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Giovanni Ferri, Pierluigi Murro and Zeno Rotondi

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Do Firm-Bank ‘Odd Couples’ Exacerbate Credit Rationing?*

Giovanni Ferri, Pierluigi Murro, and Zeno Rotondi†

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Abstract

We start considering an optimal matching of opaque (transparent) borrowing firms with relational (transactional) lending main banks. Next we contemplate the possibility that firm-bank “odd couples” materialize where opaque (transparent) firms end up matched with transactional (relational) main banks. We conjecture the “odd couples” emerge either since the bank’s lending technology is not perfectly observable to the firm or because riskier firms – even though opaque – strategically select transactional banks in the hope of being classified as lower risks. Our econometric results show the probability of rationing is larger when firms and banks match in “odd couples”.

Key words: Relationship Banking, Credit Rationing and Asymmetric Information

JEL Classification: G21; D84

1 Introduction

Whether enough bank credit is available to meet the demand of the small and medium-sized enterprises (SMEs) makes a key issue for academia as well as being a major preoccupation for the policy makers throughout the world. The theoretical models embodying the problems of adverse selection and of moral hazard of the borrowers – stemming from the information asymmetry between them and the lenders – typically prognosticate some of the borrowers will be rationed credit in the equilibrium. This prescription has a lemma for the SMEs. Since they are normally more opaque to external scrutiny with respect to the other enterprises, it is expected that the SMEs will be particularly subject to credit rationing exactly because the asymmetry of information is greater for

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†Giovanni Ferri and Pierluigi Murro: University of Bari; Zeno Rotondi: UniCredit Group’s Retail Research Division. The views put forward in the paper belong exclusively to the authors and do not involve in any way the institutions of affiliation. Corresponding author: Pierluigi Murro (pierluigi.murro@dse.uniba.it)

them. Therefore, it may be more difficult for the SMEs to obtain loans. A further aspect making the SMEs more financially vulnerable than the other enterprises descends from their virtually exclusive reliance on bank financing as a source of external funding, as these firms very rarely tap the financial markets to issue stocks or debt securities. In turn, by limiting the access to external finance, their graver asymmetries of information could jeopardize SMEs' investment and output levels.

After the seminal papers by Jaffe and Russell (1976) and by Stiglitz and Weiss (1981) demonstrated that credit rationing may persist even in equilibrium, several theoretical papers – still building on the hypothesis of information asymmetries – have tackled the impact of credit rationing on enterprises' business activity¹. All of these contributions take up the problem of the asymmetry in information in one way only. Indeed, this literature investigates situations in which the bank (the principal) suffers an information asymmetry vis-à-vis the firm (the agent) applying for credit. That asymmetry persists – though somewhat diminished – even after the banks' evaluation of the firm's quality. Along this approach, contributions study how the ensuing incomplete contract/incomplete market set up affects the equilibrium between loan demand and loan supply.

To our knowledge, no researcher has thus far addressed the possibility that there might be information asymmetries also going the other way. Namely, consider the following situation where we suppose that:

- i) the banks are not all identical but there are different types of banks, e.g. relationship lenders vs. transactional (or arm's length) lenders;
- ii) the enterprises differ in terms of the intensity of their opaqueness, e.g. most SMEs are more opaque (have more intense information asymmetry) with respect to larger enterprises;
- iii) there exist an optimal ex ante match between bank type and firm type, e.g. opaque firm/relationship bank, transparent firm/transactional bank;
- iv) in choosing their bank, we may consider two different behaviors by the firm: a) "safe" firms should try to reach the optimal match internalizing the negative consequences an imperfect match would deliver; b) "risky" and opaque firms might play strategically, trying to pretend they are transparent and searching a transactional banking partner;
- v) to expand its business, when approached by an enterprise, the bank pretends to be the type of bank she expects the borrower to consider his optimal banking partner;
- vi) the enterprise will only be able to learn ex post the actual type of bank it has ended up selecting.

In that situation, there is double-sided information asymmetry. As in the previous literature, the bank does not know exactly the type of the borrowing applicant. However, in addition to that, also the enterprise knows only imperfectly which bank type it is selecting. In this paper, we posit that an imperfect

¹Early works in this vein include Blinder and Stiglitz (1983), Besanko and Thakor (1987) and Berger and Udell (1992).

bank-type/firm-type match could result in more severe financial constraints for the borrowing firms. To be sure, as exemplified above, if the business technology employed by the bank turns out to be inappropriate to the needs of the borrower, then the asymmetries of information might be amplified by the imperfect match.

Indeed, the idea that banks do differ in the way they approach their lending is in line with a new strand of the literature that, in recent years, has investigated the methods through which the SMEs are financed by banks. Various – both theoretical and empirical – papers² highlight two extreme specific lending technologies: the “transaction lending” technology – typically based (only) on “hard” information (e.g. borrowers’ balance sheets and/or collateral guarantees) vs. the “relationship lending” technology – based instead on “soft” information (obtained via personal interaction/acquaintance and difficult to codify). This approach holds that the “transaction lending” technology is more desirable for more informationally transparent firms, while the “relationship lending” technology is more appropriate for the more opaque firms (suffering more intense asymmetries of information).

To our knowledge, up to now, no researcher has investigated the causes and the consequences of an imperfect match, i.e. a situation in which the information characteristics of the firms and the lending technology of its bank are not aligned. Obviously, in a perfect capital market this problem would be immaterial, and an imperfect match should not have consequences. In case an enterprise finds out ex post it chose the “wrong” type of bank – that is the bank the firm selected in view of its own firm-type turned out to be of the opposite type – it will immediately switch to another more “appropriate” bank (at least on the basis of the firm’s ex ante perception). However, considering that transaction and information costs could make changing the banking partner cumbersome, the enterprise might risk being stuck (for a while) with the wrong bank, thereby possibly suffering more credit rationing than would have resulted from a perfect match.

To address this issue, we use novel survey micro-data that allow us to learn the lending technology criteria according to which each firm selected ex ante its main banking partner and also whether the firm finds out ex post that, indeed, the selected bank practices those lending technologies. The data refer to the end of 2006 and come from the Tenth Survey of Italian Manufacturing Enterprises runs by UniCredit Group. Specifically, we aim to shed light on whether an imperfect match – that we identify as a situation in which the ex ante lending technology criteria employed by the firm to select its main banking partner turned out, in the view of the firm, not to be satisfied ex post by the chosen bank – affects the probability that firms will suffer credit rationing.

Building on the answers provided by the surveyed enterprises to different questions we create an indicator to identify the consistency between, on the one hand, the lending criteria used by the enterprise to select its main banking

²A survey of the literature that has lately studied the various lending technologies employed by banks (especially to lend to the SMEs) is contained in Section 2.

partner – on the basis of the bank type that was perceived *ex ante* by the firm – in view of the enterprise’s own financial needs and, on the other hand, the criteria that bank is actually using according to the *ex post* assessment of the enterprise. To complete our primary task, we then test whether the probability of being credit rationed increases for those firms where the indicator points to inconsistency.

Our results support the view that the probability of rationing increases when the firm ends up in an inconsistent match with its main bank. Assuming rational behavior on the part of the enterprise, its falling into an inconsistent match evokes the possibility that even banks may be opaque for borrowing firms, being it difficult for the latter to know precisely *ex ante* what the lending technology used by the bank will actually be.

In the rest of the paper section 2 briefly discusses the literature on credit rationing and on the ways for the SMEs to get external finance. Section 3 is devoted to present the data set we use, explaining also our methodology to construct the variables we use as well as our econometric strategy. In section 4 we show our main results. Section 5 concludes the paper.

2 Survey of the Literature

The issue of credit rationing has been the focus of very many theoretical contributions. There are various reasons behind this revealed interest on the topic. Early on credit rationing was studied because of its possible role in connection with the transmission of monetary policy. Some papers of the 1950s – e.g. Kareken (1957), and Scott (1957) – suggested that monetary policy could in part be transmitted via the channel of credit rationing, rather than through the interest rate channel. However, in these papers the existence of credit rationing was forced by the *ad hoc* assumption that interest rates were rigid.

In the following decades, the literature built on more theoretically solid grounds deriving credit rationing from the existence of asymmetries of information and of agency problems. This is the case, among others, for two influential papers like Hubbard (1990), and Bernanke and Gertler (1995) highlighting that credit rationing can negatively impinge on companies’ output and investment and, through this, damage the macroeconomy. These works are founded on the results obtained earlier by Jaffe and Russell (1976), and Stiglitz and Weiss (1981), who show the mechanisms through which credit rationing can persist in equilibrium. In Stiglitz and Weiss (1981) the bank – not being able to control all the actions of its borrowers – writes its contracts in a way to provide them incentives to take those decisions favoring the bank and to attract low risk borrowers. That strategy raises the bank’s expected return by less than the increase in the loan rate up to a certain level of the interest rate. Beyond that threshold any increase in the loan rate will cause the expected return to diminish – because of the negative self-selection effect of the increased rate that twists the composition of the borrowing pool away from safe and towards risky applicants. Accordingly, the loan rate at which the bank maximizes her ex-

pected profit is exactly the one of equilibrium. Naturally, it is possible – indeed, this will be the norm – that at that interest rate the demand for loans exceeds the related supply. However, because of the mentioned adverse selection impact of any further increase, the loan rate will not be increased by the bank and the demand not satisfied will be rationed. This is one of the best known examples of real rigidities depending on market failures.

Various subsequent papers evaluate the possibility that the banks could be able to partly solve the market failure via their own work and expertise. Specifically, through adequate screening and monitoring procedures the bank can (at least partly) overcome the asymmetric information and incentive problems (Diamond, 1984; Bhattacharya and Thakor, 1993) and, thus, reduce enterprises liquidity constraints. However, the extent to which a bank succeeds in overcoming the information asymmetry and in providing the appropriate incentive for borrowers to avoid opportunistic behavior depends also on its lending technology. Mainstream literature generally distinguishes two ways in which SMEs are financed by banks, depending on the type of information which is exchanged between the firm and the bank. A “transaction lending” technology refers to a firm-bank report in which the bank obtains from the borrowing firm “hard” type information, that is quantitative in nature and, so, easily transferable. At the other extreme, a “relationship lending” technology hinges on “soft” information, that is qualitative information that are normally obtained via long-term informal/personal interaction and are, therefore, much more difficult to transfer.

Both the theoretical and the empirical literature have mainly focused on the characteristics and the possible pros/cons of “relationship lending”. This is, in fact, considered the most appropriate technology to lend to firms with significant informational asymmetries, as a tighter firm-bank relationship helps overcome those informational asymmetries, improving the efficiency of the bank’s allocation of loans. Boot (2000) defines relationship lending as “the provision of financial services by a financial intermediary that: i. invests in obtaining customer-specific information, often proprietary in nature; and ii. evaluates the profitability of these investments through multiple interactions with the same customer over time and/or across products”. The definition hinges on two crucial aspects: eliciting the release of “proprietary” information from the client to the bank and the presence of multiple interactions between the two parts.

Some theoretical contributions have tried to model the features of this firm-bank relationship. Rajan (1992) stresses the amply recognized advantages of bank financing. In practice, thanks to their ability to reduce adverse selection problems (thanks to better information) and to lower also the moral hazard (by controlling borrowing firms investment decisions), the banks can offer the SMEs “informed” external funds that will be cheaper than those “less informed” funds the SMEs can obtain from transactional lenders. Diamond (1991) highlights that the firm-bank relationship by itself can solve the moral hazard problem for the firms, since the reputation cumulated through a good past track record dampens the risk of adverse selection. However, the rose of relationship lending also has its thorns, and some authors underline the costs of relationship banking (e.g. Sharpe, 1990; Rajan, 1992; Weinstein and Yafeh, 1998). Indeed, thanks to

its informational advantage, the bank might extract surplus from the borrowing firms. This could change the incentives for the firms. Firms could prefer to apply for credit at a transactional financier, who will have neither the advantages nor the costs of entertaining the relationship with the bank.

Some empirical research has tried to test those results derived from the theoretical models. In particular, many papers have analyzed – in various countries – the impact “relationship lending” has on the financing of the SMEs. For the US, various studies used data from the National Survey of Small Business Finance. Among these studies, Petersen and Rajan (1994) find that the firms obtaining loans from fewer banks enjoy easier access to credit and pay lower borrowing rates, while longer firm-bank relationships translate into increased availability of financing. Berger and Udell (1995) show that a longer firm-bank relationship lowers the cost of credit and reduces also the requirements of collateral guarantees. On data for Italy, Angelini et al. (1998) find that the intensity of “relationship banking” reduces the probability that borrowing firms will be rationed, even though the lending rates charged by the banks tend to increase as the firm-bank relationship lengthens. For Belgian enterprises, Degryse and Van Cayseele (2000) detect the impact relationship banking along two different dimensions: borrowing rates increase as the firm-bank relationship lengthens, while borrowing rates decrease when the scope of the firm-bank relationship – defined as the purchase of additional information intensive services (other than the loan) – increases.

Differently from what happened with the great attention for relationship lending, the literature has been rather silent about the determinants and the features of the “transaction lending” technology. Often, the literature has used the transaction lending label for any type of loan based on information that is easily verifiable by anybody, where the release of such information is typical of the most transparent enterprises. Berger and Udell (2006) criticize this oversimplification. In particular these two authors suggest that there are various technologies hinging on “hard” information, and these technologies do differ among themselves. This is not only a theory curiosum about the way SMEs obtain their financing but it has also relevant policy implications. To exemplify, referring to the simplified dichotomization between relationship lending and transaction lending, a number of authors³ have argued that the large banks are at a disadvantage in supplying funds to the more opaque SMEs. However, Berger and Udell (2006) underline that many large banks lend to opaque SMEs by means of transaction lending technologies, thereby dealing with informational asymmetries by means of “hard” information. In fact, where no detailed and trustworthy financial accounts are available, the large banks may often use other “hard” type⁴ information assess the probability that the enterprise will repay

³For a survey of the literature on this theme, see, e.g., Boot (2000), Ongena and Smith (2000), and Elyasani and Goldberg (2004).

⁴For example, with highly asset-based enterprises the large banks can employ an assessment of the assets pledged as collateral guarantees; with factoring companies they can focus on the quality of the loans purchased by those companies; for leasing companies the large banks can use an evaluation of the fixed assets owned by the companies.

the loans it was granted.

Utilizing survey micro-data on Japanese SMEs, Uchida et al. (2006) tested the importance of the various “lending technologies” proposed by Berger and Udell (2006). Specifically, they consider four lending technologies: financial statement lending, real estate lending, other fixed-asset lending, and relationship lending. Using the responding firm’s answer to the question on which were – in the firm’s own view – the criteria followed by its main banks to grant its loans, the authors created a distinct index for each of the four lending technologies. Analyzing econometrically the determinants each index the authors find there is complementarity among the indices of the four technologies. This result suggests that the banks, even though possibly employing mainly some specific criteria to lend, tend to use the various lending technologies at the same time. Complementarity is stronger between some of the technologies, such as, on the one hand, between “financial statement lending” and “relationship lending”, and, on the other, between “real estate lending” and “other-fixed asset lending”. This complementarity across technologies makes the identification of distinct determinants for the single technology quite difficult. Among the cases where such identification is possible, the authors report that firms having audited statements are significantly more likely to be lent via the “financial statement lending” (though this result applies to smaller-sized firms only). Finally, in the surveyed enterprises’ view, the small-sized banks and those banks that more extensively use soft information are more likely to employ the relationship lending technology to supply their loans.

3 Asymmetries of Information About the Bank

The main objective of this section is trying to explain the theoretical intuition on which we anchor our empirical analysis. The hypothesis we want to test regards a new possible determinant of firm’s credit rationing depending on the mismatch between the type of bank the firm tried to select and the type of main bank the firm actually ended up with. Specifically, we consider the possibility that the likelihood of rationing increases when the bank type perceived (*ex ante*) by the firm as optimal in selecting its main bank turns out not to be satisfied *ex post* by the bank actually selected. We posit this mismatch is due to two chief causes: the fact that it is difficult for the firm to identify *ex-ante* the true characteristics of the bank it selects as its partner; and the information and switching costs that, under some circumstances, may force the firm to stick to a relationship with a “wrong type” bank.

Our intuition descends from some assumptions on the features of the firm-bank relationship. Some of these assumptions are amply shared by the reference literature, while some of the other assumptions are relatively new. A first set of assumptions we refer to pertain to the various types of banks and of firms. As we outlined in the previous section, the literature has highlighted that there are differences across banks depending on the lending technologies they employ. In general, two main types of technologies – relationship lending vs. transactional

(or arm's length) lending – are identified by which banks lend to firms and it is stressed that the banks tend to specialize in the technology they use the most. Thus, though it may be familiar also with the alternative technology, each bank will be more efficient when lending through the technology it specializes in. So, it is useful distinguishing banks according to their preferred lending technology.

At the same time, most authors concur it is useful to distinguish the firms on the basis of the intensity of their information opacity. This sometimes corresponds to separating large-sized (relatively transparent) enterprises from smaller and medium-sized (relatively opaque) enterprises (SMEs). Indeed, several papers stress that the SMEs suffer more intense credit rationing because of their higher opacity. Obviously, firm size is not the only way to approximate opacity. Some authors discriminate the firms on the basis of whether their statements are audited and/or they offer real assets as collateral guarantees on the loans they obtain.

Having classified the enterprises (on the basis of their information opacity) and the banks (on the basis of their vocational lending technology) we posit there is an optimal match between bank type and enterprise type. In practice, we judge the “optimal couples” are opaque firms/relationship banks and transparent firms/transactional banks. This assumption is not entirely new in the literature. For instance, various papers have stressed that the large banks hold a comparative advantage in transactional lending – based on “hard” information – to transparent firms, while the smaller-sized banks have an edge in relationship lending – based on “soft” information – to opaque firms.

Even though the two couples above are optimal in theory, in reality we should contemplate the possibility that not always the agents – both the banks and the firms – try to reach the appropriate matching. For various different reasons, in fact, both the firms and the banks may sometimes have an incentive to attempt deviating from their optimal match.

Let's start considering the enterprises. We may distinguish “safe” enterprises from “risky” enterprises. Indeed, the firms differ not only in terms of their relative information opacity but also in terms of their degree of risk. Two enterprises that are analogous with respect to asymmetries of information may feature rather different probabilities to repay their loans. These differences, descending from various factors, such as the enterprise's profitability, its extent of financial leverage or its sector-specific risk, are however difficult to assess for the bank, even more so against opaque firms. Because of this, the firms that hold themselves “safe” will try to get the optimal banking partner, so to signal their good quality, overcoming the information asymmetry problem and getting the sought for loan. On the contrary, the companies that are aware of being “risky” could have an incentive to play strategically, thereby trying to liaise with the type of bank that would less likely be able to identify the company's risk type. So, “risky” firms try to exploit their information asymmetry to their own advantage. Naturally, the possibility of playing strategically is larger for the more opaque firms, which might therefore try securing a transactional banking partner in the hope the bank will be unable to classify their true risk.

Furthermore, since the firms are not able to perfectly tell ex-ante the true

type of the bank they are approaching, also the banks may have an incentive to deviate from the optimal firm-bank match. The objective of the bank is, in fact, maximizing the number of good firms in their borrowing pool. Unfortunately, the bank is unable to flawlessly identify ex-ante the quality of the new firms applying for credit (particularly for opaque firms). For this reason, the bank may have an incentive to maximize its number of customers, thus mimicking the behavior of the type of bank the applicant enterprise is seeking for. Only later on, will the bank try to discriminate among the various customers by means of its vocational lending technology.

The strategic behaviors on both the part of the firm as well as of the bank makes it more likely that several firm-bank couples turn out to be “odd” (or mismatched; i.e. opaque firm/transactional bank or transparent firm/relationship bank) and, consequently, this raises the probability that firms will be credit rationed.

If the capital market was perfect, the odd firm-bank couples would have no consequence, at least in the long-run. When the firm realizes it has ended up with the “wrong” type bank – unless the firm is a “risky” subject deliberately playing strategically – it could “migrate” to a more adequate bank. However, because of the existence of information and switching costs, more often than not the firm will be stuck in its relationship with the inadequate banks, continuing to suffer heightened credit rationing.

Finally, there are two possible reasons of creating odd firm-bank couples, due to the change over time of the firm and of the bank. Indeed, as time passes the firm’s needs as well as the bank’s lending specialization might vary. For example, an initially transparent enterprise could become opaque if it invests in assets breeding larger information asymmetries, while a bank at the start specialized in relationship lending could restructure and switch to transactional lending. Also in these cases it might be difficult for the firm to change its main banking partner thus making the odd couples last for a while. These considerations seem to imply that the negative effects on credit rationing stemming from mismatches between the type of firm and the type of bank could be larger for the firms endowed with longer lasting relationships with banks as this might strengthen their lock-in with the bank.

4 Data and Variables

4.1 Presenting the Dataset and Some Descriptive Statistics

Our main data source is the Tenth Survey on Italian Manufacturing Firms (SIMF), run by the Unicredit banking group in 2007. Every three years this survey gathers data on a sample of Italian manufacturing firms having more than 10 employees. The 2007 wave consists of 5,137 enterprises. All the firms with more than 500 employees are included, while those having a number of employees in the range 11 to 500 are sampled according to a stratified selection procedure based on their size, sector, and geographic localization. The main

strength of this database depends on the very detailed information it collects on individual firms. In particular, the 2007 wave features information regarding the firm's: a) ownership structure; b) number and skill degree of employees; c) attitude to invest in R&D and whether it has made innovations; d) extent of internationalization and exports; e) quality of the financial management and relationships with the banking system. These information are gathered through a survey on the three years previous to the survey year (thus, for the wave we use data go from 2004 to 2006).

The firms in the sample cover approximately 9% of the reference universe in terms of employees and some 10% in terms of value added. Thanks to its stratification, the sample is highly representative of the economic structure of Italian manufacturing. Table 1 presents some descriptive statistics. At the mean, the surveyed firms have been in business for 22 years; beyond 60% of them have fewer than 50 employees (below 4% of the firms have more than 500 employees); 70% of them are localized in the North. Only 1% are listed in the Stock Exchange, while 37% have their profit/loss and financial statements certified by external auditors. As to sectoral specialization, almost half of the enterprises belong to traditional sectors, according to the Pavitt classification, while only 5% have their business in the high tech sectors.

Moving on their financial set up, the average length of the relationship with the main bank is 17 years; 48% of the firms have a national banks as their main banking counterpart, 10% entrust a banca popolare (larger-sized cooperative banks), 7% feature a savings bank as their main bank, 5% entrust a banca di credito cooperativo (smaller-sized cooperative mutual banks), while 28% of the firms have another type of bank as their main bank. Finally, there is extensive multiple banking: on average firms have five banks and the share of loans obtained from the main bank is 32% of the total banking loans received.

Particularly relevant for our analysis, the 2007 wave of the survey features a peculiarity with respect to the previous waves. Specifically, an entirely new set of questions was introduced (partly inspired by an analogous detailed survey on SME financing run in Japan, see Uchida et al. 2006; 2008), expressly tailored to investigate in depth the relationship between the firm and its main bank. In this paper we will particularly focus on two questions where the firm is asked to state which of the characteristics – choosing from a given list – have been important in the firm's selection of its main bank, as well as stating which characteristics, in the firm's view, best describe the way its main bank grants credit. Unsurprisingly, given the fact that this section of the survey required dedication, only one third of the total number of surveyed enterprises (exactly 1,541 firms) answered these questions. Table 2 reports descriptive statistics for this sub-sample of enterprises. We cannot rule out self-selection. In other words, it is possible that the choice by a firm to answer this part of the questionnaire was not casual. The large share of credit rationed firms in this sub-sample – 15% as against 5% of the total sample – is perhaps suggestive of that. It will thus be important keeping this in mind when commenting the results. The other variables seem to be in line with the rest of the sample, excluding the share of loans granted by the main bank, which is 23% in the sub-sample with respect

to 32% in the whole sample.

4.2 Consistent Firm-Main Bank Choice and the Phenomenon of the “Odd Couples”

To distinguish the enterprises on the basis of the needs they perceive in choosing their main banks, and the banks according to the criteria they actually use – in the firms’ perception – to lend, we employed questions F1.15 and F1.17 (see the Appendix) from the Survey. Using the information obtained from the answers to these two questions we could dichotomize the firms – depending on their ex ante selection drivers – between the group of those searching a main bank more oriented to soft information and relationship lending and the group of those firms looking for efficiency at transactional lending focused main banks. Furthermore, we were also able to dichotomize the banks – following the ex post assessment based on the firms’ perception – between the group of those with a vocation to relationship lending and the group of the banks more inclined to transactional lending. Having completed the bipartition of the firms and of the banks, we could then build four indicators mapping all the possible combinations between firm type and bank type.

The distinction between the two firm types derives from inspecting the answers to the question “*Which of these characteristics are key in selecting your main bank?*”. In answering this question the firm was required to give a weight (going, in descending order, from 1, very much, to 4, nil) to 14 characteristics. Six (from 1 to 6) of the 14 characteristics emphasize the relationship motive, while most of the others (from 7 to 12 and also 14) stress the efficiency reason. In practice, we constructed dummy variables valued one if the firm answered 1 (very much) to the respective characteristic. Next, we calculated two indices (an index of relationship and an index of efficiency), as the first principal component obtained via the principal component analysis on these dummy variables. The enterprises that turned out having a relationship index larger than their efficiency index were classified as “relational”, the other firms (those having an efficiency index larger than their relationship index) were cataloged as “transactional”.

Using instead the answers to the question “*In your view, which criteria does your bank follow in granting loans to you?*”, we classified the characteristics of the banks, according to the firms’ opinion. Also here the firm was asked to give a weight on the relevance of fifteen criteria, that we could group as “relational” (criteria from 9 to 11 and from 13 to 15) and “transactional” (from 1 to 6). Following a procedure entirely analogous to that utilized before in categorizing the firms, we built two bank type indices. The banks that turned out to have a larger value for the relational index were classified “relational”, the other ones were labeled “transactional”. Having dichotomized also the banks, we could then build four dummy variables mapping all the possible combinations: relational firm with relational bank; relational firm with transactional bank; transactional firm with relational bank; transactional firm with transactional bank.

This methodology to construct the indicators of consistency between the

enterprise's ex ante needs and the ex post characteristics of the bank has some advantages. Primarily, we manage to perceive the actual features of the bank (in the firm's view) at the time the firm is asked. Thus, we can identify the possible differences between the characteristics the enterprise was looking for at the beginning of the business rapport with the bank and those the bank has turned out to actually offer the firm. An additional advantage of our index method is that, though based on the firm's perception, these indices are derived indirectly on the firm's answers. In doing so, we lower the possible distortion of the indices that could descend from the imperfect understanding of the questions.

An important feature of our indices – something to keep in mind when explaining the results – is that the firms are divided on the basis of the needs they state in motivating their main bank selection and not on the basis of the enterprises actual degree of opacity. As such, a good guess is that the firms stating they are searching for a relationship bank rapport are the firms we identified as opaque firms of good quality, while it would be rational for the opaque enterprises that perceive themselves as risky to state they are looking for a transactional bank.

Table 3 presents the descriptive statistics for these variables. 66% of the firms falls into the combination relational firm with relational bank. The odd couples are 26% of the enterprises as they end up in a sub-optimal matching: 13% of the firms looking for a relational bank has ended up with a transactional bank and an additional 13% of the firms were searching for a transactional bank and have found themselves with a relational main bank. Finally, only 8% of the enterprises were aiming at a transactional bank and have effectively liaised with a transactional bank.

To control whether the results we obtained through these indices were only due to the respondents' misinterpretation of the question on the criteria used by the bank in supplying its credit, we can consider the type of bank the firm applies to. We build here on the reasoning put forth by Stein (2002). Specifically, he argues that, in view of their organizational features, the larger banks suffer a disadvantage to offer loans based on soft information to the smaller-sized firms. Because of this, we expect that the NATIONAL banks tend to supply credit on the basis of transactional type lending technologies, whereas LOCAL banks are expected to use relationship lending technologies.

Fortunately, the survey gives us the information on the type of main bank entrusted by the firm.⁵ Through this information we will try to replicate the mismatching indices, substituting the type of bank to the firm's answers as to the criteria used by its main bank to supply credit. In this, we coded LOCAL banks the Volksbank type banks (banche popolari), the savings banks and the mutual banks (banche di credito cooperativo),⁶ while categorizing as NATIONAL both

⁵In effect, only 944 – of the 1541 enterprises responding to the two questions we used to build our indices – reported also the type of their main bank. We can imagine some self selection, where the firms unable to specify their type of main bank are those suffering more asymmetries of information on bank characteristics. This conjecture is supported observing that the degree of mismatch is much smaller for the 944 firms (15%) than for the 1541 firms (25%).

⁶We code as LOCAL banks also those cases where the firms classified their main bank

the national banks and the foreign banks. Table 4 reports the results broadly consistent with expectations: while the share of firms looking for a relational main banking partner are slightly twisted in favor of the LOCAL (44% against 40% for the NATIONAL) the opposite attains for the share of enterprises looking for a transactional main bank (10% for the NATIONAL vis-à-vis 6% for the LOCAL).

In addition, Table 5 shows that the mismatch phenomenon is much more widespread for the NATIONAL (23% of the firms with a NATIONAL main bank end up in an odd couple) than for the LOCAL (only 8% are mismatched). Possibly, this depends on the variety among the various NATIONAL banks. On this, Albareto et al. (2008) argue that, in the recent years, Italy's banking market has seen increasing diversity among the large banks in terms of organizational models.⁷ These considerations provide ground for the “reverse” asymmetry of information, whereby a firm can guess only imperfectly the actual lending technology of a new bank it is approaching.

5 Empirical Methodology

This section is devoted to outline our empirical model, explain how the dependent variable is constructed and sketch out the details of the other control variables included in our regressions. The main results of the empirical investigation will instead be undertaken in section 6.

5.1 Empirical Model

Our chief aim is testing whether inconsistency between the ex ante banking needs of the enterprise and the ex post lending specialization of its main bank – i.e. being an “odd couple” – affects the probability that the firm will suffer credit rationing. To test our hypothesis we will start building an empirical model of the probability that firms are rationed in the credit market. If we define y_1^* the amount of credit the firm would wish to obtain and y_2^* the size of the loan actually granted by the bank, we have that the firm is rationed any time $y^* = (y_1^* - y_2^*) > 0$. Thus, we can model the probability of rationing as:

$$y = 1(y^* > 0) \tag{1}$$

$$y^* = a_1x + z_1d_{11} + u_1 \tag{2}$$

“other credit intermediary”. This descends from observing that the only possibility not already specified in the survey is that of local banks other than Volksbank type banks (banche popolari), savings banks or mutual banks (banche di credito cooperativo).

⁷This is likely due to various factors: the increasing use of ICT, allowing increasing mobility of the branch managers; the increasingly frequent bank M&A and restructuring since the 1990s; the heightened degree of competition in banking, leading some of the large banks to entrust much autonomy to their branches.

where y is our measure of credit rationing (a dichotomous variable taking value one if the firm is rationed), x is a proxy of the inconsistency of the firm's bank type with respect to the firm's stated needs, z_1 is a vector of control variables, and u_1 is the error term of the "rationing equation" (2).

Usually, a_1 is interpreted as the impact of x on rationing. However, here it is possible that the inconsistency of the firm's bank type is endogenous with respect to the ex ante probability that the firm will be rationed. The possible endogeneity is due to strategic behavior of "risky" and opaque firms that may have an incentive trying to pretend they are transparent and searching a transactional banking partner. This conduct may affect the probability of rationing. It is essentially for this reason that we estimated our model also with a two-stage approach. Namely, we define z_2 as a vector of instrumental variables, which are correlated with the inconsistency but affect the probability of rationing only through the impact they have on the inconsistency. The impact of these variables on x is captured by the vector d_{22} in the "inconsistency equation":

$$x = z_1 d_{21} + z_2 d_{22} + u_2 \quad (3)$$

where z_1 refers to the control variables included in (2), z_2 is the vector of instrumental variables, and u_2 is the error term. We estimate the model (1)-(3) using a 2SCML (two-stage conditional maximum likelihood) and then compare the results⁸ with those obtained for the model (1)-(2) estimated with a simple probit. As said, this is motivated by our need to check for endogeneity in our data.

5.2 Dependent Variable

In theory, an agent is said to be rationed if, at the going lending rate as appropriate to his risk class, he demands more credit than he can obtain on the market. The extent of credit rationing might be measured as the (positive) gap between the marginal return of the enterprise on its capital investment and the going market lending rate applicable to that firm. In practice, however, direct measures of credit rationing are unobservable. That's why the empirical literature on credit rationing has employed a large range of rationing proxies. Among the early influential contributions, Fazzari et al. (1988) group the enterprises in their sample on the basis of the firms' dividend policy and they hold that the enterprises retaining a larger fraction of profits as non distributed earnings are the most likely rationed – alternatively, the sensitivity of investment to cash flow is higher for these firms. Berger and Udell (1992) employ the share of the new loans as an indicator of liquidity constraints, given that, if credit rationing is extensive, this share should increase during times of credit squeeze. Petersen and Rajan (1994) note that the credit constrained firms are willing to pay higher costs to increase the amount of credit. Accordingly, they hold credit constrained all the enterprises using non-institutional finance – e.g. trade credit – charging

⁸The comparison will be done via the tests by Durbin (1954) and Wu-Hausman (Wu, 1973, Hausman, 1978) on the first stage of the two-stage approach.

above the market rate. Korajczyk and Levy (2003) use a high retention rate, combined with the existence of investment opportunities, to identify financially constrained firms. Since dividends and security repurchases compete with investment for funds, firms that have investment opportunities and face relatively high costs of external finance should choose to retain net income for investment. At the same time, Kaplan and Zingales (1997) criticized the methodology used by Fazzari et al. (1988). Kaplan and Zingales (1997) find that firms that appear less financially constrained exhibit significantly greater sensitivities than firms that appear more financially constrained. For this reason they sustain that higher investment-cash flow sensitivities cannot be interpreted as evidence that firms are more financially constrained.

All these indices are indirect indicators and suffer some drawbacks. The main problem with these indicators is that it is impossible to validate the assumption that the variable selected as a proxy of rationing is appropriate. Furthermore, regardless of how good these proxies are, they may reflect other effects that have little or nothing to do with liquidity constraints. This is the essential reason we will employ a direct measure of credit rationing. The idea of this method is to directly ask borrowers whether they would have liked to borrow more at the prevailing interest rate. In case of a positive answer, respondents are classified as “credit constrained.” The same applies to non-borrowers who respond that they could not get credit although they liked to. This methodology of direct measurement is not new. It has been extensively used in the literature. Jappelli (1990) analyzed the characteristics of credit constrained households in the U.S. economy in order to challenge the life-cycle model of consumption. Angelini et al. (1998) use this measure to investigate the effects of bank-firm relationships on the cost and the availability of credit for a sample of small Italian firms. Levenson and Willard (2000) measure the extent to which small businesses in the United States in the late 1980s were able to access the external credit finance they desired.

Using the enterprises’ answers to the question “*In 2006 would your firm have desired a larger amount of credit at the lending rate it had agreed with the bank?*” we will build a dummy variable taking value one in the case the firm replies yes, and is zero otherwise.

SIMF asks the firms replying yes to the previous question to answer two additional questions on credit rationing: “*In 2006 did your firm apply for more credit without obtaining it?*” and “*To obtain more credit, were you willing to pay a higher interest rate?*”. Using the answers to these questions we will perform some robustness checks of our results. Indeed, the logic behind these two questions is sometimes used to come up with a “strong” definition of rationing. In practice, we built a new dummy variable (STRONGRATIO) equal to one when the weakly rationed firm has answered yes to at least one of the two additional rationing questions. Alas, as Table 1 and Table 2 show, this variable has only few observations. This endangers our control.

5.3 Control Variables

While our key explanatory variable – the inconsistency between the firm’s needs and the characteristics of the bank – was already introduced above, here we summarize the variables included in vector $z1$. The control variables we use may be grouped into three clusters: those referring to the firm’s features, those measuring the firm-bank(s) relationship, and those relating to characteristics external to the firm.

Among the firm’s features, we will firstly control for those associated with the information opaqueness of the enterprise. In practice, we will include the variable `AUDIT`, a dummy variable which is one if the firm has its profit/loss and financial statements certified by external auditors. This is a key feature in our analysis since it provides us with a direct measure of the firm’s extent of informational opaqueness. In fact the “hard” information, when coming from audited statements, makes the firm more transparent for the banks, allowing also the efficient use of lending technologies based on accounting information only.

Other indirect measures indirectly impinging on the firm’s informational opaqueness include the enterprise’s dimension (`SIZE`) – that we quantify as the logarithm of the total number of employees –, the time it has been in business for (`AGE`), and the company form type (we will include a variable indicating whether the firm is a limited company).

Finally, among the firm’s features we will consider two basic performance indicators: leverage and return. A higher degree of financial leverage (`LEVERAGE`), given by the ratio of total liabilities to the sum of the total liabilities and the firm’s assets, points to more intense firm risk and, so, it will likely raise the likelihood the company is rationed. On the opposite, we expect firms enjoying higher returns (as measured by `ROA`, return on assets given by the ratio of operating profits to total assets) to be less likely rationed for credit.

As to the variables addressing the enterprise’s relationship with the banking system, we will include the specific ones measuring the intensity of the relationship with the main bank. This can be measured directly thanks to some variables. Specifically, we consider `SHARE`, the share of loans obtained from the main bank on the total bank loans received by the firm; `LENGTH` measured by (logarithm of) the number of years the firm has being doing business with its current main bank; we also introduce a variable interacting `SHARE_LENGTH`; and `NOTURNOVER`, a dummy variable taking value one if the firm’s main bank did not change its credit officer in charge of the relationship with the firm over the five years previous to the survey. In addition, as an indirect measure of the firm’s relationship with its main bank, we also introduce the number of banks (`NBANKS`) with which the firm does business stably. Finally, we take into account the official classification of the main bank introducing in our regressions a dummy variable, `LOCAL`, that takes value one if the main bank is a saving bank, a large-sized cooperative bank, a mutual coop bank or other type of bank.

Finally, we control for the firm’s geographical localization (`CENTER` and `SOUTH` dummies), its sector according to two-digit `SITC` classification and the

mean of the province level Herfindahl-Hirschman concentration index from 1990 to 2006 (HHI).

6 Results of the Empirical Analysis

6.1 Inconsistency Between the Firm's Needs and the Characteristics of the Bank

We report the first results obtained as to the determinants of the probability of credit rationing in Table 6. This estimate, performed utilizing the maximum likelihood probit model, supports the hypothesis we conjectured that the inconsistency between the needs of the enterprise and the characteristics – as to lending specialization – of its main bank (i.e. the phenomenon of the “odd couples”) increases the likelihood of credit rationing. Indeed, the inconsistency variable turns out significant at the 1% level has a prominent marginal effect. This result is achieved controlling for the firm's opaqueness, as well as for the features of its relationship with the banking system.

As regards the firm's informational opaqueness, we find that firm size is significant (though only at the 5% level) and it is associated with lower probability of rationing. Instead, the other variables aimed to capture the firm's informational opaqueness do not turn out significant. Among the other firm features that we consider, we highlight that higher ROA associates with systematically lower probability of rationing, while the extent of financial leverage is not significant.

Regarding the rapport between the firm and the banking system, we highlight primarily that a stronger relationship with the main bank lowers the probability of rationing. In fact we detect a negative and significant effect for the length of the firm's relationship with its main bank as well as with the stability (lack of turnover) of the main bank's credit officer. Furthermore, it is also in line with the result just outlined the additional evidence of a positive and significant effect of the number of banks among which the firm splits its overall relationship with the banking system, where, obviously, the larger this number the less intense the relationship with the main bank. We cannot rule out that some form of self-selection bias in our data might have favored the emergence of this last result. As we noticed in commenting the descriptive statistics, in fact, the number of banks is somewhat larger when we move from the overall sample to the sub-sample of the firms answering the relationship banking section of the questionnaire.

A separate issue regards the type of bank engaged as the firm's main bank. Our results show that a lower probability of rationing associates with having a local bank as the main bank. Considering, instead, the characteristics of the firm's business environment, we notice that practically none of the included variables is significant.

To control for the possible endogeneity between credit rationing and the mismatch of firm type versus main bank type we also estimate the model through a

two-stage approach. In practice, we estimate model⁹ (1)-(3) both via a two-stage last square model (2SLS) and via a two-stage conditional maximum likelihood model (2SCML).

We report separately the first-stage regression in Table 7. Controlling for exogenous firm, and province level characteristics, we can reject the null that the instruments are jointly insignificant in the equation of the inconsistency (3): the F-statistic is 4.94 with a p-value of 0.007.¹⁰ The nature of our instruments and the conflicting predictions offered by the theory suggest that the signs of our instruments are ambiguous a priori. Therefore, it is perhaps more useful to look at the effect of other variables in the first stage: for example, it is interesting to observe that the length of lending relationship and the share of loan obtained from the main bank reduce the probability of mismatch. Instead, the interaction between these variables (that might isolate the lock-in effect) is associated with higher probability of “odd-couple”.

Moving to the second-stage regressions, the results, conveyed in Table 8, do not substantially differ from those obtained without instrumenting. Moreover the tests (we report the Durbin test) tell us that there is no endogeneity in our regressions. Thus, the basis probit model would be the appropriate one to consider.

The first robustness test we perform consists in considering as dependent variable *STRONGRATIO*, equal to one when the weakly rationed firm has answered yes to at least one of the two additional rationing questions (whether the firm did apply for credit without getting it and whether it was willing to pay a higher loan rate). Table 9 presents the results. It is easy to appreciate that in this specification almost all the independent variables lose their explanatory power, as testified by the Wald chi-square test not rejecting the hypothesis that all the coefficients of the dependent variables are jointly zero. This outcome likely descends from the paucity of observations.

We perform a further check splitting the sample depending on the main bank type. As noted, in fact, the mismatch cases are more widespread with the *NATIONAL* type main banks. The results (Table 10) show the inconsistency bears a significant impact also for *LOCAL* main banks. This corroborates our

⁹We use two instruments found in the literature on bank- firm relationship. The instruments, measured at the province level, refer to 1936, when a long-lasting new banking law virtually froze Italy’s banking structure for several decades: the number of saving banks – per thousand inhabitants – and the share of branches on the part of local banks. See Guiso et al. (2003, 2004) and Herrera and Minetti (2007) for a more detailed justification of these instruments.

¹⁰The p-values for the individual coefficients are: for the number of savings banks 0.004; for the share of branches on the part of local banks 0.021. Note that an F-statistic of 4.94 could signal that we have a weak instruments problem (see, e.g., Stock and Yogo (2003), for more on these issues). To the best of our knowledge, no formal test for weak instruments is currently available for non-linear IV regressions such as the 2SCML estimation employed in this paper. Yet, since (i) in linear IV models limited information maximum likelihood (LIML) is known to be more robust to weak instruments than 2SLS (Staiger and Stock, 1997) and its coverage rate is close to the nominal coverage rate (Stock and Yogo (2003)), and (ii) the 2SCML estimator is a LIML estimator, the problem might be considerably less perverse in the 2SCML.

previous findings.

Particularly interesting appears the result for the control variables relationship length and turnover of the credit manager. Indeed, when the main bank is LOCAL the relationship length significantly lowers the probability of rationing, while the turnover of the credit manager is insignificant. For the NATIONAL main banks exactly the opposite is found. This result suggests a different use of information (particularly soft information) between NATIONAL and LOCAL main banks. Namely, the role of the credit manager seems less relevant for the LOCAL main banks, apparently in contrast with the theoretical literature. Stein (2002) and Berger et al. (2005) hold that the large banks suffer a disadvantage in producing soft information and that credit managers play a minor role in these banks.¹¹ Our results seem to suggest instead that the role of soft information is essential in both bank types. However, the use of soft information is detached from the credit manager for the LOCAL banks – perhaps able to capture soft information through their engagement in the local community – while the lack of turnover of the credit manager appears key for the use of soft information at NATIONAL banks.

6.2 Lending Relationship Length

One of the hypotheses we put forward is that the impact of the mismatch between the ex ante firm’s needs and the ex post characteristics of the bank – i.e. the problems of being an odd couple – be stronger for those enterprises with longer-lasting banking relationships. The reason to expect this is that as the length of the lending relationship with the main bank increases, this will likely heightens the switching costs. In addition, the fact that both the firm’s needs and the bank’s characteristics might evolve over time makes the longer-lasting relationship more likely mismatched. To test this differential effect, we sub-divided the sample putting in the first group the enterprises with a banking relationship shorter than the mean and assigned the other firms to the second group. The results of the sample split are supportive of our hypothesis (Table 11). The effect on the likelihood of credit rationing of being an odd couple is indeed larger for the firms of the latter group.

Interestingly, for the enterprises having longer-lasting bank relationships we detect a change in the sign of the relationship length. While in the whole sample – and also for the firms with shorter bank relationships – the length of the relationship decreases the probability of rationing, the opposite holds for the enterprises with longer bank relationships.

Instead, for the enterprises having shorter bank relationships we find that `SHARE_LENGTH` – the interaction between the relationship length and the dummy valued one when the main bank’s share of the total bank loans received by the enterprise is beyond 25% – associates with a larger probability of rationing. Thus, even though the direct impact of longer-lasting relationships still

¹¹Less extreme conclusions are reached by Uchida et al. (2008) showing that the production of soft information is similar across large and small banks.

lowers the probability of rationing, this impact is weakened by the interaction term. The interaction might, in fact, single out the firms “stuck” in their relationship with the main bank. In line with the literature, these firms are more likely rationed.

6.3 Type of Mismatch

We might expect that the impact on rationing of the firm-bank mismatch depends on which type is the odd couple. Theory suggests, in fact, that the impact should differ between the case of an opaque (and, thus, relational main bank seeking) enterprise wrongly matched to a transactional bank and the other case of a transparent (and, thus, transactional main bank seeking) firm wrongly matched to a relational bank. On the surface, it would seem the effect should be larger for the relational firm/transactional bank odd couple (RT) than for the odd couple of the other type (TR). Effectively, suffering more intense informational asymmetry, the relational enterprises are more likely credit rationed and, exactly for this reason, they should be most motivated to liaise with a relational main banking partner, which is better suited to overcome these firms’ asymmetries of information.

Table 12 presents the results of two additional estimates. In the first column we excluded from the estimate the enterprises falling into the second type odd couple (transactional enterprise/relational bank; TR) and focused the related explanatory variable on the other mismatch type (relational firm/transactional bank; RT). On the opposite, the results in the second column refer to an estimate where we have dropped the first type odd couples and have considered as explanatory variable only the mismatch between transactional enterprises and relational banks. While the impact of the mismatch is confirmed positive and statistically significant in both cases, the size of the coefficient ranks opposite than we expected: it is almost twice as large in the second type odd couple than for the first type (0.43 against 0.26). However, upon further reflection this result is not unexpected. As already mentioned in the discussion about the theoretical setup, it is very likely that among the firms stating they are transparent and are therefore in search of a transactional banking partner we find many enterprises that are opaque in reality but are also of the risky type and are trying to disguise themselves avoiding the in depth scrutiny of a relational main bank. These firms think they might be able to get away and obtain credit from the less substantive inspection of a transactional main bank, which would less likely uncover their risk type. If this is the situation, then the higher probability of rationing for the second type odd couples could simply depend on the fact that the group includes a larger share of risky enterprises.

As a first check on the appropriateness of our conjecture, we examined the ROA across the first type odd couples (RT) and that on the second type odd couples (TR). If we consider all the RT firms as against all the TR enterprises the ROA means are very close, being approximated to 4.4% in both cases. However, if we restrict the two sub-samples to the TR and RT enterprises not having audited statements (where we should single out the more opaque firms)

we notice that TR firms have a much lower ROA than the RT ones (2.3% vs. 4.1%).

A legitimate doubt one can have at this point is that perhaps the impact of the mismatch could actually differ between the more transparent and the more opaque enterprises. It is, in fact, possible that, irrespectively of the type of main bank, the firms with lower informational opaqueness are less likely rationed. Considering as transparent the firms with audited statements, we address again the impact of the mismatch from this specific angle. As the results in Table 13 show, the effect does not change. This result suggests that the reasons behind the impact exerted by the mismatch on the likelihood of rationing go beyond the problems of the enterprises' informational asymmetry.

7 Conclusions

The literature on credit rationing has extensively studied how the equilibrium of the credit market is affected by the asymmetry of information between the borrowing enterprise and the banking system. Most studies have addressed the problem considering only one direction, namely they have addressed how the firm's opaqueness (the firm is not fully transparent in the eyes of the bank) affects the credit decision outcome, while the literature seems to have overlooked the fact that also the bank may to some extent be opaque in the eyes of the potential customer enterprise, which could also impact the credit outcome. In a sense, the possibility that this reverse asymmetry of information might play a substantive role seems to follow from the increasing attention a growing strand of the literature has given to the fact that banks do differ in terms of the lending technology they specialize in. Next, since it may be hard for outsiders to identify the lending technology actually employed by the bank and the bank might have no incentive to practice complete disclosure about that, it is possible that the enterprises end up with a type of bank different than the one they needed (and they thought they got). We argued this could pose a problem in view of the fact that not all the firm type/main bank type couples are optimal and also because the presence of switching costs could cause some enterprises to stably stay stuck in a suboptimal firm-bank couple, we called these the "odd couples".

In this paper, we employed a large sample of Italian manufacturing enterprises to test whether ending up in an odd couple raises the probability that a firm will be rationed for credit, as the firm itself reports in the survey. The results support our conjecture. Also, the importance of the switching costs is suggested by the evidence that the enhancing effect on rationing of the odd couples is larger for the enterprises with longer length of the credit relationship with their main banks. The above results are attained controlling for various canonical determinants of rationing.

A further result of some interest was that, in line with the literature, the probability of rationing is lower for the enterprises holding a more intense relationship with their main bank, as indicated by the length of the relationship and if there was no turnover of the credit officer at the main bank, while the

likelihood of rationing increases for firms splitting their bank rapport among a larger number of banks.

Our evidence might warrant some policy considerations on measures to increase the transparency of the bank as to the lending technology it employs and to lower the switching costs. Such policies would help reduce the probability that odd couples ensue and, when they do, that they last. As to future research, our paper suggests developing a theoretical model featuring the specific form of bilateral asymmetry of information could be a promising avenue.

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Appendix

Table 1: Summary statistics: full sample

Variable	N	Mean	Std. Dev.	Min.	Max.
AUDIT	1294	0.376	0.485	0	1
LISTED	5137	0.013	0.113	0	1
AGE	4779	22.663	14.388	1	134
EMPLOYEES	5086	87.241	305.641	0	8898
ROA	4877	0.025	2.097	-146.311	0.836
LEVERAGE	4877	0.899	0.113	0.092	1
SPA	5137	0.332	0.471	0	1
NORTH	5137	0.719	0.449	0	1
CENTER	5137	0.162	0.369	0	1
SOUTH	5137	0.118	0.323	0	1
TRADITIONAL	5137	0.497	0.5	0	1
SPECIALIZED	5137	0.267	0.443	0	1
SCALE	5137	0.19	0.392	0	1
HIGHTECH	5137	0.046	0.209	0	1
RATIONED	4474	0.052	0.221	0	1
STRONGRATIO	223	0.426	0.496	0	1
NOTURNOVER	948	0.259	0.439	0	1
LENGTH	3873	17.362	12.201	0	140
ln_LENGTH	3866	2.595	0.782	0	4.942
NBANKS	4853	4.973	3.959	0	100
NATIONAL	949	0.49	0.5	0	1
LOCAL	949	0.51	0.5	0	1
HHI	5125	0.11	0.048	0.048	0.369

Table 2: Summary statistics: sub-sample

Variable	N	Mean	Std. Dev.	Min.	Max.
AUDIT	1002	0.345	0.476	0	1
LISTED	1541	0.018	0.134	0	1
AGE	1394	24.499	15.634	2	116
EMPLOYEES	1528	128.27	417.6	0	8898
ROA	1446	0.053	0.069	-0.339	0.836
LEVERAGE	1446	0.89	0.113	0.092	1
SPA	1541	0.409	0.492	0	1
NORTH	1541	0.733	0.442	0	1
CENTER	1541	0.17	0.376	0	1
SOUTH	1541	0.097	0.296	0	1
TRADITIONAL	1541	0.483	0.5	0	1
SPECIALIZED	1541	0.291	0.454	0	1
SCALE	1541	0.182	0.386	0	1
HIGHTECH	1541	0.044	0.205	0	1
RATIONED	1481	0.153	0.36	0	1
STRONGRATIO	219	0.434	0.497	0	1
NOTURNOVER	944	0.258	0.438	0	1
LENGTH	1343	17.7	12.072	0	80
ln_LENGTH	1340	2.623	0.766	0	4.382
NBANKS	1510	5.69	4.286	0	50
NATIONAL	944	0.5	0.5	0	1
LOCAL	944	0.5	0.5	0	1
HHI	1536	0.11	0.048	0.048	0.332

Table 3: Indicators of consistency

Variable	N	Mean	Std. Dev.	Min.	Max.
RR	1541	0.659	0.474	0	1
RT	1541	0.129	0.335	0	1
TR	1541	0.124	0.33	0	1
TT	1541	0.088	0.283	0	1
INCONSISTENCY	1541	0.253	0.435	0	1

Table 4: Consistency with bank types

Variable	N	Mean	Std. Dev.	Min.	Max.
RLOCAL	944	0.445	0.497	0	1
RNATIONAL	944	0.397	0.489	0	1
TLOCAL	944	0.056	0.230	0	1
TNATIONAL	944	0.102	0.302	0	1

Table 5: Indicators of Inconsistency

Variable	TOTAL		NATIONAL		LOCAL	
	N	Mean	N	Mean	N	Mean
RR	944	0.751	471	0.649	473	0.852
RT	944	0.091	471	0.146	473	0.036
TR	944	0.065	471	0.085	473	0.044
TT	944	0.093	471	0.119	473	0.068

Table 6: Basic Model

Variable	Marg. Eff.	(Std. Err.)
INCONSISTENCY	0.326***	(0.061)
NBANKS	0.016***	(0.004)
ln_LENGTH	-0.058**	(0.026)
SHARE	0.001	(0.001)
SHARE_LENGTH	0.023	(0.019)
NOTURNOVER	-0.088***	(0.028)
LOCAL	-0.050*	(0.076)
AUDIT	0.058*	(0.034)
SIZE	-0.038**	(0.015)
AGE	-0.001	(0.001)
ROA	-0.646***	(0.237)
LEVERAGE	0.093	(0.145)
SPA	0.061	(0.043)
CENTER	0.046	(0.045)
SOUTH	0.008	(0.071)
HHI	-0.081	(0.333)
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Number of observations	693	
$\chi^2_{(36)}$	135.32***	
Pseudo R^2	0.192	

The table reports regression marginal effects and associated robusted standard errors (between parentheses). The dependent variable is RATIONED, a dummy variable that take on a value of one if the firm declare itself as rationed. The regression is estimated by maximum likelihood probit model. The regression includes sector dummies. ***, **, * indicate statistically significant at the 1%, 5%, and 10% level, respectively. The table also reports, as goodness-of-fit tests, the Pseudo R^2 ; as well as the χ^2 for a likelihood ratio test.

Table 7: Determinants of the inconsistency

Variable	Coef	(Std. Err.)
rapsportr	0.000**	(0.000)
ncrispr_p	-17.523***	(6.138)
NBANKS	-0.002	(0.003)
ln_LENGTH	-0.051**	(0.022)
SHARE	-0.002*	(0.001)
SHARE_LENGTH	0.049***	(0.018)
NOTURNOVER	0.032	(0.035)
LOCAL	-0.133***	(0.029)
AUDIT	0.037	(0.035)
SIZE	-0.001	(0.014)
AGE	0.001	(0.001)
ROA	-0.454**	(0.210)
LEVERAGE	0.091	(0.120)
SPA	0.027	(0.033)
CENTER	0.112**	(0.047)
SOUTH	0.046	(0.060)
HHI	-0.043	(0.337)
Intercept	-0.132	(0.197)
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Number of observations	697	
R ²	0.119	
F (38,658)	2.556***	
F instr (2,658)	4.94***	
Sargan (score) $\chi^2(1)$	0.163	
p (Sargan)	0.686	

The table reports regression coefficients and associated robusted standard errors (between parentheses). The dependent variable is INCONSISTENCY. The regression is estimated by OLS. The regression includes sector dummies. ***, **, * indicate statistically significant at the 1%, 5%, and 10% level, respectively. The table reports the F-test, as goodness-of-fit tests, and the R^2 . The table also reports the F-statistic for the F-test that the instruments are jointly insignificant, and Sargan score (and its p-value) as test of validity of the instruments.

Table 8: Model with instrumental variables

Variable	2SLS		2SCML	
	Coeff	(Std. Err.)	Marg. Eff.	(Std. Err.)
INCONSISTENCY	0.690**	(0.326)	0.777***	(0.152)
NBANKS	0.015***	(0.004)	0.016***	(0.004)
ln_LENGTH	-0.032	(0.032)	-0.031	(0.035)
SHARE	0.002	(0.001)	0.002*	(0.001)
SHARE_LENGTH	0.004	(0.028)	-0.000	(0.029)
NOTURNOVER	-0.103***	(0.040)	-0.102***	(0.034)
LOCAL	0.017	(0.054)	0.010**	(0.010)
AUDIT	0.030	(0.041)	0.042	(0.039)
SIZE	-0.034**	(0.015)	-0.037**	(0.016)
AGE	-0.001	(0.001)	-0.001	(0.001)
ROA	-0.333	(0.262)	-0.415	(0.345)
LEVERAGE	0.006	(0.129)	0.046	(0.175)
SPA	0.048	(0.041)	0.047	(0.046)
CENTER	0.028	(0.041)	0.030	(0.048)
SOUTH	0.020	(0.051)	0.016	(0.054)
HHI	0.068	(0.358)	0.060	(0.367)
Intercept	0.479	(0.330)		
Number of observations	697		693	
R ²	0.099			
$\chi^2_{(37)}$	120.521***		183.16***	
Durbin (score) $\chi^2_{(1)}$	1.398			
Prob $\chi^2_{(1)}$	0.236			
Wald exog. $\chi^2_{(1)}$			1.46	
Prob > χ^2			0.226	

The table reports regression coefficients, marginal effects and associated standard errors (between parentheses). The dependent variable is RATIONED, a dummy variable that take on a value of one if the firm declare itself as rationed. To control for endogeneity of INCONSISTENCY, regressions are estimated by two-stage least squares (2SLS) and by two-stage conditional maximum likelihood (2SCML). ***, **, * indicate statistically significant at the 1%, 5%, and 10% level, respectively. The table reports the χ^2 for a likelihood ratio test, and R². The table also reports the Durbin score as a test of exogeneity for 2SLS model, and Wald test for 2SCML estimation.

Table 9: Strong definition of rationed

Variable	Marg. Eff.	(Std. Err.)
INCONSISTENCY	-0.087	(0.114)
NBANKS	0.018	(0.013)
ln_LENGTH	-0.215**	(0.083)
SHARE	-0.002	(0.003)
SHARE_LENGTH	0.089	(0.061)
NOTURNOVER	0.055	(0.137)
LOCAL	0.054	(0.105)
AUDIT	-0.106	(0.112)
SIZE	-0.006	(0.054)
AGE	-0.000	(0.004)
ROA	-1.030	(0.925)
LEVERAGE	0.656	(0.587)
SPA	0.251*	(0.133)
CENTER	0.183	(0.154)
SOUTH	0.135	(0.170)
HHI	-2.102*	(1.128)
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Number of observations	136	
LR $\chi^2_{(30)}$	30.81	
Prob > χ^2	0.425	
Pseudo R^2	0.165	

The table reports regression marginal effects and associated standard errors (between parentheses). The dependent variable is STRONG RATIONED, a dummy variable that take on a value of one if the firm declare itself as "strong" rationed. The regression is estimated by maximum likelihood probit model. The regression includes sector dummies. ***, **, * indicate statistically significant at the 1%, 5%, and 10% level, respectively. The table also reports, as goodness-of-fit tests, the Pseudo R^2 ; as well as the LR χ^2 for a likelihood ratio test.

Table 10: Basic Model split according to bank type

Variable	National		Local	
	Marg. Ef.	(Std. Err.)	Marg. Ef.	(Std. Err.)
INCONSISTENCY	0.337***	(0.070)	0.412***	(0.113)
NBANKS	0.023***	(0.007)	0.010***	(0.003)
ln_LENGTH	-0.013	(0.041)	-0.086***	(0.040)
SHARE	-0.013	(0.002)	0.001	(0.021)
SHARE_LENGTH	0.002	(0.032)	0.026	(0.017)
NOTURNOVER	-0.130**	(0.049)	-0.049	(0.029)
AUDIT	0.009	(0.052)	0.089	(0.051)
SIZE	-0.059**	(0.026)	-0.016	(0.016)
AGE	-0.004*	(0.002)	0.001	(0.001)
ROA	-0.248	(0.397)	-0.611***	(0.219)
LEVERAGE	-0.085	(0.247)	0.295*	(0.173)
SPA	0.093	(0.070)	0.056	(0.046)
CENTER	0.108	(0.074)	0.011	(0.042)
SOUTH	0.120	(0.086)	-0.063*	(0.024)
HHI	-0.508	(0.550)	0.331	(0.308)
Number of observations	333		343	
$\chi^2_{(34)}$	62.29***		106.30***	
Pseudo R^2	0.160		0.316	

The table reports regression marginal effects and associated robust standard errors (between parentheses). The dependent variable is RATIONED, a dummy variable that take on a value of one if the firm declare itself as rationed. The sample is split between firms that have a national bank as main bank, and firms that have a local bank as main bank. The regression is estimated by maximum likelihood probit model. The regression includes sector dummies. ***, **, * indicate statistically significant at the 1%, 5%, and 10% level, respectively. The table also reports, as goodness-of-fit tests, the Pseudo R^2 ; as well as the χ^2 for a likelihood ratio test.

Table 11: Lending relationship length

Variable	Length < Mean		Length > Mean	
	Marg. Eff.	(Std. Err.)	Marg. Eff.	(Std. Err.)
INCONSISTENCY	0.287***	(0.075)	0.520***	(0.106)
NBANKS	0.022***	(0.007)	0.009***	(0.003)
ln_LENGTH	-0.092**	(0.043)	0.102**	(0.052)
SHARE	-0.001	(0.001)	0.003*	(0.001)
SHARE_LENGTH	0.080**	(0.034)	-0.024	(0.019)
NOTURNOVER	-0.026	(0.050)	-0.103***	(0.027)
LOCAL	-0.005	(0.046)	-0.074**	(0.033)
AUDIT	0.103*	(0.055)	0.024	(0.037)
SIZE	-0.026	(0.021)	-0.053***	(0.019)
AGE	0.001	(0.002)	-0.003**	(0.001)
ROA	-0.336	(0.311)	-0.855***	(0.246)
LEVERAGE	0.183	(0.265)	0.190	(0.128)
SPA	0.032	(0.069)	0.097**	(0.044)
CENTER	0.092	(0.067)	-0.002	(0.037)
SOUTH	0.090	(0.077)	0.037	(0.031)
HHI	-0.144	(0.498)	-0.025	(0.274)
Number of obs.	386		278	
$\chi^2_{(21)}$	80.14***		85.27***	
Pseudo R^2	0.174		0.393	

The table reports regression marginal effects and associated robust standard errors (between parentheses). The dependent variable is RATIONED, a dummy variable that take on a value of one if the firm declare itself as rationed. The sample is split putting in the first group the enterprises with a banking relationship shorter than the mean and assigned the other firms to the second group. The regression is estimated by maximum likelihood probit model. The regression includes sector dummies. ***, **, * indicate statistically significant at the 1%, 5%, and 10% level, respectively. The table reports, as goodness-of-fit tests, the Pseudo R^2 ; as well as the χ^2 for a likelihood ratio test.

Table 12: Type of mismatch

Variable	RT		TR	
	Marg. Eff.	(Std. Err.)	Marg. Eff.	(Std. Err.)
INCONSISTENCY	0.257***	(0.073)	0.429***	(0.088)
NBANKS	0.014***	(0.004)	0.015***	(0.004)
ln_LENGTH	-0.048**	(0.023)	-0.072***	(0.023)
SHARE	0.001*	(0.001)	0.001	(0.001)
SHARE_LENGTH	0.012	(0.018)	0.029	(0.018)
NOTURNOVER	-0.068**	(0.029)	-0.066**	(0.030)
LOCAL	-0.059**	(0.030)	-0.041	(0.030)
AUDIT	0.042	(0.035)	0.076**	(0.037)
SIZE	-0.039***	(0.014)	-0.031**	(0.014)
AGE	0.001	(0.001)	0.000	(0.001)
ROA	-0.594***	(0.218)	-0.560***	(0.206)
LEVERAGE	0.109	(0.144)	0.077	(0.140)
SPA	0.064*	(0.040)	0.050	(0.041)
CENTER	0.046	(0.042)	0.006	(0.041)
SOUTH	0.019	(0.046)	-0.009	(0.042)
HHI	-0.084	(0.312)	0.080	(0.292)
Number of obs.	652		635	
$\chi^2_{(21)}$	101.66***		122.29***	
Pseudo R^2	0.161		0.203	

The table reports regression marginal effects and associated robust standard errors (between parentheses). The dependent variable is RATIONED, a dummy variable that take on a value of one if the firm declare itself as rationed. In the first column we excluded from the estimate the enterprises falling into the first type odd couple (TR) and focused the related explanatory variable on the other mismatch type (RT). On the opposite, the results in the second column refer to an estimate where we have dropped the second type odd couples and have considered as explanatory variable TR. The regression is estimated by maximum likelihood probit model. The regression includes sector dummies. ***, **, * indicate statistically significant at the 1%, 5%, and 10% level, respectively. The table also reports, as goodness-of-fit tests, the Pseudo R^2 ; as well as the χ^2 for a likelihood ratio test.

Table 13: More transparent firms

Variable	Coefficient	(Std. Err.)
INCONSISTENCY	0.296***	(0.096)
NBANKS	0.006	(0.008)
ln_LENGTH	-0.144**	(0.058)
SHARE	-0.000	(0.002)
SHARE_LENGTH	0.052	(0.041)
NOTURNOVER	-0.116*	(0.065)
LOCAL	-0.008	(0.067)
SIZE	0.004	(0.034)
AGE	-0.003	(0.003)
ROA	-0.440	(0.447)
LEVERAGE	-0.148	(0.323)
SPA	0.060	(0.086)
CENTER	0.022	(0.106)
SOUTH	0.060	(0.106)
HHI	-0.051	(0.671)
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Number of Obs.	198	
$\chi^2_{(29)}$	39.56*	
Pseudo R^2	0.149	

The table reports regression marginal effects and associated robust standard errors (between parentheses). The dependent variable is RATIONED, a dummy variable that take on a value of one if the firm declare itself as rationed. In this regression we consider only the firms with audited statements. The regression is estimated by maximum likelihood probit model. The regression includes sector dummies. ***, **, * indicate statistically significant at the 1%, 5%, and 10% level, respectively. The table also reports, as goodness-of-fit tests, the Pseudo R^2 ; as well as the χ^2 for a likelihood ratio test.

Survey questions

F1.15: Which of these characteristics are key in selecting your main bank?

1. The bank knows you and your business.
2. The bank knows a member of your Board of directors or the owners of the firm.
3. The bank knows your sector.
4. The bank knows your local economy.
5. The bank knows your relevant market.
6. Frequent contacts with the credit officer at the bank.
7. The bank takes quick decisions.
8. The bank offers a large variety of services.
9. The bank offers an extensive international network.
10. The bank offers efficient internet-based services.
11. The bank offers stable funding.
12. The bank offers funding and services at low cost.
13. The bank's criteria to grant credit are clear.
14. The bank is conveniently located.

F1.17: In your view, which criteria does your bank follow in granting loans to you?

1. Ability of the firm to repay its debt
2. Financial solidity of the firm (capital/asset ratio).
3. Firm's profitability (current profits/sales ratio).
4. Firm's growth (growth of sales).
5. Ability of the firm to post (not personal) real estate collateral.
6. Ability of the firm to post tangible non-real estate collateral.
7. Support by a guarantee association (e.g. loan, export, R&D).
8. Personal guarantees by the firm's manager or owner.
9. Managerial ability on the part of those running the firm's business.
10. Strength of the firm in its market
11. Intrinsic strength of the firm (e.g. ability to innovate).
12. Firm's external evaluation or its evaluation by third parties.
13. Length of the lending relationship with the firm.
14. Loans are granted when the bank is the firm's main bank.
15. Fiduciary bond between the firm and the credit officer at your bank.