %	73.67 %
	up to 20 links	95.58 %	89.79 %	86.88 %
	up to 50 links	98.70 %	96.94 %	96.03 %
	Average number of peers	5.7	10.5	12.69
Sellers only	up to 5 links	74.6 %	52.7 %	46.4 %
	up to 10 links	86.6 %	70.9 %	65.1 %
	up to 20 links	93.7 %	84.7 %	81.0 %
	up to 50 links	98.0 %	94.8 %	93.4 %
	Average number of peers	5.7	18.8	19.6
Buyers only	up to 5 links	74.8 %	55.8 %	48.2 %
	up to 10 links	84.9 %	72.3 %	65.6 %
	up to 20 links	93.3 %	85.3 %	80.3 %
	up to 50 links	97.7 %	94.9 %	92.6 %
	Average number of peers	7.9	14.5	18.7

Notes: The table gives the cumulative distribution and the average number of peers in the network for 2015-2017.

Table 5
Trade value characteristics

	Average	p25	p50	p75	p95
All	53	6.8	12.9	29.5	135.7
Buyers	50.7	6.8	12.8	29	131
Sellers	51.6	6.8	12.9	29.2	132

Notes: The table shows the distribution of traded values in million HUF for all links, purchase values for buyer links and sale values for seller links for the period 2015-2017 on quarterly data.

4 Empirical strategy

4.1 NETWORK EFFECT ESTIMATION

We assume that learning about bank specific lending is important when a firm borrows a new loan. Such information is discussed among buyer-supplier firms and we expect that if at least one of the peers has borrowed from a specific bank in the past, then the firm is more likely to borrow a new loan from that bank.

Using our compiled dataset, in Table 6 we motivate our main hypothesis by showing that if the firm's peer borrowed from bank *b*, then it is more likely for the firm to borrow from the same bank *b*. The columns represent the bank choice of peers, whereas the rows represent the bank choice of a given firm. Given that the peer has a loan from bank *b*, or from any other bank out of the eight banks, the table shows the probability that the firm takes out a new loan from bank *b*. We calculate the probabilities for each bank *b* and we report average shares weighted by the number of observations for each bank from our sample. For all definitions of connectedness (trading partners, seller-only relationships, buyer-only relationships) the share of firms which choose to obtain a new bank loan from bank *b* if at least one of the peers has a loan from bank *b* is higher compared to the probability when the peer has exposure with any other bank. We interpret this result as a suggestive evidence on peers' past bank choice influencing the bank choice of the firm.

4.2 EMPIRICAL SPECIFICATION AND IDENTIFICATION

In the ideal experiment, firms would match randomly in the production network. Given random matching, one would regress the bank choice of the firm on the bank choice of the peers as well as own and peers' characteristics. However, with observational data, this approach would yield biased estimates for at least three reasons, as detailed in Manski (1993) and other papers (e.g. Angrist (2014); Sacerdote (2001)) . First, the actions and outcomes of firms in a network are determined contemporaneously in equilibrium, thus it might be impossible to distinguish the effect of peers on firm *i* from the effect of firm *i* on peers, if the outcomes for both firm *i* and peers are determined simultaneously. Second, network form endogenously, e.g. more productive firms sell to more productive ones who might have relationships with specific banks. Third, firms in a network could be exposed to the same unobserved shocks, e.g. bank specific supply shocks, influencing both peers' and own bank choice.

Instead, we exploit variation in peers' bank connections in our estimations. Following Bisztray et al. (2018) and Mion and Opromolla (2014), we specify a linear probability model, on the firm-bank-quarter level:

$$Newloan_{ib,q+t} = \beta Connected_{ib,q} + \alpha_{iq} + \mu_{bq} + \varepsilon_{ibq}, \tag{1}$$

where *i* denotes firm, *b* denotes bank and *q* denotes time in quarters. Our outcome variable $Newloan_{ib,q+t}$ is an indicator which equals one if firm *i* obtains a new loan from bank *b* after time *q*. The sample used for this estimation contains firm-bank-quarter observations where firm *i* has not obtained a bank loan from bank *b* before *q*. Given this sample construction, we estimate the probability that a firm obtains a loan from a particular bank for the first time. [7] [8] The right hand side variable $Connected_{ib,q}$ is also an indicator which equals one if firm *i* is connected to at least one peer in *q*, which had an outstanding exposure with bank *b* before *q*. We consider past peer bank experience as it is expected that information diffusion takes time. [9] α_{iq} refer to

[7] Our estimation can be interpreted as a staggered difference-in-differences, as the right-hand-side variable takes value 1, if two firms were (i) connected (ii) in the past. Thus, treated firms are those who became connected to at least one peer in time q. Our main identifying assumption is that there are no time varying firm level shocks to borrowing/bank choice that are correlated with peers previous bank choice, on the bank level.

[8] As our credit registry starts in 2012, we have the credit history of each firm until the beginning of 2012.

[9] In our regressions, we look at new borrowing up to 4 quarters after the trade between two firms is observed, i.e. $t <= 4$. Similarly, at least one of the connected firms should have a bank connection up to 4 quarters before the connection with firm *i* is observed. The timeline of events is illustrated in Figure 8 in the Appendix. Robustness checks for the lead and lag structure of the regression are presented in Table 19 in the Appendix.

firm-quarter fixed effects, μ_{bq} denote bank-quarter fixed effects and ε_{ibq} is the error term. We cluster our standard errors at the firm level.

We expect $\beta > 0$ due to information transmission about banks in firm networks, meaning that there are spillovers in bank choice. In our baseline specification, we will define linked firms by considering all interfirm relationships, by considering only supplier relationships and by considering only buyer relationships.

We believe that by using this specification we address most of the concerns with network effect estimation detailed above. First, by looking at connected firms' past experience with banks and by constructing a sample with firms who never had a bank loan before from that specific bank, we overcome the problem of connected firms' and firm's behavior being jointly determined.

Second, by exploiting variation on the bank level, we can overcome the selectivity problem in network formation, namely that certain types of firms trade with certain types of firms who might borrow from the same bank. Estimating our regression on a firm-bank-quarter level database allows us to include firm-quarter fixed effects which implies that no other standard observable firm level characteristics have to be controlled for (e.g. employment, sales).

Third, this specification allows us to control for any unobserved shock by including bank-quarter fixed effect. A main concern would be that there are changes in the supply of credit at certain banks, influencing the availability of credit for firms in a network. Bank-quarter fixed effects capture such changes in credit supply and it allows us to disregard any other bank level controls.

Given this specification, a remaining concern is that the variation in connected firms' bank choice is unknown, i.e. it is not known how firms in the network choose banks. This could lead to omitted variable bias. For instance, it could be the case that some banks are present only in some regions, so that it is rather availability of credit through distance to a bank that determines bank choice. To mitigate such bias, we choose the eight main banks from Hungary which have a wide territorial coverage for our estimation sample. We also showed earlier that the lending conditions at these banks are very similar and that firm borrowing from these banks are similar in their observable characteristics (e.g. Table 1 and Table 2). Thus, we think that it is less likely that certain types of firms borrow from certain banks and those firms trade with each other. Nevertheless, we complement our estimations with a wide set of robustness checks where we rule out alternative stories.

Table 6
Firm's bank choice

	Firm has peer with the same bank	
Share of firms that obtained a new loan	Only from bank b	From any other bank
Network		
Only from bank b	17.4%	8.4%
Sellers only		
Only from bank b	17.3%	7.8%
Buyers only		
Only from bank b	17.3%	8.1%

Notes: For each bank *b*, we calculate the share of firms that obtained a new loan only from bank *b*, given that the partner has a loan only from bank *b* or from any other bank. The table shows a weighted average across the 8 banks, with the number of observations by bank as weight. Our sample is for the period 2015q1-2017q4.

5 Results

We start this section by presenting the results for spillover estimation from our baseline regression. Then, we detail the heterogeneity of spillover effect by quartiles of various firm level characteristics and trade value between firms. In all specifications we find positive and significant spillover effects. Last, we present spillover effects for different credit types and by borrowing experience.

5.1 BASELINE RESULT

Column 1 in Table 7 reports the result for the baseline regression equation 1. [10] The estimated coefficient of interest shows that having a peer with a loan from a specific bank increases the probability that the firm obtains a new loan from the same bank by 0.36 percentage points. This effect is large compared to the baseline probability of 0.55 percent of obtaining a new loan for our sample. [11] In this specification, firms' connections are defined considering both buyer and supplier links.

Table 7
Baseline regressions

	(1)	(2)	(3)
	All	Suppliers	Buyers
connected	0.36^{***}	0.37^{***}	0.34^{***}
	(0.01)	(0.01)	(0.01)
Bank FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
R-squared	0.1389	0.1397	0.1406
Number of observations	5,619,238	4,159,193	3,773,870

Notes: The sample includes firm-bank pairs for which the firm has no bank exposure in the previous quarters. The dependent variable is an indicator that equals one if firm i obtained a new loan from bank b in quarters $q+1$, $q+2$, $q+3$ or $q+4$. The main explanatory variable is also an indicator that equals one if there is at least one firm in the network of firm i which had an outstanding exposure with bank b in quarters $q-1$, $q-2$, $q-3$ or $q-4$. The coefficient of the variable connected is the estimated spillover effect. Coefficients are multiplied by 100 to read as percentage point marginal effects. The baseline probability of obtaining a new loan (in %) for the columns are 0.55, 0.58 and 0.66, respectively. Robust standard errors are shown in parentheses. Standard errors are clustered at the firm level. *** = significant at 1-percent level; ** = significant at 5-percent level; * = significant at 10-percent level.

Columns 2 and 3 in Table 7 report regressions separately for supplier and buyer links. As the coefficient for suppliers and buyers are similar to the estimated coefficient using all interfirm links, around 0.37 and 0.34 percentage point, it seems that the direction of trade does not matter in information diffusion about banks. Thus, we will not differentiate the direction of trade between firms and all our other regressions will include both types of interfirm links.

[10] Estimation results excluding controls are reported in Appendix Table 18. Estimation result considering various time windows for obtaining a new loan and earlier bank connection in the network are presented in Table 19 in the Appendix.

[11] The baseline probability of obtaining a *new loan from a bank* in our estimation sample is calculated as the share of new loans to the total number of observations in the non-treated group (firm-bank-quarter observations without peers at that specific bank).

5.2 HETEROGENEOUS SPILLOVER EFFECTS

In this section we aim to estimate the heterogeneity of bank choice spillovers by firm characteristics and strength of the trading relation. This exercise allows us to understand how information diffusion operates between certain groups of firms in terms of their observable characteristics. We group firms by quartiles of their main characteristics such as size (employment and total assets) and productivity (estimated TFP) for each quarter. In addition, we look at the strength of the spillover effect by quartiles of traded value between firms.

The heterogeneity regression specification is a slight modification of the main equation:

$$Newloan_{ib,q+t} = \sum_{Q} \beta_Q Connected_{ib,q} * I^{Q}_{i,q-4} + \alpha_{iq} + \mu_{bq} + \varepsilon_{ibq}, \quad (2)$$

where I is an indicator which equals one if firm i in time $q-4$ belongs to a particular quartile Q for a given observable characteristic.

Table 8 reports the results from quartile regressions, where β_Q is the estimated coefficient for quartiles of observable firm characteristics listed in the top row of the table. Column 1 reports the spillover effect for the quartiles defined by the number of employees of firm i. For example, group 1 includes firms with less than 2 employees, group 2 firms with 2-4 employees, group 3 with 5-11 employees and group 4 those with at least 12 employees. For firms with less employees than the first quartile threshold, the estimated spillover effect is 0.48 percentage point, while the effect is smaller for firms with more employees. Column 2 reports the regression for firms in different quartiles sorted by their assets. Again, the estimated effect is the largest for new borrowers in the lowest quartile and the lowest for firms in the last quartile. Column 3 reports the results by TFP groups. Here we notice that the effect is very similar for the first three quartiles and the lowest when firms in the network are the most productive. Finally, in column 4, firms are grouped in quartiles based on their trade value with peers. [12] The estimated coefficients show that the larger the trade volume among connected firms, the larger is the spillover effect and it varies between 0.19 percentage point and 0.51 percentage points.

5.3 CONTRACT CHARACTERISTICS

In this subsection we aim to understand what kind of information is transmitted in firm networks and analyse the spillover effect by credit types and characteristics as observed in the credit registry for each contract. We look at the main types of lending in our database such as bank loan, leasing, bank guarantee and credit line and whether the obtained loan enters the balance sheet of the bank.

In this specification the left hand side variable is an indicator that equals one if firm i obtained a specific type of new loan from bank b after time q. The main explanatory variable is also an indicator that equals one if there is at least one firm in time q in the network of firm i which had an outstanding exposure with bank b with the same type of credit before time q. The coefficients for spillovers in loan characteristics are reported in Table 9. We find the largest spillover effect for bank loans, whereas for bank guarantee, credit line and leasing a somewhat smaller. In the last column, the coefficient of having the credit entering the balance sheet is also significant at one percent. The results suggest that firms not only recommend specific banks to the firms in their network, but also specific types of credit.

5.4 EXPERIENCE IN BORROWING

The estimated spillover effect of 0.36 percentage point in Column 1 in Table 7 comprises both the extensive (i.e. obtain a loan or not) and intensive margin (from which bank obtain the loan) firm responses. In order to be able to answer who benefits more from the information in the network, we look at firms with absolutely no loans before and firms with at least one loan before

[12] If firm i has several trade partners which had a loan from a specific bank b, then we consider the maximum of the different trade volumes among these connected firms.

Table 8
Heterogeneity of peer effect by firm characteristics and link strenght

	(1) Employment	(2) Assets total	(3) TFP	(4) Trade value
Q1	0.48***	0.44***	0.37***	0.24***
	(0.06)	(0.05)	(0.05)	(0.03)
Q2	0.43***	0.40***	0.37***	0.19***
	(0.04)	(0.04)	(0.05)	(0.03)
Q3	0.32***	0.43***	0.38***	0.27***
	(0.04)	(0.04)	(0.04)	(0.03)
Q4	0.26***	0.24***	0.27***	0.51***
	(0.03)	(0.03)	(0.04)	(0.03)
Bank FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
R-squared	0.1396	0.1392	0.1411	0.1416
Number of observations	5,539,455	5,599,204	5,416,003	5,527,059

Notes: The sample includes firm-bank pairs for which the firm has no exposure with that specific bank in the previous quarters. The dependent variable is an indicator that equals one if firm *i* obtained a new loan from bank *b* at quarters $q+1$, $q+2$, $q+3$ or $q+4$. The main explanatory variables are indicators for firms in the network with prior bank specific exposure interacted with quartile group indicators for firm *i*. The coefficients are multiplied by 100 to read as percentage point marginal effects. The baseline probability of obtaining a new loan (in %) in column 1 are 0.46, 0.58, 0.66, 0.64, in column 2 0.43, 0.64, 0.60, 0.55 and 0.51, 0.70, 0.71, 0.56 in column 3 for each quartile, respectively. Robust standard errors are shown in parentheses. Standard errors are clustered at the firm level. *** = significant at 1-percent level; ** = significant at 5-percent level; * = significant at 10-percent level.

Table 9
Spillover effects in loan characteristics

	(1) Bank loan	(2) Leasing	(3) Bank guarantee	(4) Credit line	(5) In balance sheet
connected	0.43***	0.20**	0.23***	0.19***	0.39***
	(0.02)	(0.07)	(0.02)	(0.02)	(0.02)
Bank FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.1390	0.1387	0.1388	0.1388	0.1390
Number of observations	5,619,238	5,619,238	5,619,238	5,619,238	5,619,238

Notes: The sample includes firm-bank pairs for which the firm has no exposure with that specific bank in the previous quarters. The dependent variable is an indicator that equals one if firm *i* obtained a a new loan of a specific type (bank loan, leasing, bank guarantee and credit line or lending which enters the balance sheet) from bank *b* at quarters $q+1$, $q+2$, $q+3$ or $q+4$. The main explanatory variable is also an indicator that equals one if there is at least one firm in the peer group of firm *i* which had an outstanding exposure with bank *b* in quarters $q-1$, $q-2$, $q-3$ or $q-4$, in that same type of loan. The coefficient of connected is the estimated spillover effect. The coefficients are multiplied by 100 to read as percentage point marginal effects. The baseline probability of obtaining a new loan (in %) for the columns are 0.63, 0.64, 0.64, 0.64 and 0.63, respectively. Robust standard errors are shown in parentheses. Standard errors are clustered at the firm level. *** = significant at 1-percent level; ** = significant at 5-percent level; * = significant at 10-percent level.

(from a different bank). Our estimation sample contains firm-bank-quarter level data for observations where the firm never borrowed from a specific bank in the past. To disentangle the extensive and intensive margins as defined earlier, we separate the dataset into two samples, one with firms with no borrowing at all and one with firms which did borrow, but not from that specific bank.

The estimated spillover effect for the extensive margin is shown in column 1, whereas the intensive margin effect is shown in column 2 in Table 16. The estimated spillover effect for those firms with no loans before is 0.46 percentage point, while for those with at least one loan before (from a different bank) is 0.19 percentage point. This result strongly supports that peers' information has the highest impact on new borrowing when firms have no borrowing experience and suggests that there is more information transmitted than loan type that we can observe and quantify.

6 Mechanism behind our results

So far we have presented evidence on spillover effect in bank choice when firms obtain a new loan. We claimed that our results are due to information transmission among firms, however, a plausible alternative story behind our results could be banks favoring specific firms which are connected to their current customers when they decide about giving a new loan. In this section, we provide suggestive evidence for the learning effect.

6.1 SYMMETRIC BASELINE EFFECTS

As shown in Table 7, the estimated baseline spillover effects are very similar for buyer and supplier links, around 0.37 and 0.34 percentage point. As we look at firms who obtain a new loan for the first time from a specific bank, we can argue that banks have limited information about the new client *i* and it might be the case that banks give a new loan to these firms based on the cash flow from selling to their network and a general trust in and informational advantage about connected firms. In this case, we would expect higher coefficients for new borrower sellers, which is not what we observe in our sample. Thus, we interpret the symmetricity of baseline effects for buyers and sellers as suggestive evidence in favor of information transmission among firms.

6.2 HETEROGENEITY OF PEER EFFECT BY FIRM AND PEER CHARACTERISTICS

We estimate heterogeneous spillover effects by firm and peer characteristics using the following regression, which is a modified version of equation 1:

$$\begin{aligned} Newloan_{ib,q+t} &= \beta_1 Connected_{ib,q} + \beta_2 Connected_{ib,q} * I^l_{iq} \\ &+\beta_3 Connected_{ib,q}(l) + \beta_4 Connected_{ib,q}(l) * I^l_{iq} + \alpha_{iq} + \mu_{bq} + \varepsilon_{ibq}, \end{aligned} \tag{3}$$

where $Connected_{ib,q}$ is an indicator for having a peer in time q who had a bank exposure with a specific bank b before q, while $Connected_{ib,q}(l)$ is an indicator for having a 'large' peer in time q who had a bank exposure with a specific bank b before q. I^l_{iq} is an indicator that equals 1 if firm i in quarter q is a 'large' firm. 'Large' firms are those in the highest quartile of the employment, assets total, TFP or revenue distribution. Therefore, β_1 measures the spillover from a small firm to a small firm, while β_2 and β_3 the additional gains in the spillover for a large firm and from large peers, respectively. The estimated spillover effect from a large firm to a large firm is the sum of all four *beta* coefficients. The estimated results of equation 3 are presented in Table 10.

If the spillover effect operates via the bank information channel, then we would expect that banks are more willing to offer loans to small firms with large peers (who are better, more productive, more creditworthy, etc.). However, if the estimated spillover effect is due to information transmission between firms, then we would expect that this effect is the strongest between small firms. In the first case, the estimated coefficients in the third line in Table 10 are expected to be positive and significant. In the second case, the spillover from small to small firm is expected to be the largest.

The estimated results of equation 3 are presented in Table 10. The significant negative estimated coefficients of β_3 at Column 1-3 suggest that the spillover is much weaker from large peers to small firms compared to small peers to small firms, and at least not stronger in Column 4. This provides evidence against the bank information channel. Moreover, the estimated spillover effect is the strongest from small peers to small firms among the four specified groups based an all size specifications (employment, assets total, TFP, revenue), suggesting the firm-to-firm information transmission mechanism explaining our results.[13]

[13] The estimated spillover effect is the following from small peers to small firm: β_1, from small peers to large firm: β_1+β_2, from large peers to small firm: β_1+β_3, from large peers to large firm: β_1+β_2+β_3+β_4.

Table 10
Interaction between firm and peer characteristics

	(1) Employment	(2) Assets total	(3) TFP	(4) Revenue
small firm	0.55***	0.64***	0.46***	0.46***
* small peer	(0.05)	(0.06)	(0.03)	(0.05)
large firm	-0.42***	-0.59***	-0.21***	-0.31***
* small peer	(0.07)	(0.08)	(0.06)	(0.08)
small firm	-0.19***	-0.26***	-0.12***	-0.07
*large peer	(0.05)	(0.06)	(0.04)	(0.06)
large firm	0.35***	0.48***	0.15**	0.26***
* large peer	(0.08)	(0.08)	(0.07)	(0.08)
Bank FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
R-squared	0.139	0.139	0.139	0.139
Number of observations	5,619,293	5,619,293	5,619,293	5,619,293

Notes: The sample includes firm-bank pairs for which the firm has no exposure with that specific bank in the previous quarters. The dependent variable is an indicator that equals one if firm *i* obtained a new loan from bank *b* in quarters *q+1, q+2, q+3 or q+4*. Right hand-side variables are indicators for peers with prior bank experience, separately for large peers and also interacted with large firm indicator. We define large firm as those above the 75th percentile. The coefficients are multiplied by 100 to read as percentage point marginal effects. Robust standard errors are shown in parentheses. Standard errors are clustered at the firm level. *** = significant at 1-percent level; ** = significant at 5-percent level; * = significant at 10-percent level.

6.3 HUBS

We eliminate hubs from our network to provide further suggestive evidence that the connected firm *i* does not obtain a new loan based on being the peer of a well-performing large firm. It is expected that hubs are large, well known firms trusted by banks, which due to their reputation can provide collateral for smaller firms when these apply for a new loan.

We define hubs based on the upper one percentile of link distribution. In our sample, hubs are firms with at least 45 links. Table 11 depicts the characteristics of firms remaining in the sample and excluded firms defined as hubs. It is visible that hubs have more employees, larger balance sheet and are more productive.

If the spillover effect operates via the bank information channel, then we would expect that banks are more willing to offer loans exactly to the firms linked to these large hubs. In this case the estimated spillover effect should be much weaker when hubs and connected peers are excluded. Column 3 in Table 16 shows the estimated spillover effect from Equation 1 when we exlude hubs. The estimated effect is even slightly higher than the effect in the main specification, ruling out the possibility that our result is driven by being connected to large hubs.[14] [15]

6.4 NUMBER OF BANK CONNECTIONS OF PEERS

We estimate the peer effect in bank choice by the number of peers' banks. The result shows that if the information signal about the recommended bank is more univocal, then the peer effect is stronger. The first column of Table 12 reports the result for those firms with peers' outstanding exposure to only one bank, the second column for firms with peers' exposure to exactly two banks, etc. [16] The estimated coefficient is the largest for those firms with peers exposed to exactly one bank. The larger the peers' various bank exposure number the smaller the estimated peer spillover coefficient. This result suggests that peer's information diffusion is more relevant and has higher impact on new borrowing when peers have only few bank connection as in this scenario the firm receives a clear and univocal signal of a recommended bank.

6.5 LOAN DEMAND

Whether firm level new borrowing is realized depends both on firm applying for a loan and bank deciding positively about giving a new loan to the firm. As a consequence, the estimated network effect also depends on whether a given bank is willing to lend to the firm. With realized new borrowing as an outcome variable, we might underestimate the effect on bank choice. Following Jiménez et al. (2012), we use loan applications data as an equivalent to observed loan demand by firms. Loan applications are defined based on the credit registry query database, which gives the day on which a bank accessed information about the firm from the credit registry. Banks have to query the credit history of firms yearly, if firms are current customers or at the time when they receive a loan application and seriously consider giving a new loan to the firm. As our sample contains firms that never had loan from bank *b*, the observed queries are related to firms expressing their demand for new loans from bank *b*.

In Table 13 we present some statistics for being queried for connected and non-connected firms. For our estimation sample, the top panel of the table reports the share of connected firms by being queried by a bank and by new loan status. The bottom panel of the table reports the same numbers for firms without connected firms. The percentage share of queried firms among connected and non-connected firms is reported in the last column of the table. Connected firms are more likely to be queried by a bank *b* (4.54% vs. 1.67 %), which might suggest that firms in the network transmit information and influence peers to submit loan requests at their own bank. Firms with connected peers also get more new loans compared to not connected firms as shown in the first column of the table (0.96% vs. 0.56 %).

We reestimate our baseline regression for firm-bank-quarter observations where instead of new borrowing, we define the dependent variable as a binary outcome variable which takes value one if the firm's credit history was queried by bank *b* at

[14] We also run regressions where the top 5 percentile (at least 13 links) of firms based on the number of their links are excluded, and we obtain similar results.

[15] Arguably, a firm connected to an existing client may be deemed more creditworthy even if the current client is not very large or prominent.

[16] The subsample for those firms with peers exposed to all 8 banks are missing as in this case there is no variance in the main explanatory variable *connected*.

time q using information from the query database. Results for this regression are presented in Table 14. The estimated spillover coefficient for loan demand is 1.16 percentage point and significant. This effect is much larger than our baseline spillover result of 0.36 percentage point, suggesting that information from peers increases loan requests from the same bank, however not all requests are accepted by the bank and realised as a new borrowing.

Table 11
Hubs and small firm characteristics

	Hubs	Small firms
Employment	5.28	1.88
	(1.59)	(1.34)
Assets total	16.2	11.48
	(1.6)	(1.9)
TFP	9.4	7.6
	(1.28)	(1.06)
Number of links	108	3.7
	(144)	(5.3)
Number of obs.	9,296	739,194

Notes: The table includes average firm characteristics for the period 2015-2017. Hubs are firms with at least 45 links (the top 1 percentile of firms in the link distribution). Small firms are firms with less than 45 links. Employee number, total assets and TFP are in logs. Standard deviations are included in parentheses.

Table 12
Spillover effect by the number of peers' different banks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
connected	0.62***	0.32***	0.25***	0.19***	0.23***	0.24**	0.11
	(0.04)	(0.04)	(0.05)	(0.06)	(0.07)	(0.09)	(0.11)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.1369	0.1368	0.1384	0.1431	0.1430	0.1455	0.1483
Number of observations	1,314,670	529,000	270,383	154,664	103,245	91,744	111,543

Notes: The sample includes firm-bank pairs for which the firm has no exposure with that specific bank in the previous quarters. The dependent variable is an indicator that equals one if firm i obtained a new loan from bank b in quarters $q+1$, $q+2$, $q+3$ or $q+4$. The main explanatory variable is also an indicator that equals one if there is at least one firm in the peer group of firm i which had an outstanding exposure with bank b in quarters $q-1$, $q-2$, $q-3$ or $q-4$. In column 1, only firms with peers having outstanding exposure exactly from 1 bank in quarters $q-1$, $q-2$, $q-3$ or $q-4$ are included. Similarly, in column 2,3,4,5,6 and 7 firms with peers having outstanding exposure exactly from 2, 3, 4, 5, 6 and 7 banks in quarters $q-1$, $q-2$, $q-3$ or $q-4$ are included. The coefficients are multiplied by 100 to read as percentage point marginal effects. The baseline probability of obtaining a new loan (in %) for each column are 0.53, 0.64, 0.60, 0.70, 0.64, 0.62 and 0.68, respectively. Robust standard errors are shown in parentheses. Standard errors are clustered at the firm level. *** = significant at 1-percent level; ** = significant at 5-percent level; * = significant at 10-percent level.

Table 13
Statistics - firm connection, bank query, new loan

	Connected		
	New loan	No new loan	Sum
Query	0.46 %	4.08 %	4.54 %
No query	0.50 %	94.96 %	95.46 %
Sum	0.96 %	99.04 %	100 % (N=1,317,818)
	Not connected		
	New loan	No new loan	Sum
Query	0.23 %	1.43 %	1.67 %
No query	0.32 %	98.01 %	98.33 %
Sum	0.56 %	99.44 %	100 % (N=4,301,475)

Notes: The table shows the percentage of connected and non-connected firms, by being queried by a bank and by new loan status. The top panel of the table refers to observations with connected peers (i.e. there is at least one firm in the peer group of firm *i* which had an outstanding exposure with bank *b* before time *q*), while the bottom panel refers to observations without connected peers at bank *b*. Queried status is defined as the firm being queried from the credit registry in quarter *q*. These statistics refer to the period 2015-2017, for firm-bank-quarter observations.

Table 14
Bank query

	(1)
connected	1.16^{***}
	(0.03)
Bank FE	Yes
Firm FE	Yes
R-squared	0.1789
Number of observations	5,619,293

Notes: The sample includes firm-bank pairs for which the firm has no exposure with that specific bank in the previous quarters. The dependent variable is an indicator that equals one if bank *b* queried firm *i* in quarter *q* from the credit registry. The main explanatory variable is an indicator that equals one if there is at least one firm in the peer group of firm *i* which had an outstanding exposure with bank *b* in quarters *q-1, q-2, q-3 or q-4*. The coefficient of connected is the estimated spillover effect. The coefficients are multiplied by 100 to read as percentage point marginal effects. Robust standard errors are shown in parentheses. Standard errors are clustered at firm level. *** = significant at 1-percent level; ** = significant at 5-percent level; * = significant at 10-percent level.

7 Robustness checks

In this section we address some alternative hypotheses which could pose threats to identification.

7.1 CORRELATED DECISION MAKING DUE TO COMMON OWNERSHIP

Firms might have common ownership or common management which could already explain correlated decision making in networks, including obtaining a new loan from the same bank for ownership connected firms. If this would be the case, we would falsely attribute the estimated effect to learning among networked firms. So far, we have ignored the fact that firms in the production network might have common ownership, even if we observe them as separate tax paying entities in the firm census database. We redefine our network data by eliminating firms with common owners any time in the period 2012-2017. Column 5 of Table 16 shows the result of equation 1 for the ownership corrected sample. With this new definition of firm connectedness, the probability of obtaining a new loan from the same bank decreases slightly, to 0.27 percentage point and it remains significant.

7.2 DISTANCE FROM THE BANK

Firm-bank specific factors might influence our results and one such prominent factor we have information on is distance form the bank. Brevoort and Wolken (2008) shows that most small firm-bank distances are around 8 km, meaning that bank-firm relationships are rather local.

If distance matters for borrowing outcomes, the estimated spillover effect might be underestimated if the firm received information about a specific bank from the peer, but that bank is located far from the firm. In this case, the travel cost can be higher than the value of the information, deterring the firm to follow the information received from its network. To rule out the problem of geographic distance in firm-bank relationship formation, we limit our sample to firms located in the capital, Budapest, where the eight banks from our sample have a dense branch network, 36 branches on average.

Column 6 in Table 16 presents the results from a regression restricted to firm *i* and firm's peers with headquarters in Budapest. The effect of obtaining a new loan from the same bank slightly increases to 0.39 percentage point if the peer had a loan from the same bank in the past for connections with headquarters in Budapest. [17]

7.3 NETWORK SIZE

As an alternative measure of connectedness, for each new borrower firm-bank observation we count the number of firms in the network connected to the same bank. Table 15 shows the results of our estimation when instead of a dummy variable indicating connectedness, we include the number of peers at bank *b* on the right hand side of the regression. According to the result in column 1, one extra connection at bank *b* increases the probability of obtaining a new loan from the same bank by 0.01 percentage point. Columns 2 and 3 show that once we exclude observations with a high number of links (top 1% firms with at least 11 links are excluded in column2 and top 5%, firms with at least 5 links are excluded in column 3) the effect of an additional connection with the same bank increases. In column 4, the main explanatory variables are indicators for a specific number of connections. In this specification, the coefficient for one firm in the network is similar to our baseline result, whereas for higher number of links it is larger.

[17] We rerun our regression for only *i* firms located in the capital and our results are similar to the baseline. In column 1 in Table 20 we restrict the sample to *i* firms in Budapest, whereas in column 2 to *i* firms located in Budapest or Pest county. The estimated coefficient in both cases is 0.36 percentage point.

Table 15
Spillover effects by number of connected firms

	(1)	(2)	(3)	(4)
Number of peers	0.10***	0.20***	0.28***	
	(0.00)	(0.01)	(0.01)	
1 peer				0.35***
				(0.01)
2 peer				0.59***
				(0.02)
3 peer				0.68***
				(0.04)
4 peer				0.71***
				(0.05)
5-10 peers				0.60***
				(0.05)
>10 peers				0.79***
				(0.11)
Bank FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
R-squared	0.1414	0.1415	0.1421	0.1390
Number of observations	5,527,059	5,513,278	5,463,933	5,619,238

Notes: The sample includes firm-bank pairs for which the firm has no exposure with that specific bank in the previous quarters. The dependent variable is an indicator that equals one if firm i obtained a new loan from bank b at quarters $q+1$, $q+2$, $q+3$ or $q+4$. In column 1 the main explanatory variable is the number of peers which had an outstanding exposure at bank b in quarters $q-1$, $q-2$, $q-3$ or $q-4$. In column 2, observations with the top 1 % number of peers are excluded (less than 11 peers). In column 3, observations with the top 5 % number of peers are excluded (less than 5 peers). In column 4, the main explanatory variables are indicators for a specific number of peers. The coefficients are multiplied by 100 to read as percentage point marginal effects. Robust standard errors are shown in parentheses. Standard errors are clustered at firm level. *** = significant at 1-percent level; ** = significant at 5-percent level; * = significant at 10-percent level.

7.4 REGIONAL EFFECTS

Certain firms might be exposed to specific regional-bank effects, such as a bank marketing campaign targeted at specific clusters of firms. To account for such effects, we include two digit industry-county-bank fixed effect in equation 1. The estimated coefficient of 0.33 presented in column 7 of Table 16 is very close to the baseline estimate of 0.36, excluding the possibility that the estimated spillover effect is due to some specific regional-bank effect.

7.5 BANK SAMPLE CHOICE

Based on Tables 1 and 2 showing lending conditions and connected-firm characteristics by banks one could argue that banks are not entirely similar in all the listed characteristics. We rerun our main regression for different subsamples of the main sample containing the 8 largest banks. In all these subsample specifications the estimated spillover effect is about two third of the actual baseline probability in that subsample similarly to the main sample. The results from equation 1 for different subsets of banks are reported in Table 21.

First, bank 1 to 5 in our sample have lower corporate lending market shares compared to the rest of the banks. While these firms were lending on lower interest rate, it might be the case that these banks were less accessible to some types (e.g. riskier) of firms. The results for the subsample of banks 1 to 5 are shown in column 1. The estimated coefficient is 0.29 percentage point, while the baseline probability is 0.51, thus having a peer with a loan from a specific bank increases by more than half as much the probability that the firm obtains a new loan from the same bank.

Second, it is possible that banks specialize in lending to some segments of the corporate sector, e.g. Paravisini et al. (2017) show that banks in Peru are specialized in firms' export market destination countries. Motivated by this evidence and by the fact that exporter firms are better in various firm level characteristics than non-exporters with possibly better access to banks, we rerun our main regression for a subsample containing Bank2, Bank6 and Bank8. Among these firms, the share of exporters is the lowest. The result in column 2 show an increased coefficient of 0.47 percentage point. However, when compared to the baseline probability of 0.68 the relative spillover effect is similar to the one in the main sample.

Third, banks might specialize in lending to some sectors, where firms might already know each other through other business links. We exclude banks 4, 6 and 8 from our sample, as these banks have relatively higher shares of firms operating in the construction sector. We obtain a network effect of 0.28 percentage point, shown in column 3. Compared to the baseline probability of 0.4, the additional spillover effect is again about two third. Fourth, we exclude banks 1,2,6 and 7 from our estimation sample as the firms connected to these banks have relatively larger share of firms in the service sector and we obtain a large, positive coefficient of 0.52 percentage point, reported in column 4. Compared to the baseline probability of 0.72, the additional spillover effect is again about two third as in the main sample.

In the last step of our robustness check, we rerun our baseline regression for different combinations of banks in our sample. The result are always significant and positive, pointing to spillover effects in bank choice. We omit the tables for this set of robustness checks from our paper, but they are available upon request.

7.6 UNDERSTANDING CONNECTEDNESS

The main right hand side variable $Connected_{ib,t}$ in equation 1 is an indicator which equals one if firm i is connected to at least one other firm from its network which had an outstanding exposure with bank b before time q. In this way, $Connected_{ib,q}$ can change either if firm i connects to (starts to trade with) a new firm or if an existing connected firm connects to (received a loan from) a new bank. To disentangle the two channels we reestimate the baseline regression where peers' bank connection is fixed at the 2014 level. [18] In this way, the second channel is excluded and identification only comes from the new peers. The estimated spillover effect of 0.30 percentage point in column 4 in Table 16 is very close to the baseline 0.36 percentage point effect, suggesting that the identification is based on new peer connections.

[18] We consider those observations where there was a bank connection in any quarter in 2014.

Table 16
Spillover effects in various samples

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
connected	0.46***	0.19***	0.51***	0.30***	0.27***	0.39***	0.33***
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.01)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location-industry FE	No	No	No	No	No	No	Yes
R-squared	0.1291	0.1572	0.1385	0.1389	0.1390	0.1392	0.1459
Number of observations	3,684,480	1,934,758	4,725,412	5,619,238	5,434,536	2,366,700	5,462,926

Notes: The sample includes firm-bank pairs for which the firm has no exposure with that specific bank in the previous quarters. The dependent variable is an indicator that equals one if firm i obtained a new loan from bank b at quarters $q+1$, $q+2$, $q+3$ or $q+4$. The main explanatory variable is also an indicator that equals one if there is at least one firm in the peer group of firm i which had an outstanding exposure with bank b in quarters *q-1, q-2, q-3 or q-4*. The coefficient of connected is the estimated spillover effect. In column 1, spillover effect is estimated for a sample where firms had no loan before from any of the 8 banks. In column 2, spillover effect is estimated for a sample where firms had at least one loan before from one of the 8 banks. In column 3, spillover effect is estimated for a sample where we exclude hubs. In column 4, the main explanatory variable is an indicator that equals one if there is at least one firm in the peer group of firm i which had an outstanding exposure with bank b in 2014. In column 5, the spillover effect is estimated for common ownership corrected network. In column 6, the spillover effect is estimated for networked firms located in Budapest. In column 7, industry-county-bank fixed effect is added. The coefficients are multiplied by 100 to read as percentage point marginal effects. The baseline hazard (in %) for the columns are respectively: 0.54, 0.59, 0.57, 0.57, 0.57, 0.56, 0.56. Robust standard errors are shown in parentheses. Standard errors are clustered at firm level. *** = significant at 1-percent level; ** = significant at 5-percent level; * = significant at 10-percent level.

8 Conclusion

In this paper we provide evidence on a new channel of firm-bank relationship formation. Combining domestic production network data from VAT declarations and firm level credit registry for Hungary, we show that having at least one connection with bank specific experience has a positive effect on the firm choosing the same bank upon obtaining a new loan.

We find that having at least one connection who has an existing loan with a bank increases the probability that the firm will obtain a new loan from the same bank by 0.36 percentage point. This spillover effect is large compared to the baseline probability of 0.55 percent of obtaining a new loan in our sample. As the obtained coefficients are similar for buyer and supplier links, the direction of trade does not matter in information diffusion about banks. Next, we turn to the estimation of heterogeneous spillover effects by firm characteristics. Network effects are stronger for smaller firms in terms of employment and total assets and they are increasing in traded value size. In addition, we show that spillover effects are the strongest when firms obtain a bank loan, in comparison with other types of borrowing. We provide suggestive evidence that the main mechanism behind our results is information transmission between firms.

Our results imply that beyond the diffusion of various firm level decisions in firm networks, firms learn about banks from their peers and turn to banks connected to their firm network for new borrowing. This suggests a new channel of bank-firm relationship formation. In addition, our results point to important aggregate effects stemming from the selective choice of banks due to network effects, which in case of shocks to supply chains, raises financial stability concerns.

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Appendix

Figure 1
Timeline of identification

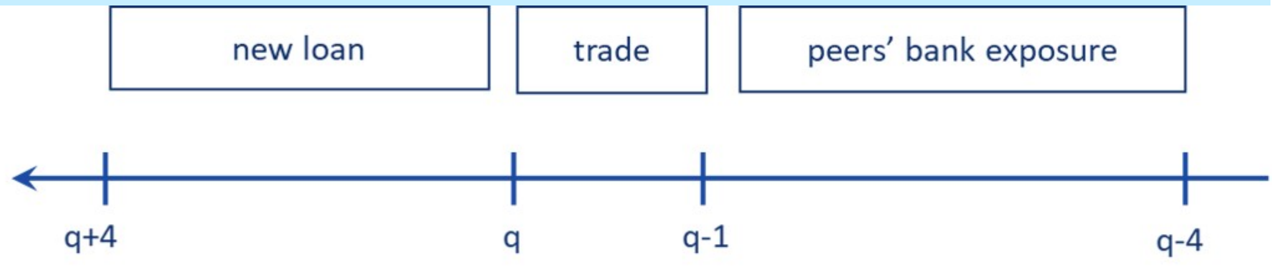

Table 17
Variable definition

Productivity	Productivity is estimated using the Olley and Pakes (1996) method.
Employment	Headcount of the number of employees.
Assets total	Total assets refer to the sum of current and fixed assets.
Value added	Revenue less intermediate inputs used for production.
Sales	Revenues from sales.
Export sales	Revenue from selling abroad.
Age	Age of the firm in years.
Exporter	A firm is exporter if at least 10 percent of its sales are from selling abroad.
Manufacturing industry	Based on 2-digit NACE Rev. 2 classification those firms which belong to industries 10-33.
Construction industry	Based on 2-digit NACE Rev. 2 classification those firms which belong to industries 41-44.
Services industry	Based on 2-digit NACE Rev. 2 classification. Industries in 45-82, with the exception of ind. 64, 65 and 66.

Table 18
Baseline regression without controls

	(1)	(2)	(3)
	All	All	All
connected	0.41***	0.43***	0.36***
	(0.02)	(0.01)	(0.01)
Bank FE	No	No	Yes
firmyq	No	Yes	Yes
R-squared	0.0005	0.1359	0.1389
Number of observations	5,619,293	5,619,238	5,619,238

Notes: SThe sample includes firm-bank pairs for which the firm has no exposure with that specific bank in the previous quarters. Dependent variable is an indicator that equals one if firm *i* obtained a new loan from bank *b* at quarters *q+1, q+2, q+3 or q+4*. The main explanatory variable is also an indicator that equals one if there is at least one firm in the peer group of firm *i* which had an outstanding exposure with bank *b* in quarters *q-1, q-2, q-3 or q-4*. The coefficients are multiplied by 100 to read as percentage point marginal effects. The baseline hazard (in %) is 0.52. Robust standard errors are shown in parentheses. Standard errors are clustered at the firm level. *** = significant at 1-percent level; ** = significant at 5-percent level; * = significant at 10-percent level.

Table 19
Baseline regression for different new loan and connected definitions

	(1)	(2)	(3)
	All	All	All
connected	0.13***	0.13***	0.35***
	(0.01)	(0.01)	(0.01)
Bank FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
R-squared	0.1364	0.1364	0.1389
Number of observations	5,619,238	5,619,238	5,619,238

Notes: The sample includes firm-bank pairs for which the firm has no exposure with that specific bank in the previous quarters. The dependent variable is an indicator that equals one if firm *i* obtained a new loan from bank *b* for column 1 and 2 at quarter *q+1* and for column 3 at quarters *q+1, q+2, q+3 or q+4*. The main explanatory variable is also an indicator that equals one if there is at least one firm in the peer group of firm *i* which had an outstanding exposure with bank *b* for column 1 in quarter *q-1*, for column 2 in quarters *q-1, q-2, q-3 or q-4* and for column 3 in quarters *q-1, q-2 ... or q-8*. The coefficients are multiplied by 100 to read as percentage point marginal effects. The baseline hazard (in %) is 0.16, 0.16 and 0.55. Robust standard errors are shown in parentheses. Standard errors are clustered at the firm level. *** = significant at 1-percent level; ** = significant at 5-percent level; * = significant at 10-percent level.

Table 20
Firms located in Budapest or Pest county

	(1)	(2)
	Budapest	Budapest and Pest county
connected	0.36***	0.36***
	(0.03)	(0.03)
Bank FE	Yes	Yes
Firm FE	Yes	Yes
R-squared	0.1394	0.1390
Number of observations	1,998,819	2,778,622

Notes: The sample includes firm-bank pairs for which the firm has no exposure with that specific bank in the previous quarters. The dependent variable is an indicator that equals one if firm *i* obtained a new loan from bank *b* in quarters *q+1, q+2, q+3 or q+4*. The main explanatory variable is also an indicator that equals one if there is at least one firm in the peer group of firm *i* which had an outstanding exposure with bank *b* in quarters *q-1, q-2, q-3 or q-4*. In column 1, only those *i* firms are included which are located in Budapest. In column 2, only those *i* firms are included which are located in Budapest or Pest county. The coefficients are multiplied by 100 to read as percentage point marginal effects. The baseline hazard (in %) for the columns are respectively: 0.50 and 0.53. Robust standard errors are shown in parentheses. Standard errors are clustered at the firm level. *** = significant at 1-percent level; ** = significant at 5-percent level; * = significant at 10-percent level.

Table 21
Baseline regression for different bank samples

	(1)	(2)	(3)	(4)
connected	0.29^{***}	0.47^{***}	0.28^{***}	0.53^{***}
	(0.03)	(0.04)	(0.02)	(0.03)
Bank FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
R-squared	0.2186	0.3568	0.2155	0.2733
Number of observations	3,529,565	2,077,875	3,541,657	2,771,944

Notes: The sample includes firm-bank pairs for which the firm has no exposure with that specific bank in the previous quarters. The dependent variable is an indicator that equals one if firm *i* obtained a new loan from bank *b* in quarters *q+1, q+2, q+3 or q+4*. The main explanatory variable is also an indicator that equals one if there is at least one firm in the peer group of firm *i* which had an outstanding exposure with bank *b* in quarters *q-1, q-2, q-3 or q-4*. In column 1, only banks 1,2,3,4,5 are in the sample. In column 2, only banks 2,6,8 are in the sample. In column 3, banks 4,6,8 are excluded from the sample. In column 4, banks 1,2,6,7 are are excluded from the sample. The coefficients are multiplied by 100 to read as percentage point marginal effects. The baseline hazard (in %) for the columns are respectively: 0.51, 0.68, 0.40 and 0.74. Robust standard errors are shown in parentheses. Standard errors are clustered at the firm level. *** = significant at 1-percent level; ** = significant at 5-percent level; * = significant at 10-percent level.

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