Endogenous Bank-Firm Matching: Time-variation and Effects

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Abstract

This paper documents changes in bank-firm matching in the U.S. syndicated loan market and studies their causes and effects on lending. We find that the empirically observed match between unrated firms and well-capitalised banks until the Global Financial Crisis (GFC) has disappeared since 2010. We argue that the prolonged low-interest rate environment and the concurrent expansion of the bond market after the GFC largely explain this disappearance. Our empirical analysis shows that, in the post-GFC period, unrated firms with better access to the bond market are as likely to match with well-capitalised banks as rated firms. We then test the effect of the disappearing match. In particular, we find that matching with well-capitalised banks or not do not affect unrated firms' loan access during the COVID period, unlike in previous downturns. Moreover, we propose new post-GFC matching between risky banks and unrated firms. As the low-interest environment eroded banks' profitability, riskier banks tend to reach yields by exploiting rents from unrated firms.

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1 Introduction

Due to the prolonged low-interest rates period and stricter capital requirements, banks' operating environment changed markedly after the Global Financial Crisis (GFC). Did these changes impact the way in which banks and firms match in lending markets? This paper studies the post-GFC evolution of endogenous two-sided bank-firm matching and identifies its causes. Schwert (2018) provided the first robust evidence of the fact that bank-dependent firms tend to borrow from well-capitalised banks while less-dependent firms match with poorly-capitalised banks. In this paper, we show that this matching is time-varying and explore how it evolved since the GFC. We find that the matching *disappears* after the GFC.[1]

Figure 1 describes the presence of the matching by plotting the conditional correlation between banks' capital ratio and firms' unrated status.[2] It shows that the correlation varies in a cyclical pattern between 1987 and 2009 until it becomes essentially null during 2010-2019. This indicates that bank-dependent firms no longer match with well-capitalised banks after the GFC.

Insert Figure 1 here.

We propose three possible explanations for the new stylised fact we document, exploring both the demand side and the supply side of credit. From a borrower's perspective, the decision to borrow from a high-capital or low-capital bank depends on the solution of a trade-off between benefits and costs. By borrowing from a more solvent bank, a firm can avoid relationship termination when a macroeconomic shock, for example, the GFC, erodes banks' ability to supply credit. The cost is that the firm need to (at least partially) bear banks' additional cost of maintaining higher capital ratios (Bolton and Freixas, 2000). For bank-dependent firms, the reduction of the risk of relationship termination during crises is larger than the cost of borrowing from well-capitalised banks, a consideration that forms the basis of relationship matching. However, we argue that from the point of view of bank-dependent firms, this saving becomes

[1]Two examples can illustrate this stylised fact. Saga Communications obtained three loans from Fleetboston Financial Corp and three loans from Bank of New York Mellon during 2001-2006; both banks' capital ratios are in the top terciles of banks by capital ratios. After the GFC, however, the firm turned to JP Morgan Chase&CO and Bank of America Corp whose capital ratios are in the bottom tercile. Similarly, Scansource Inc switched from a well-capitalised bank (Trust Financial Corp) to an under-capitalised bank (JP Morgan Chase&CO) after the GFC.

[2]First, for each of the rolling four-quarters, we run a pooled regression of bank capital ratio on a dummy variable indicating whether the borrower is unrated or not while including various controls. Then, we plot the coefficients of the unrated dummy over time.

smaller after the GFC, and we propose two sources as a potential explanation. The first source is increasing opportunities to issue bonds at lower yields due to the prolonged low-interest rate environment post-GFC. The favourable bond market conditions allowed bank-dependent firms to switch more smoothly from loans to bonds, potentially helping to buffer the termination of lending relationships. This unties some unrated firms from well-capitalised banks and leaves most remaining unrated firms to match with banks. We use firm size, estimated bond issuing costs compared to loans, and loans outstanding as a share of total debt to measure a firm's ability to enter the bond market or stickiness to loans. The empirical analysis supports this argument: in the post-GFC sample, unrated firms that can more easily enter the bond market are as likely to match with well-capitalised banks as with relatively less capitalised banks, compared to rated firms, in sharp contrast with the pre-GFC sample. On the other hand, unrated firms that are small in size, face higher costs of accessing the bond market than borrowing using loans, and are previously entirely financed by loans, are more likely to borrow from well-capitalised banks. We find further evidence supporting this bond market access explanation: Unrated firms borrowing from low-capital banks tend to obtain a credit rating after the GFC. This finding indicates that unrated firms are preparing to turn to the bond market as a "spare tire" or a complementary source of funding. Moreover, after the COVID shock, the change in bond outstanding of the unrated firms that borrow from low-capital banks is larger than that of those from high-capital banks.

Our empirical results are robust to linear and logit regression models. We also obtain similar results by estimating the semiparametric model developed by Fox (2018). The model estimates whether the covariance of banks' and firms' characteristics affects the value of matching without requiring data on loan rates and specifying a functional form of the error term's distribution. As in Schwert (2018), the semiparametric model also helps to test the impact of the disappearing matching in the COVID period.

The second possible demand-side explanation comes from the overall improved capital adequacy of the banking system after the GFC, due, in large part, to the implementation of stricter capital requirements, including several stress test programs and the adoption of various Basel III provisions. As a result, even banks considered to have relatively low capital measures can maintain their lending when hit by shocks, reducing the benefit for firms of matching with a well-capitalised bank. To test this explanation, we explore unrated firms' credit access during the COVID shock constructing two counterfactuals. In the first counterfactual, unrated firms form the same matches as they did pre-GFC. In the second counterfactual, we constrain unrated firms to borrow from all-else-equal-but high-capital banks. We find that the loan supply of unrated firms' banks under the benchmark is indistinguishable from the loan supply under the counterfactuals. Thus, the disappearing matching does not produce a significant credit disadvantage for unrated firms during crisis time compared to borrowing from well-capitalised banks. Comparatively, in the GFC, unrated firms' credit access was largely reduced if they did not borrow from well-capitalised banks.

We also explore a supply-side factor to explain the disappearing matching. From the lenders' perspectives, well-capitalised banks have advantages in lending to bank-dependent firms because high capital helps banks to absorb losses and commit them to syndication monitoring. However, we argue that low-capital banks' incentives to match with bank-dependent firms increase after the GFC because they tend to search for yield. The stricter capital requirements request under-capitalised banks to adjust (up) their capital quickly. At the same time, when interest rates are close to the zero lower bound, the rigidity of deposit rates impairs banks' interest margins. Thus, low-capital banks are incentivised to pursue short-term earnings by lending to unrated firms because banks are able to extract information rents or request higher risk premiums from bank-dependent firms. If the reach-for-yield argument is valid, we expect to observe risky banks lending to unrated firms after the GFC. The empirical evidence confirms a matching between unrated firms and banks with more non-performing assets, larger loan provisions, or higher liquidity risk measures.

Next, we test the relative importance of the supply-side vs. demand-side factors finding that both are at play. If the supply-side factor is the only relevant consideration to explain the disappearing matching, once we rule out poorly-capitalised banks' incentives to "reach-for-yield", we would expect the matching to reappear. In order to discriminate between explanations, we exploit the finding in Heider et al. (2019) that whether a bank's profits contract or expand in a low-interest rate environment depends on their reliance on deposits. These results suggest that poorly-capitalised banks are less likely to "reach-for-yield" if they have lower deposit ratios. As we find that even for low deposit banks, the matching has disappeared, the supply side explanation is unlikely to be the only driver. On the other side of the spectrum of reliance on deposits, in the subsample of high-deposit banks, we find evidence of matching between poorly-capitalised and unrated firms, consistent with the reach-for-yield supply-side motivation prediction.

The remainder of this paper is organised as follows. Section 2 discusses the rationales behind the matching between bank-dependent firms and well-capitalised banks and proposes explanations for the disappearing matching after the GFC. This section specifies testable hypotheses corresponding to each explanation connecting them to the related literature. Section 3 elaborates on the testing methodology, and Section 4 presents the empirical results. In Section 5, we further discuss our results and extend the results with robustness tests. Finally, Section 6 concludes.

2 Theoretical Underpinnings of the Disappearing Matching

The matching between bank-dependent firms and well-capitalised banks was first documented in Schwert (2018) (also verified by Farinha et al. (2022) with Portuguese loan-level data). Before exploring the rationales, we first characterise a bank-dependent firm. Bank-dependent firms can be defined as those firms that do not have a credit rating. This definition is widely used in prior literature (e.g., Kashyap et al., 1994; Faulkender and Petersen, 2006; Chava and Purnanandam, 2011). On the one hand, the unrated status means no access to the public bond market.[3] If a firm cannot borrow from the public, bank credit is a preferred private source of funding due to its flexibility (Darmouni and Siani, 2020) and the information it signals (Fama, 1985). On the other hand, a firm without a rating tends to be more informationally opaque, given that it has a limited tractable history of repaying debts and lacks a third-party assessment of its

[3]According to Schwert (2018), on average, firms with access to the public bond market have 62.55% bond outstanding at the time of loan origination, while firms without access only have 10.26% bond outstanding.

creditworthiness (Frank and Goyal, 2009; Sufi, 2007).[4] Thereby, unrated firms rely more on banks' advantages in information production and monitoring. The lack of access to the public bond market and the opacity are important in explaining the matching.

2.1 The demand-side rationale behind the matching

Deciding whether to borrow from a well-capitalised bank, firms trade off the benefits and costs. The benefits are arguably more pronounced for a bank-dependent firm.

High capital allows banks to supply more lending, especially during crises (Cornett et al., 2011; Berger and Bouwman, 2013; Gambacorta and Shin, 2018; Roulet, 2018). This avoids the termination of lending relationships. Bank-dependent firms rely more on private information that is hard to be transferred (Rajan, 1992). Also, bank-dependent firms have difficulties switching to other funding sources. Thus, bank-dependent firms benefit more from a more stable lending relationship. In contrast, firms with access to the bond market can easily withstand the bank credit shortage; thus, the solvency of a well-capitalised bank is less valuable to them.

Also, higher capital indicates that a bank's shareholders have more stakes in loan performance (Goodhart, 2013; Levine et al., 2020). This lowers the cost of information dilution and brings the value of certification. Since bank-dependent firms suffer more from information asymmetry, they will benefit more from matching with well-capitalised banks. The benefits and costs determine the equilibrium of the matching. Because the benefits exceed the cost, bank-dependent firms prefer to borrow from well-capitalised banks. This is supported by the evidence in Schwert (2018) and our pre-GFC results in the next section. However, a reduction in benefits (or an increase in costs) may shift the equilibrium. That is, a proportion of bank-dependent firms now choose not to borrow from high-capital banks because the value of stable lending and intensive monitoring cannot cover the costs of holding high capital transmitted to borrowers. Therefore, using our definition of bank dependence, we observe that unrated firms' preferences for well-capitalised banks fall after the GFC, leading to a disappearing matching. Also, in the new equilibrium, only the unrated firms that value the two benefits the most stay with well-capitalised banks.

The cost of borrowing from high-capital banks is straightforward. Equity capital is a more

[4]According to this study's sample, an average unrated firm is 1.43 times smaller in book assets, has 1.33 times lower tangible asset ratio, and is less likely to be listed than a rated firm.

expensive funding source than debts. Therefore, in exchange for stable lending relationships and intensive monitoring, firms will bear well-capitalised banks' expenses of holding large capital.

The benefits and costs determine the equilibrium of the matching. Because the benefits exceed the cost, bank-dependent firms prefer to borrow from well-capitalised banks. This is supported by the evidence in Schwert (2018) and our pre-GFC results in the next section. However, a reduction in benefits could change the equilibrium. Specifically, a proportion of bank-dependent firms now choose not to borrow from high-capital banks because the costs exceed the benefits of doing so. Therefore, we observe that unrated firms' preferences for well-capitalised banks fall after the GFC, leading to a disappearing matching. In the next two subsections, we propose two sources that result in lower benefits of borrowing from well-capitalised banks.

2.1.1 The post-GFC expansion in the bond market reduces the benefits of borrowing from well-capitalised banks

We propose that the bond market expansion (e.g., Çelik et al. (2020) and Berg et al. (2021) document the post-GFC increasing bond issuances) after the GFC reduces the benefits of borrowing from a high-capital bank.

The low-interest rate environment after the GFC, to some extent, drives the bond market boom. The federal reserve banks significantly reduced the policy rate. The long-term rates, which are relevant to bonds, also hit a historically low level due to large-scale asset-purchasing programs after the GFC Bikker and Vervliet (2018). As a result, there is a downward trend for the corporate bond yields of both Aaa-grade and Bbb-grade firms (see Figure B1 in Appendix B). Moreover, in Figure B2, we plot two quarterly time series of average bond yields relative to loan yields. One of the time series (the solid black line) is calculated among investment-grade firms, and the other (the dashed red line) is in speculative-grade firms. In the figure, the bond yields fall faster than the loan yields after the GFC. There are several reasons why loan rates fall slowly. First, the GFC questions banks' balance sheets, enlarging their funding costs relative to the policy rates (Kapuściński and Stanisławska, 2018). The low-interest rate environment also lowers banks' interest margins (Borio and Gambacorta, 2017). Both factors indicate that banks may increase loan rates to maintain profits. Secondly, the GFC could have reduced banks' risk appetite, making them lift lending standards by increasing loan rates (Illes and Lombardi, 2013; Hasan et al., 2014). The last possible reason is that banks may intendedly lift their loan rates to restore their banks' capital positions or to comply with a new capital regulation (Kapuściński and Stanisławska, 2018). Regardless of the various reasons, according to the market timing theory of Baker and Wurgler (2002), continuously lower bond yields provide firms with opportunities to issue bonds during the post-GFC period. Also, due to a lower interest rate that deteriorates mutual funds' performance, fund managers could have increased the supply of non-investment grade bonds.[5] This feeds bond-issuing opportunities to opaque and risky firms.

Given the increasing bond opportunities and lowering bond yields, firms are constrained less by the bond market and are more easily switching from loans to bonds (Petersen and Rajan, 1995; Boot, 2000). Therefore, favourable market conditions help to buffer the sudden separation of bank-firm relationships. Moreover, because bond issuances rely more on public information, making intensive monitoring from well-capitalised banks becomes less attractive (Datta et al., 1999; Ma et al., 2019).

2.1.2 The post-GFC improvement in overall capital adequacy reduces the benefits of borrowing from well-capitalised banks

The second source of the demand-side explanation is the implementation of stricter capital requirements after the GFC.

The increased solvency is a result of several official stress tests as well as the Basel III capital requirement.[6] In 2009, the Federal Reserve designs a stress test, namely the Supervisory Capital Assessment Program (SCAP), to ensure the capital adequacy of large bank holding companies (BHCs). This program assesses BHCs' capital levels under a worse-than-expected scenario during 2009–2010. If the BHC fails the test, the Fed asks the bank to implement a plan to improve its capital adequacy within six months. Given that most banks have already kept their capital levels exceeding the required minimum capital ratios in 2009, the stress test

[5] Becker and Ivashina (2015) document that mutual funds held 16% of corporate bonds in 2010.

[6] By collecting the BHCs' names participating in each of the capital adequacy programs, it is found that 99% of the bank-quarter observations in this study are subject to all three programs. Thus, it is reasonable to deduce that all sample banks' stability is reinforced after the GFC.

can effectively improve the stability of the BHCs.[7] Extending the scope of the SCAP, the Fed conducts annual assessments of BHCs' internal capital plans since 2011. The series of assessments is named Comprehensive Capital Analysis and Review (CCAR). The CCAR contains both a qualitative part that evaluates the banks' capital plans and a quantitative part that assesses BHCs' ability to pass stress tests.[8] If a BHC's plan is rejected by the Fed, the bank is required for a re-submission; if the plan is approved, the Fed will monitor the implementation of the plan. The CCAR, thus, raises the BHCs' subjective initiatives in improving solvency and increases the public's confidence in the overall banking industry. Moreover, under the Dodd-Frank Act Stress Test (DFAST), the Fed conducts stress tests on large BHCs on an annual basis beginning in 2013. The act also asks the banks to report their own stress tests.

Apart from the governmental assessments, U.S. banks' capital positions are further improved by the implementation of Basel III in 2013. This new Basel accord aims to enhance bank capital quality by lifting the minimum requirement of the tier-one capital ratio and introducing several additional buffers. Importantly, Basel III requires global systemically important banks (G-SIBs) and domestic systemically important banks (D-SIBs) to hold additional capital, which applies to the sample banks in this paper. Because the stability of the overall banking industry gains significantly, we argue that low-capital banks do not provide significantly less robust lending than high-capital banks. Supporting evidence comes from Li et al. (2020), who find that the equity level does not significantly affect bank lending during the COVID-19 pandemic. They explain that banks have accumulated "enough capital" after the GFC. Also, when we compare the capital ratio between well- and poorly-capitalised banks, we find a reducing difference from pre- to post-GFC periods (see Figure B3 where we plot two quarterly time series of capital ratios for banks in both the top and the bottom terciles). From borrowers' points of view, unrated firms can avoid costly relationship termination even from relatively low-capital banks. If bank-dependent firms realise this fact, they would have no preference for well-capitalised banks.

[7]Indeed, the SCAP identifies 10 out of 19 banks fail the test. See "The Supervisory Capital Assessment Program: Overview of Results"

[8]See "2011 CCAR Objectives and Overview"

2.2 The supply-side rationale behind the matching

From lenders' viewpoints of matching, well-capitalised banks have two advantages to matching with bank-dependent firms. First, because high capital ratios absorb losses and encourage monitoring, well-capitalised banks are better positioned to deal with uncertainty and asymmetric information when lending to risky and opaque firms. Second, in loan syndication, participants face risks that lead arrangers could shrink their responsibilities to monitor the borrower. This moral hazard issue is more severe when lending to an unrated borrower whose creditworthiness is untraceable. As a result, participant banks will join the contract until they know that the lead banks are going to monitor diligently (Holmstrom and Tirole, 1997; Sufi, 2007). Since high equity represents more stakes in the loan, well-capitalised lead arrangers ensure sufficient commitment to monitor when lending to a bank-dependent firm.

2.2.1 The post-GFC incentives of reaching for yield encourage under-capitalised banks to lend to bank-dependent firms

However, poorly-capitalised banks may also have incentives to lend to bank-dependent firms. Minimum capital requirements impose regulatory pressures on low-capital banks, compelling them to replenish capital quickly (Gambacorta and Mistrulli, 2004; Fonseca and González, 2010). Threats of a bank run also increase the fewer solvent banks' demand for liquidity (Diamond and Rajan, 2000). Thus, low-capital banks target bank-dependent borrowers because the banks can extract rents and retain the earnings to replenish capital (Santos and Winton, 2019). Moreover, bank-dependent firms tend to be small and young, which allows the banks to receive higher risk premiums.

We argue that the incentives of poorly-capitalised banks to lend aggressively to bank-dependent firms are stronger in the post-GFC period than the pre-GFC period, leading to the disappearing matching (and potentially a reversing matching).

Under the tightened capital requirements, banks with low capital have to increase their capital more quickly than before. At the same time, the prolonged low-interest rates reduce banks' abilities to accumulate retained earnings, making low-capital banks chase for yield (Acharya et al., 2019; Schivardi et al., 2022). Conventionally, deposits are priced as a markdown on money market rates. When the policy rate hits a low level, the markdown between deposit rates and market rates shrinks because deposits cannot reduce to negative (Borio and Gambacorta, 2017). However, as banks lower their loan rates to maintain competition under the low-interest rate environment, the rigidity of deposit rates impairs bank interest margins. As a result, low-capital banks have more incentives to exploit bank-dependent borrowers after the GFC. Further, because of the low-interest rates, low-capital banks are encouraged to expand their loans aggressively to unrated firms to pursue target returns (Borio and Zhu, 2012).

2.3 Testing Implications and Hypotheses

In this subsection, we specify hypotheses to test the three explanations. In the first explanation, we argue that the bond market expansion helps buffer relationship termination, thus reducing the benefits of borrowing from well-capitalised banks. Thus, bank-dependent firms that can easily enter the bond market can take advantage of the expansion and care less about bank solvency. In contrast, the unrated firms that face high switch costs from loans to bonds will still rely on well-capitalised banks' lending to prevent relationship termination. In other words, after the GFC, most bank-dependent firms prefer to borrow from well-capitalised banks, compared to less-dependent firms and nonbank-dependent firms.

Hypothesis 1. *(Bond Market Expansion) During the post-GFC period, unrated firms that face large loan-bond switching difficulties have a higher probability of matching with well-capitalised banks than rated firms.*

Hypothesis 2. *(Bond Market Expansion) During the post-GFC period, unrated firms that face small loan-bond switching difficulties do not have a higher probability of matching with well-capitalised banks than rated firms.*

The second explanation states that the benefit of borrowing from well-capitalised banks reduces after the implementation of the post-GFC stricter capital regulations. If the overall capital adequacy improves after the GFC, all else equal, even relatively low-capital banks can provide continuous lending in a crisis. In order to test this argument, we compare unrated firms' credit access during the COVID-19 pandemic under two scenarios. In the first scenario, unrated firms match with their banks in the actual loan contracts. Because of the disappearing matching, in the first scenario, unrated firms have no preferences for high- or low-capital banks. In the second scenario, we create a counterfactual where the unrated firms match with high-capital banks. We expect that there is no significant difference in credit availability between the two scenarios.

Hypothesis 3. *(Improved Capital Adequacy) Unrated firms' credit access is not considerably higher under the scenario where they borrow from well-capitalised banks than in the scenario where they have no preferences for high- or low-capital banks.*

As in the supply-side explanation, the low-interest rate environment impedes banks' interest income, making low-capital banks to peruse short-term earnings by aggressively lending to unrated firms. We test the behaviour of searching-for-yield by asking whether risky banks are likely to match with unrated firms. Similar to poorly-capitalised banks' intention to replenish capital, risky banks chase for yield to meet target returns required by shareholders (Becker and Ivashina, 2015; Naqvi and Pungaliya, 2023).

Hypothesis 4. *(Reaching for Yield) During the post-GFC period, the probability of matching is higher if the bank loads higher risks and the firm is unrated.*

This study lies at the nexus of multiple research agendas. Thus, the following section reviews related literature and specifies the contributions.

2.4 Literature Review and Contribution

The prior literature mainly studies a one-sided lending relationship; that is, financially opaque firms borrow more from banks than transparent firms – bank-dependent firms. The relationship is ascribed to banks' advantages in processing borrowers' information and mitigating information asymmetry (Berlin and Loeys, 1988; Rajan, 1992; Schenone, 2010; Schwert, 2018). For example, in Diamond (1984)'s model, banks enjoy economies of scale in monitoring their lending. Also, Fama (1985) argues that the history of deposit accounts allows banks to obtain more low-cost information about their borrowers' repaying ability. This study contributes to the literature by refining the choices of bank-dependent firms between well-capitalised banks and low-capital banks. The stepping stone for this study is Schwert (2018), which documents the two-sided matching between bank-dependent firms and well-capitalised banks for the first time. We extend the scope of this paper by exploring the time-variation of the matching and especially point out the tendency of disappearing matching after 2010.

There are other papers studying two-sided bank-firm matchings in loan contracts. For example, using Portuguese loan-level data and a similar regression model to this paper, Farinha et al. (2022) confirm the matching between bank-dependent firms and well-capitalised banks. The prior literature also documents another well-documented matching between small firms and small banks (Berger et al., 2005; Levine et al., 2020). Using survey data, Berger et al. (2017) find no disappearance of the matching between small banks and small firms over time. Instead, the size-specific matching is more substantial when the economic conditions. This paper finds that capital-specific matching is more vulnerable and more fragile over time. In addition, Accetturo et al. (2023) describes a matching if banks and firms are close in culture. However, they show that it is the demand-side incentive that mainly drives the matching, while we find that both supply-side and demand-side factors can affect the strength of the matching between bank-dependent firms and well-capitalised banks.

This study also relates to the literature studying interactions between the loan and bond markets. First, Datta et al. (1999) and Ma et al. (2019) find that the holding of loans imposes a certification effect on bond prices, while Booth (1992) documents the impact of bonds on loan pricing. Second, Chemmanur and Fulghieri (1994), Bolton and Freixas (2000), De Fiore and Uhlig (2011), and Crouzet (2018) literature discuss capital structures by comparing firms' choices between loans with bonds in firms' debt choices. Lastly, Goel and Zemel (2018) and Darmouni and Siani (2020) study the tendency to switch from loans to bonds during crises. Also, Becker and Benmelech (2021) and Berg et al. (2021) document that bonds are the preferable sources over loans to finance the liquidity shock during the COVID period. The evidence is consistent with our bond market-related explanation for the disappearing matching.

Last but not least, this study relates to the literature studying the changes in bank lending during the post-GFC period. Similar to this study, the literature discusses the impact of the prolonged low-interest rate environment on bank lending. Papers such as Claessens et al. (2018), Molyneux et al. (2020), and Lopez et al. (2020) find that, due to the rigidity of deposit rates raising banks' funding costs, the low-interest rates negatively affect banks' net interest incomes and profitability. As a consequence of the shrunk interest margins, Borio and Gambacorta (2017) and Heider et al. (2019) provide evidence that banks slow down their lending activities in such a low-rate environment. Another piece of literature studies the introduction of bank regulations after the crisis. Bordo and Duca (2018) and Hogan and Burns (2019) argue that the Dodd-Frank Act increased the regulatory burden on banks. The additional constraints can discourage banks from lending to small and riskier businesses because risky loans lower the chance of passing the stress tests under the act. Moreover, Acharya et al. (2018) find the negative impact of the U.S. stress tests on bank lending supply. The papers listed above conclude that the post-GFC changes in monetary policies and capital regulations alter banks' lending, while we show that these changes in banks' lending behaviours will ultimately disturb firms' borrowing choices of banks.

3 Data and Methodology

Section 3.1 describes the sample and data sources. Section 3.2 introduces two alternative methodologies to test the hypotheses.

3.1 Data sources and sample description

In this paper, the loan information comes from Thomson Reuters Loan Pricing Corporation's DealScan (DealScan). This database contains detailed variables describing syndicated loans, but it only provides limited balance sheet information for the contracting parties. The primary sources for bank and firm quarterly data are Compustat North America and Compustat Bank, respectively. Thus, our sample only contains publicly held banks and firms. We use the linking tables provided by Chava and Roberts (2008) and Schwert (2018) to merge DealScan with Compustat datasets.[9] After the merge, the original sample contains DealScan loans for each

[9]We thank Sudheer Chava, Michael Roberts and Michael Schwert for making these data available on WRDS. The lenders in Schwert (2018)'s linking table are those who acted as lead arrangers on at least 50 loans or at least $10 billion in volume in the set of loans in Chava and Roberts (2008)'s linking table.

quarter from quarter one of 1982 (1982Q1 for short) to 2016Q4. Since Chava and Roberts (2008)'s linking table only updates to 2017, we create a novel dataset by manually matching Dealscan firms to Compustat firms during the 2017-2020 period (Appendix A.2 provides more details of the method and process). [10] However, the data availability of the early part of the original sample is not ideal. In particular, the number of loans per quarter keeps at a three-digital number until 1987, and the observations in 2020 are quite limited at the time of writing.[11] Thus, the final sample period spans from 1987Q1 to 2019Q4.

Following Sufi (2007); Schwert (2018), this study focuses on lead arrangers to explore the bank-firm relationship. In a typical syndicated loan, it is the lead arranger(s) that contracts the terms with the borrower and approaches potential participants (Sufi, 2007). Also, during the life of a loan, the lead arranger(s) charges administrative and monitoring responsibilities. Following the convention of bank capital literature, the lead bank is defined on a consolidated basis.[12] On average, each loan has 1.05 lead arrangers in the pre-2010 sample and 1.40 lead arrangers after the GFC.

This paper focuses on U.S. companies and excludes all loans to financial firms (SIC between 6000 and 6999) as well as all observations with non-positive assets, equity, and share prices. These restrictions exclude about 20% of loans in the original DealScan-Compustat merged sample. The final sample contains 10737 loans pre-GFC and 19581 loans post-GFC. There are 18.27 banks and 220.37 firms during 2000-2007, while 12.08 banks and 172.15 firms during 2010-2019.

There are two other data sources in this paper. One is the Mergent Fixed Income Securities (FISD), and the other is the Capital I.Q. Capital Structure. FISD is a database recording detailed terms - including bond types, offering yield, offering amount, etc. - of all U.S. public

[10]The authors update the linking table at the end of 2017. In case Dealscan updates more 2017 loans in the following years, our manual merge starts in 2017.

[11]In DealScan, the number of loans per quarter reaches one thousand only after 1986. Also, in the original DealScan-Compustat merged sample, the issuance of loans (borrowers) per quarter reaches three- (two-) digital numbers in the last quarter of 1987 (1986).

[12]The definition of lead arrangers follows Bharath et al. (2011), who also study the relationships between banks and firms. In particular, Dealscan specifies a field called "Lead Arranger Credit", which takes values of "Yes or "No" for each bank. Any bank assigned "Yes" in that field is recognised as a lead arranger. Papers like Sufi (2007) and Gopalan et al. (2011) also use the field as the sole criteria. Bharath et al. (2011) identify lead arrangers using another Dealscan variable named "lender role". They require a lead arranger to have one of the following "lender role": admin agent, arranger, lead bank, and sole lender. Whether the lender is a lead arranger defined in each of the different definitions has a correlation of more than 0.85 with the definition used in this study.

bond issuances. We exclude all convertible bonds and all bonds to financial companies since these bonds differ significantly in timing and purposes from the others. Capital I.Q. provides data on the capital structure of firms worldwide. For example, this dataset reports the term loan outstanding of a firm in a given year. Using the Capital I.Q. data, we are able to measure how much a firm's total debts consist of bank loans. However, the data is only comprehensive from 2002 and on an annual basis. The debt types include loans (drawn credit lines and term loans), bonds (senior bonds and notes and subordinated bonds and notes), commercial paper, capital leases and other borrowings.

3.2 Empirical Models

In this study, we use two models to estimate the strength of bank-firm matching. The first one is a regression model which estimates how characteristics of banks and firms affect the probability of matching. We also estimate a semiparametric model developed by Fox (2018). This model allows us to generate counterfactuals where firms match with different banks deviating from their actual loan contracts.

3.2.1 The regression model

We run a linear probability regression model to estimate the probability of bank-dependent firms matching with well-capitalised banks (in robustness, we also estimate a logistic regression model). We construct all possible bank-firm combinations given the available lenders and borrowers in each quarter, including both actual and counterfactual pairs. For example, if there are ten banks and ten firms in a given quarter, the regression runs over the total 100 observations. Take 2013Q3 as an example. There are 13 banks and 174 firms, forming 2262 combinations of bank-firm pairs. Thus, 225 out of the 2262 pairs (close to 10%) are actual lending relationships observed in Dealscan. Note that the number of actual matches is slightly larger than the total number of firms. This is because 33 borrowers have multiple lead arrangers. Also, 10 out of the 13 banks lend to more than one firm. Thus, the setting forms a many-to-many matching game.

In Figure 1, we use the loan-level data to calculate the correlation between bank capital ratio and firm unrated status. Comparatively, the advantage of the linear probability model is it takes into consideration the out-of-sample potential bank-firm matches given all banks and firms on the concurrent lending market. Moreover, using the loan-level data may double-count a given bank-firm matching because a borrower can have two loan facilities with the same bank in one deal, which misleadingly reduces the standard errors (Sufi, 2007). The unique observation in the current sample is a bank-firm-quarter tuple, thus solving the problem. In order to test whether any characteristics of banks and firms contribute to the matching between them, we regress the dummy of the actual match (Observed Pair_{bft}) on a vector of bank and firm characteristics and their interaction terms. If the matching between unrated firms and well-capitalised banks exists, one should find that it is more likely to observe the actual match for an observed bank-firm pair with a high capital ratio and unrated status. The regression is specified more formally in the following equation.

$$\begin{aligned}\text{Observed Pair}_{bft} = {} & \theta_1\text{Bank Capitalisation}_{bt} + \theta_2\text{Unrated Dummy}_{ft} \\ & + \beta_1\text{Bank Capitalisation}_{bt} \times \text{Unrated Dummy}_{ft} \\ & + \theta_1\text{Bank Size}_{bt} + \theta_2\text{Firm Size}_{ft} + \beta_2\text{Bank Size}_{bt} \times \text{Firm Size}_{ft} \\ & + \beta_3\text{Relationship Lending Dummy}_{bft} + \beta_4\text{Top Industry}_{bft} + \beta_5\text{Bank-Firm Distance}_{bft} \\ & + \sum_{i=5}^{11}\beta_i\text{Other Firm Controls}_{ft} + d_b + d_f + d_t + u_{bft} \qquad (1)\end{aligned}$$

Variables are defined in Table A1 in Appendix A.1. The dependent variable is a dummy taking one if a bank-firm pair is observed in the Dealscan database. The key variable is the product of the bank capital ratio and the unrated dummy. Following Schwert (2018), Bank $\text{Capitalisation}_{bt}$ is the market capital ratio, which is defined as market capitalisation (the product of the share price and common share outstanding) divided by quasi-market assets (a sum of market capitalisation and book liabilities).[13] Unrated Dummy_{ft} is a dummy variable taking one if a firm does

[13]The focus on the market definition is because this measure of capital is forward-looking while the book value is backwards-looking. Also, the book capital ratio is vulnerable to earnings manipulation (Frank and Goyal, 2009). Bank capital ratio also has a regulatory definition (defined by Basel Committee on Banking Supervision Basel Accords). The use of the regulatory capital ratio is subject to some criticism. For instance, Demirguc-Kunt et al. (2013) argue that the Basel-defined capital ratios are less informative to investors than the equity ratio, especially during a crisis. Also, Schwert (2018) finds that bank-dependent firms have no preference for high-regulatory-capital banks. Since the focus is not to evidence a matching, we use market capital ratios to explore the time variation of the matching.

not have a long-term issuer rating from S&P in the loan origination month. Compustat no longer updates S&P longer-term issuer rating since 2017Q1. We then use the relevant information in the Capital IQ S&P Credit Ratings database to update.[14]

This interaction variable Bank Capitalisation$_{bt}$×Unrated Dummy$_{ft}$ tests whether a matching between an unrated firm and a well-capitalised bank (we can refer to it as an unrated-high matching) is more likely to be observed, relative to alternative matchings – an unrated-low and a rated-high matching. For example, consider two firms (rated and unrated) and two banks (with a one-unit difference in their capital ratios). The probability of observing the unrated-high matching is (θ_1+β_1) higher than the probability of the unrated-low matching. The probability of observing the rated-low matching is θ_1 higher than the probability of the rated-high matching. Adding the two values cancels out θ_1. Thus, a positive β_1 implies the existence of the unrated-high matching that we observe before the GFC in Figure 1. The magnitude of β_1 can be interpreted as the extent of an increase in matching probability if the firm is unrated and the bank has one unit higher capital ratio above the average. According to the previous evidence of the disappearing matching, we expect an insignificant coefficient in the post-GFC sample.

Equation 1 controls several bank-firm-level factors affecting a bank-firm matching. The first one is a product of bank size and firm size (Bank Size$_{bt}$×Firm Size$_{ft}$). Literature finds that small banks have more advantages in lending to small firms (see Berger et al. (2017), among others). Thus, the size interaction separates the size effect, and it is expected to have a positive coefficient. Prior literature finds that a bank and a firm are more likely to match if they have less information asymmetry (Degryse and Van Cayseele, 2000; Boot, 2000; Bolton et al., 2016) and/or are closer in geographic distance Chen and Song (2013); Farinha et al. (2022). In order to control for the informational closeness, Equation 1 includes two dummies. Relationship Lending$_{bft}$ considers whether the bank-firm pair has a prior relationship. Prior literature uses different ways to define relationship intensity, and we follow (Bharath et al., 2007; Schenone, 2010) to define a dummy taking one if the current firm and current bank have ever made a lending contract within 20 quarters before the loan. Another dummy (Top Industry$_{bft}$) measures a bank's information over the firm's industry; it takes one if a firm's industry is in the top three industries to which the

[14]The results are similar when I use Capital IQ data to measure the unrated dummy for the whole sample period.

bank makes loans in a given quarter. In order to capture the geographic closeness, Equation 1 includes the physical distance between banks and firms (Bank-Firm Distance$_{bft}$). A bank is more likely to lend to a closer firm because this facilitates monitoring (Agarwal and Hauswald, 2010; Levine et al., 2020). All three variables are expected to have positive coefficients.

The borrower-specific variables contain Altman's z-score measuring default risks, asset tangibility, profitability, cash holdings, leverage, Tobin's Q, years since IPO, measuring credit demands.

Lastly, both bank-(d_b) and firm-(d_f)fixed effects are included to capture unobservable time-invariant factors from both the supply-side and demand-side. Quarter-fixed effects (d_t) controls for macroeconomic factors. The standard errors are clustered at the bank level to account for the within-bank correlation in the error terms (Petersen, 2009). In the empirical tests, we use both ordinary linear squares and logit regressions to estimate Equation 1.

Next, we further unrated firms into two groups based on their abilities to switch from loans to bonds. Specifically, we generate two dummies – a hardly-switch unrated dummy taking one if a firm is unrated and face high friction to switch from loans to bonds and an easily-switch unrated dummy taking one if a firm is unrated and faces low friction to switch. We introduce three proxies for switching difficulties in the next section. For H1 and H2, we test the matching between well-capitalised banks and either unrated firms that can hardly switch or unrated firms that can easily switch in the post-GFC sample of 2010-2019. Thus, in Equation 1, we replace Bank Capitalisation$_{bt}\times$Unrated Dummy$_{ft}$ with an interaction between capital ratio and hardly-switch unrated dummy and an interaction between capital ratio and easily-switch unrated dummy. We expect a positive and significant coefficient of the former interaction (H1) and an insignificant interaction coefficient of the latter interaction (H2).

Then, we include an interaction between bank riskiness and the unrated dummy in Equation 1 to test H2. We expect a significant coefficient of the interaction and a sign being consistent with the matching between risky banks and unrated firms. We use three proxies for bank riskiness in the next section.

3.2.2 The semiparametric model

Next, we estimate a semiparametric model to verify the results of the linear probability regressions. The use of the semiparametric model allows us to test H3 by generating counterfactual matchings. In addition, the semiparametric model has two other advantages over the regression model. First, since loan rates and other nonpecuniary terms are the value transferred from borrowers to lenders, they can be important determinants of bank-firm matching. Because we can only observe the transferred value for actual bank-firm pairs, we are unable to include loan terms in the regressions. Rather, the estimation of the semiparametric model does not require data on loan terms. Second, the model does not require a known function form of the error term's distribution (e.g., the logistic function in a logit regression). Instead, it assumes a rank-order property which holds for various distributions Fox (2007).

The semiparametric model estimates the value of banks' and firms' characteristics to a matching. Thus, in this study, we test whether the combination of high capital ratio and unrated status are no longer value-added after the GFC. The estimation of Fox (2018) model relies on pairwise stability. Considering a bank-firm matching between Bank_1 and Firm_1. We can write the value of the matching from a bank's perspective as synergy enjoyed by the bank plus transferred payments from the firm to the bank. For example, the synergy can be thought of as the value of improved screening by matching with a close borrower. The transferred value includes loan rate and other contracting terms such as covenants. We specify the payoff to the bank as follows.

$$V_b\left(\text{Bank}_1, \text{Firm}_1\right) + t\left(\text{Bank}_1, \text{Firm}_1\right)$$

Similarly, we can write the matching value from a firm's point of view as synergy shared by the firm minus the transferred payments.

$$V_f\left(\text{Bank}_1, \text{Firm}_1\right) - t\left(\text{Bank}_1, \text{Firm}_1\right)$$

Thus, the total value of the matching is:

$$V_{b_1,f_1} = V_b\left(\text{Bank}_1, \text{Firm}_1\right) + V_f\left(\text{Bank}_1, \text{Firm}_1\right)$$

The pairwise stability says that the value of actual bank-firm matching is larger than and other counterfactual bank-firm pair. As we introduce a second firm – Firm_2, the payoff to Bank_1 under the actual matching (i.e., matching with Firm_1).is larger than the payoff under the counterfactual matching (i.e., matching with Firm_2.).

$$\begin{aligned}V_b\left(\text{Bank}_1, \text{Firm}_1\right) + t\left(\text{Bank}_1, \text{Firm}_1\right) \geq V_b\left(\text{Bank}_1, \text{Firm}_2\right) + \\ \left(V_f\left(\text{Bank}_1, \text{Firm}_2\right) + t\left(\text{Bank}_2, \text{Firm}_2\right) - V_f\left(\text{Bank}_2, \text{Firm}_2\right)\right),\end{aligned}$$

where $V_f(\text{Bank}_1, \text{Firm}_1)+t(\text{Bank}_2, \text{Firm}_2)-V_f(\text{Bank}_2, \text{Firm}_2)$ is the maximum transferred value Firm_2 is willing to pay Bank_1, which includes the synergy obtained from the counterfactual matching, the saving of transferred payments from the actual matching, and the loss of the synergy from the actual matching.

Then, consider another matching between Bank_2 and Firm_2. The pairwise stability compares the value of the matching between Bank_2 and Firm_2 to the value of the matching between Bank_2 and Firm_1.

$$\begin{aligned}V_b\left(\text{Bank}_2, \text{Firm}_2\right) + t\left(\text{Bank}_2, \text{Firm}_2\right) \geq V_b\left(\text{Bank}_2, \text{Firm}_1\right) + \\ \left(V_f\left(\text{Bank}_2, \text{Firm}_1\right) + t\left(\text{Bank}_1, \text{Firm}_1\right) - V_f\left(\text{Bank}_1, \text{Firm}_1\right)\right)\end{aligned}$$

Estimating the parameters using one pairwise stability condition involves transferred payments. However, summing the two pairwise conditions can cancel out the transferred payments.

$$\begin{aligned}&V_b\left(\text{Bank}_1, \text{Firm}_1\right) + V_f\left(\text{Bank}_1, \text{Firm}_1\right) + V_b\left(\text{Bank}_2, \text{Firm}_2\right) + V_f\left(\text{Bank}_2, \text{Firm}_2\right) \\ &\geq V_b\left(\text{Bank}_1, \text{Firm}_2\right) + V_f\left(\text{Bank}_1, \text{Firm}_2\right) + V_b\left(\text{Bank}_2, \text{Firm}_1\right) + V_f\left(\text{Bank}_2, \text{Firm}_1\right)\end{aligned}$$

The left-hand side of the inequality is the total value of two actual matchings, while the left-hand side is the total value of two counterfactual matchings. Thus, the inequality can be re-written as $V_{b_1,f_1} + V_{b_2,f_2} \geq V_{b_1,f_2} + V_{b_2,f_1}$, where the total value of each matching, V_{bf}, is defined in the following linear function.

$$
\begin{aligned}
V_{bf} &= \boldsymbol{X}'_{bf}\boldsymbol{\beta} + \epsilon_{bf} \\
&= \beta_1 \text{Bank Capitalisation}_b \times \text{Unrated Dummy}_f + \beta_2 \text{Bank Size}_b \times \text{Firm Size}_f \\
&+ \beta_3 \text{Relationship Lending Dummy}_{bf} + \beta_4 \text{Top Industry}_{bf} + \beta_5 \text{Bank-Firm Distance}_{bf} + \epsilon_{bf}
\end{aligned}
\tag{2}
$$

In Equation 2, the first component is a vector of observable characterises multiplying a vector of parameters, and the second component is an error term representing the unobservable factors determining the matching value. Note that Equation 2 does not include bank- or firm-specific variables because these variables are cancelled by each other in the inequality.

Fox (2018) specifies a rank order property which assumes the decision of matching is only determined by the observable characterises. Thus, we can rewrite the inequality without the error term. The rank order property assures consistency of the parameters being estimated from the following inequality.

$$
\boldsymbol{X}'_{b_1,f_1}\boldsymbol{\beta} + \boldsymbol{X}'_{b_2,f_2}\boldsymbol{\beta} \geq \boldsymbol{X}'_{b_1,f_2}\boldsymbol{\beta} + \boldsymbol{X}'_{b_2,f_1}\boldsymbol{\beta}
$$

We then use all sets of actual matchings in a given quarter to construct inequalities and include inequalities in all sample quarters.[15] To estimate $\boldsymbol{\beta}$, Fox (2018) defines a matching maximum score objective function as follows.

$$
\text{M}(\boldsymbol{\beta}) = \sum_{q=1}^{Q} \sum_{[(b_1,f_1),(b_2,f_2)]\epsilon\mu_a} \mathbf{1}\left\{\boldsymbol{X}'_{b_1,f_1}\boldsymbol{\beta} + \boldsymbol{X}'_{b_2,f_2}\boldsymbol{\beta} >= \boldsymbol{X}'_{b_1,f_2}\boldsymbol{\beta} + \boldsymbol{X}'_{b_2,f_1}\boldsymbol{\beta}\right\}, \tag{3}
$$

where Q is the number of quarters in the sample period, μ_q is all pairs of actual bank-firm matchings in a given quarter q, and $\mathbf{1}\{\cdot\}$ is an indicator function. Estimation of the parameters should satisfy the inequalities (i.e., the pairwise stability) as much as possible. Thus, the

[15] When estimating the semiparametric model, as Schwert (2018), we drop loan facilities with multiple lead arrangers.

optimisation problem is to find a set of parameters maximising M($\boldsymbol{\beta}$). Because M($\boldsymbol{\beta}$) is a step function, we use direct search methods. Specifically, we use the differential evolution algorithm, which is better for jumping out of a local maximisation. Also, we use the subsampling procedure developed by Politis et al. (1999) to construct confidence intervals.[16]

Following Schwert (2018), we subtract quarterly averages from all firm- and bank-specific variables and set the parameter on Relationship Lending Dummy$_{bf}$ (i.e., β_3) to be 1000 (if we set β_3 to be -1000, the number of inequality satisfied is much lower, indicating that the model fits poorly). Thus, the estimates of other parameters indicate relative the importance of the characteristics relative to lending relationships. Similar to the regression coefficient, we expect $\hat{\beta}_1$ to be positively significant in the pre-GFC sample, meaning that the matching between well-capitalised banks and unrated firms is the value added. We expect an insignificant $\hat{\beta}_1$ in the post-GFC sample, implying the irrelevance of bank solvency to unrated firms and vice versa.

Again, we test H1 and H2 in the post-GFC sample by replacing Bank Capitalisation$_b$×Unrated Dummy$_f$ in Equation 2 with an interaction between capital ratio and hardly-switch unrated dummy and an interaction between capital ratio and easily-switch unrated dummy. We expect the coefficient of the former interaction to be positive (H1) and the coefficient of the latter interaction to be insignificant (H2). Then, we add an interaction between bank riskiness and the unrated dummy in Equation 2 to test H4.

To test H3, we construct a counterfactual scenario where unrated firms match with well-capitalised banks and then compare it with the observed benchmark.

We assume a bank-dependent firm borrows from relationship banks in the COVID crisis. This is supported by Bolton et al. (2016), who find that relationship banks have more informational advantages and provide favourable loan conditions than transaction banks during crises. Thus, we define a firm's pre-crisis relationship bank as the matched bank indicated by the parameter estimated before the crisis. First, we estimate the parameters in Equation 2 from 2015Q1 to

[16]Following Schwert (2018), we draw (without replacement) 100 subsamples of one-quarter of the full set of inequalities. The sampling distribution is

$$\boldsymbol{\beta}_s = \left(\frac{n_s}{N}\right)^{\frac{1}{3}} \left(\widehat{\boldsymbol{\beta}}_s - \widehat{\boldsymbol{\beta}}\right) + \widehat{\boldsymbol{\beta}},$$

where n$_s$ is the size of the subsample, N is the number of all inequalities, $\boldsymbol{\beta}_s$ is the subsample estimate, and $\boldsymbol{\beta}$ is the full sample estimate.

2019Q4 because relationship banks are conventionally identified in the past five years (Schenone, 2010). Then, we use the estimates to calculate the matching value using Equation 2. A firm's matched bank is the one that generates the highest matching value among all bank-firm matching in a quarter. We then change the parameter estimates to change a firm's pre-crisis relationship bank. To test H3, we would like to match unrated firms with well-capitalised banks. Specifically, we use the parameters estimated from the pre-GFC sample. This allows us to evaluate unrated firms' credit access during the COVID if they follow the same matching practise as they did pre-GFC. Alternatively, we follow Schwert (2018) by altering $\hat{\beta}_1$. Imagine that the original $\hat{\beta}_1$ estimated in the post-GFC sample is insignificant; then, we can take the absolute value of it to make the firms' pre-crisis matched banks strictly high-capital. We use either counterfactual matching assignment to compare with the observed scenario where the unrated firms are matched with their actual banks in loan contracts. After identifying the matched bank, we measure a firm's credit access as a change in the lending amount of that bank when the COVID crisis hits. If the relationship bank significantly cuts lending, we expect the unrated firm to suffer from severe credit constrain because it has limited access to other funding sources. We expect there is not a significant difference in an unrated firm's credit access between the observed and counterfactual scenarios. The testing procedure of H3 can be summarised in the following steps.

Step 1: We estimate Equation 2 from 2015Q1 to 2019Q4.

Step 2: To generate the counterfactual scenario, we either use the estimates from a pre-GFC sample or take the absolute value of $\hat{\beta}_1$. Then, in each quarter, we sort all bank-firm matchings in a descending order based on the estimated value of V_{bf} in Equation 2. We assign a firm to a bank from the first to the last bank-firm matching in the ladder until all firms have a matched bank and all banks use up their quotes. The quote of a bank is the number of firms it lends to in the quarter. For all unrated firms, we identify their pre-crisis relationship bank as the matched bank in the most recent quarter.

Step 3: In the observed scenario, we identify an unrated firm's pre-crisis relationship bank as the bank from which the unrated firm actually borrows in the most recent quarter.

Step 4: We calculate a bank's total annualised syndicated loan amount both in the pre-COVID period (2017Q1-2019Q4) and in the first year of the COVID period (2020Q2-2020Q4);

then, we measure the change in lending supply as the percentage change of the bank's pre- and within-COVID loan amount.[17] We then average changes in lending supply across all unrated firm's pre-crisis relationship banks to measure credit access during the COVID – we do this for both counterfactual and observed scenarios.

Step 5: Following the same procedure of constructing confidence intervals for the parameter estimate, we first extract 50 subsamples of original inequalities to get 50 sets of parameter estimates. Then, we redo Step 2 to obtain counterfactual matchings and conduct a bootstrap by obtaining 20 random draws from the counterfactual matchings for each set of parameters. Lastly, we redo Step 4 to obtain sampling distribution for the lending growth. The 95% confidence interval is between the 5^{th} and 95^{th} percentiles of the sampling distribution.

[17]Because a syndicated loan involves multiple participants, we also split the loan amount equally to each bank and construct an alternative measure for lending supply. The results are reported in Appendix C.2.

4 Empirical Results

This section presents summary statistics of key variables and empirical results from both the regression model and the semiparametric model. Section 4.2, Section 4.3, and Section 4.4 respectively describe the testing results for each of the explanations for the disappearing matching.

4.1 Summary statistics

Table 1 reports the summary statistics of key variables used in this study in both periods of 2001-2006 (Panel A) and 2010-2019 (Panel B). We do not use a full pre-GFC sample here in order to maintain the comparability between the pre-and post-GFC periods. On average, banks and firms have a probability of 11.70% to match in the post-GFC sample, compared to 5.74% in the pre-GFC sample. This is partially due to a smaller lead arranger pool in syndicated loans after the GFC. According to firm-specific characteristics, post-GFC borrowers are, on average, larger, hold more cash assets, and have a higher leverage ratio. Moreover, the proportion of relationship lending has doubled after the GFC, while the distance between banks and firms remains similar. Banks become larger, which could be attributed to mergers and acquisitions during and after the GFC. Also, banks hold more liquidity, which could be explained by stricter regulatory requirements post-GFC.

Insert Table 1 here.

4.2 The disappearing matching between bank-dependent firms and well-capitalised banks

Table 2 presents the results of testing the disappearing matching using either the regression model (Column 1-2) or the semiparametric model (Column 3-4). We multiply OLS coefficients by 100, so the coefficients are interpreted as the impacts on the probability percentage of matching. The first column reports the coefficients in a pre-GFC sample. As shown in Figure 1, the matching weakens during the banking crises. We exclude from our pre-GFC sample the two banking crisis periods, which are not the focus of this paper (but the results are unchanged if crisis periods are included). The interaction between bank capitalisation and the unrated dummy has a significantly positive coefficient, confirming the observation of the matching in Schwert (2018). Specifically, before the GFC, we have a 0.32% (representing one standard deviation of the unconditional matching probability) higher probability of observing a matching if the firm is an unrated firm and the bank has a one-standard-deviation higher capital ratio. Turning to the second regression in the post-GFC sample, the coefficient of the capital-rating interaction becomes insignificant. Thus, during the post-GFC period, unrated firms are not more likely to match with high-capital banks than rated firms. Overall, the regression results are consistent with the movement of the plot in Figure 1, and thus, we find the matching disappears after the GFC.

Regarding the reported control variables, except for the size interaction, all other variables have expected coefficients. Moreover, the statistical significance of these coefficients remains the same before and after the GFC. For example, both regressions show that a lender and a borrower are more likely to match if they have a tighter relationship and are closer in geographical distance. However, the magnitude of the distance coefficient is smaller in the pre-GFC sample than in the pre-GFC sample. Short distance facilitates the collection of soft information through, for instance, in-person visits (Agarwal and Hauswald, 2010; Gustafson et al., 2021). Liberti and Petersen (2019) point out the trend of "hardening" soft information; the rising popularity of "FinTech" and "Robo-advising" can be examples. Thus, less reliance on soft information can explain the smaller impact of distance in Column 2. In Section 5, we use logit regressions to check the robustness of the results and obtain similar coefficients, especially confirming the post-GFC disappearance.

The next two columns show estimates from the semiparametric model. The results verify the disappearing matching. In the pre-GFC sample, the interaction between bank capitalisation and the unrated dummy has a significantly positive coefficient, which is consistent with the finding in Schwert (2018).[18] However, the coefficient turns out to be insignificant in the post-GFC sample. As shown in the square bracket, the 95% confidence interval of the capital-unrated interaction

[18] The number of inequalities in Column 3 is larger than that in Schwert (2018) whose sample period is 1987-2012. This could be because the definition of lead arrangers in our paper is different from Schwert (2018), resulting in larger numbers of banks and firms in our sample. During 1987-2012, we have, in total, 64 banks and 4993 firms.

contains zero. This indicates that higher covariance between banks' capital ratios and firms' unrated status does not add value to a bank-firm matching after the GFC. The estimates of all other variables have significant impacts on the value of a bank-firm matching. Especially, the size interaction presents significantly positive coefficients, meaning that it is still value-added to match small firms with small banks after the GFC (Berger et al., 2017). Therefore, the disappearing matching is a distinct finding from other matchings. The model fit is reported as the fraction of inequalities satisfied, which is over 90% in both samples. This indicates that the variables we include in the model explain well why a certain firm matches with a certain bank in pairwise stability.

Insert Table 2 here.

4.3 The matching between unrated firms facing high switching costs and well-capitalised banks

Next, we explain the disappearing matching. Our first demand-side explanation is the bond market expansion during the low-interest rate period. We hypothesise that only the unrated firms with the largest frictions to switch from loans to bonds still match with well-capitalised banks, while those with smaller frictions no longer do so after the GFC. Thus, we separate unrated firms into two groups based on each of the three switching-friction proxies and estimate the empirical models in the post-GFC period.

The first proxy is firm size. Larger firms can issue bonds more easily either because they have more assets to back up or because they are better known by the market (Frank and Goyal, 2009; Bharath et al., 2011). By contrast, small firms lacking public information have larger barriers to the bond market (Ma et al., 2019). We separate unrated firms based on quarterly quintiles of firm size. The small unrated group falls in the smallest quintile, thus facing the largest entry frictions to the bond market. The results are presented in Table 3. Note that because we include both small and large unrated dummies, the reference group is rated firms. In column 1, the interaction term between the small unrated dummy and the capital ratio has a significantly negative coefficient, while the coefficient between the large unrated dummy and the capital ratio is insignificant. In particular, the matching probability increases by 1.5% if the bank has a one-standard-deviation higher capital ratio and the firm is a large unrated firm. The magnitude is five times the coefficient of the pre-GFC matching in Table 2. This is consistent with the expectation because a small unrated firm is more bank-dependent than an average unrated firm, thus, having a stronger preference for a high-capital bank. In contrast, there is no significant difference between a large unrated firm and a rated firm in matching with a well-capitalised bank. This result shows that some larger unrated firms no longer prefer well-capitalised banks, while the smallest ones still benefit from bank solvency because they are too small to enter the bond market. Thus, the evidence supports H1 and H2. In Column 4, we confirm the finding using the semiparametric model. We can interpret the estimates by trading off the factors affecting the matching value (Schwert, 2018). Specifically, a small unrated firm is willing to scarify, for example, geographical proximity to borrow from a well-capitalised bank, while a large unrated firm would not do so. Again, all other variables have expected signs in both models.

The second proxy estimates an unrated firm's cost if it switches from loans to bonds. Indeed, we calculate the interest-rate difference between bonds and loans. A negative difference indicates that it is cheaper to issue bonds than loans. Then, if unrated firms expect that it is costless to switch, they will care less about bank capitalisation because issuing bonds becomes an option for them. In contrast, a positive difference means switching from bonds to loans is costly. Consequently, even if it is easier to issue bonds after the GFC, the unrated firms with positive switching costs cannot enjoy the bond market expansion and will still rely on well-capitalised banks. We estimate the yield that an unrated firm would pay for a bond by matching the firm to bond-issuing firms with similar characteristics. Estimating yields instead of spreads takes into account the post-GFC low-interest rate environment. To do so, we first group both Dealscan firms and FISD firms into terciles based on each of the three financial variables in a given quarter. We use three variables – firm size, operating income over total assets, and Tobin's Q to emphasise the impact of cash follow and growth opportunities on the funding constraint (Lian and Ma, 2021). Then, we match each Dealscan firm with the FISD firm(s) in the same tercile for each financial variable as well as in the same industry (according to the two-digit SIC code). We average bond yields of all matched FISD firm(s) to proxy for the bond yields of the estimated

Dealscan firm. For loan yields, we average the all-in-drawn spreads plus 12-month LIBOR across all of the Dealscan firm's loans in the quarter. In Table 1, the mean switching cost reduces by 0.5% after the GFC. Then, Column 2 in Table 3 presents the relevant empirical result.[19]. The interaction term of the costly-switch unrated dummy has a significantly positive coefficient. Thus, unrated firms that face high switching costs are more likely to match with well-capitalised banks than rated firms after the GFC, supporting H1. In the next row, the interaction between the costless-switch unrated dummy and the capital ratio has an insignificant coefficient. Thus, for the unrated firms expecting a cheaper funding source in the bond market, their preference for high-capital banks is indifferent from rated firms, supporting H2. The semiparametric model presents a similar finding in Column 5.

The third proxy uses the data on a firm's capital structure. This balance-sheet data summarises a firm's financing history. For firms historically stick to loans, they are less likely to change funding sources by issuing bonds or other forms of debt, such as commercial papers (Denis and Mihov, 2003). On average, a firm has a 41.44% loan outstanding over debts before new loan origination. This is not surprising because our sample is biased towards the firms that are interested in bank financing. We define a firm that heavily relies on bank financing if all of its debt outstanding are loans at the end of the previous year. Thus, those firms are the most loan-dependent firms, and we expected that they are more likely to borrow from well-capitalised banks. In our post-GFC sample, 22% of the unrated firms previously fully rely on loans. Column 3 of Table 3 reports the OLS result. The coefficient of interaction between the loan-heavy unrated dummy and the capital ratio is positive, while the second interaction is insignificant. Thus, after the GFC, the matching only exists between well-capitalised banks and unrated firms that have borrowed predominantly from loans. Again, the semiparametric model presents the same finding. All other control variables have significant coefficients whose signs are consistent with our expectations.

Overall, post-GFC matching exists between a well-capitalised bank and an unrated firm that face high frictions to enter the bond market, while the less-dependent unrated firms have the same chance of matching with low-capital as rated firms.

[19]The reduction in the number of observations is because some Dealscan firms do not have matched FISD firms that satisfy the criteria.

Insert Table 3 here.

4.4 Stricter capital requirements improve low-capital banks' ability to provide lending in the COVID pandemic

Next, we test how the disappearing matching affects credit allocation. Specifically, we assess unrated firms' credit availability in the COVID period under different scenarios. Given another demand-side explanation we have proposed – the improved capital adequacy, we expect that the disappearing matching does not make unrated firms suffer more from credit losses during the COVID.

The results are in Panel A of Table 4.[20] The first row illustrates our benchmark, where unrated firms are matched with their original banks observed in loan contracts. If unrated firms borrow from their actual relationship banks during the COVID, they will have an average 69% reduction in loan supply (it is -33% when we equally split the loan amount to each syndicate participant). The interaction coefficient between bank capitalisation and the firm unrated dummy in the semiparametric model (i.e., $\hat{\beta}_1$) is still insignificant in the sample period where we define the relationship banks (i.e., 2015Q1-2019Q4) (see Column 1 of Table C1 in Appendix C for the estimates). Thus, the first number in Table 4 indicates that the disappearing matching results in a 69% reduction in unrated firms' credit access during the COVID.

To quantify the impact of the disappearing matching, we compare the benchmark with the counterfactuals where unrated firms instead match with well-capitalised banks. We report the difference in lending growth between the benchmark and the counterfactuals – "Observed – Counterfactual (%)". In the first counterfactual, the unrated firms follow the same way to match as they did before the GFC. To achieve this, we use estimates $\hat{\beta}_1$ in the pre-GFC sample. The estimates are reported in Column 2 in Table C1. The pre-GFC $\hat{\beta}_1$ is significantly positive, so the unrated firms are indeed assigned to well-capitalised banks in this counterfactual. The second row in Panel A presents the result. If unrated firms follow what they did before the GFC, they will have 1.22 percentage points lower reduction in lending growth relative to the benchmark.

[20]Table C2 in Appendix C reports the lending growth when we equally split the amount of each loan to each syndicate participant

However, the difference is statistically insignificant. In the alternative counterfactual, we take the absolute value of $\hat{\beta}_1$ and keep the other estimates the same. Thus, we make unrated firms match with all-else-equal well-capitalised banks. Similar to the first counterfactual, we find a negative but insignificant difference in lending growth. Therefore, both counterfactuals indicate that, in the COVID crisis, there is no significant loss in credit availability if unrated firms choose not to borrow from well-capitalised banks, supporting H3.

To emphasise the insignificant impact of the disappearing matching on credit access in the COVID period, we also report the differences in loan access during the GFC in Panel B. The benchmark scenario leads to an average of 62.29% (-57.66% when we equally split the loan amount to each syndicate participant) lending reduction in the GFC. Then, we create two counterfactuals analogy to the post-GFC disappearing matching – making unrated firms' choices of matching not dependent on bank capitalisation. To achieve this, we either replace the estimates with the pre-COVID estimates where $\hat{\beta}_1$ is insignificant or "shut off" $\hat{\beta}_1$ where we set $\hat{\beta}_1$ to be zero. Importantly, both counterfactuals induce significantly lower lending growth than the benchmark. For example, if the firms follow the same way of matching as they did in the pre-COVID period, they will face a 3.49 percentage points reduction in loan supply in the GFC. Thus, whether matching with well-capitalised banks or not leads to a considerable difference in credit supply during the GFC period, which confirms (Schwert, 2018)'s finding.

Overall, the pre-GFC prominent matching matters for the credit allocation during the GFC, while the post-GFC disappearing matching does not lead to bad outcomes during the COVID period.[21] Moreover, the insignificant difference in lending supply from different matched banks during the COVID is not caused by the lack of variation in lending growth; in 2020, the standard deviation of bank lending growth is 23.83, which is higher than the 18.08 in the GFC.

Insert Table 4 here.

[21] There is one concern related to our conclusion. The COVID shock is not a banking crisis like the GFC, and this may affect our interpretation of how bad the disappearing matching could be. But we argue that the findings are still meaningful in two points. First, the COVID shock actually reduced aggregate demand and slowed down the economy, so credit availability is still a concern for bank-dependent firms. Second, COVID is the most recent testable shock that we can test in the US, and regardless of its origin and severity, the fact is that the disappearing matching does not have significant impacts on unrated firms' loan access.

4.5 Search-for-yield facilitates the matching between unrated firms and risky banks

So far, we propose two explanations for why bank-dependent firms no longer prefer well-capitalised banks. But, the result from the semiparametric model indicates that the matching between unrated firms and well-capitalised banks is not value-added to not only borrowers but also lenders. So, we also propose a lender-side explanation. From the supply side, we argue that the low-capital banks' incentive to reach for yield under the low-interest rate environment drives the post-GFC disappearing matching. If the story of "reach-for-yield" is relevant, we expect to observe that risky banks are also more likely to match with unrated firms than safer banks because they pursue short-term earnings to meet their target returns. We use three proxies for banks' riskiness. One is non-performing assets over total assets, reflecting the riskiness in a bank's total asset portfolio. The second proxy is loan loss provision over gross loans, capturing a bank's estimates of lending risk. The last one is liquidity assets over total assets, proxying for a bank's liquidity risk. A bank lacking liquidity is in danger of a bank run (Gorton and Metrick, 2012), thus having incentives to chase for yield under the low-interest rate environment. The risk measures are lagged by one quarter to avoid any accounting-related change in the numbers - resulting from increasing exposures to unrated firms - that drives the results. We also include the interaction between the capital ratio and the unrated dummy because there is a high correlation between banks' financial variables. This controls for low-capital banks' incentives of reaching for yield – replenishing capital.

Table 5 presents the results. The evidence in the first OLS regression shows the matching between risky banks and unrated firms existing after the GFC. Regarding the economic magnitude, the matching probability increases by about 1% if the firm is unrated and the bank has a one-standard-deviation higher non-performing asset ratio. Thus, a bank having substantial problematic assets tends to follow its risky lending strategy in the low-profit environment after the GFC. Turning to the next two regressions, the coefficient of the interaction between either of the two risk measures and the unrated dummy has an expected sign. Thus, banks prefer bank-dependent firms over rated firms if they anticipate more bad loans or suffer more from illiquidity. The semiparametric model also confirms the post-GFC matching between unrated firms and banks with high asset risks or credit risks. Moreover, the interaction between the liquidity asset ratio and the unrated dummy has an expected negative sign though statistically insignificant. The illiquidity risk may not encourage banks to reach for yield as much as other risks. Overall, the evidence supports H4. That is, the extreme loosening of monetary policy encourages risky banks to pursue information rents and risk premiums from unrated firms. Thus, we believe the "reaching-for-yield' is the supply-side driver for the disappearing matching.

Insert Table 5 here.

5 Further Discussions and Robustness Test

In this section, we conduct further tests and check the robustness of previous results.

5.1 Addressing concerns on the finding of the disappearing matching

In this subsection, we test the robustness of the finding of the disappearing matching.

In our main empirical tests, we include all bank-firm pairs. Some firms choose to borrow from their prior lenders. To those firms, past lending relationships could be the first-order consideration in forming the matching, while bank capitalisation may become less important. If the disappearing matching is the result of borrowers choosing to borrow from their relationship banks, the explanations we proposed are irrelevant. In our main tests, we rule out this possibility by including lending relationships as a control. In this subsection, we test the matching by excluding all loans where the bank and the firm have prior relationships during the pre-GFC period. We report the results in Column 1&2 in Table 6. Column 1 reports the results from the post-GFC OLS regression, and the sample reduces by about 40% relative to the sample where we include all loans. Interestingly, the coefficient of the interaction term is significantly negative. This implies a matching between unrated firms and poorly-capitalised banks, consistent with our supply-side explanation. The reason for the negative coefficient could be that we exclude all pre-GFC relationship loans where the unrated firms match with well-capitalised banks in the past. Then, in the semiparametric model in Column 2, however, the coefficient is insignificant, still suggesting the disappearing matching.

Next, we test our finding of the disappearing matching at the intensive margin. Our previous test on the probability of matching between unrated firms and well-capitalised focuses on the extensive margin. To test the intensive margin, we ask that, condition on matching, whether unrated firms borrow more from well-capitalised banks than from poorly-capitalised banks. Thus, we use the loan-level data. Specifically, we regress loan amount (in logarithms) on the interaction between bank capitalisation and the unrated dummy with firm-fixed effects and bank-fixed effects. Table 6 presents the results. In the pre-GFC sample, the coefficient of the interaction term is significantly positive. An unrated firm's loan is 7.6% larger if the firm borrows from a well-capitalised bank whose capital ratio is one standard deviation higher than the average. In the next column, the coefficient turns out to be insignificant. Thus, after the GFC, unrated firms no longer borrow more from well-capitalised banks than from low-capital banks. This confirms the disappearing matching at the intensive margin.

Insert Table 6 here.

Lastly, recent papers such as Aldasoro et al. (2022, 2023) have documented the increasing participation of shadow banks (e.g., mutual funds and investment banks) in syndicated loans. These studies point out that the loan portfolios of shadow banks are different from commercial banks. Also, the shadow banks are more likely to provide transaction lending than relationship lending so unrated firms may care less about these banks' capitalisation, and the disappearing matching could be caused by the rising participation of shadow banks. According to the Dealscan item institution type, we find that only about 0.63% loan facilities have shadow banks as lead arrangers (see Aldasoro et al. (2022, 2023) for definitions of shadow banks). Thus, although we acknowledge that shadow banks' participation could affect bank-firm matching, it is not a concern in our study.

5.2 The follow-up of unrated firms that borrow from low-capital banks

We provide additional evidence for our first demand-side explanation – the post-GFC bond market expansion. The bond market expansion indicates that bank-dependent firms have better access to another funding source to buffer potential losses from the termination of lending relationships. Thus, by giving up stable lending from well-capitalised banks, an unrated firm should prepare to turn to the public bond market. A firm needs a credit rating to issue public bonds. Therefore, for the unrated firms borrowing from poorly-capitalised banks, we expect that they are more likely to obtain a credit rating. We use the loan-level data to test this. We first identify the unrated firms that obtain a credit rating during 2010-2019; in total, there are 217 such firms that contract 853 loan facilities. Accordingly, we create a "Obtaining Rating" dummy which takes one if the borrower in a loan obtains a rating after the loan origination. Then, we regress the dummy on the bank capital ratio. To resolve the fundamental differences between an unrated firm that obtains a rating and an unrated firm that does not, we use propensity score matching to match each treatment firm with two control firms. The matching criteria include Altman's z-score, asset tangibility, profitability, cash holdings, leverage, Tobin's Q, IPO years, industry, state, loan types, loan purposes, and loan maturity. Figure 2 plots a fitted line of regressing the "Obtaining Rating" dummy on bank capitalisation using the matched sample (the sample size is 2463). The downward sloping supports the expectation: an unrated firm has a higher probability of issuing a credit rating if it borrows from a low-capital bank than from a well-capitalised bank.

Insert Figure 2 here.

Our bond market explanation predicts that unrated firms that do not rely on well-capitalised banks will use bonds to finance a potential reduction in the loan market. We have already found that these unrated firms are switching to the bond market by issuing credit ratings. We then test whether their bond borrowing during the COVID increases more than that of the unrated firms who still borrow from well-capitalised banks. To test this, we calculate the changes in each unrated firm's debt outstanding for different debt types from the pre-COVID period (averaging across 2017-2019) to the end of 2020. We then regress the changes in bank capitalisation. Table 7 presents the results. The coefficients in Column 1 are significantly negative. Thus, unrated firms that borrow from low-capital banks increase their bond outstanding more than those borrowing from high-capital banks. A one-standard-deviation decrease in the capital ratio will increase the change in bond outstanding by about 7.66%. We then decompose the total bond outstanding into senior bonds and notes as well as subordinated bonds and notes. It shows that the larger increase in bond outstanding of unrated firms that borrow from low-capital banks during the COVID mainly comes from the increase in senior bonds and notes. Although the coefficient in the regression of subordinated bonds and notes is positive, the result is not representative because only less than 10% observations have non-zero changes in subordinated bonds and notes. We also test the coefficients of bank capitalisation on changes in loan outstanding. The coefficient in the regression of revolving credit is significantly positive. Therefore, unrated firms that borrow from high-capital (low-capital) banks rely more on loans (bonds) than bonds (loans) to finance themselves during the COVID shock. This finding is consistent with the prediction of our bond market explanation.

Insert Table 7 here.

5.3 Logit regressions

Next, we check the robustness of our results by replacing OLS with logit estimators in Equation 1. Using a logit model restricts the probability of matching within 0-1 and allows non-linearity. However, it is more difficult to interpret coefficients of interaction terms in a logit regression than in a linear probability regression. Table 8 presents the results, and we report the coefficients in the form of log-odd ratios. The logit results generally follow the previous findings. We first confirm the disappearing matching by comparing the coefficient of the interaction between bank capitalisation and the unrated dummy in the pre-GFC sample to that in the post-GFC sample. The first coefficient is positively significant at the 1% level, while the second one is insignificant. Then, supporting H1 and H2, the next three columns show that while the unrated firms that have better access to other funding sources care less about bank capitalisation, most bank-dependent firms still prefer well-capitalised banks. In the rest of the table, we find evidence supporting the supply-side factor. The coefficient of the interaction between the non-preforming asset ratio and the unrated dummy is significantly positive. For other risk measures, the sign is consistent with the prediction of the matching between unrated firms and either banks with high credit risks or with high liquidity risks, although they are statistically insignificant.

Insert Table 8 here.

5.4 Isolating the supply-side from the demand-side factors

Our results show that both demand-side and supply-side factors can potentially drive the disappearing matching. In testing each explanation, we explore the cross-section variations (of the matching) with respect to both borrowers and lenders separately. In this subsection, we isolate the supply-side factor from the demand-side ones by dividing the sample based on banks' incentives of reaching for yield.

Under the low-interest rate environment, reductions in bank profitability mainly come from the rigidity of deposit rates (Claessens et al., 2018; Molyneux et al., 2020; Lopez et al., 2020). Accordingly, If a bank holds a low level of deposits, the bank's interest margins are likely to be immune to the low-interest rate environment (Heider et al., 2019). Then, the bank has little incentive to chase yields, shutting down the supply-side effect. If the supply-side factor can solely explain the disappearing matching, we would expect that the matching restores among banks with low deposits. Alternatively, if the matching is still insignificant even if banks' potential to suffer from the profit damage is minimised, we believe that the demand-side driving factors (i.e., firms benefit less from well-capitalised banks) are important. In contrast, for banks exposed considerably to the low-interest rate environment, "reaching-for-yield' makes low-capital banks' incentive to lend to unrated firms dominate that of well-capitalised banks. Thus, we expect a reverse matching among banks with large deposits.

We separate the sample into two based on quarterly terciles of banks' interest-bearing deposits to assets ratios. The "High Deposit Ratio" sample includes banks falling into the top tercile while the "Low Deposit Ratio" sample contains the rest. Then, we estimate both the regression model and the semiparametric model in the two subsamples. We expect a negative coefficient of the interaction term between bank capitalisation and firm unrated status in the "High Deposit Ratio" sample, while an insignificant coefficient in another subsample.

Table 9 presents the results. In the "High Deposit Ratio" sample (Column 1), the coefficient of the interaction term reverses. The probability of matching is higher if the bank is low-capital and the firm is unrated. The result confirms our discussion above; that is, low-capital banks are more likely to pursue information rents from unrated firms when their profits are affected more by deposit rigidity. The reversed matching, thus, validates the supply-side factor in driving the disappearing matching. The logit regression confirms the negative covariance between bank capitalisation and firm unrated status. The coefficient of the interaction is insignificant in the semiparametric model, possibly because the low number of inequalities reduces the precision of estimation.[22]. Next, when the "reaching for yield' incentive is reduced in the "Low Deposit Ratio" sample, we still do not find significant coefficients of the interaction term in all models. Therefore, the proposed demand-side factors (either the favourable bond market condition or the improved capital adequacy) are critical in explaining the disappearance of the matching.

Insert Table 9 here.

[22]The estimation of the model requires two different banks in an inequality. When we subsample banks into terciles, the number of inequalities reduces sharply.

6 Conclusion

In this paper, we study the matching between firms and banks in the syndicated loan market. We find that the documented matching between bank-dependent (unrated) firms and well-capitalised banks has been disappearing since 2010. We argue that the post-GFC prolonged low-interest environment provides firms with better access to the bond market, making bank solvency less a concern to bank-dependent firms. The low-interest rates are a consequence of the accommodative monetary policy after the GFC. The policy rates start to rise gradually in 2016 (though the trend of reducing bond yields continues until 2021). Thus, a follow-up question can be whether the disappearing matching is a permanent phenomenon or a temporary response to the easing monetary policy. Further studies can re-evaluate the matching after the rise of interest rates in 2022.

Alternatively, the disappearing matching can be explained by the improved capital adequacy after the GFC. The aim of the capital regulations, especially the stress test requirements, is to ensure bank solvency in crisis times. Thus, because of the lifted minimum requirements, relatively low-capital banks can also provide solid lending to bank-dependent firms. We test this in the COVID crisis and find that credit access does not significantly increase even if unrated firms change their matching strategy to well-capitalised banks. After the GFC, many countries adopted the new Basel III capital requirement. The European banking authorities also introduced stress test requirements.

We suggest future researches to study matching in an international context. The different timeline of implementing the capital requirements in different courtiers provides some cross-country variations to test whether the improved capital adequacy is a driving factor of the disappearing matching.

We also propose a supply-side explanation for the disappearing matching. Specifically, the low-interest rates erode banks' profitability, encouraging low-capital banks to exploit rents from bank-dependent firms. Because the supply-side and the demand-side factors are not mutually exclusive, we differentiate their impacts using banks' deposit rates. We find both supply- and demand-side factors contribute to the weak matching.

A recent study by Papoutsi and Darmouni (2022) documents a sharp increase in bond issuances in the European bond market from small and unrated firms since 2010. However, the authors also find that banks' share of the unrated bond issuances is considerably larger than their holdings of rated bonds. This indicates that the lending relationships between firms and banks could have extended to the bond market. If a similar phenomenon is found in the U.S., it can be an important complement to our findings such that the matching is not only disappearing in the syndicated loan market but also shifting to the bond market. Thus, we suggest future works on whether there is a matching between bank-dependent firms and well-capitalised banks existing in other financing markets such as bonds or commercial paper.

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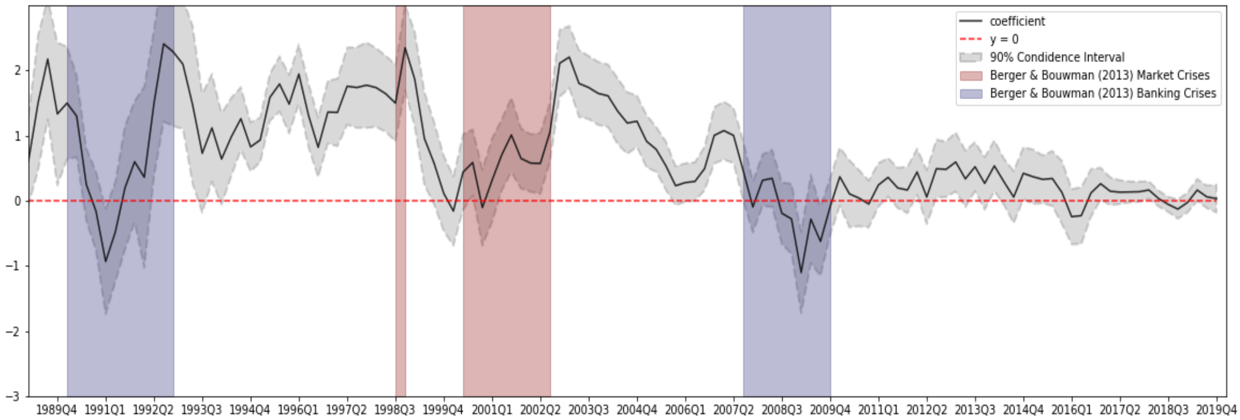
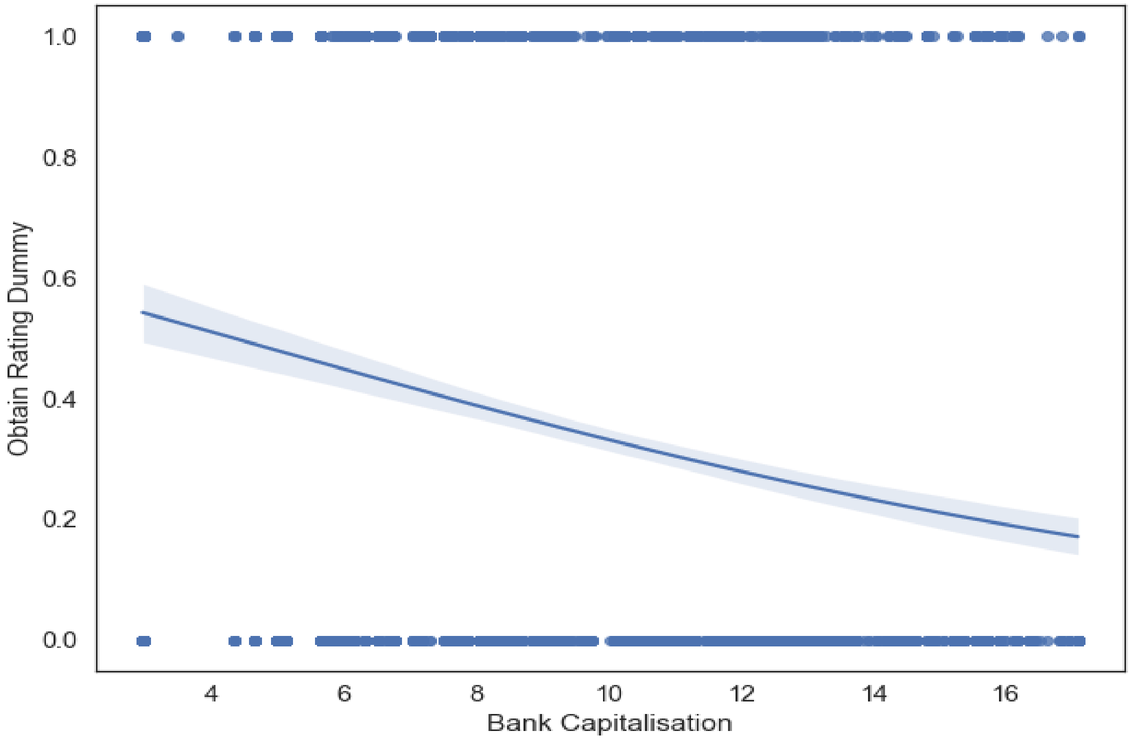
Figure 1: A Plot of the Conditional Correlation between Bank Capitalisation and Unrated Status Over Time



This figure illustrates the strength of the matching between well-capitalised banks and bank-dependent firms. It plots the coefficients of the unrated dummy from a series of regressions of bank capitalisation on Unrated and a set of controls, including lender size, lending relationship dummy, Altman's z-score, asset tangibility, profitability, cash, leverage, Tobin's Q, years since IPO, state dummies, industry dummies, covenant inclusion dummy, loan maturity, loan type dummies, loan purpose dummies, and quarter dummies. We measure bank capitalisation using the market equity value of a bank divided by the sum of market equity and book liabilities). Unrated Dummy takes one if a firm does not have an S&P long-term issuer rating in the quarter of loan origination. We run the regressions each quarter with a rolling window of four quarters, i.e., from t to t-4. The grey area surrounding the line depicts the 90% confidence intervals (with heteroskedasticity-consistent standard errors) for the coefficients; the horizontal red line is y=0; the red pillars represent two market crisis periods; the blue pillars represent two banking crisis periods, following the definition in Berger and Bowman (2013).

Figure 2: Unrated Firms that Borrow from Low-capital Banks Are More Likely to Obtain Credit Ratings



This figure plots a fitted line of regressing the "Obtaining Rating" dummy on bank capitalisation. The "Obtaining Rating" dummy takes one if the borrower in a loan obtains a rating after the loan origination. We use propensity score matching to match each treatment firm with two control firms. The matching criteria include Altman's z-score, asset tangibility, profitability, cash holdings, leverage, Tobin's Q, IPO years, industry, state, loan types, loan purposes, and loan maturity.

Table 1: Summary Statistics of Key Variables before and after the GFC

	Mean	SD	25^{th}	Median	75^{th}	Mean	SD	25^{th}	Median	75^{th}
	Panel A Pre-GFC					***Panel B Post-GFC***				
Observed Pair Dummy	0.057	0.233	0	0	0	0.117	0.321	0	0	0
Market Capital Ratio (%)	17.47	5.31	13.88	16.47	20.34	11.95	3.27	9.69	11.93	14.22
Unrated Dummy	0.50	0.50	0	0	1	0.45	0.50	0	0	1
Firm Size (in Logarithm)	6.83	1.92	5.56	6.79	8.05	8.05	1.58	6.93	7.93	9.05
Estimated Costs of Switching from Loans to Bonds (%)	1.96	2.23	.463	2.03	3.34	1.49	2.03	.096	1.27	2.71
Loan Outstanding over Debts at Previous Year-end (%)	34.77	37.79	0.00	18.75	68.74	41.44	39.75	0.36	31.02	86.15
Non-performing Assets Ratio (%)	0.49	0.29	0.31	0.44	0.59	0.85	0.70	0.37	.589	1.11
Loan Loss Provision over Loans (%)	0.18	0.20	0.06	0.13	0.24	0.15	0.19	0.06	0.09	0.16
Liquidity Ratio (%)	10.04	6.31	5.32	8.70	13.71	17.32	11.82	4.60	18.45	27.49
Interest-bearing Deposit Ratio (%)	47.54	7.30	43.53	48.44	52.53	47.55	6.99	44.62	49.01	52.17
Lender Size (in Logarithm)	11.48	1.34	10.79	11.43	12.41	12.58	1.315	11.72	12.201	14.03
Lending Relationship Dummy	0.06	0.23	0	0	0	0.12	0.32	0	0	0
Top Industry Dummy	0.104	0.31	0	0	0	0.15	0.35	0	0	0
Bank-firm Distance (in Kilometres)	1592	1118	721	1297	2296	1598	1138	712	1220	2353
Altman's Z-score	67.62	92.05	31.18	79.44	123.47	72.25	75.13	29.77	74.34	119.5
Asset Tangibility (%)	29.88	22.47	12.70	23.83	41.70	27.01	23.47	9.26	18.57	38.01
Profitability (%)	3.24	2.98	1.960	3.30	4.78	3.33	2.218	2.24	3.206	4.311
Cash Holdings (%)	8.02	10.51	1.41	3.68	10.14	9.83	10.18	2.65	6.36	13.61
Financial Leverage (%)	27.27	17.31	14.29	26.43	38.28	31.03	17.79	18.5	29.58	42.95
Tobin's Q	1.71	0.95	1.10	1.42	2.00	1.80	0.93	1.19	1.53	2.08

Notes: This table presents summary statistics for the sample of all potential bank-firm pairs. Panel A reports statistics for the bank-firm pairs in the quarters in the pre-GFC period (2000Q1-2007Q2), while Panel B reports statistics for post-GFC periods (2010Q1-2019Q4). Observed Pair Dummy indicates whether a bank-firm pair shares a loan contract in that given quarter. We measure bank capitalisation using the market equity value of a bank divided by the sum of market equity and book liabilities. Firm Size is a firm's total assets measured in logarithms. Estimated Costs of Switching from Loans to Bonds are estimated by matching the firm with the bond-issuing firms in the same terciles based on three financial variables and the two-digit SIC industry code. Loan Outstanding over Debts at the Previous Year-end is the loan outstanding divided by total debts at the end of the previous year. Non-performing Asset Ratio is a bank's non-performing assets divided by total assets. Loan Loss Provision over Loans is loan loss provision divided by total gross loans. Liquidity Ratio is a bank's liquidity assets divided by total assets. Interest-bearing Deposit Ratio is a bank's interest-bearing liabilities divided by total assets. Lending Relationship Dummy is a binary variable taking one if a firm and a bank have a past contract within 20 quarters prior to the loan origination quarter. Bank-firm Distance is the physical distance between a firm's headquarter and a bank's headquarter in thousand kilometres. Top Industry Dummy is a dummy taking one if a firm's industry falls in the top three industries of a bank's borrowers in a given quarter. See Table A1 for further information on variable definitions.

Table 2: The Matching between Well-capitalised Banks and Unrated Firms before and after the GFC

	1	2	3	4
	OLS Regression Model	OLS Regression Model	Semiparametric Model	Semiparametric Model
Bank Capitalisation	-0.0292	0.190**		
	(-0.81)	(2.60)		
Unrated Dummy	-1.296^a	-2.712		
	(-1.64)	(-1.54)		
Bank Capitalisation×Unrated Dummy	0.0974**	0.193	15.42**	0.31
	(2.01)	(1.43)	[7.48, 32.49]	[-6.18, 24.24]
Bank Size×Firm Size	0.151	0.201	11.46**	30.71**
	(0.89)	(0.67)	[7.64, 40.50]	[11.27, 40.35]
Lending Relationship Dummy	53.91***	56.86***	1000	1000
	(27.72)	(24.75)	[-]	[-]
Top Industry Dummy	12.77***	10.02***	280.13**	397.58 **
	(22.78)	(11.01)	[222.46, 355.29]	[276.84, 395.54]
Bank-firm Distance	-0.00114***	-0.00045**	-0.0357**	-0.0252**
	(-5.41)	(-2.12)	[-0.1074, -0.0297]	[-0.0565, -0.0034]
Sample	Pre-GFC	Post-GFC	Pre-GFC	Post-GFC
Quarter-, Bank-, and Firm-FEs	Yes	Yes	N/A	N/A
Observations/Number of Inequalities	214901	64110	1443901	365620
Adjusted R^2/Fraction of Inequalities Satisfied	0.385	0.489	0.933	0.903

Notes: This table reports estimates from linear probability regression model (Column 1-2) and semiparametric model (Column 3-4). There are two sample periods – the pre-GFC period is 1987Q1-2007Q2 (excluding periods of banking crises), and the post-GFC is 2010Q1-2019Q4. The sample includes all possible pairs between banks and firms recorded in Dealscan in a given quarter. The linear probability model regresses the observed pair on a set of banks' and firms' characteristics. The dependent variable observed pair is a dummy taking one if the bank-firm pair is observed in Dealscan. This table reports the coefficients of key independent variables. Bank capitalisation is a bank's market equity value divided by the sum of market equity and book liabilities. Unrated Dummy takes one if a firm does not have an S&P long-term credit rating. Bank Size is a bank's total assets measured in logarithms. Firm Size is a firm's total assets measured in logarithms. There are three other variables constructed at the bank-firm level. Lending Relationship Dummy is a binary variable taking one if a firm and a bank have a past contract within 20 quarters prior to the loan origination quarter. Bank-firm Distance is the physical distance between a firm's headquarter and a bank's headquarter in thousand kilometres. Top Industry Dummy is a dummy taking one if a firm's industry falls in the top three industries of a bank's borrowers in a given quarter. Quarter-, bank-, and firm-fixed effects are included in OLS regressions. The other (unreported) controls include bank size, firm size, z-score, asset tangibility, profitability, cash, financial leverage, Tobin's Q, and years since IPO. See Table A1 for further information on variable definitions. All OLS coefficients are multiplied by 100. T-statistics based on standard errors clustered by banks are reported in brackets. a, *, **, and *** indicate that the corresponding p-values are less than 0.11, 0.1, 0.05, and 0.01, respectively. In the semiparametric model, we estimate the parameters by maximising the number of inequalities that satisfy the pairwise stability condition. The inequalities are constructed from all combinations of two actual matchings in a given quarter, and we include all sample quarters. All borrower and bank-specific characteristics are demeaned each quarter. Number of Inequalities is the number of total inequalities. Fraction of Inequalities Satisfied is the fraction of inequalities satisfied by the pairwise stability condition under the model prediction. 95% confidence intervals are constructed by subsampling and are reported in square brackets. ** indicates that the confidence interval does not contain zero.

Table 3: Unrated Firms that Face High Switching Costs Still Match with Well-capitalised Banks after the GFC

	1	2	3	4	5	6
	OLS Regression Model	OLS Regression Model	OLS Regression Model	Semiparametric Model	Semiparametric Model	Semiparametric Model
Bank Capitalisation×Small Unrated Dummy	0.459*			53.76**		
	(1.81)			[6.00, 84.94]		
Bank Capitalisation×Large Unrated Dummy	0.135			-5.62		
	(1.20)			[-14.29, 27.03]		
Bank Capitalisation×Costly-switch Unrated Dummy		0.332**			162.23**	
		(2.49)			[14.61, 169.85]	
Bank Capitalisation×Costless-switch Unrated Dummy		0.178			113.13	
		(0.86)			[-18.48, 142.78]	
Bank Capitalisation×Loan-heavy Unrated Dummy			0.430***			145.27**
			(3.24)			[15.34, 170.31]
Bank Capitalisation×Loan-light Unrated Dummy			0.123			70.60
			(0.79)			[-30.36, 125.33]
Bank Size×Firm Size	0.190	0.187	0.193	10.48**	44.90**	11.91**
	(0.63)	(0.78)	(0.64)	[1.64, 37.22]	[20.54, 80.47]	[9.61, 50.80]
Lending Relationship Dummy	56.85***	58.63***	56.50***	1000	1000	1000
	(24.69)	(27.95)	(24.13)	[-]	[-]	[-]
Top Industry Dummy	10.03***	8.417***	10.33***	339.97**	422.78**	427.78**
	(11.01)	(10.03)	(11.22)	[270.29, 569.61]	[317.19, 664.78]	[313.91, 651.80]
Bank-firm Distance	-0.00045**	-0.00056***	-0.343	-0.0935**	-0.0282**	-0.0037**
	(-2.14)	(-2.99)	(-1.64)	[-0.0793, -0.0348]	[-0.0561, -0.0059]	[-0.0325, 0.0037]
Sample	Post-GFC	Post-GFC	Post-GFC	Post-GFC	Post-GFC	Post-GFC
Quarter-, Bank-, and Firm-FEs	Yes	Yes	Yes	N/A	N/A	N/A
Observations/Number of Inequalities	64110	26998	59884	365620	38394	177444
Adjusted R^2/Fraction of Inequalities Satisfied	0.489	0.493	0.494	0.901	0.906	0.907

Notes: This table reports estimates from linear probability regression model (Column 1-2) and semiparametric model (Column 3-4). There are two sample periods – the pre-GFC period is 1987Q1-2007Q2 (excluding periods of banking crises), and the post-GFC is 2010Q1-2019Q4. The sample includes all possible pairs between banks and firms recorded in Dealscan in a given quarter. The linear probability model regresses the observed pair on a set of banks' and firms' characteristics. The dependent variable observed pair is a dummy taking one if the bank-firm pair is observed in Dealscan. This table reports the coefficients of key independent variables. Bank capitalisation is a bank's market equity value divided by the sum of market equity and book liabilities. Small (Large) Unrated Dummy takes one if an unrated firm falls in the bottom (top four) size quintile(s). Costly-switch (Costless-switch) Unrated Dummy takes one if an unrated firm's estimated interest-rate difference between bonds and loans is positive (non-positive). Loan-heavy (Loan-light) Unrated Dummy takes one if an unrated firm's loan outstanding over total debt outstanding is 100% at the end of the previous year. Bank Size is a bank's total assets measured in logarithms. Firm Size is a firm's total assets measured in logarithms. For all interactions, we do not report the coefficients of the two interacting variables. There are three other variables constructed at the bank-firm level. Lending Relationship Dummy is a binary variable taking one if a firm and a bank have a past contract within 20 quarters prior to the loan origination quarter. Bank-firm Distance is the physical distance between a firm's headquarter and a bank's headquarter in thousand kilometres. Top Industry Dummy is a dummy taking one if a firm's industry falls in the top three industries of a bank's borrowers in a given quarter. Quarter-, bank-, and firm-fixed effects are included in OLS regressions. The other (unreported) controls include z-score, asset tangibility, profitability, cash, financial leverage, Tobin's Q, and years since IPO. See Table A1 for further information on variable definitions. All OLS coefficients are multiplied by 100. T-statistics based on standard errors clustered by banks are reported in brackets. a, *, **, and *** indicate that the corresponding p-values are less than 0.11, 0.1, 0.05, and 0.01, respectively. In the semiparametric model, we estimate the parameters by maximising the number of inequalities that satisfy the pairwise stability condition. The inequalities are constructed from all combinations of two actual matchings in a given quarter, and we include all sample quarters. All borrower and bank-specific characteristics are demeaned each quarter. Number of Inequalities is the number of total inequalities. Fraction of Inequalities Satisfied is the fraction of inequalities satisfied by the pairwise stability condition under the model prediction. 95% confidence intervals are constructed by subsampling and are reported in square brackets. ** indicates that the confidence interval does not contain zero.

Table 4: Lending Supply during the GFC and COVID periods under Counterfactual Matching Assignments

	Panel A Lending Growth in COVID		***Panel B Lending Growth in GFC***	
	Lending growth (%)	Observed − Counterfactual (%)	Lending growth (%)	Observed − Counterfactual (%)
Observed Matchings	-68.98		-62.29	
	[-]		[-]	
Estimates from the Pre-GFC Sample		-1.22		1.63**
		[-3.49, 0.98]		[0.65, 2.82]
Absolute $\hat{\beta}_1 = \lvert\hat{\beta}_1\rvert$		-1.83		1.63**
		[-1.34, 3.57]		[0.67, 3.92]
Estimates from the Pre-COVID Sample		2.03		3.49**
		[-1.23, 3.93]		[1.99, 4.09]
Shut-off $\hat{\beta}_1 = 0$		0.82		2.35**
		[-2.06, 2.54]		[1.38, 3.40]

Notes: This table presents unrated firms' credit access during the COVID and the GFC. For the credit access, we proxy it using the average loan growth of all unrated firms' (most recent) pre-crisis relationship banks under observed matching and counterfactuals. The counterfactual relationship banks are assigned by using the model estimates or altering the estimates or randomly assigning using Bootstrap. We estimate the parameters by maximising the number of inequalities that satisfy the pairwise stability condition. The inequalities are constructed from all combinations of two actual matchings in a given quarter, and we include all sample quarters. The estimated sample is 20 quarters prior to the COVID (GFC) for Panel A (Panel B). Each bank's lending growth is the growth rate of the annualised total amount of syndicated loans from the pre-crisis period to the crisis period. For the COVID (GFC), the pre-crisis and crisis period are 2017Q1-2019Q4 (2004Q4-2007Q2) and 2020Q2-2020Q4 (2008Q4-2009Q2). In the 'Observed' scenario, an unrated firm is matched with the bank in its actual loan contract in the most recent loan facility. In the counterfactuals, we make the firms match with well-capitalised banks. First, we use the estimates that are used in Panel B. Secondl, we take an absolute of $\hat{\beta}_1$, which is the estimate of the impact of the covariance between bank capitalisation and borrowers' unrated status. We also use the pre-COVID estimates and take $\hat{\beta}_1$ to be zero. 95% confidence intervals (reported in square brackets) are obtained by estimating 50 sets of parameter estimates based on subsampling, then drawing 20 times from the counterfactual matchings for each set of estimates. ** indicates that the confidence interval does not contain zero. In the 'Random Assignment' scenario, we randomly assign a bank to an unrated firm. The 95% confidence interval is obtained using Bootstrap. Observed – Counterfactual (%) is the lending growth of the matched banks in observed matchings minus that of the banks in counterfactual matchings, reported in percentage points.

Table 5: Risky Banks Match with Unrated Firms after the GFC

	1	2	3	4	5	6
	OLS Regression Model	OLS Regression Model	OLS Regression Model	Semiparametric Model	Semiparametric Model	Semiparametric Model
Non-performing Asset Ratio×Unrated Dummy	1.448*			163.47**		
	(1.99)			[40.37, 180.09]		
Loan Loss Provision×Unrated Dummy		1.470*			130.51**	
		(1.82)			[3.70, 166.81]	
Liquidity Ratio×Unrated Dummy			-0.0365*			-0.81
			(-1.81)			[-8.27, 15.83]
Bank Capitalisation×Unrated Dummy	0.265	0.216	0.149	2.92	4.96	-7.72
	(1.71)	(1.52)	(0.91)	[-14.12, 20.38]	[-5.16, 28.10]	[-17.01, 38.11]
Bank Size×Firm Size	0.186	0.204	0.188	28.84**	27.43**	21.61**
	(0.66)	(0.68)	(0.59)	[12.46, 45.70]	[12.41, 47.64]	[9.44, 57.23]
Lending Relationship Dummy	56.81***	56.86***	57.00***	1000	1000	1000
	(25.00)	(24.81)	(24.38)	[-]	[-]	[-]
Top Industry Dummy	10.05***	10.03***	9.914***	491.65**	450.03**	337.22**
	(10.98)	(11.01)	(10.30)	[336.90, 578.94]	[330.10, 577.39]	[282.21, 596.77]
Bank-firm Distance	-0.00044**	-0.00044**	-0.00040*	-0.050**	0.0035	-0.0345**
	(-2.13)	(-2.10)	(-1.96)	[-0.063, -0.015]	[-0.0477, -0.0047]	[-0.0546, -0.0002]
Sample	Post-GFC	Post-GFC	Post-GFC	Post-GFC	Pre-GFC	Post-GFC
Quarter-, Bank-, and Firm-FEs	Yes	Yes	Yes	N/A	N/A	N/A
Observations/Number of Inequalities	64110	64110	57439	365620	365620	332685
Adjusted R^2/Fraction of Inequalities Satisfied	0.489	0.489	0.491	0.903	0.903	0.899

Notes: This table reports estimates from linear probability regression model (Column 1-2) and semiparametric model (Column 3-4). There are two sample periods – the pre-GFC period is 1987Q1-2007Q2 (excluding periods of banking crises), and the post-GFC is 2010Q1-2019Q4. The sample includes all possible pairs between banks and firms recorded in Dealscan in a given quarter. The linear probability model regresses the observed pair on a set of banks' and firms' characteristics. The dependent variable observed pair is a dummy taking one if the bank-firm pair is observed in Dealscan. This table reports the coefficients of key independent variables. Non-performing Asset Ratio is a bank's non-performing assets over total assets. Loan Loss Provision over Loans is loan loss provisions over total gross loans. Liquidity Ratio is a bank's liquidity assets over total assets. Bank capitalisation is a bank's market equity value divided by the sum of market equity and book liabilities. Unrated Dummy takes one if a firm does not have an S&P long-term credit rating. Bank Size is a bank's total assets measured in logarithms. Firm Size is a firm's total assets measured in logarithms. For all interactions, we do not report the coefficients of the two interacting variables. There are three other variables constructed at the bank-firm level. Lending Relationship Dummy is a binary variable taking one if a firm and a bank have a past contract within 20 quarters prior to the loan origination quarter. Bank-firm Distance is the physical distance between a firm's headquarter and a bank's headquarter in thousand kilometres. Top Industry Dummy is a dummy taking one if a firm's industry falls in the top three industries of a bank's borrowers in a given quarter. Quarter-, bank-, and firm-fixed effects are included in OLS regressions. The other (unreported) controls include z-score, asset tangibility, profitability, cash, financial leverage, Tobin's Q, and years since IPO. See Table A1 for further information on variable definitions. All OLS coefficients are multiplied by 100. T-statistics based on standard errors clustered by banks are reported in brackets. a, *, **, and *** indicate that the corresponding p-values are less than 0.11, 0.1, 0.05, and 0.01, respectively. In the semiparametric model, we estimate the parameters by maximising the number of inequalities that satisfy the pairwise stability condition. The inequalities are constructed from all combinations of two actual matchings in a given quarter, and we include all sample quarters. All borrower and bank-specific characteristics are demeaned each quarter. Number of Inequalities is the number of total inequalities. Fraction of Inequalities Satisfied is the fraction of inequalities satisfied by the pairwise stability condition under the model prediction. 95% confidence intervals are constructed by subsampling and are reported in square brackets. ** indicates that the confidence interval does not contain zero.

Table 6: Robustness Checks on the Disappearing Matching

	1	2	3	4
	OLS Regression Model	Semiparametric Model	Loan-level Regression	Loan-level Regression
Bank Capitalisation	0.761**		-0.00819*	-0.00171
	(2.37)		(-1.93)	(-0.36)
Unrated Dummy	4.086**		-0.354***	-0.0568
	(2.36)		(-7.14)	(-1.00)
Bank Capitalisation×Unrated Dummy	-0.362**	-22.13	0.0137***	0.00281
	(-2.31)	[-35.72, 4.64]	(4.29)	(0.60)
Sample	Post-GFC	Post-GFC	Pre-GFC	Post-GFC
Quarter-, Bank-, and Firm-FEs	Yes	N/A	Yes	Yes
Observations/Number of Inequalities	39853	149993	18308	13535
Adjusted R^2/Fraction of Inequalities Satisfied	0.337	0.88	0.786	0.638

Notes: This table presents additional results checking the robustness of the disappearing matching. In Column 1-2, we report coefficients from the OLS regression model and the semiparametric model, respectively. The sample period is 2010Q1-2019Q4. We exclude all loans where the firm and the bank have prior relationships during the pre-GFC period. We then generate a sample by constructing all possible pairs between banks and firms using the loan-level data. The OLS model regresses the observed pair on a set of banks' and firms' characteristics. The dependent variable observed pair is a dummy taking one if the bank-firm pair is observed in Dealscan. The independent variables reported include Bank capitalisation which is a bank's market equity value divided by the sum of market equity and book liabilities, Unrated Dummy which takes one if a firm does not have an S&P long-term credit rating and their interaction. Quarter-, bank-, and firm-fixed effects are included in the OLS regressions. The other (unreported) controls include lending relationship dummy, top industry dummy, bank-firm distance, bank size, firm size, z-score, asset tangibility, profitability, cash, financial leverage, Tobin's Q, and years since IPO. See Table A1 for further information on variable definitions. All OLS coefficients are multiplied by 100. T-statistics based on standard errors clustered by banks are reported in brackets. a, *, **, and *** indicate that the corresponding p-values are less than 0.11, 0.1, 0.05, and 0.01, respectively. In the semiparametric model, we estimate the parameters by maximising the number of inequalities that satisfy the pairwise stability condition. The inequalities are constructed from all combinations of two actual matchings in a given quarter, and we include all sample quarters. All borrower and bank-specific characteristics are demeaned each quarter. Number of Inequalities is the number of total inequalities. Fraction of Inequalities Satisfied is the fraction of inequalities satisfied by the pairwise stability condition under the model prediction. 95% confidence intervals are constructed by subsampling and are reported in square brackets. ** indicates that the confidence interval does not contain zero. In Column 3-4, we report the results from loan-level OLS regressions. The sample period is 1987Q1-2007Q2 (excluding periods of banking crises) in Column 3 and the post-GFC is 2010Q1-2019Q4 in Column 4. The dependent variable is the loan amount in logarithms. The control variables are lender size, lending relationship dummy, Altman's z-score, asset tangibility, profitability, cash, leverage, Tobin's Q, years since IPO, covenant inclusion dummy, and loan maturity. We also include loan type-, loan purpose-, quarter-, firm- and bank-fixed effects. T-statistics based on standard errors clustered by banks are reported in brackets.

Table 7: Changes in Unrated Firms' Bond Outstanding during the COVID Shock

	1	2	3	4	5	6
Dependent Variable	ΔTotal Bond Outstand-ing	ΔSenior Bonds and Notes	ΔSubordinated Bonds and Notes	ΔTotal Loan Out-standing	ΔTerm Loan	ΔRevolving Credit
Bank Capitalisation	-2.565*	-2.726**	0.609**	-0.578	-10.00	6.955*
	(-2.03)	(-2.76)	(2.70)	(-0.16)	(-0.66)	(1.84)
Sample	Post-GFC	Post-GFC	Post-GFC	Post-GFC	Post-GFC	Post-GFC
Quarter-, Loan Type-, Loan Purpose-, and Bank-FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1113	1113	1113	1113	1113	1113
Adjusted R^2	0.220	0.216	0.239	0.211	0.358	0.177

Notes: This table reports estimates from loan-level OLS regressions. The sample period is 2010Q1-2019Q. The dependent variable is the change in a firm's debt outstanding from the pre-COVID period (averaging cross 2017-2019) to the end of 2020. The debt outstanding in Column 1-6 are Senior Bonds and Notes, Subordinated Bonds and Notes, Total Bond Outstanding, Term Loan, Revolving Credit, and Total Loan Outstanding, respectively. The independent variable is Bank capitalisation which is a bank's market equity value divided by the sum of market equity and book liabilities. The control variables are lender size, lending relationship dummy, Altman's z-score, asset tangibility, profitability, cash, leverage, Tobin's Q, years since IPO, covenant inclusion dummy, and loan maturity. We also include loan type-, loan purpose-, quarter- and bank-fixed effects. T-statistics based on standard errors clustered by banks are reported in brackets. a, *, **, and *** indicate that the corresponding p-values are less than 0.11, 0.1, 0.05, and 0.01, respectively

Table 8: Replicating OLS Regressions using Logit Regressions

	1	2	3	4	5	6	7	8
	Logit Regression	Logit Regression	Logit Regression	Logit Regression	Logit Regression	Logit Regression	Logit Regression	Logit Regression
Bank Capitalisation×Unrated Dummy	0.0664***	0.0209				0.0228	0.0237	0.0177
	(4.22)	(0.94)				(1.18)	(1.02)	(0.67)
Bank Capitalisation×Small Unrated Dummy			0.0545					
			(1.11)					
Bank Capitalisation×Large Unrated Dummy			0.0135					
			(0.80)					
Bank Capitalisation×High-cost Unrated Dummy				0.0468*				
				(1.89)				
Bank Capitalisation×Low-cost Unrated Dummy				0.0378				
				(0.97)				
Bank Capitalisation×High-reliance Unrated Dummy					0.0683***			
					(5.36)			
Bank Capitalisation×Low-reliance Unrated Dummy					0.00975			
					(0.43)			
Non-performing Asset×Ratio Unrated Dummy						0.162**		
						(2.21)		
Loan Loss Provision×Unrated Dummy							0.171	
							(0.99)	
Liquidity Ratio UnratedDummy								-0.00132
								(-0.26)
Sample	Post-GFC	Post-GFC	Post-GFC	Post-GFC	Post-GFC	Post-GFC	Post-GFC	Post-GFC
Quarter-, Bank-, and Firm-Dumies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	208651	63835	63835	26072	59616	63835	63835	56769
Pseudo R^2	0.498	0.531	0.531	0.549	0.537	0.531	0.531	0.531

Notes: This table reports estimates from logit regression model. The sample includes all possible pairs between banks and firms recorded in Dealscan in a given quarter. The logit regression regresses the observed pair on a set of banks' and firms' characteristics. The dependent variable observed pair is a dummy taking one if the bank-firm pair is observed in Dealscan. This table reports the coefficients of key independent variables. Bank capitalisation is a bank's market equity value divided by the sum of market equity and book liabilities. Unrated Dummy takes one if a firm does not have an S&P long-term credit rating. Small (Large) Unrated Dummy takes one if an unrated firm falls in the bottom (top four) size quintile(s). High-cost (Low-cost) Unrated Dummy takes one if an unrated firm's estimated interest-rate difference between bonds and loans is positive (non-positive). High-reliance (Low-repliance) Unrated Dummy takes one if an unrated firm's loan outstanding over total debt outstanding is 100% at the end of the previous year. Non-performing Asset Ratio is a bank's non-performing assets over total assets. Loan Loss Provision over Loans is loan loss provision over total gross loans. Liquidity Ratio is a bank's liquidity assets over total assets. Bank Size is a bank's total assets measured in logarithms. Firm Size is a firm's total assets measured in logarithms. For all interactions, we do not report the coefficients of the two interacting variables. There are three other variables constructed at the bank-firm level. Lending Relationship Dummy is a binary variable taking one if a firm and a bank have a past contract within 20 quarters prior to the loan origination quarter. Bank-firm Distance is the physical distance between a firm's headquarter and a bank's headquarter in thousand kilometres. Top Industry Dummy is a dummy taking one if a firm's industry falls in the top three industries of a bank's borrowers in a given quarter. Quarter, bank, and firm dummies are included in logit regressions. The other (unreported) controls include z-score, asset tangibility, profitability, cash, financial leverage, Tobin's Q, and years since IPO. See Table A1 for further information on variable definitions. We report the log-odd ratios. T-statistics based on standard errors clustered by banks are reported in brackets. a, *, **, and *** indicate that the corresponding p-values are less than 0.11, 0.1, 0.05, and 0.01, respectively.

Table 9: The Matching between Well-capitalised Banks and Unrated Firms When Banks Have High or Low "Chasing for Yield" Incentives

	1	2	3	4	5	6
	OLS Regression Model	OLS Regression Model	Logit Regression Model	Logit Regression Model	Semiparametric Model	Semiparametric Model
Bank Capitalisation	0.057	0.247	-0.040	0.041***		
	(0.26)	(1.34)	(-0.53)	(2.90)		
Unrated Dummy	3.201**	-3.414	1.047***	-0.317		
	(2.59)	(-1.50)	(2.71)	(-1.45)		
Bank Capitalisation×Unrated Dummy	-0.214*	0.220	-0.0713***	0.0106	63.13	1.18
	(-2.01)	(1.15)	(-2.58)	(0.52)	[-18.94, 98.02]	[-18.07, 25.97]
Bank Size×Firm Size	-0.743**	0.286	-0.0649	0.116***	58.15**	15.25 **
	(-2.23)	(0.91)	(-1.59)	(4.25)	[3.87, 65.65]	[8.06, 57.98]
Lending Relationship Dummy	47.57***	58.33***	3.423***	3.577***	1000	1000
	(14.08)	(30.67)	(9.03)	(20.22)	[-]	[-]
Top Industry Dummy	11.91***	9.476***	2.830***	1.427***	558.36**	389.60 **
	(17.65)	(9.16)	(7.78)	(4.06)	[459.28, 789.58]	[284.41, 539.03]
Bank-firm Distance	-0.00056	-0.00067**	-0.150**	-0.0824**	-0.0441**	-0.0308**
	(-1.49)	(-2.52)	(-2.16)	(-2.07)	[-0.0899, -0.0152]	[-0.0649, -0.0064]
Sample	Post-GFC	Post-GFC	Post-GFC	Post-GFC	Post-GFC	Post-GFC
Subsamples by Bank Deposit Ratio	High Deposit Ratio	Low Deposit Ratio	High Deposit Ratio	Low Deposit Ratio	High Deposit Ratio	Low Deposit Ratio
Quarter-, Bank-, and Firm-FEs/Dummies	Yes	Yes	Yes	Yes	N/A	N/A
Observations/Number of Inequalities	18049	41537	7144	40307	6256	232601
Adjusted R^2/Pseudo R^2/Fraction of Inequalities Satisfied	0.390	0.498	0.518	0.530	0.907	0.896

Notes: his table reports estimates from linear probability regression model (Column 1-2), logit regression model (Column 3-4), and semiparametric model (Column 5-6). The sample includes all possible pairs between banks and firms recorded in Dealscan in a given quarter. We divide the sample into two based on bank interest-bearing deposit ratio. For each model, we estimate it in two subsamples. Both the linear probability model and logit model regress the observed pair on a set of banks' and firms' characteristics. The dependent variable observed pair is a dummy taking one if the bank-firm pair is observed in Dealscan. This table reports the coefficients of key independent variables. Bank capitalisation is a bank's market equity value divided by the sum of market equity and book liabilities. Unrated Dummy takes one if a firm does not have an S&P long-term credit rating. Bank Size is a bank's total assets measured in logarithms. Firm Size is a firm's total assets measured in logarithms. For all interactions, we do not report the coefficients of the two interacting variables. There are three other variables constructed at the bank-firm level. Lending Relationship Dummy is a binary variable taking one if a firm and a bank have a past contract within 20 quarters prior to the loan origination quarter. Bank-firm Distance is the physical distance between a firm's headquarter and a bank's headquarter in thousand kilometres. Top Industry Dummy is a dummy taking one if a firm's industry falls in the top three industries of a bank's borrowers in a given quarter. Quarter-, bank-, and firm-fixed effects are included in OLS regressions. The other (unreported) controls include z-score, asset tangibility, profitability, cash, financial leverage, Tobin's Q, and years since IPO. See Table A1 for further information on variable definitions. All OLS coefficients are multiplied by 100. In the logit regressions, we report log-odd ratios. T-statistics based on standard errors clustered by banks are reported in brackets. a, *, **, and *** indicate that the corresponding p-values are less than 0.11, 0.1, 0.05, and 0.01, respectively. In the semiparametric model, we estimate the parameters by maximising the number of inequalities that satisfy the pairwise stability condition. The inequalities are constructed from all combinations of two actual matchings in a given quarter, and we include all sample quarters. All borrower and bank-specific characteristics are demeaned each quarter. Number of Inequalities is the number of total inequalities. Fraction of Inequalities Satisfied is the fraction of inequalities satisfied by the pairwise stability condition under the model prediction. 95% confidence intervals are constructed by subsampling and are reported in square brackets. ** indicates that the confidence interval does not contain zero.

Appendix A Construction of the dataset: Additional details

A.1 Variable definition

Table A1 contains the definitions, references, and sources of key variables used in this study.

Insert Table A1 here.

A.2 Details about manual matching Dealscan with Compustat from 2017 to 2019

We use firms' balance sheet information to measure borrower-specific variables. Dealscan only provides detailed loan-level data such as loan spreads, loan maturities, and so on. The source of balance sheet information comes from Compustat. Since the databases have no common digital identifier, We need to match the firms in Dealscan with those in Compustat manually. Prior literature has done some work on matching, and (Chava and Roberts, 2008)'s matching table is the most popular. Since their 2008 paper, Chava and Roberts have kept publishing and updating their matching results. Their latest matching table contains loans originating from 1987 to 2017 and is updated in 2017. In Dealscan, however, some loans that originated in 2017 could be added to the database after 2017. Therefore, We use Chava and Roberts's matching results up to 2016 and manually match firms' balance sheet information of all loans made from 2017 to 2020. In total, (Chava and Roberts, 2008) have matched 177012 loans, and there are 331593 loans originated before 2018. There are several reasons for a firm being unmatched. One of the possible reasons is that Dealscan records loans from privately-held firms, while Compustat only contains publicly-held companies. Another reason could be that the two databases are sourced differently. For a North American company to be added to Compustat, it must fill distinct 10K's or 10Q's with the SEC, while Dealscan data is compiled from a broader source, including the SEC fillings other than 10K or 10Q. The next paragraphs briefly specify the way We process the matching. Because there is no common digital identifier between the databases, a successful match depends on the similarity of the other identifying information (which is most likely to be string-type). The identifying information used by Chava and Roberts is company names. For example, a Dealscan firm named "oaktree specialty lending corp" is matched to a

Compustat firm with name of "oaktree specialty lending cp". We use a Python package called "FuzzyWuzzy" to calculate the similarity between two strings. This package provides several techniques to perform the calculation. Following (Chava and Roberts, 2008), We use the one called "partial_ratio". "partial_ratio" compares the shorter string with the substring of the same length in the longer string and gives a score from 1 to 100 (a higher score means higher similarity). In the previous example, "partial_ratio" will give multiple matches for 'oaktree specialty lending corp' with different scores. Among all the matches, the greatest score is 96 when the Dealscan firm is matched with "oaktree specialty lending cp", which We consider as a successful match. However, the highest score may not always produce a successful match - there could be false matches. For example, a Dealscan company named "nextcare inc" and a different Compustat company named "nextcure inc" have a score of 92 because of the high similarity of the letters involved in the strings. To avoid false matches, We manually check each match and drop the false ones.[23] A firm in Dealscan may change its name to Compustat. Following (Chava and Roberts, 2008), We conduct the matching loan by loan because a loan-level matching can locate the date of the borrower appearing in Dealscan. In Dealscan, there are 64411 loans during 2017-2020, and 26937 of those are borrowed by North American companies (identified by the Dealscan variable "country"). To date, We have manually checked all matching pairs with a score greater than or equal to 90 (In (Chava and Roberts, 2008), only 23.78% of matches have a score lower than 90). As a result, We have matched 8559 loans, among which 6698 are borrowed by North American companies. Besides company names, we also use the tickers and the names of parent companies to match. Here is an example of using the parent name to match. Searching all names in Compustat, there is not a close match for a Dealscan firm named "sc realty private reit inc". Then, using the name of that company's parent - "sumitomo corp", We find a perfect match in Compustat. In addition, some firms borrowing before 2017 borrow again. These firms already have matching results in (Chava and Roberts, 2008). These firms may be taken over or go private during 2017-2020, but if they are still contained in Compustat with the same name, We include them in my matching table. Taking those further steps, we extend the matches to 12947 loans, among which 9737 are borrowed by North American companies.

[23] Another way to address the false matches is to use more identifications, such as states and industries, to make a match of names more precise (see Cohen et al. (2021)).

Given the total number of loans, the matching rate (matching rate for North American loans) is 20.10% (36.15%), compared to 53.38% (56.88%) in (Chava and Roberts, 2008). As a result, the final sample increases by 1927 loans. From 2018Q1 to 2019Q4, the loan observations are 234, 340, 191, 280, 205, 243, 221, and 213. Noticed that the average loan observation during 2010Q1-2017Q4 is 232.75, and this indicates that my matching results are representative.

Appendix B Falling Bond Yields and Narrowing Capital Differences

B.1 Moody's Seasoned Corporate Bond Yields

Figure B1 plots two time series of Moody's seasoned corporate bond yields.

Insert Figure B1 here.

B.2 Time-series of Bond Yields Relative to Loan Yields

Figure B2 plots two time series of bond yields relative to loan yields.

Insert Figure B2 here.

B.3 Time-series of Capital ratios of Well-capitalised Banks and Poorly-capitalised Banks

Figure B1 plots two time series of capital ratios of well-capitalised banks and poorly-capitalised banks.

Insert Figure B3 here.

Appendix C Additional Results of the Semiparametric Matching Model

C.1 Estimates of the Semiparametric Model in the Pre-COVID and the Pre-GFC Periods

Table C1 estimates the Semiparametric Matching Model from 2015Q1 to 2019Q4 and from to 2007Q2.

Insert Table C1 here.

C.2 Lending Growth under Counterfactuals - Loan Amount is Equally split to Each Syndicate Participate

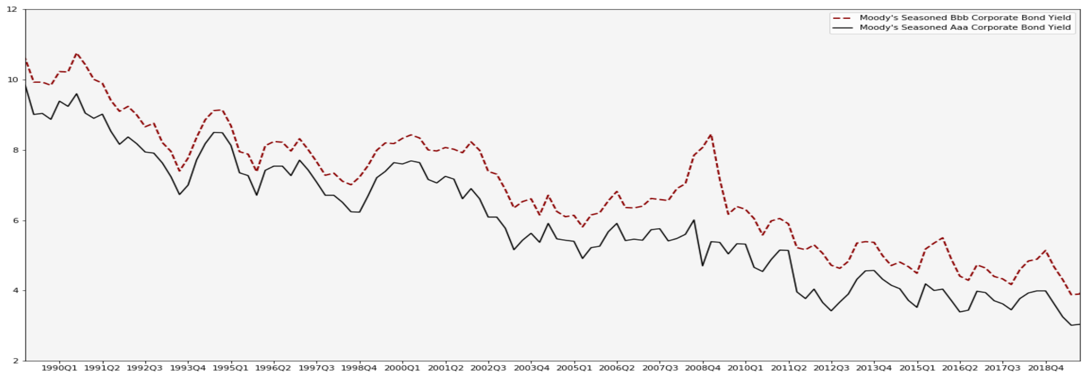
Table C2 estimates the credit access of unrated firms under counterfactuals. We equally split the loan amount to each syndicate participate.

Insert Table C2 here.

Table A1: Variable Definitions

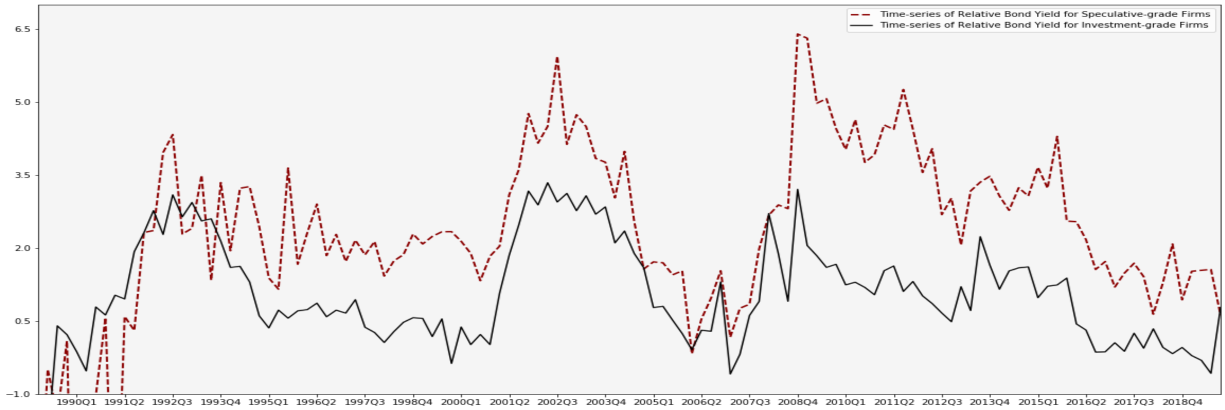
Name	Measure	Source	Name	Measure	Source
		Dependent Variable			
Observed Match	A dummy takes one if the bank-firm pair is observed in Dealscan	Dealscan			
		Main Independent Variables			
Bank Capitalisation	Market capitalization (product of share price and common share outstanding) divided by quasi-market assets (sum of market capitalization and book liabilities)	Compustat Bank	Unrated Dummy	A dummy taking the value of one if a firm does not have an S&P long-term issuer rating in the loan origination month	Compustat North America
Firm Size	Natural logarithm of a firm's total book assets	Compustat North America	Small (Large) Unrated Dummy	A dummy taking the value of one if a firm is unrated and is in the bottom (top) tercile (terciles) based on the firm size in a given quarter	Compustat North America
Estimated Costs of Switching from Loans to Bonds	The average bond yields of the closest bond issuing firms minus the average loan rates paid by the estimated firm in a given quarter. The closest bond issuing firms are those being in the same two-digit SIC as the estimated firm and in the same tercile as the estimated firm based on firm size, operating income over total book assets, and Tobin's Q.	DealScan; Compustat North America; FISD; authors own calculation.	Costly-switch (Costless-switch) Unrated Dummy	A dummy taking the value of one if a firm is unrated and has positive (nonpositive) estimated switching costs	DealScan; Compustat North America; FISD; authors own calculation.
Loan Outstanding over Debts at Previous Year-end	The proportion of a firm's loan outstanding in total debts in a given year	Capital IQ Capital Structure	Loan-heavy (Loan-light) Unrated Dummy	A dummy taking the value of one if a firm is unrated and has 100% (less than 100%) loan outstanding over debts	Capital IQ Capital Structure
Non-performing Asset Ratio	Non-performing assets divided by total book assets	Compustat Bank	Loan Loss Provision over Loans	Loan loss provision divided by total gross loans	Compustat Bank
Liquidity Ratio Asset	Liquidity assets divided by total book assets	Compustat Bank	Interest-bearing Deposit Ratio	Interest-bearing deposits divided by total book assets	Compustat Bank
		Control Variables			
Lending Relationship Dummy	A dummy takes one if a firm and a bank have a loan within twenty quarters before the loan origination quarter	DealScan	Bank-firm Distance	The geographic distance between a firm's headquarter and a bank's headquarter in kilometres.	Compustat North America and Compustat-Computstat Bank
Top Industry Dummy	A dummy takes one if a firm's industry falls into its bank's top three industries according to the number of the bank's borrowers in a given quarter	Compustat North America	Altman's Z-score	The sum of 1.2*working capital, 1.4*retained earnings, 3.3*pretax income, and 0.999*total sales over total book assets	Compustat North America
Profitability	Operating income over the average total assets between this quarter's and last quarter's numbers	Compustat North America	Asset Tangibility	Fixed assets (sum of property, plant and equipment) over total book assets	Compustat North America
Cash Holdings	Cash and short-term investment over total book assets	Compustat North America	Financial Leverage	Short-term liabilities plus long-term liabilities divided by total book assets	Compustat North America
Tobin's Q	Quasi-market assets (sum of market capitalization and book liabilities) over total book assets	Compustat North America	Year since IPO	Number of year to date of a company's initial public stock offering	Compustat North America
loan Type	A discrete variable representing the type of the loan with 65 categories, such as term loan and bridge loan	DealScan	Loan Purpose	A discrete variable representing the primary purpose of the loan with 42 categories, such as LBO and working capital	DealScan

Figure B1: Moody's Seasoned Corporate Bond Yields



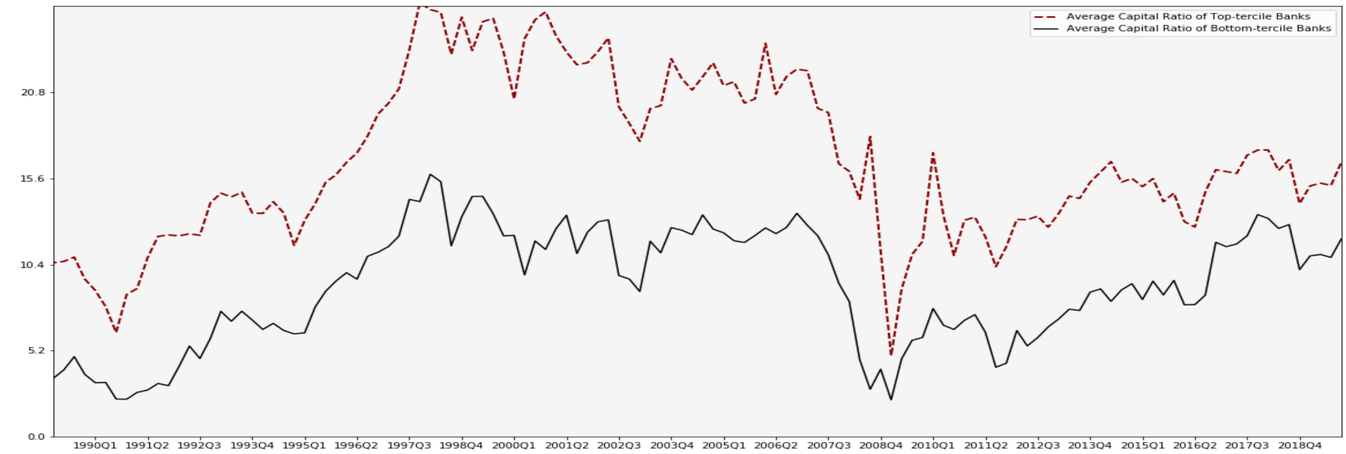
This Figure plots two quarterly time-series of Moody's Seasoned Corporate Bond Yields. The data is sourced from the Federal Reserve Economic Data of St. Louis Fed. The dashed red line is the Bbb bond yields, and the solid black line is the Aaa bond yields.

Figure B2: Time-series of Bond Yields Relative to Loan Yields



This Figure plots two quarterly time series of bond yields relative to loan yields. In each quarter, the bond yield is an average across all public bonds. The bond information comes from FISD, excluding nonconvertible bonds and all bonds to financial companies. The loan yield is an average of the sum of the loan spread and the 12-month LIBOR rate of the quarter. The loan information comes from Dealscan, excluding all loans to financial companies. Each point in the figure is the difference between the average bond yield and the average loan yield. The dashed red line is the yield difference calculated from all bonds and loans to speculative-grade firms (i.e., a firm with an S&P rating lower than BBB-). The solid black line is the yield difference calculated from all bonds and loans to investment-grade firms (i.e., a firm with an S&P rating equal to or higher than BBB-).

Figure B3: Time-series of Capital Ratios of Well-capitalised Banks and Poorly-capitalised Banks



This Figure plots two quarterly time-series of average capital ratios. We divide the sample banks into terciles in each quarter based on bank capitalisation. Bank capitalisation is a bank's market equity value divided by the sum of market equity and book liabilities. The dashed red line is the capital ratio of the banks in the top tercile, and the solid black line is the ratio of those in the bottom tercile.

Table C1: Estimates of the Semiparametric Model in the Pre-COVID and the Pre-GFC Periods

	1	2
Bank Capitalisation Unrated Dummy	-34.96	54.25**
	[-48.53, 17.97]	[30.69, 68.12]
Bank Size Firm Size	49.19**	11.92**
	[22.25, 68.26]	[5.67, 34.58]
Lending Relationship Dummy	1000	1000
	[-]	[-]
Top Industry Dummy	400.56**	224.68**
	[285.48, 452.44]	[180.83, 393.32]
Bank-firm Distance	-0.0183	-0.0474**
	[-0.0362, 0.0228]	[-0.0901, -0.0226]
Sample	2015Q1-2019Q4	2002Q3-2007Q2
Number of Inequalities	128269	488759
Fraction of Inequalities Satisfied	0.95	0.930

Notes: This table reports estimates of the semiparametric model. There are two sample periods – 2015Q1-2019Q4 and 2002Q3-2007Q2. The sample includes all possible pairs between banks and firms recorded in Dealscan in a given quarter. In the semiparametric model, we estimate the parameters by maximising the number of inequalities that satisfy the pairwise stability condition. The inequalities are constructed from all combinations of two actual matchings in a given quarter, and we include all sample quarters. All borrower and bank-specific characteristics are demeaned each quarter. Number of Inequalities is the number of total inequalities. Fraction of Inequalities Satisfied is the fraction of inequalities satisfied the pairwise stability condition under the model prediction. 95% confidence intervals are constructed by subsampling and are reported in square brackets. ** indicates that the confidence interval does not contain zero. Bank capitalisation is a bank's market equity value divided by the sum of market equity and book liabilities. Unrated Dummy takes one if a firm does not have an S&P long-term credit rating. Bank Size is a bank's total assets measured in logarithms. Firm Size is a firm's total assets measured in logarithms. For all interactions, we do not report the coefficients of the two interacting variables. There are three other variables constructed at the bank-firm level. Lending Relationship Dummy is a binary variable taking one if a firm and a bank have a past contract within 20 quarters prior to the loan origination quarter. Bank-firm Distance is the physical distance between a firm's headquarter and a bank's headquarter in thousand kilometres. Top Industry Dummy is a dummy taking one if a firm's industry falls in the top three industries of a bank's borrowers in a given quarter. Quarter-, bank-, and firm-fixed effects are included in OLS regressions. The other (unreported) controls include z-score, asset tangibility, profitability, cash, financial leverage, Tobin's Q, and years since IPO. See Table A1 for further information on variable definitions. All OLS coefficients are multiplied by 100. T-statistics based on standard errors clustered by banks are reported in brackets. a, *, **, and *** indicate that the corresponding p-values are less than 0.11, 0.1, 0.05, and 0.01, respectively. In the semiparametric model, we estimate the parameters by maximising the number of inequalities that satisfy the pairwise stability condition. The inequalities are constructed from all combinations of two actual matchings in a given quarter, and we include all sample quarters. All borrower and bank-specific characteristics are demeaned each quarter. Number of Inequalities is the number of total inequalities. Fraction of Inequalities Satisfied is the fraction of inequalities satisfied by the pairwise stability condition under the model prediction. 95% confidence intervals are constructed by subsampling and are reported in square brackets. ** indicates that the confidence interval does not contain zero.

Table C2: Lending Growth under Counterfactuals - Loan Amount is Equally Split to Each Syndicate Participate

	Panel A Lending Growth in COVID		***Panel B Lending Growth in GFC***	
	Lending growth (Equally-split) (%)	Observed − Counterfactual (%)	Lending growth (Equally-split) (%)	Observed − Counterfactual (%)
Observed Matchings	-32.77		-57.66	
	[-]		[-]	
Estimates from the Pre-GFC Model		-3.11		1.15
		[-7.46, 0.87]		[-0.29, 2.98]
Absolute $\hat{\beta}_1 = \lvert\hat{\beta}_1\rvert$		-4.41		1.15
		[-7.28, 1.74]		[-0.37, 2.81]
Estimates from the Pre-COVID Model		3.90		4.60**
		[-3.40, 7.32]		[1.02, 5.97]
Shut-off $\hat{\beta}_1 = 0$		1.40		3.08**
		[-3.65, 4.44]		[1.24, 4.67]

Notes: This table presents unrated firms' credit access during the COVID and the GFC. For the credit access, we proxy it using the average loan growth of all unrated firms' (most recent) pre-crisis relationship banks under observed matching and counterfactuals. The loan amount is equally split among each syndicate participant. The counterfactual relationship banks are assigned by using the model estimates or altering the estimates, or randomly assigning using Bootstrap. We estimate the parameters by maximising the number of inequalities that satisfy the pairwise stability condition. The inequalities are constructed from all combinations of two actual matchings in a given quarter, and we include all sample quarters. The estimated sample is 20 quarters prior to the COVID (GFC) for Panel A (Panel B). Each bank's lending growth is the growth rate of annualised amount of syndicated loans from the pre-crisis period to the crisis period. The amount of each loan is equally split among each lender in the contract. For the COVID (GFC), the pre-crisis and crisis period are 2017Q1-2019Q4 (2004Q4-2007Q2) and 2020Q2-2020Q4 (2008Q4-2009Q2). In the 'Observed' scenario, an unrated firm is matched with the bank in its actual loan contract in the most recent loan facility. In the counterfactuals, we make the firms match with well-capitalised banks. First, we use the estimates that are used in Panel B. Second, we take an absolute of $\hat{\beta}_1$, which is the estimate of the impact of the covariance between bank capitalisation and borrowers' unrated status. We also use the pre-COVID estimates and take $\hat{\beta}_1$ to be zero. 95% confidence intervals (reported in square brackets) are obtained by estimating 50 sets of parameter estimates based on subsampling, then drawing 20 times from the counterfactual matchings for each set of estimates. ** indicates that the confidence interval does not contain zero. In the 'Random Assignment' scenario, we randomly assign a bank to an unrated firm. The 95% confidence interval is obtained using Bootstrap. Observed – Counterfactual (%) is the lending growth of the matched banks in observed matchings minus that of the banks in counterfactual matchings, reported in percentage points.