It Takes More than Two to Tango: Understanding the Dynamics behind Multiple Bank Lending

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Abstract

In this paper we investigate the matching process between banks and large borrowers that switch from single to multiple bank lending relationships in the corporate loan market. Using a unique dataset on all large credit exposures of all Israeli commercial banks in the period between 2005 and 2015, we highlight the systemic externalities of micro-prudential regulation. We find, *inter alia*, that regulatory limits on credit exposures aimed at limiting an individual bank's concentration risk lead large borrowers to turn to multiple lending and by that increase the level of asset commonality among banks. We find that large borrowers are more likely to establish a new lending relationship with big banks and with the banks that are familiar with the borrower's business profile, whether through existing loans to a group of borrowers to which the borrower belongs, or through acquaintance with the industry in which the borrower operates. Furthermore, we find that borrowers tend to establish a new lending relationship with banks whose asset portfolio is correlated with that of their original lender. This result reveals another channel through which banks engage in collective risk taking in order to benefit from a "too many to fail" implicit guarantee.

Keywords: Bank Lending; Firm-Bank Relationship; Portfolio Choice; Diversification; Interconnectedness; Bank Regulation; Overlapping Portfolios

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1. Introduction

The literature on systemic risk and contagion in the financial system points to two types of channels through which an idiosyncratic shock turns into a systemic one. The first type is a direct contagion channel, arising from contractual obligations such as interbank loans, swap agreements or other bilateral exposures between two (or more) financial institutions (Rochet and Tirole, 1996; Allen and Gale, 2000; Allen et al., 2012; Duffie, 2013; Kallestrup et al., 2016; Diebold and Yilmaz, 2014; Gorton and Metric, 2012; and Giglio, 2011); and the second is an indirect contagion channel, through which financial institutions are exposed to mark-to-market losses due to common asset holdings. While there is substantial evidence exploring the origins and the dynamics of the former, the indirect contagion channel remains less explored.

The risk arising from common asset holding (overlapping portfolios) is described in many theoretical, but few empirical, works (Acharya and Yorulmazer, 2008; Acharya, 2009; Allen et al., 2012; Wagner, 2010; Wagner, 2011; Caccioli et al., 2014 and Greenwood et al., 2015). These studies focus on traded assets and highlight the role of "fire sale" dynamics (Coval and Stafford, 2007; Duffie, 2013; Shleifer and Vishny, 2011; Ellul et al., 2011; Ellul et al., 2014) as a transmission mechanism through which the overlapping portfolios contribute to and amplify financial contagion. Nevertheless, the empirical evidence on this phenomenon and its origins remains scarce. In this study we try to shed light on these issues and, more specifically, to explore on the determinants behind the emergence of asset commonality in banks' (non-traded) loan portfolios.

In general, asset commonality results from either unintentional or intentional actions or causes. It can arise unintentionally due to the limits of diversification of asset portfolios (Wagner, 2011; Ibragimov et al., 2011), especially in the presence of home bias. In contrast, financial institutions might intentionally increase their common exposures (i.e. choose to make correlated investments) due to government and regulatory distortions (Farhi and Tirole, 2012; Horvath and Wagner, 2017) or/and when they jointly finance different projects—through syndicated loans, for example (Jain and Gupta, 1987). Usually, these loans take two major forms: in one case a loan is structured, arranged and exercised by one bank (or several)—known as the lead arranger—which holds explanatory meetings, invites other banks to participate, arranges a contractual agreement among them, etc. This case represents "formal" loan syndication. In the other case, each bank independently and non-cooperatively determines the extent of its loans to a firm, which results in *multiple lending*. This type of syndication represents "de facto"[2] or "implicit" loan syndication. Even though the research data and empirical evidence show that formal syndication is economically significant[3], multiple-bank relationships – despite large variation across countries in the average number of bank relationships per firm - seem to be the common and the most prevalent characteristic of credit markets in nearly all countries (Degryse et al., 2009). [4]

From the theoretical point of view, at least, the difference between "formal" and "de facto" syndication is clear: in "formal" syndication, banks can agree on their terms of lending before the contract is signed and can make a cooperative contract. This type of collaboration is a kind of "cartel" in which banks maximize their joint profit and distribute it later to the satisfaction of all the participants of syndicate. In "de facto" syndication, in contrast, each bank tries to maximize its own profit non-cooperatively, while conjecturing the action of the other banks.[5] As such, two distinct types of loans exist and are practiced in Nash equilibrium and thus must be distinguished. Obviously, these types of syndication incorporate different implications for financial risk. While in the case of formal syndication the risks, when they exist,[6] are often shared, monitored and moderated by the participants of the loan contract (Simons, 1993; Dennis and Mullineaux, 2000; Sufi, 2007; Ivashina and Scharfstein, 2010), a "de facto"

[2] The term "de facto" loan syndication means a syndication in which banks lend non-cooperatively, while the term "formal" loan syndication implies the case in which the banks make agreements before the contract is signed and lend as if they were joint profit maximizers.

[3] According to a Thomson Reuters the share of syndications loans granted in 2017 out of total outstanding credit to the nonfinancial corporations in the EU is 6 percent, in Japan—5 percent, the UK—8 percent and in the US—19 percent. Available at: https://www.thomsonreuters.co.jp/content/dam/openweb/.../2017/loan-4q-2017-e.pdf. The figures for total outstanding credit to the nonfinancial corporates are from the BIS website: https://www.bis.org/statistics/totcredit.htm.

[4] Notwithstanding, the systematic evidence on the extent (credit amount) of multiple lending is lacking as the measuring of cross and mutual exposures between different lenders is quite challenging. A few examples of such evidence include: Jimenez et al., (2011) who report that in Spain 80 percent of overall bank credit is due to multiple lending; and Cappelletti and Mistrulli (2017) who argue that in Italy, where syndication loans account for about 5 percent of total outstanding credit, multiple credit supply is estimated at 65 percent.

[5] In this vein, a contract between a borrower and a lender cannot be made contingent on other lenders and in particular on future lenders who have not yet lent to the borrower. Contractual terms could help enforce exclusivity or mitigate the negative externalities from non-exclusivity—the extent and efficiency with which this can be achieved depends on the institutional framework (Degryse et al., 2016). Bennardo et al. (2015) show how this setting affects the contractual terms of the first lender.

[6] Cai et al. (2014) find a positive correlation between interconnectedness (measured by being a member of the same loan syndicate) and standard bank-level systemic risk measures including SRISK, CoVaR, and DIP, during recessions.

syndication, which arises from multiple lending, can be harmful to market developments and liquidity, and can suffer from coordination failure (Bolton and Sharfstein, 1996). First, multiple lending may induce both borrowers and lenders to behave opportunistically and can lead to credit rationing and high interest rates (Parlour and Rajan, 2001; Bennardo et al., 2015). Second, despite the fact that multiple banking may well be beneficial in normal times, as it alleviates the hold-up risk inherent in single-source bank financing (Rajan, 1992), and protects the debtor against a sudden deterioration of the liquidity position of the bank (Detragiache et al., 2000), in other times — when the borrower himself is in distress —multiple bank lending is likely to be a disadvantage. Thus, due to non-exclusivity of credit contracts and the lack of coordination mechanisms[7] multiple bank lending may generate important negative contractual externalities (Degryse et al., 2016)[8]. Finally, when the typical markets for liquidity are impaired, multiple lending, especially if the credit lines to borrowers are granted, may give rise to liquidity hoarding, and, thus, may amplify and propagate liquidity shock throughout the banking system.[9]

In this study, we focus on "de facto" syndication which stems from the pool of large corporate loans (large borrowers). Due to their high credit demand, large borrowers have a higher impact on the emergence of asset commonality, and the propagation of shocks within the system, should they be in distress, is expected to be more severe.[10]

[7] A large body of literature focuses on the difficulties experienced by multiple lenders attempting to coordinate their actions. For example, Gertner and Scharfstein (1991) analyze the free-rider problem in corporate distress, and Morris and Shin (2004) emphasize the associated welfare loss of a creditor run (see also von Thadden et al., 2010).

[8] The common-pool problem, in which creditors race to the courthouse to collect their loans, occurs because creditors do not internalize the costs and benefits that their actions impose on other creditors. A creditor that chooses to pursue its individual, state law collection rights may be causing the premature liquidation of a viable firm, and this may hurt all creditors. The common-pool problem persists because creditors act in their self-interest.

[9] Cappelletti and Mistrulli (2017) find that this channel of contagion may have a significant impact on the stability of the banking system, especially when it interacts with other channels for contagion related to direct interbank exposures. All in all, there is a the trade-off between the benefits of diversification of the liquidity risk that borrowers may pursue by establishing multiple lending relationships, especially when they are granted credit lines, and the cost of propagating liquidity shocks within the banking system. This trade-off depends on the structure of the network and the severity of the liquidity shock that hits a bank or part of the banking system. Multiple lending, in line with Detragiache, at al. (2000), may mitigate the impact of banks' liquidity shocks on the economic activity of borrowers. However, this holds in normal times when the market for liquidity works smoothly. In contrast, in a crisis, when the interbank market is impaired, a dark side of multiple lending may emerge since it may give rise to contagion and financial instability.

[10] It is hard to assume that the classical fire sale dynamics explanation is presumable in this case—the process of selling the existed loans is complicated, but theoretically possible. It should be noted, however, that in contrast with typical loan syndications, the secondary loan sales market is often dominated by

And indeed, to control the risk of credit concentration, regulators have established policies for lending limits or large exposures[11], which set a maximum exposure as a share of a bank's capital that can be extended to a single borrower or a group of related borrowers.[12]

On such background and analyzing the settings of multiple bank lending different questions emerge: Which kind of (large) borrowers prefer to borrow from more than one bank? What are their incentives? How do they choose the additional (second, third, etc.) bank to borrow from and why; what are the incentives of the additional bank to lend to this borrower? Is the decision to grant a loan affected by the borrower having already established lending relationships with another bank? And, finally—do the decisions by the borrower and the new lender to establish lending relationship depend on the economic profile of the original lender, and in what manner? The existing literature on multiple lending describes the borrowers' motives and the perspectives of borrowing from more than one bank and banks' motivation to lend them, separately. To the best of our knowledge, however, no study to date has tested the determinants of the lending match between a borrower and an additional new lender as a function of an existing single loan relationship - i.e. given the characteristics of the potential lending banks, borrowing firm, the original lending bank and the distance between them in the asset space.[13]

In attempting to answer these questions, we explore a novel dataset consisting of firm-bank loan data on about 213,453 large credit exposures of the seven largest banks in the Israeli banking system over the period 2005 to 2015 (around 4,800 loans per quarter to 9,577 unique borrowers), reported to the Bank of Israel's Banking Supervision Department (hereinafter, BSD). This database accounts for over 70 percent of total

leveraged, risky loans and the majority of loans are purchased by nonbank, institutional investors (Yago and McCarty, 2004).

[11] See "Measuring and Controlling Large Credit Exposures", January 1991 (Basel Committee) and "Supervisory framework for measuring and controlling large exposures", April 2014 (BIS).

[12] The limit of large exposure represents a direct limit on banks' risk taking (Schooner and Taylor, 2010). According to the Global Macroprudential Policy Instruments survey taken by the IMF (IMF, 2013), 86 out of 97 countries surveyed have limits on large exposures. The limits vary in the scope of the borrowers to which they are applied, the limit itself and in benchmark used to calculate the maximum exposure. The most common limit used is 25 percent of the lender's own capital.

[13] Cole et al. (2004) and Chen and Song, (2013) focus on the initial match between a borrower and a lender, explaining why a certain firm borrows from a certain bank. In our study we try to reveal the determinants of a new lending match conditional on existing lender-borrower match characteristics.

nonfinancial corporate business sector credit supplied by Israeli commercial banks.[14] Based on these data we identify 2,197 large corporate borrowers that added another bank as a lender during the sample period, and derive 1,250 cases of large corporate borrowers that replaced a single relationship with multiple-bank relationships.

We find that overlap in loan portfolios and asset commonality (through multiple bank lending) are created, inter alia, due to the regulatory restrictions on a single bank's exposure (e.g. restricted exposure to a single borrower, group of borrowers, or industry) that force large borrowers to seek alternative sources of financing – either capital markets or other banks. [15] This finding is a good example of a conflict between micro-prudential and macro-prudential goals in the banking sector.[16] More specifically, we argue that in this case micro-prudential tools, used to mitigate and diminish idiosyncratic risk (single bank concentration risk), create externalities and increase the systemic risk through overlapping portfolios. It seems that banks optimizing behavior against multiple constraints lead them to pursue similar strategies and become more homogenous over time (Goel et. al., 2017).

Moreover, we show that the likelihood of providing new credit to a borrower, who already has a single-bank relationship, increases with the size of the potential lender (bank), but also with: (a) the bank's familiarity with the borrower's business, whether through existing loans to a group of borrowers to which the borrower belongs, or through acquaintance with the industry in which the borrower operates (i.e., lender specialization and credit exposure to the industry with which the potential borrower is affiliated); and (b) it increases with the level of similarity in equity returns movements and asset-portfolio composition between the candidate (potential) lender and the original lending bank. Such collective risk taking behavior (strategy) or, so-called, the

[14] This is a first study in Israel to be based on large credits register data. The database is very helpful as it exhibits a panel data structure for three levels: lenders, borrowers and the groups of borrowers. In general, the data are confidential and may only be used with the BSD's permission and is subject to restrictions.

[15] In contrast to domino contagion interconnectedness through common assets mentioned above, large exposures does not necessary reflect whether banks are sequentially affected or not. In fact, if shocks are large enough, banks with large common exposures to these shocks might default simultaneously even before a domino effect sets in.

[16]According to Hanson et al. (2011), a micro-prudential approach is one in which regulation is partial equilibrium in its conception and aimed at preventing the costly failure of individual financial institutions. In contrast, a "macro-prudential" approach recognizes the importance of general equilibrium effects and seeks to safeguard the financial system as a whole. Hanson et. al. (2011) argue that in the aftermath of the crisis, there seems to be agreement among both academics and policymakers that financial regulation needs to move in a macro-prudential direction.

investment mimicking is similar to evidence from studies on "formal" syndications (Gong and Wagner, 2016; Cai et al., 2014), and may be possibly related to a "too-many-to-fail" guarantee and the associated collective moral hazard of "love for correlation" among the lenders (banks) (Acharya and Yorulmazer, 2007; Acharya, 2009 Ibragimov et al., 2011; Farhi and Tirole, 2012). [17] We argue, however, that in case of "de-facto" syndication, and due to potential coordination failure, the negative impact of such (herding) behavior among different lenders on the stability of the financial system and banking system in particular is significantly higher.

The outline of the paper is as follows: in Section 2 we review the existing literature; in Section 3 we present the data and estimations used to test our predictions; and in Section 4 we discuss our results and their policy implications; Section 5 concludes.

2. Literature Review and Empirical Predictions

The literature on multiple-bank relationships (and the systemic risk) addresses three major questions: (a) who borrows from multiple banks, (b) why do firms borrow from more than one bank, and (c) why do banks lend to firms that already borrow from other banks?

According to Degryse et al. (2009), who summarize findings from different studies on multiple-bank lending, borrowers (companies) who borrow from more than one bank are (on average) bigger, older, less profitable, distressed, low-cash flow, intangible and highly leveraged. In addition, Farinha and Santos (2002) show that the probability for multiple-bank lending increases for firms with high growth opportunities which require high (re)investments or for firms facing financial difficulties and/or experiencing poor performance.

Another strand of the literature emphasizes the incentives of borrowing from multiple banks. One possible explanation of this phenomenon is that the borrower tries to diversify his credit portfolio to avoid the hold-up problem and to eliminate any potential rents that can be extracted by an exclusive lender[18] (Farinha and Santos, 2002; Elsas et

[17] In the presence of public guarantees (implicit or explicit) for bailout, joint defaults often result in joint bailouts. In line with this prediction, Brown and Dinç (2009) show that the ex-post effect of “too-many-to-fail” is that when a banking system is weak, it is less likely that a government will close or take over a failed bank.

[18] Thus, for example, in the case of relatively small or young firms, whose access to external, non-banking financing is quite limited, such firms will try to find another source to fund its activity.

al. (2004)). This incentive may be greater when banking markets are less competitive, offering fewer potential alternatives in the future event that their main bank tightens contract terms dramatically (Berger et al., 2008). Other studies emphasize the role of confidential information in a firm's choice of the number of lenders (Bhattacharya and Chiesa, 1995; Von Rheinbaben and Ruckes, 1998). According to these, the firm trades off the benefits from competition against the costs of information leakage to its competitors when it chooses the number of lenders. Yosha (1995) focuses on the signal that the choice of lenders sends to competition. Thus, borrowing from a single lender avoids the disclosure of information that occurs when the firm borrows from multiple lenders, but it leads the firm's competitors to infer that the firm is concealing information and react accordingly. Therefore, firms with the most to lose, if private information is disclosed, borrow from a single lender. Bolton and Scharfstein (1996) in their study emphasize the negotiation costs and predict that low-default risk firms, those with strong asset complementarities, and those in noncyclical businesses will tend to borrow from more creditors. The choice between single and multiple banking relationships depends on optimization by firms weighing the costs and benefits of the additional monitoring. Monitoring duplication benefits the firm by increasing the success probability of the project, but, at the same time, it reduces the firm's expected private return and increases total monitoring costs (Carletti, 2004). Thus, establishing multiple-banking relationships implies that firms' benefits outweigh the costs. Carletti et al. (2007) predict greater use of multiple-bank lending when banks have lower equity, when firms are less profitable, and monitoring costs are high due to poor financial integration, strict regulation, and inefficient judicial systems.

From the lender's point of view, the incentive to become an additional lender and to create the de facto syndication can be rationalized on different grounds. First, it may reflect a desire to reduce the costs of monitoring (Carletti et al., 2007). In addition, Acharya and Yorulmazer (2007), Ratnovski (2009), Acharya (2009) and Ibragimov et al. (2011) argue that banks strategically choose to become an additional lender and tend to herd into loans (asset classes) in order to create, de-facto, a "too many to fail" guarantee[19]. Such a strategy is beneficial when assuming the potential severe shock to

[19] According to Ibragimov et al. (2011), this happens only when the risk's distribution is moderately heavy-tailed and when the uncertainty about correlations between a large number of thin-tailed risks is high. It also depends on the number of distinct asset classes in the economy, the discount rate, and the time to recover after a massive intermediary default. Acharya's (2009) result arises if banks are large, essential and unique in their business.

the banking system. Gong and Wagner (2016) show empirically, using the sample of syndicated loans that banks, especially smaller ones, underestimate the systemic risk that borrowers bear, and explain this result by the increased expectations of banks to be bailed out in a case of a systemic event. Phelan (2017) and Morrison and Walther (2017) show that correlated exposures may not necessarily be driven by distorted incentives due to implicit bailout guarantees, but rather as a mechanism to provide ex-post incentives for enforcement and create market discipline. Common loan portfolio choices may also be explained by learning motives (i.e., free-riding in information acquisition) which can lead to inefficient outcomes with fully rational agents (e.g., Banerjee, 1992). In such case, banks may rationally put more weight on the choices of others than on their own information, particularly when other banks are perceived as having greater expertise (Bikhchandani et al., 1998).[20] Uchida (1999), by applying the theory of common agency, formally explains the fact that there are two forms of loan syndication, "de facto" and "formal". He shows that banks may choose both forms and that the key to the choice is a free rider problem among banks in giving the borrowing firm an incentive to take appropriate actions (moral hazard).

Another important aspect that is relevant to our study is the effect of regulation on banks' lending decisions and activities. Laeven and Levin (2009), in a cross-country analysis, include several regulatory tools and examine their effect on risk taking. More specifically, they test the impact of capital requirements, deposit insurance and restrictions on non-banking activities. The closest regulation to one whose impact we examine in our study—"limits on large exposures"—is the restriction on a bank's activities. They find this tool to have a positive effect on risk-taking when the bank has a sufficiently powerful owner. Agoraki et al. (2011) find that the same regulatory tool, in combination with high market power, reduces both credit risk and the risk of default in the banking system. Anginer et al. (2014) show that regulatory restrictions on a bank's asset diversification—a class of regulations that also include limits on large exposures—are efficient in reducing systemic risk, but only in less competitive markets. More broadly, an earlier study Barth et al. (2004) examines the correlation between various regulations and measures of banking-sector development, efficiency

20 In a different framework, Thakor (2016) shows that periods of sustained profitability are characterized by high (overestimation) of bankers' skills by all agents. This lowers credit spreads and encourages banks to invest in increasingly risky and correlated assets.

and fragility and finds that government policies that rely excessively on direct government supervision and regulation of bank activities are not sufficient and, sometimes, even not/less efficient. Barth et al. (2004) stress the importance of accurate information disclosure and the private sector corporate control of banks in achieving stability, development and performance.

3. Data and Estimation

3.1 The Israeli Banking System

The Israeli banking system is made up of 16 commercial banks, 12 of which are domestic.[21] Five banking groups are quite dominating: these holding groups hold 94 percent of total assets, while two additional banks/bank groups hold together another 5 percent (Figure 1): The Herfindahl-Hirschman Index[22] of banking system, calculated based on the total assets, is 0.2 - which is a relatively high number in comparison with the EU average of 0.11. Indeed, Israel is a small country with a high level of concentration in almost all other sectors of the economy. Nonetheless, it can be said that the level of concentration in Israel's banking sector is not out of line in comparison to other (similar) economies, and to other sectors.

Banks are the main players in the Israeli financial system. They supply 64.2 percent of all credit in the private sector and almost 50 percent of the credit in the business sector. The rest of the credit for the business sector is provided through tradeable bonds, foreign lenders and institutional investors who started granting credit relatively recently, in 2009. These alternative sources, however, are practically available for very large firms, especially public firms; while for the rest of the firms the banking system has been and continues to be the most exclusive source of credit supply.

3.2 Large Borrowers' Exposures Data

In order to monitor the risk in credit portfolios of banks based in Israel, the Banking Supervision Department (BSD) maintains a credit register for credit exposure

[21] The data and description of the Israeli banking system is for 2015 and is based on "Israel's Banking System – Annual Survey, 2015", published by the Banking Supervision Division.

[22] The index is calculated as: $HHI = \sum_{i=1}^{N} s_i^2$, where N is number of banks in the system and s_i is the share of bank i assets in the total assets of the system.

exceeding a threshold that is considered as significant for the solvency of banks. The threshold is applied to single borrower and to groups of borrowers alike in order to account for contagion. Each quarter, banks report to the Banking Supervision Department their overall current exposure to each large borrower.[23] The dataset we use consists of all "large borrower" reports from the seven largest Israeli commercial banks in the period between 2005 and 2015. The definition of "large" borrower is based upon the amount of a bank's credit exposure to a given borrower relative to the bank's equity capital: according to banks' balance sheets, the equity capital of the six largest banks in Israel is above 5 billion NIS (~$1.3 billion). This fact and the Banking Supervisor directive in particular requires Israeli banks to report credit exposures equal to or exceeding NIS 20 million (~$5 million) [24]. The smallest bank out of seven largest Israeli banks is obligated to report every exposure of NIS 4 million (~$1 million) or higher. In general, and in line with these definitions, over the sample period our comprehensive database includes detailed information of banking system exposure to large borrowers, which, in its turn, accounts for 73.6 percent of total nonfinancial corporate business sector credit supplied by Israeli commercial banks (Figure 2).

The data reported by Israeli banks to the BSD are divided into three categories[25]:

1) Borrower data—these include a borrower's unique identifying number, legal status (e.g., firm, individual, foreign firm, citizen), industry affiliation and its affiliation to group of borrowers, if such exists.[26]
2) Banks credit exposure data—a full, detailed, credit exposure composition that includes total and specific banks' balance sheet and off-balance sheet exposure, net exposure[27], deductions, provisions, amount of non-performing loans, etc.
3) Collateral data—type of collateral, value and value for the bank

[23] Except for the borrower's size, there are other criteria for which exposures are to be reported. For example, most banks must confirm that their total reported exposure does not fall short of 25 percent of total bank's credit risk. In addition, if a reported borrower belongs to a group of borrowers, the bank must report all other, existing, exposures to that group.
[24] More precisely, every exposure above NIS 20 million should be reported, while every exposure over NIS 200 million should be reported with enhanced details regarding the structure of the exposure.
[25] A full description of the variables is in Table 1A in the Appendix.
[26] In addition, we include the public legal status of borrower - whether the borrower is a public/listed company, and also an indicator on borrower's exposure (if it exists) to the corporate bonds market.
[27] Net exposure is calculated as a sum of balance and off-balance credit, after subtracting deductible items (e.g., the borrower’s deposit in the lending bank) and all kinds of non-preforming loans.

The full database on large exposures consists of 304,843 loans (around 7,000 loans per quarter) to 19,273 unique borrowers. (Figure 3 and Table 1 preset the distribution of sample by different populations of borrowers). In this study, we focus on exposures to local nonfinancial corporates (including government-owned corporates). This subsample consists of 72 percent (NIS 270 billon) of total credit exposures (NIS 375 billion) included in full "large borrowers" database and of 213,453 loans (4,800 loans per quarter) to 9,577 unique borrowers. The average credit exposure of borrowers is NIS 81 million out of total indebtedness and the median is NIS 37.4 million. The distribution of loans to large borrowers is concentrated and has a heavy right tail, reflected by the fact that the sum of exposure of the first 50 percent of all borrowers (ordered by the size of the exposure) consists of only 12.5 percent of total exposure (Figure 4).

As noted above, Israeli banks are also obligated to report their aggregate credit exposure to "groups of borrowers". The number of unique groups of borrowers reported throughout the sample period is 786. Descriptive statistics of borrowing group (for 2015:Q4) are presented in Table 1 and Table 2. However, since the borrowing groups' exposures include most of the single borrowers' exposures (consisting of individually reported exposures by single borrowers), we exclude the observations related to "group of borrowers" from our sample. This allows us to avoid the double counting bias.

According to simple descriptive statistics, during the sample period about 83 percent of large borrowing corporates reported to BSD have a single banking relationship[28], while their share in total large corporate exposures is 39.2 percent (NIS 115 billion), on average (Figure 5).[29] Borrowing corporates with multiple relationships (17 percent of large borrowing corporates reported to BSD) account for 60.8 percent (NIS 154 billion) of large corporate exposures. This figure consists of 39.2 percent of total nonfinancial corporate business sector credit supplied by Israeli commercial banks.[30] The median (mean) number of banking relationship maintained by nonfinancial corporates is 1

[28] Qian and Strahan (2007) found that the median number of banking relationships in Israel between 1994 and 2003 is 3, but their sample is very small and limited only to syndicated loans, which by definition involve more than one lending bank.

[29] The numbers refer to the last data point in our dataset - 2015:Q4, but these numbers are quite stable over the full period considered.

[30] The total banks outstanding volume of syndication loans in Israel, for comparison, is NIS 13.4 billion (3.4 percent out of total outstanding credit to the nonfinancial corporations). This includes all the existing syndications: between banks and between banks and the institutional investors as well.

(1.4), and is quite stable throughout the sample.[31] Given this background, we do find that many borrowers replace single relationships with multiple relationships. About 1 percent to 2 percent of firms in our sample match this pattern on quarterly basis. We identify these borrowers by tracking the changes in borrower's status between two consecutive reports. Thus, a borrower who is identified as a "large borrower" in a quarterly report of a single bank, and who appears in the reports of the same bank and in another bank's report in the following quarter, is defined as a borrower who has established multiple bank relationships. Since excluding or including the borrower from the large borrowers report might be merely a technical result of exceeding the minimum exposure threshold, we use different constraints to avoid this problem. More precisely, the treatment group in this study consists only of those borrowers who are included in four consecutive reports on large borrowers of the same bank and in the last two reports of both the original lender and new one. This feature, of course, cannot rule out the possibility that the firm has lending relationship with so-called "a new lender": the fact that borrower's exposure is not marked as "large" for the specific bank simply means that his exposure is not sufficient to exceed the threshold required by BSD directive for reporting the credit exposure as a "large" one.[32]. Hence, in this study, we do not cover *all* newly emerged bank-lender relationships, but rather the *new significant* relationships.[33] According to these constraints and the definitions used in this study, we identify 2,197 cases of corporates that added a lending bank,[34] but choose to focus on 1,250 cases of corporates that replace single relationship by multiple-bank relationships. Another 78,508 observations of corporates that did not add a lending bank make up the control group. Due to the fact that our data is an unbalanced panel, firms can appear more than one time, both in the treatment and the control group.

3.3 Regulatory framework on large exposures

[31] In comparison to other markets/countries: firms in the UK, Norway, Sweden and US maintain relatively few bank relationships – fewer than three on average – while for firms in Italy, Portugal, Spain and Belgium, for example, the average is 10 or more bank relationships.

[32] In addition, due to the high switching costs in banking services (Kim et al., 2003), large borrowers do not usually eliminate their entire relationship with one bank and move to another.

[33] The categorization of a borrower into the "large borrower" niche is not just a technical nuance: by changing its status, such borrower becomes more significant to the bank and thus so does its bargaining power. The costs of monitoring its activity are higher and therefore banks' chief loan officers, rather than loan officers, are always in charge of approving and dealing with the exposures to these borrowers.

[34] Out of the remaining 947 cases, 476 are cases in which a borrower switched from 2 to 3 lending banks, 219 cases from 3 to 4 banks, 122 from 4 to 5 and the rest are other cases (including rare cases in which a borrower added more than one lender in a quarter).

The regulatory framework on banking activity in Israel, in general, and prudent limits on large exposures to a single borrower or closely related group of borrowers in particular, are in line with Basel III principles and guidelines (see "Supervisory framework for measuring and controlling large exposures", April 2014). Starting already at 1991, the Basel Committee suggests that to prevent credit risk concentration, limits should be set on large exposures. The final standard (BIS, 2014) is recommended for national implementation to the exclusion of conflicting rules by January 1, 2019. The term "large exposure" includes the exposures to a single large borrower, affiliated/group of borrowers and industry credit exposure. Following such definition, the Banking Supervision Department—Israel's banks regulating authority—imposed limits on different kinds of exposures. The limits are set on:

1) Exposure to a single borrower: a single borrower's indebtedness must not exceed 15 percent of bank's capital.
2) Exposure to a group of borrowers[35]: The total indebtedness limit to a group of borrowers before 2012 was set on 30 percent of bank's capital and changed to 25 percent afterward. Group of borrowers is defined as a group of individuals, corporates etc. that are controlled by the same entity, have strong economic affiliation to each other, have significant interests in each other, or which are dependent on each other.

Exposure to an industry: bank's credit exposure to a particular industry cannot exceed 20 percent of credit total supply.

3.4 Estimation

3.4.1 The probability of establishing a multiple banking relationship

We start our analysis by estimating the probability of replacing a single relationship with multiple relationships (see Ongena and Smith, 2000; Farinha and Santos, 2002;

[35] See Proper Conduct of Banking Business Directive #313 on "Limitations on the indebtedness of a borrower and a group of borrowers", Banking Supervision Department, Bank of Israel.

Berger et al. 2005; Gopalan, 2011). Specifically, we estimate a logit model of the following form:

$$\begin{aligned}\Pr\ (new\ lending\ relationship = 1)_{i,q} \\ = \alpha + \beta' borrower_{i,q-1} + \gamma' exposure_{i,q-1} + \delta' bank_{i,q-1} \\ + \theta' borrower\_bank_{i,q-1} + \varepsilon\end{aligned}$$

where the dependent variable takes 1 if firm *i* replaced in quarter *q* a single with multiple bank relationship, and 0 otherwise. To satisfy the assumptions and the empirical predictions, in the regressions mode we use four sets of following independent variables:

Borrower variables—most borrowers in BSD data are not required to report their financial statements, thus classic size indicators (e.g., total assets or revenue) are available only for insignificant pool of (mostly listed) corporates in our sample. Therefore, we calculate the natural log of borrowers' net gross exposure (L_TOT_DEBT) as a proxy for borrower size.[36] We expect the size effect to be positive; PUBLIC is a dummy variable taking the value of 1 when the borrower is a public firm and 0 otherwise. After controlling for the size, this variable accounts for the potential transparency of the borrower. The dummy variable BONDS takes the value of 1 if the borrower's corporate bonds are tradable and 0 otherwise. We assume that bonds are an alternative/substitute source of financing that can affect a borrower's decision to borrow from an additional lender (another bank), and to affect the preference of "de facto" type of syndication to "formal" one[37].

Exposure variables—NET_GROSS_SHARE variable measures the share of borrower (firm) net exposure out of gross exposure. The difference between net and gross exposure is the amount of deductions the banks considers (deposits the borrower holds in the lending bank, for example); COLL_DEBT_SHARE is the share of exposure secured by collaterals. We assume that a high share of debt secured by collateral has a positive effect on the probability of replacing a single relation with multiple-bank

[36] The correlation between gross exposure and log of total assets of public firms is relatively high: 0.33.
[37] If a firm can raise funds from capital markets, it has some power in the loan market by threating banks "not to borrow". Once the borrower offers terms of contracts, no externalities can occur. Therefore, "de facto" syndication strictly dominates the "formal" by the amount of cooperation costs (Uchida, 1999).

relationships (Booth and Booth, 2006)[38]; BALANCE_DEBT is the share of the balance of credit to the borrower out of its total exposure (which consists of both balance sheet items and off-balance sheet items). We explain the motivation to include this variable by the fact that according to Basel directives, on-balance and off- balance credit imply different capital allocations and therefore affect the price of the credit (BIS, 2004)[39]. Finally, we include a dummy variable, PROBLEM, that takes the value of 1 if any, even negligible, amount of the borrower's credit exposure is defined as either impaired, substandard, special mention or problem debt, and 0 otherwise.

Original lender (Bank) variables—We include the original bank's total assets (BANK_SIZE), share of the credit portfolio in total assets (BANK_CREDIT) and capital-assets ratio (BANK_CAPITAL).

Borrower-bank relation variables—One of the main motives for extending or not extending the credit lines to an existing borrower is regulatory limits. We find three relevant limits in the Israeli banking regulation: 1) "Industry limit" – according to which a bank's credit exposure to a particular industry cannot exceed 20 percent of credit total supply. Since the definition of the relevant limited exposure has changed through the sample period and so have the limits, we define IND_CREDIT to be the share of the on-balance sheet credit of the borrower's industry in the bank's credit portfolio. We expect this variable to have a positive effect on the probability of switching from a single bank relationship to a multiple banking relationships. We add IND_CREDIT_SQ - the square term of IND_CREDIT - to control for any potential non-linear effects; 2) "Single Borrower Limit" – according to banking regulation, net credit exposure to single borrower must not exceed 15 percent of bank's capital. Following this regulatory limit, we calculate GAP_SINGLE as the difference between the "Single Borrower Limit" and the borrower actual (net) exposure as a share of capital. We expect a negative sign of the estimated coefficient; 3) "Group of borrowers" limit – in addition

[38] Booth and Booth (2006) examine the relation between borrowing costs and the presence of loan collateral. They find that the presence of collateral increases with default risk, which is consistent with low quality borrowers trying to reduce their risks and borrowing costs through the use of collateral. By explicitly controlling for the interdependence between the decision to pledge collateral and borrowing costs, the researchers find that secured loans have predicted spreads substantially lower than if they had been made on an unsecured basis. Alternatively, loans made on an unsecured basis have spreads that are not substantially different than if they had been secured. The evidence suggests that collateral pledging decisions are generally consistent with borrowing cost minimization.

[39] In Basel II, which governed for most of the period included in our study, for capital allocation means, off-balance sheet items were converted into credit exposure equivalents through the use of credit conversion factors. Some of these factors were changed in Basel III (BIS, 2010).

to the single borrower limit, the banks' net exposure to a group of borrowers cannot exceed 25 percent of bank's capital (30 percent until 2012). GAP_GROUP is the difference between this limit and the actual exposure of the "group of borrowers" to which the borrower belongs.[40] Finally, we define the duration of relationship between the borrower and the original lender—TIME—as the number of quarters for which the bank includes the borrower in its reports on large borrowers' exposures.

Table 3 presents the descriptive statistics[41] of all variables for both categories of borrowers—those who replaced single relationship by multiple relationships and those that did not. The t-tests show that the means of most variables are significantly different between these groups, except for the "original lender" set of variables.

We estimate the probability of switching to a multiple banking relationship using a classical logit model where the dependent variable takes the value of 1 if the borrower switched to multiple relationships in time *t*, and the independent variables are the set of lagged (*t-1*) variables described above. All the financial/accounting variables are in thousands of NIS and in 2015 prices. The results are presented in Table 4.

The full specification, including all four groups/categories of variables (borrower, exposure, bank and borrower-bank relationship), is in Column 5. Most of the results are in accord with the expected sign. Some of the variables related to "exposure" and "borrower-bank relationship" sets of variables are found to be significant. The share of balance sheet credit out of total exposure (BALANCE_DEBT) and the PROBLEM variable negatively and significantly affect the decision to form multiple relationships. While the interpretation of the first result is less clear, the second result can be explained by unwillingness of a new lender to lend to a distressed borrower. Although the fact that part of the exposure is a problematic loan is the original lending bank's private information, it is reasonable that other non-private soft or hard information, which is also available for the bank that is interested in providing a loan to the borrower, also point to the fact that this borrower is in some type of distress. However, this result contradicts the findings of Farinha and Santos (2002).

The set of borrower-bank relationship variables indicates that regulatory limits are binding. These limits are set to enhance diversification in each bank, but they also force

[40] When the borrower is not a part of borrowing group, the variable takes the value of 0.25 (or 0.3 before 2012).

[41] Correlations between the variables are reported in Table 2A in the Appendix.

the large borrowers to seek additional credit in other banks, as the gap between the maximum allowed credit line and de facto exposure decreases, and by that contribute to the emergence of overlapping portfolios. In other words, a potential byproduct of regulatory limits used to decrease banks' idiosyncratic risk is an increasing of the systemic risk posed by overlapping portfolios (Acharya, 2009; Haiss, 2010; Wagner, 2011). This may be a good example of micro-prudential tool deficiency, which should be completed by a macro-prudential one (Hanson et al., 2011).

3.4.2 With whom does the borrower match? A mixed logit approach

In this section we focus on the treatment group which consists of 1,250 cases in which a borrower that had only one banking relationship establishes a new one. We adopt the discrete choice analysis approach to understand what affects the identity of the new lending bank. For such purpose, we use a conditional logit model with the following mixed logit specification[42]:

$$Pr\left(\mu_{ij}^{t} = 1 \middle| \mu_{ij}^{t-1} = 0\right) = \frac{\exp(\beta_{j} \mathrm{X}_{ji}^{t-1} + \gamma D_{ji}^{t-1})}{\sum_{k\epsilon B} \exp(\beta_{j} \mathrm{X}_{j}^{t-1} + \gamma D_{kj}^{t-1})}$$

The new loan matching between bank *i* and firm *j* in time *t* (μ_{ij}^{t}) is characterized by the set of lagged firm variables, X_{j}^{t-1} such as its size, debt, legal status and industry affiliation, and the distance D_{ji}^{t-1} between the borrower and the new lender in the asset space. This includes the gap between the actual exposure and regulatory limits on credit lines, as well as the interactions between the financial and accounting characteristics of the original lender and the potential lender.

The data are organized as follows: Each one of the 1,250 cases of borrowers that had a single banking relationship in time *t-1* appears six times, for each one of the six potential lenders (banks) the borrower has the potential to create a new lending relationship by time *t*. The dependent variable, MATCHED, takes the value of 1 if the match is realized in time *t*. Since borrowers' characteristics are fixed for all possible combinations (the one that is realized and the 5 other alternative combinations) they are eliminated through the (econometric) estimation process. Therefore, we use only

[42] This specification is more general and does not rely on the independence of irrelevant alternatives (IIA) assumption and allows for random taste variation, unrestricted substitution patterns and correlation in unobserved factors over time (Train, 2009).

candidate banks' characteristics and variables that interact with their characteristics, including borrowers' and the original bank's characteristics.

It should be noted, that despite extensive literature and the existing analysis of different aspects of multiple-bank lending, there is no study, to the best of our knowledge, which formulates testable empirical predictions regarding the determinants of new banking relationship formation. Therefore, based on the motivation of both lenders and borrowers, as summarized in Section 2 and in order to explore the characteristics of the new loan match we define different sets of following explanatory variables:

We first include different measures of credit availability of the candidate bank: C_RATIO - the capital to assets ratio of the candidate bank; IND_CREDIT- the candidate bank's credit exposure (the share of total credit) to the industry to which the borrower belongs; and GAP_GROUP - the difference between the maximum exposure limit to a single group of borrowers and the actual exposure of the candidate bank to the group of borrowers to which the borrower belongs. We expect C_RATIO to have a positive effect on the probability of matching. As for the two other variables, the expected direction isn't clear. On the one hand, we expect the IND_CREIDT to have a negative sign (because higher, existed, exposure to the borrower's industry is associated with low credit availability to a new borrower coming from this industry); and GAP_GROUP to have a positive sign (the higher the distance from the regulatory constrain, the higher the credit availability). On the other hand, these measures can also point at the level of familiarity a candidate bank has with the borrower – through exposure to its industry or other companies from the group of borrowers the new borrower belongs. Therefore the expected signs (effect) should be opposite.

We also include a set of size variables: CAND_BANK_SIZE is the log assets of the candidate bank and BOR_BANK_SIZE is the interaction (product) between the size of the borrower and the size of the candidate bank. We expect this variable to be positively correlated with the probability of new match implying that bigger borrowers need large loans and, therefore, try to match with large banks. As for the former variable, our expectations are ambiguous: from the one hand, bigger banks have more funding availability, but on the other hand, borrower might prefer smaller banks as their second lender in order to mitigate the hold-up problem (Elsas et al, 2004).

We define SIZE_PRODUCT as the interaction (product) between the size, measured by log total assets, of the original and the candidate bank, assuming a negative effect: a relationship with two big banks is less likely to emerge than a relationship with a larger and smaller bank in the presence of hold-up externalities. As an alternative, we use the difference between the original and the candidate bank (SIZE_DIF).

Another set of variables reflects the relations between the original and the candidate banks beyond size measures. First, assuming that borrowers tend to diversify their lenders portfolio, we include a measure of relative risk between the original and the candidate bank. For such purpose, we define EQ_VOL_90D_DIF as the difference between the candidate and the original banks' equity volatility within the last 90 days. As an alternative measure for relative risk we use the difference between candidate and original traded bonds spread[43] (BOND_DIF), assuming again a negative effect. We expect both measures to have a negative effect, implying that borrowers are reluctant to borrow from a riskier bank, relative to their current lending bank.

To test another aspect of diversification we use the extent to which the original and candidate banks are correlated in their business lines. In order to control for this effect, we include the correlation between lenders' equity returns (EQ_CORR). Following the same rational, we assume this variable to have a decreasing effect. Since the equity correlation is market based, we include as well a more robust book-based measure of business correlation—the distance between the original and the candidate banks loan portfolios (DISTANCE). We calculate this measure as the Euclidean distance between a candidate and the original lender (bank) loan portfolios:

$$Distance_{ii'} = \sqrt{\sum_{n=1}^{N} \left(w_{n,i} - w_{n,i'}\right)^2},$$

where $w_{n,i}$ and $w_{n,i'}$ are the shares of credit to industry *n* in bank *i* (the original bank) credit portfolio and in bank i' (the candidate bank) credit portfolio respectively. The higher the index (distance), the more divergent the lenders are.[44] Thus, we assume this

[43] All banks have for most of the period traded bonds. The spread is calculated as the difference between the bond's yield to maturity and a matching government bond (matching is based on duration).
[44] See Cai et al. (2014) for a similar use of the index.

variable to have a positive effect: borrowers prefer their lenders portfolio to be diversified.

Finally, we include a set of variables that reflect the level of bank's acquaintance (expertise) with the borrowers' field of operations. We define the dummy variable NEW_BORROWER, which takes the value of 1 in a case where there is no historical evidence on candidate-borrower lending relationships in the past. We expect this coefficient to be negative. In addition, the variable IN_GROUP takes the value of 1 if the candidate bank has an exposure to one of the entities in the borrower's group of borrowers and 0 otherwise. Through this variable, we control for any previous information/experience the bank has with the group of borrowers to which the borrower belongs, and we expect this variable to have a positive effect. It is worth mentioning that the variables GAP_GROUP and IND_CREDIT can also be included in this group of variables (see above).

The descriptive statistics of the explanatory variables is presented in Table 5.

Due to the absence of data for one of the banks (the smallest one) in the period between 2005 to 2007, we define two subsamples: the first subsample (hereafter: Sample 1) includes all years (2005–2015) but excludes the bank with the missing data. Since this bank is the smallest one and its activity in corporate lending is negligible, the size neither of the control group nor of the treatment group are affected. In the second subsample (hereafter: Sample 2) we include the bank with the missing data but limit the sample only for those years the data are available, i.e. for 2008–15.

The results (Table 6) show that high credit availability as measured by capital to assets ratio (C_RATIO) is associated with higher probability of observing a match between a borrower and a new lending bank. The size of the candidate bank, however, is negatively correlated with the probability to observe a match - which is in line with the borrower incentive to mitigate the potential hold-up problem. The bank's exposure to the borrower's group of borrowers or its industry also increases matching probability. It seems that these variables reflect better the effect of lender familiarity and expertise (with borrower's industry or the group he belongs to) on the probability to observe the loan match rather than the effect of credit availability. In addition, this result is supported by the fact that, throughout the sample period, the regulatory constraints on exposure limits were not binding.

The interaction between the borrower and the lender size is found to be negative but not significant, while the interaction between the size of the original and candidate bank is positive: holding the size of the candidate bank fixed, we find that the bigger the original bank is, the higher the probability of observing a match. Since the difference in size (original bank size minus candidate bank size) is easier to interpret, we replace the candidate bank's size and its interaction with the original bank's size (Column 2) with the difference between the size of these banks (SIZE_DIF). The result stays the same: the larger is the difference the smaller is the probability, implying that borrowers tend to borrow from a bigger bank, relatively to their original one.

Another result arising is that excess risk of the candidate bank over the original bank lowers the probability of a match. In other words, if the candidate bank is less risky (and therefore the value of EQ_VOL_90D_DIF is negative), the probability of matching increases - in line with our predictions.[45] The level of correlation between the original and the candidate bank, as measured by the correlation in their equity returns (EQ_CORR) and the distance between their loan portfolios (DISTANCE), however, is found to significantly increase the probability of observing a match, at least by the measure of correlation in equity returns. This result is opposite to our prediction.

Re-estimating the model using Sample 2 (which includes all banks but shorter period) provides results that are somewhat similar but that differ in the effects of bank's size variables—either original or candidate (Table 6, Column 3). The reason for this, as mentioned above, is that the omitted bank in sample 1 is the smallest (in terms of assets/size) lender, with only a few large borrowers who borrow from it and from the other bank. The results show that other, non-size related, variables significantly affect the probability of observing a match in the expected direction. Specifically, we find that candidate bank's credit availability (capital to asset ratio), familiarity with borrower group lending history or the industry in which it is active, relatively lower riskiness[46], and higher similarity with the original bank in terms of equity returns correlation—all increase the probability of observing a match.

[45] In another specification (not shown) we replace the measure of relative risk with BOND_DIF. Due to data limitations, we need to leave out the first 5 quarters of the period. Nevertheless, the results remain the same with very few effects becoming non-significant.
[46] Using the BOND_DIF as a measure of the relative risk does not change the results.

In terms of goodness of fit, there is no single measure that represents this statistical parameter in a best way under a mixed logit model. Based on the likelihood ratio, we calculate seven different measures to reflect the goodness of fit. Six of these provide us with very similar (within the narrow range) results.[47] Following these results, we infer two main conclusions. First, estimating the model using Sample 2 produces better fit; second, when we test a full specification, we get a high measure that ranges between 0.53 and 0.74.[48]

We now go back to the result that contradicts our a-priori expectations - the positive effect the extent of similarity between the candidate and the original bank has on the probability to observe a match. Although the underlying assumption that banks are passive in their choice within the matching process, in our assessment, this result reflects the candidate banks' motives: by lending to a borrower that has a single bank relationship with a lender similar to the candidate bank, the latter maintains and even increases the level of similarity between them. Interestingly, while Gong and Wagner (2016) find the same behavior in the loan syndication market, where banks deliberately form a loan syndicate that increases their level of similarity, we find that the new lending bank acts in the same way when establishing "de-facto" syndication via multiple lending. In other words, banks can mimic each other by lending to the same borrower either within formal or "de-facto" syndication.

In order to further support this result, we follow Acharya and Yorulmazer (2007), Farhi and Tirole (2012) and Silva (2018) who argue that big and especially the small banks tend to mimic other big banks in their investment decisions. We include an interaction between the correlation in candidate and original banks equity movement and the size of the original bank – E_CORR X ORIGINAL_SIZE. If big banks are more mimicked, we expect for a positive effect, implying that the incentive to mimic indeed increases with the size of the original bank. The results in Table 7 confirm our expectations. The effect of the interaction term is positive and significant, as expected.

In the same manner, we estimate the model within the following two sub-samples: the first sample includes only borrowers whose original bank is one of the two major banks,

[47] The seventh – McFadden's Likelihood-Ratio Index – is much lower, but according to McFadden (1974), an index higher than 0.2 maps into an R-square of 0.4, which more or less are the levels of the other measures.
[48] And a McFadden's LRI of 0.31 which is comparable to approximately 0.6.

and the second includes the rest of the borrowers, i.e. those who borrow from the other 5 medium and small banks. Again, if mimicking is more prevalent when the original bank is a big one, we expect E_CORR to have a positive and significant effect within the first sub-sample only. The results are to be found in Table 8.

The first column in the table presents the coefficients from the estimation when we use the first sub-sample. The effect of variable in focus, E_CORR, is positive and significant – in line with our expectations. In contrast, we find this variable insignificant when estimating the model using the second sub-sample. These results reinforce our conclusion regarding the mimicking behavior between banks.

4. Discussion and policy implications

Syndication loans, either formal or "de-facto", increase the overlap of bank loan portfolios and therefore overall asset commonality. This makes the banking system, and the financial system as a whole, more vulnerable to contagious effects. Using a novel database on large exposures in the Israeli banking system, we find that interconnectedness of banks is explained by both the behavior of large borrowers and by the strategic choices of lenders (banks) providing the credit supply.

The results presented in our study highlight several important factors determining the emergence of overlapping portfolios through "de-facto" syndication in the banking system, and they have several important implications for regulators. First, the results of the analysis of the probability of switching from single to multiple lending relationships confirm some of the findings of earlier studies: the likelihood of a firm to substitute a single bank relationship with multiple relationships increases with its size and transparency level[49].

Above all, we find that regulatory limits on large exposures are binding both in the case of overall industry exposure and in the case of banks' overall exposure to a group of borrowers. These limits lead borrowers, especially the large ones, to seek alternative sources of funding, thus increasing the probability for observing high asset commonality. Regulation and the gradual development of capital markets provide these

[49] We find this feature to be especially relevant for borrowers who do not have access to capital markets, i.e. relatively small and medium corporates.

borrowers both with the demand for new credit sources and with the variety of financing sources. While existing regulation is important and supposed to diversify the concentration risk of a single bank, it also reduces the level of actual systemic diversification, because banks, and financial institutions in general, become more similar to one another through multiple lending and form so-called, "de-facto" syndication. Despite the fact that the issue of choice between two forms of syndication—formal and "de-facto"—is beyond the scope of this study, we do find the latter phenomenon to be prevalent and argue that the key to the choice is explained by the "free-rider" problem among banks and high bargaining power of large borrowers.

The empirical results partly confirm the conjectures explaining the incentives and determinants that lead the borrowers to establish multiple banking relationships. In addition, they also confirm the motives for a bank to lend to a borrower in a single bank relationship. From the borrower's point of view, the two most empirically supported rationales are the "availability" and "familiarity" motives, suggesting that a borrower turns to borrow from a bank that has more funding availability and that is more familiar with the borrower's economic activity.

Another important result arises from testing borrower's motives for "diversification" of his loan (credit) sources. We find that a borrower is more likely to establish multiple relationships with a bank less risky than the original one. In addition, after controlling for risk difference, we find that the similarity in the composition of banks' assets portfolio has a positive effect on the matching probability.

In our assessment, this result reflects the candidate banks' motives: by lending to a borrower that has a single bank relationship with a lender similar to the candidate bank, the latter maintains and even increases the level of similarity between them. While other studies (Gong and Wagner, 2016) find the same behavior in the loan syndication market, we find that the new lending bank acts in the same way when establishing a "de-facto" syndication via multiple lending. Such collective risk taking strategy is more likely to be observed when both the original and candidate lenders are large and when the candidate bank is small relatively to the original lender.

What do banks gain from imitating other banks? According to the theoretical literature mentioned above, several explanations exist. First, an existing banking relationship provides a signal of the borrower's creditworthiness and eliminates at least some of the asymmetric information embedded in granting a loan. Second, the existence of a credit relationship with another bank ensures that the borrower is already monitored, so the monitoring costs for the new lender can be reduced. Last, a higher level of credit portfolio similarity implies a higher level of credit risk similarity. Given that governments are more likely to act in order to rescue the system as a whole than in a case where there is a risk for a single bank, such herding behavior creates the potential of a "too many to fail" guarantee and ensures the stability of the single bank.

This study focuses on the Israeli banking system, but its implications are relevant for other, similar, financial systems. That is, it is particularly relevant for financial systems in which banks are the dominant funding source, the banking system is concentrated and where the investment opportunities are limited (strong home bias effect).

The findings of this study emphasize not only the effect regulatory limits have on the distribution of credit in the banking system but also the byproducts that, probably, less or not fully considered when setting these regulations. Since banks do not internalize the risks they create for the financial system through asset commonality, a complete and comprehensive regulatory approach when developing regulatory tools should take into account not only the idiosyncratic risk of each bank but also the potential externalities of regulations that might increase systemic risk. The importance of regulatory limits on large and concentrated exposures is clear, but it should be completed with better monitoring, at least by the regulator, of the outcomes, i.e. - the extent to which banks are becoming similar to each other in their asset portfolio composition. Since our results show that similarity is probably not an unintentional consequence arising out of full diversification of loan portfolios, which is likely to increase the level of similarity among banks, but rather a strategic choice - regulators should adopt measures to reduce such behavioral patterns in their individual supervision directives.[50]

5. Conclusions

In this study we explore the determinants behind the emergence of asset commonality in banks' loan portfolios. We focus on the multiple lending channel, which, for

[50] Puzanova and Düllmann (2013), for example, provide a framework for capital surcharges from banks based on their contribution to systemic risk.

simplicity, we define as a "de-facto" syndication, and examine the incentives of both lenders and borrowers to establish multiple lending relationships. In particular, we are the first to document the effect that regulatory limits on total exposures have on the motivation to establish new relationships and thus on the systemic risk arising from asset commonality. In addition, we go a step further from the existing literature on multiple bank lending and analyze the determinants of the lending process between a borrower and an additional lender as a function of existing single loan relationship. We find that the likelihood of providing new credit to a borrower, who already has single bank relationship, increases with the size of the potential lender (bank) but also with the bank's familiarity with the borrower's business, whether through existing loans to a group of borrowers to which the borrower belongs, or through acquaintance with the industry in which the borrower operates (i.e., lender specialization and credit exposure to the industry the potential borrower is affiliated with). It also grows with the level of similarity in asset portfolio composition between the candidate (potential) lender and the original lending bank. This result may possibly be related to the "too-many-to-fail" guarantee and the associated collective moral hazard of "love for correlation" among the lenders (banks). We argue, however, that in case of large exposures' "de-facto" syndication, and due to the coordination problem, the negative impact of such (herding) behavior among different lenders on the stability of the financial system, and the banking system in particular, is significantly higher.

Figure 1. Distribution of the banking system's assets by banking groups (December 2015, total assets=NIS 1,469 billion)

This figure displays the distribution of assets between the Israeli commercial banks updated to December 2015.

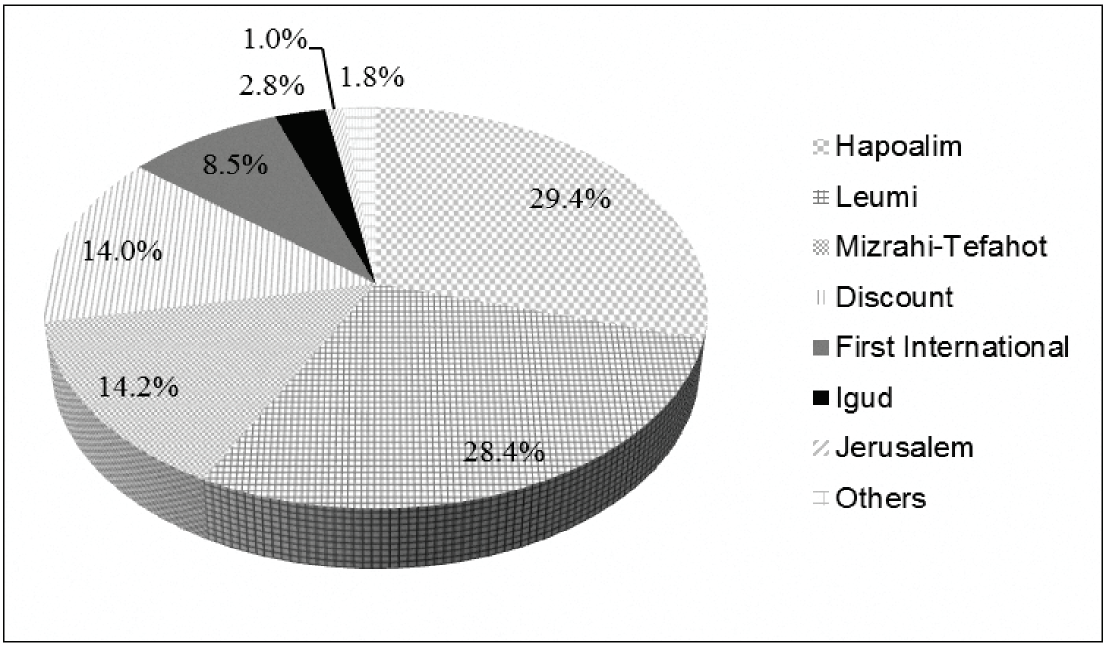

Figure 2. Composition of banks' balance sheet in Israel (NIS million, 2015:Q4)
The figure displays the breakdown of the banking system and the portion of credit covered in our detailed database. The figures are for 2015:Q4 but the same ratios hold throughout the whole period.

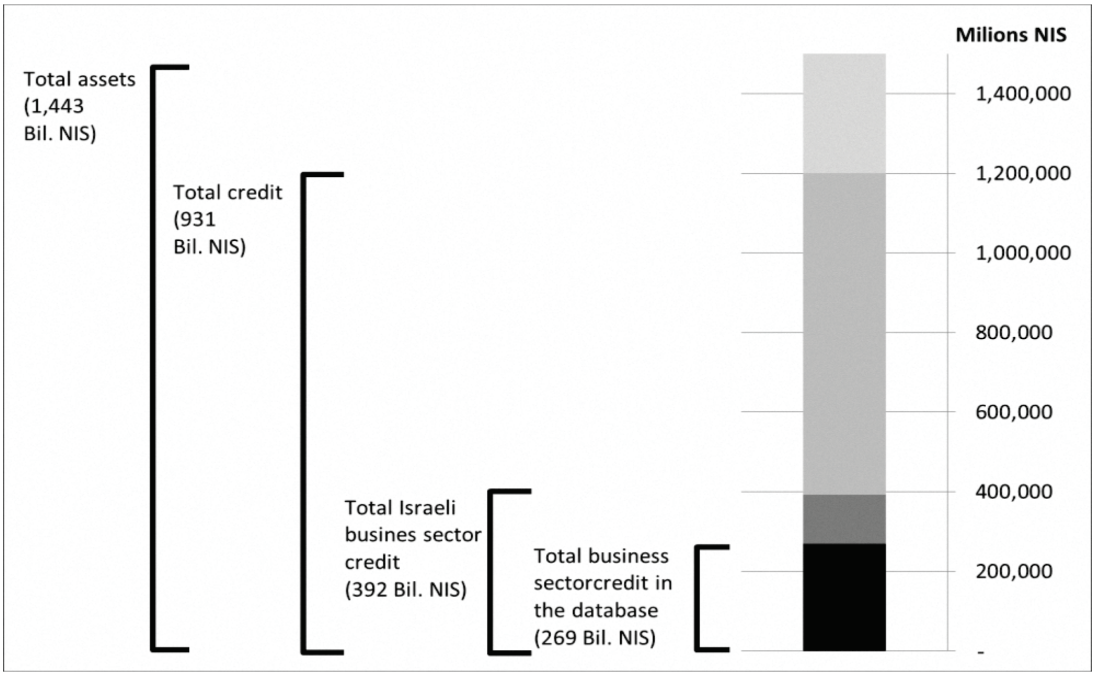

Figure 3. Composition of big borrowers' total exposure by borrower type (2015:Q4)

This figure displays the distribution of total indebtedness of large exposures by borrower type. The number of observations is in parenthesis. The figures are for 2015:Q4 but the same ratios hold throughout the whole period.

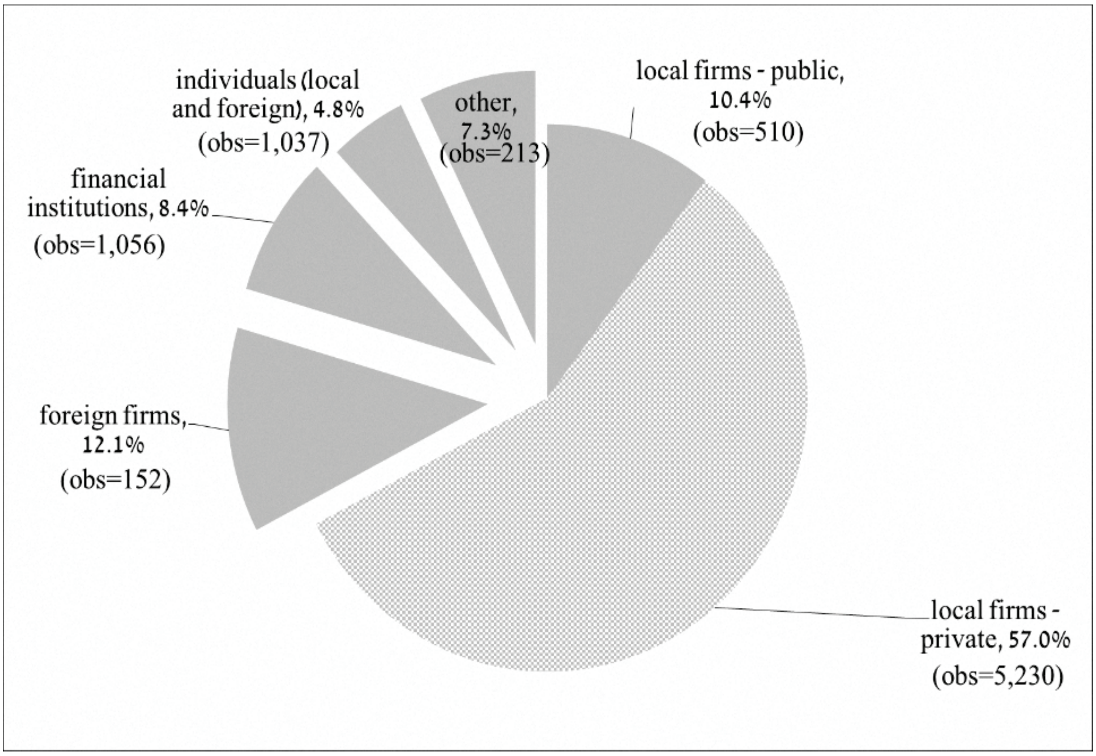

Figure 4. Cumulative distribution of total indebtedness by the number of borrowers (2015:Q4)

This figure displays the cumulative distribution of total indebtedness in the large borrowers dataset by the cumulative number of borrowers. Vertical lines are drawn in the 25, 50 and 75 percentiles. The figures are for 2015:Q4.

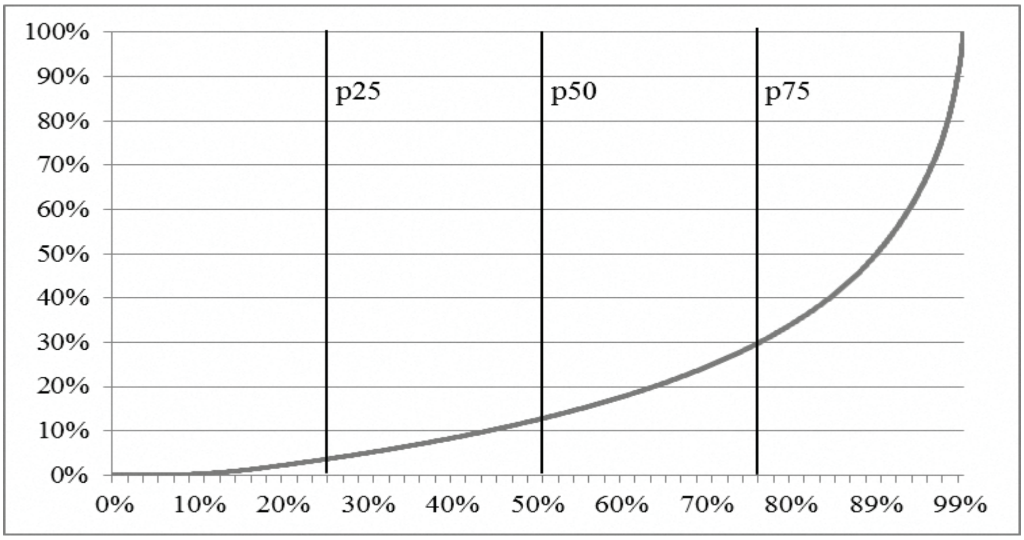

Figure 5. Number of borrowers by number of lending banks (2015:Q4)

This figure displays the distribution of borrowers by the number of lending banks and by their share in large total exposures. The share (number) of borrowers with only one lending bank is on the right axis. The figures are for 2015:Q4.

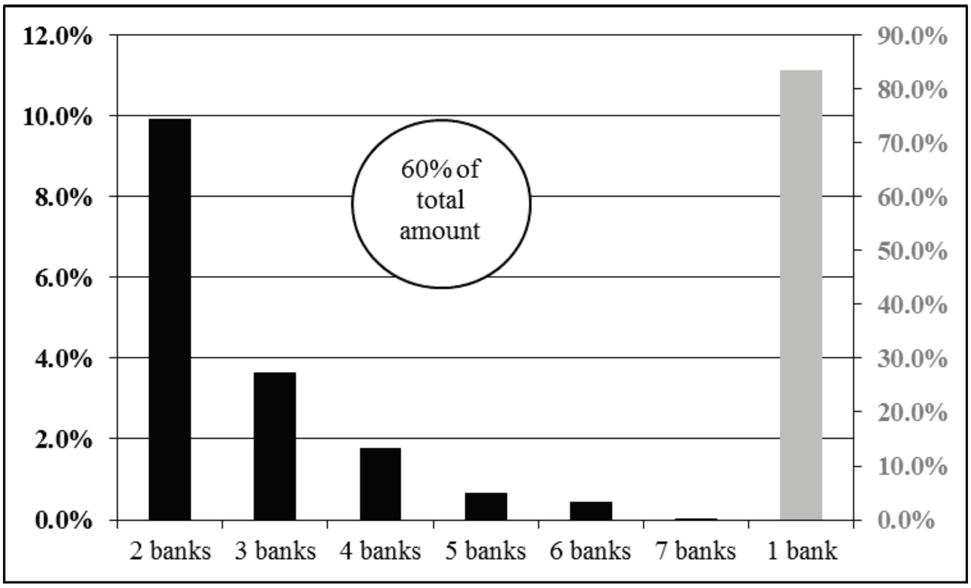
12.0%
10.0%
8.0%
6.0%
4.0%
2.0%
0.0%
90.0%
80.0%
70.0%
60.0%
50.0%
40.0%
30.0%
20.0%
10.0%
0.0%
60% of
total
amount
2 banks
3 banks
4 banks
5 banks
6 banks
7 banks
1 bank

Table 1. Total exposure summary statistics by borrower type (2015:Q4, NIS million)

This table presents the descriptive statistics of large exposures net indebtedness by the borrower type as for 2015:Q4. Except for the number of firms, amounts are in NIS millions.

	N	Sum	Mean	Median	Minimum	Maximum
Local firms	5,533	448,238.2	81.0	37.4	0	4,477.7
firms belonging to borrowers group	1,751	286,767.1	163.8	87.6	0	4,477.7
firms that do not belong to borrowers group	3,782	161,471.1	42.7	30.6	0	1,356.1
public firms	682	95,830.4	140.5	54.6	0	4,477.7
private firms	4,851	352,407.8	72.6	36.0	0	1,895.6
Foreign firms	966	80,548.9	83.4	52.7	0	1,693.6
Financial institutions	145	55,891.3	385.5	208.7	9.3	2,447.1
Individual (local and foreign)	1,191	31,965.3	26.8	21.6	0	354.3
Other	363	48,426.3	133.4	41.7	0	5,043.4
Total	8,198	665,070.0	81.1	36.4	0	5,043.4
Borrower's group						
groups	439	374,032	852.0	306.3	0	15,383.5

Table 2. Local firms distribution by belonging to a borrowers group (2015:Q4)

This table presents the distribution of local firms (row 1 in Table 1) by belonging to a borrowers group or not, and descriptive statistics of the number of firms within a borrowers group. Except for the number of firms, amounts are in NIS million.

	All local firms	Local firms not belonging to a borrowers group	Local firms belonging to a borrowers group
N of borrowers	**5,533**	**3,782**	**1,751**
(%)	(100%)	(68.4%)	(31.6%)
Sum	**448,238**	**161,471**	**286,767**
(%)	(100%)	(41.6%)	(58.4%)
Mean	**81.0**	**42.7**	**163.8**
Number of firms within a borrowers group			
Average			4.04
Median			2
Minimum			1
Maximum			47

Table 3. Descriptive statistics of the independent variables used to explain the probability of establishing multiple banking relationships

This table presents a descriptive statistics of the independent variables explaining the probability to establish multiple banking relationships, for the treatment group (borrower that added a bank as a lender) and the control group (borrower that didn’t add a bank as a lender). Also included is the t-value for an equal mean between the two groups.

	Description	Mean			Standard Deviation		Median		Minimum		Maximum	
		didn't add bank	added bank	t-value (*H0: equal mean*)	didn't add bank	added bank	didn't add bank	added bank	didn't add bank	added bank	didn't add bank	added bank
Borrower												
L_TOT_DEBT	Natural log of borrower's total net exposure	10.345	10.757	-9.640	2.087	1.489	10.585	10.732	-0.007	0	14.6	13.98
PUB	Is it a public firm (0=no, 1=yes)	0.039	0.114	-8.340	0.194	0.318	0	0	0	0	1	1
BOND	Does the firm have tradeable bonds (0=no, 1=yes)	0.017	0.050	-5.400	0.129	0.219	0	0	0	0	1	1
Exposure												
NET_GROSS_SHARE	Net exposure / gross exposure	0.945	0.961	-3.850	0.184	0.139	1	1	0	0	1	1
COLL_DEBT_SHARE	Collateral value / net exposure	2.694	0.733	2.170	247.2	7.023	0.094	0.022	0	0	49,547.9	180.4
BALANCE_DEBT	On-balance credit / net exposure	0.627	0.571	5.140	0.405	0.383	0.838	0.667	0	0	1	1
PROBLEM	Does the borrower have any exposure defined as a problem loan? (0=no, 1=yes)	0.139	0.061	11.430	0.346	0.239	0	0	0	0	1	1
Bank												
L_BANK_SIZE	Natural log of bank's total assets	19.2	19.2	0.360	0.794	0.798	19.6	19.6	16.122	16.1	19.9	19.9
BANK_CREDIT	Bank's credit portfolio / total assets	0.661	0.662	-0.530	0.057	0.058	0.657	0.657	0.531	0.531	0.827	0.827
BANK_CAPITAL	Bank's capital / total assets	0.101	0.102	-0.760	0.016	0.017	0.098	0.098	0.064	0.064	0.131	0.131

(continued)

	Description	**Mean**			**Standard Deviation**		**Median**		**Minimum**		**Maximum**	
Bank-Borrower Relationship		didn't add bank	added bank	t-value (*H0: equal mean*)	didn't add bank	added bank	didn't add bank	added bank	didn't add bank	added bank	didn't add bank	added bank
IND_CREDIT	Borrower's industry credit in the bank / total credit	12.5	12.1	2.440	6.695	6.073	13.6	12.1	0.007	0.444	80.4	29.9
IND_CREDIT_SQ	(Borrower's industry credit in the bank / total credit)^2	201.764	183.355	4.350	220.0	146. 9	186.1	146.7	0	0.197	6,467.0	897.1
GAP_SINGLE	Single borrower regulatory gap – borrower's net exposure	0.146	0.145	4.980	0.006	0.008	0.148	0.148	0.003	0.061	0.150	0.150
GAP_GROUP	Borrowing group regulatory gap – borrower's borrowing group net exposure	0.238	0.233	4.330	0.037	0.045	0.250	0.250	-0.097	-0.042	0.250	0.250
TIME	Number of quarters in the bank	12.949	12.906	0.160	9.393	9.345	10.000	10.000	1	1	42	42

Table 4. The probability of adding a lending bank

The dependent variable takes 1 if the the borrower added a lending bank in time *t* and 0 otherwise. L_TOT_DEBT is the natural log of borrower's total net exposure; PUB takes 1 if the borrower is a public company and 0 otherwise; BOND takes 1 if the firm has tradeable bonds and 0 otherwise; NET_GROSS_SHARE is the net exposure divided by the gross exposure; COLL_DEBT_SHARE is the collateral value divided by the net exposure; BALANCE_DEBT is the on-balance sheet credit divided by net exposure; PROBLEM takes 1 if the borrower has any exposure defined as a problem loan; BANK_SIZE is the natural log of bank's total assets; BANK_CREDIT is calculated as bank's credit portfolio divided by total assets; BANK_CAPITAL is calculated as bank's capital divided by total assets; IND_CREDIT is the borrower's industry credit in the bank divided by total credit and IND_CREDIT_SQ is the squared term; GAP_SINGLE is the difference between single borrower regulatory gap and borrower's net exposure; GAP_GROUP is the difference between borrowing group regulatory gap and borrower's borrowing group net exposure; TIME is the number of quarters the borrower-lender relationship exist. All independent variables are taken (lags) at *t-1*. Nominal variables are in log terms of their 2015 fixed value. All specifications include dummy variables for banks and quarter.

* - lower than 10 percent significance level; ** - lower than 5 percent significance level; *** - lower than 1 percent significance level.

	(1)		(2)		(3)		(4)		(5)	
	Point Estimate	Odds Ratio	Point Estimate	Odds Ratio	Point Estimate	Odds Ratio	Point Estimate	Odds Ratio	Point Estimate	Odds Ratio
Intercept	-5.612		-4.271***		-2.011		-0.662		-0.902	
Borrower										
L_TOT_DEBT	0.156***	1.169							0.112***	1.119
PUB	1.066***	2.904							1.003***	2.729
BOND	0.147	1.159							0.132	1.142
Exposure										
NET_GROSS_SHARE			0.487**	1.629					0.02	1.021
COLL_DEBT_SHARE			-0.001	1					-0.001	1
BALANCE_DEBT			-0.372***	0.69					-0.409***	0.664
PROBLEM			-0.874***	0.417					-0.621***	0.538
Bank										
BANK_SIZE					-0.188	0.829			-0.152	0.859
BANK_CREDIT					0.628	1.875			-0.431	0.65
BANK_CAPITAL					4.918	136.836			8.278	>999.999
Bank-Borrower Relationship										
IND_CREDIT							0.096***	1.101	0.078***	1.082
IND_CREDIT_SQ							-0.006***	0.995	-0.005***	0.996
GAP_SINGLE							-21.42***	<0.001	-8.898*	<0.001
GAP_GROUP							-2.482***	0.084	-2.056***	0.128
TIME							-0.002	0.999	-0.002	0.999
Quarters dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banks dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cox-Snell R-squared	0.02984		0.0235		0.0144		0.0229		0.0409	

Table 5. **Descriptive statistics of the independent variables used to explain the matching between a borrower and a new lending bank**

This table presents the descriptive statistics of the independent variables used to explain the matching between a borrower and a new lending bank, for matches that were realized and potential matches that were not realized. The analysis was made using two samples: sample 1 consists of all banks as candidates but for a shorter period (12 quarters are left out); sample 2 consists of all quarters but with one bank not included in the set of candidate banks.

	Description	Sample	Mean			Standard Deviation		Median		Minimum		Maximum	
			matched	*non-matched*	t-value (*H0: equal mean*)	*matched*	*non-matched*	*matched*	*non-matched*	*matched*	*non-matched*	*matched*	*non-matched*
CAND_BANK_ SIZE	Natural log assets of the candidate bank	Sample 1	19.17	18.67	-21.59	0.71	0.77	19.61	18.67	17.22	17.22	19.88	19.88
		Sample 2	19.14	18.24	-28.88	0.84	1.18	19.63	18.53	16.13	16.12	19.88	19.88
C_RATIO	Capital to assets ratio the candidate bank holds	Sample 1	0.10	0.09	-14.21	0.02	0.01	0.10	0.09	0.06	0.06	0.13	0.13
		Sample 2	0.10	0.09	-19.24	0.02	0.01	0.10	0.09	0.07	0.07	0.13	0.13
IND_CREDIT	Share of credit to the borrower's industry in the candidate bank	Sample 1	11.76	11.48	-1.34	6.27	6.33	11.49	11.83	0.39	0.18	29.95	29.95
		Sample 2	11.70	10.55	-5.20	6.24	7.08	11.41	11.02	0.12	0.00	25.69	25.69
GAP_GROUP	Borrowing group regulatory gap – borrower's borrowing group net exposure, in the candidate bank	Sample 1	0.27	0.27	1.71	0.05	0.04	0.30	0.30	0.005	-0.004	0.30	0.30
		Sample 2	0.27	0.27	3.06	0.04	0.04	0.28	0.30	0.005	-0.004	0.30	0.30
BOR_BANK_SIZE	The product between the size of the borrower and the size of the candidate bank	Sample 1	206.28	200.87	-5.72	29.65	29.05	206.78	201.14	0	0	273.97	275.20
		Sample 2	204.59	195.02	-8.93	30.92	31.06	205.24	196.63	0	0	273.97	275.20
SIZE_PRODUCT	The product between the original and the candidate bank's natural log total assets	Sample 1	369.10	359.33	-16.97	18.27	17.63	374.38	363.34	315.09	314.54	393.90	393.90
		Sample 2	367.28	349.91	-22.12	22.10	25.69	374.91	354.16	281.41	278.98	393.90	393.90

(continued)

	Description	Sample	Mean			Standard Deviation		Median		Minimum		Maximum	
			matched	*non-matched*	t-value (*H0: equal mean*)	*matched*	*non-matched*	*matched*	*non-matched*	*matched*	*non-matched*	*matched*	*non-matched*
SIZE_DIF	The difference between the original and the candidate bank's natural log total assets	Sample 1	0.08	0.58	15.25	0.99	1.11	0.01	0.65	-2.37	-2.41	2.37	2.41
		Sample 2	0.05	0.59	15.25	0.97	1.11	0.01	0.67	-2.36	-2.37	-2.37	-2.37
IN_GROUP	Does the candidate bank supply credit to an entity that belongs to the borrower's borrowing group (0=no, 1=yes)	Sample 1	0.15	0.11	-3.55	0.36	0.31	0	0	0	0	1	1
		Sample 2	0.15	0.09	-5.05	0.36	0.28	0	0	0	0	1	1
NEW_ BORROWER	Did the candidate bank used to have any kind of exposure to the borrower in the past (0 = no, 1 = yes)	Sample 1	0.55	0.89	22.12	0.50	0.32	1	1	0	0	1	1
		Sample 2	0.51	0.89	23.33	0.50	0.31	1	1	0	0	1	1
EQ_VOL_90D_DIF	The difference between the original and the candidate bank 90-day equity volatility	Sample 1	0.002	0.18	1.53	3.57	3.76	0.00	0.01	-10.14	-10.14	10.14	10.14
		Sample 2	-0.11	-0.01	0.86	3.24	3.52	-0.01	-0.03	-9.28	-9.76	9.36	9.76
BOND_DIF	The difference between traded bond spread of a candidate and the original bank	Sample 1	-0.001	0.07	6.26	0.35	0.38	-0.001	0.07	-1.78	-1.78	1.78	1.78
		Sample 2	-0.02	0.12	10.36	0.37	0.42	-0.01	0.10	-1.78	-1.78	1.78	1.78
EQ_CORR	The correlation between the original and the candidate bank 90-day equity volatility	Sample 1	0.44	0.38	-10.45	0.19	0.17	0.45	0.39	-0.08	-0.08	0.84	0.84
		Sample 2	0.42	0.31	-15.78	0.20	0.21	0.44	0.33	-0.15	-0.25	0.79	0.79

DISTANCE	The Euclidean distance between a candidate and the original bank loan portfolios	Sample 1	0.13	0.16	11.45	0.09	0.09	0.11	0.13	0.03	0.03	0.46	0.46
		Sample 2	0.13	0.21	20.15	0.11	0.15	0.10	0.15	0.03	0.03	0.60	0.60

Table 6. With which bank does the borrower establish multiple relationships? Mixed logit estimation results

Estimation of the effect each dependent variable has on the choice of the additional bank. Sample 1 includes the full period but excludes one bank as a candidate bank and all borrowers that established or had a banking relationship with it; Sample 2 includes all 7 banks but for a shorter period due to lack of data for one bank in the first 12 quarters. CAND_BANK_SIZE is the natural log assets of the candidate bank; C_RATIO is the capital to assets ratio the candidate bank holds; IND_CREDIT is the share of credit to the borrower's industry in the candidate bank; GAP_GROUP is the difference between borrowing group regulatory gap and borrower's borrowing group net exposure; BOR_BANK_SIZE is the product between the size of the borrower and the size of the candidate bank; SIZE_PRODUCT is the product between the original and the candidate bank's natural log total assets and SIZE_DIF is the difference (original minus candidate); IN_GROUP takes 1 if the candidate bank has an exposure to one of the entities in the borrower's borrowing group, and 0 otherwise; NEW_BORROWER takes 1 in case the candidate never used to have any kind of exposure to that borrower in the past, and 0 otherwise; EQ_VOL_90D_DIF is the difference between original and candidate bank's 90-day equity volatility; EQ_CORR is the correlation between original and candidate bank's equity returns; DISTANCE is the Euclidean distance between a candidate and the original bank loan portfolios.
* - lower than 10 percent significance level; ** - lower than 5 percent significance level; *** - lower than 1 percent significance level. The goodness-of-fit measures include 6 different measures based on the likelihood ratios of the full and empty model. Some use also the number of observations and/or regressors as inputs. The McFadden's LRI measure has different distribution so it is presented separately.

	(1)		(2)		(3)		(4)	
	Sample 1				Sample 2			
	Point estimate	p-value	Point estimate	p-value	Point estimate	p-value	Point estimate	p-value
CAND_BANK_SIZE	-3.876**	0.0169			-0.517	0.6804		
C_RATIO	6.786*	0.0897	8.051**	0.0423	10.516**	0.0119	13.372***	0.0013
IND_CREDIT	0.05***	0.0002	0.049***	0.0003	0.053***	0.0006	0.05***	0.0012
GAP_GROUP	-5.513**	0.033	-3.995	0.1195	-6.912**	0.0124	-4.693*	0.09
BOR_BANK_SIZE	-0.035	0.3712	-0.024	0.5334	-0.068*	0.0661	-0.06	0.1041
SIZE_PRODUCT	0.247***	0.0032			0.088	0.173		
SIZE _DIF			-0.745*	0.0743			-1.058**	0.0102
IN_GROUP	0.943***	<.0001	0.978***	<.0001	0.919***	0.0004	0.991***	0.0001
NEW_BORROWER	-2.067***	<.0001	-2.064***	<.0001	-2.142***	<.0001	-2.147***	<.0001
EQ_VOL_90D_DIF	-0.03**	0.0336	-0.028**	0.0465	-0.036**	0.0332	-0.035**	0.0431
EQ_CORR	0.634*	0.0718	0.879***	0.0081	0.862**	0.0255	0.971***	0.0082

DISTANCE	-0.098	0.8803	-0.042	0.9487	0.218	0.6886	0.200	0.7095
goodness-of-fit range	0.4558 - 0.6209		0.4536 - 0.6172		0.5315 - 0.7443		0.5314 - 0.7442	
McFadden's LRI	0.260		0.258		0.317		0.316	

Table 7. Testing for mimicking: mixed logit estimation results with interaction between size and equity correlation

Estimation of the effect each dependent variable has on the choice of the additional bank. The sample for this estimation is Sample 2, which includes all 7 banks but for a shorter period due to lack of data for one bank in the first 12 quarters. The variable E_CORR X ORIGINAL_SIZE is the product between E_CORR (defined above) and the size (log assets) of the original lender. Other control variables are defined above. * - lower than 10 percent significance level; ** - lower than 5 percent significance level; *** - lower than 1 percent significance level. The goodness-of-fit measures include 6 different measures based on the likelihood ratios of the full and empty model. Some use also the number of observations and/or regressors as inputs. The McFadden's LRI measure has different distribution so it is presented separately.

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	Point estimate	p-value
CAND_BANK_SIZE	0.153	0.9019
C_RATIO	7.709*	0.0756
IND_CREDIT	0.052***	0.0004
GAP_GROUP	-6.492**	0.0193
BOR_BANK_SIZE	-0.072*	0.0515
CAND_ORG_BANK_SIZE	0.056	0.3823
IN_GROUP	0.94***	0.0003
NEW_BORROWER	-2.144***	<.0001
EQ_VOL_90D_DIF	-0.04**	0.0199
EQ_CORR	-0.46	0.5664
EQ_CORR_SIZE	0.093**	0.0484
goodness-of-fit range	0.5584 - 0.7898	
McFadden's LRI	0.633	

Table 8. Testing for mimicking: separating big banks borrower and mid-small banks borrowers

Estimation of the effect each dependent variable has on the choice of the additional bank. The sample for this estimation is Sample 2, which includes all 7 banks but for a shorter period due to lack of data for one bank in the first 12 quarters. * - lower than 10 percent significance level; ** - lower than 5 percent significance level; *** - lower than 1 percent significance level. The goodness-of-fit measures include 6 different measures based on the likelihood ratios of the full and empty model. Some use also the number of observations and/or regressors as inputs. The McFadden's LRI measure has different distribution so it is presented separately.

	Big banks borrowers (number of cases=608)		*Mid-small banks borrowers (number of cases=398)*	
	Point estimate	p-value	Point estimate	p-value
CAND_BANK_SIZE	0.611	0.9747	2.651	0.1753
C_RATIO	15.49***	0.0059	8.984	0.1641
IND_CREDIT	0.059***	0.0024	0.036	0.118
GAP_GROUP	0.402	0.911	-14.946***	0.0004
BOR_BANK_SIZE	-0.047	0.3406	-0.109*	0.0714
CAND_ORG_BANK_SIZE	0.019	0.9845	-0.061	0.5659
IN_GROUP	1.078***	0.0006	0.839*	0.0809
NEW_BORROWER	-2.191***	<.0001	-2.111***	<.0001
EQ_VOL_90D_DIF	-0.048**	0.032	-0.017	0.5502
EQ_CORR	0.865*	0.0866	0.487	0.4428
goodness-of-fit range	0.5584 - 0.7898		0.4946 - 0.6811	
McFadden's LRI	0.353		0.273	

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Appendix

Table 1A. List of variables in the database

Variable	Note
Date	
Bank name	
Borrower identifier	
Borrower name	
Borrower type	Can be either an individual, a firm, partnership, financial institution, with distinction between local and foreign entities
Borrowing group name	
Borrowing group identifier	
Reason of inclusion in borrowing group	Controlled firm, held without control, guaranteed, financial dependency etc.
Industry classification	By main order, 2, 3 and 4 digits
Credit rating	Each bank has its own rating scales. We unified it to an eight level scale
Is it a public firm?	1 – yes, 0 – no
Does it have tradeable bonds?	1 – yes, 0 – no
Total credit before write-offs and provisions	on-balance items
Value of borrower's securities held by the bank	on-balance items
Commitment due to involvement in OTC derivatives	on-balance items
Total credit risk before write-offs and provisions	on-balance items
Write-offs	on-balance items
Total credit risk after write-offs and before provisions	on-balance items
Special mention credit risk	on-balance items
Substandard credit risk	on-balance items
Impaired credit risk	on-balance items
Total problematic credit risk	on-balance items
Indivudual credit risk loss provisions	on-balance items
Total credit risk after write-offs and provisions	on-balance items
Group provisions for credit loss	on-balance items
Additional provision	on-balance items
Non-indexed credit risk	on-balance items
Indexed credit risk	on-balance items
Foreign currency and foreign currency indexed credit risk	on-balance items
Nonrecourse credit	on-balance items

Total credit before write-offs and provisions	off-balance items
Write-offs	off-balance items
Total credit risk after write-offs and before provisions	off-balance items
Special mention credit risk	off-balance items
Substandard credit risk	off-balance items
impaired credit risk	off-balance items
Total problematic credit risk	off-balance items
Individual credit risk loss provisions	off-balance items
Total credit risk after write-offs and provisions	off-balance items
Group provisions for credit loss	off-balance items
Additional provision	off-balance items
On and off balance credit risk after write offs and provisions	
Gross exposure	
Total deductions	
Net exposure	
Bank deposits	Collateral. Appears in its original value and the value for collateral
Tradeable bonds	Collateral. Appears in its original value and the value for collateral
Other tradeable securities	Collateral. Appears in its original value and the value for collateral
Non-tradeable securities	Collateral. Appears in its original value and the value for collateral
Subordinated real-estate	Collateral. Appears in its original value and the value for collateral
State guarantee	
Tradeable documents	

Table 2A. Pearson correlations between the independent variables

	L_TOT_DEBT	PUB	BOND	NET_GROSS_SHARE	COLL_DEBT_SHARE	BALANCE_DEBT	PROBLEM	L_BANK_SIZE	BANK_CREDIT	BANK_CAPITAL
L_TOT_DEBT	1.0000	0.0259	0.0376	0.6943	-0.0069	0.0969	-0.4012	0.1806	0.0608	0.0513
PUB	0.0259	1.0000	0.5372	0.0098	-0.0019	0.0081	-0.0174	0.0389	0.0142	0.0133
BOND	0.0376	0.5372	1.0000	0.0142	-0.0013	0.0091	-0.0189	0.0135	0.0235	0.0202
NET_GROSS_SHARE	0.6943	0.0098	0.0142	1.0000	-0.0063	0.1549	-0.1875	0.0913	0.0312	0.0333
COLL_DEBT_SHARE	-0.0069	-0.0019	-0.0013	-0.0063	1.0000	-0.0070	-0.0010	-0.0020	-0.0061	-0.0064
BALANCE_DEBT	0.0969	0.0081	0.0091	0.1549	-0.0070	1.0000	0.0264	0.0190	-0.0499	-0.0087
PROBLEM	-0.4012	-0.0174	-0.0189	-0.1875	-0.0010	0.0264	1.0000	0.0026	-0.0139	-0.0142
L_BANK_SIZE	0.1806	0.0389	0.0135	0.0913	-0.0020	0.0190	0.0026	1.0000	0.1016	0.5793
BANK_CREDIT	0.0608	0.0142	0.0235	0.0312	-0.0061	-0.0499	-0.0139	0.1016	1.0000	0.2816
BANK_CAPITAL	0.0513	0.0133	0.0202	0.0333	-0.0064	-0.0087	-0.0142	0.5793	0.2816	1.0000
IND_CREDIT	0.0424	-0.0248	-0.0084	0.0047	-0.0037	-0.0719	-0.0255	-0.1274	-0.0732	-0.0043
IND_CREDIT_SQ	0.0098	-0.0309	-0.0125	0.0050	-0.0025	-0.0358	-0.0232	-0.1661	-0.0326	-0.0104
GAP_SINGLE	-0.2871	0.0014	-0.0366	-0.0852	0.0027	0.0396	0.1026	0.4394	-0.0307	0.2965
GAP_GROUP	-0.1453	-0.0291	-0.0378	-0.0284	0.0025	-0.0437	0.0848	-0.0452	-0.0277	-0.0226
TIME	0.0463	0.0027	0.0193	0.0242	0.0001	0.0454	0.0940	0.0762	-0.0212	0.3157

	IND_CREDIT	IND_CREDIT_SQ	IND_CREDIT	GAP_SINGLE	GAP_GROUP	TIME
L_TOT_DEBT	0.0424	0.0098	0.0424	-0.29	-0.15	0.05
PUB	-0.0248	-0.0309	-0.0248	0.00	-0.03	0.00
BOND	-0.0084	-0.0125	-0.0084	-0.04	-0.04	0.02
NET_GROSS_SHARE	0.0047	0.0050	0.0047	-0.09	-0.03	0.02
COLL_DEBT_SHARE	-0.0037	-0.0025	-0.0037	0.00	0.00	0.00
BALANCE_DEBT	-0.0719	-0.0358	-0.0719	0.04	-0.04	0.05
PROBLEM	-0.0255	-0.0232	-0.0255	0.10	0.08	0.09
L_BANK_SIZE	-0.1274	-0.1661	-0.1274	0.44	-0.05	0.08
BANK_CREDIT	-0.0732	-0.0326	-0.0732	-0.03	-0.03	-0.02
BANK_CAPITAL	-0.0043	-0.0104	-0.0043	0.30	-0.02	0.32
IND_CREDIT	1.0000	0.8361	1.0000	-0.13	0.01	-0.01
IND_CREDIT_SQ	0.8361	1.0000	0.8361	-0.11	0.01	-0.01
GAP_SINGLE	-0.1253	-0.1107	-0.1253	1.00	0.21	0.02
GAP_GROUP	0.0084	0.0139	0.0084	0.21	1.00	-0.03
TIME	-0.0132	-0.0074	-0.0132	0.02	-0.03	1.00