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JEL Classifications G21, L51, G28, O52, L31, I38, C25, M13

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The Regulation of Prosocial Lending: Are Loan Ceilings Effective?*

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Abstract

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1. Introduction

How prosocial lending should be regulated is still an open question. In most industrialized countries, regulators have imposed loan ceilings on microcredit to curtail the temptation of serving better-off borrowers. This paper shows how an apparently benign constraint, capped loan size, can unintendedly make prosocial lenders deviate from their social mission. Our contribution lies at the intersection of two fields of sustained scholarly interest in banking and finance, namely the regulation of credit markets and social finance.

Why should we care about the regulation of microcredit in high-income countries? Admittedly, microfinance in these countries is still a niche market. But it is also a young industry that warrants a well-adapted regulatory framework. This can make a difference and foster the development of a prosocial lending methodology that has already proven successful in developing countries. In developed economies, and more specifically in Europe, microcredit addresses the pervasive credit rationing endured by small and medium-sized enterprises (SMEs) and start-ups, which are typically underserved by traditional banks. The steady growth of this industry[1] shows that microfinance institutions (MFIs) fill a market gap and, at the same time, help vulnerable businesses achieve financial sustainability. For example, Permicro, the largest Italian MFI, focuses on migrants, while in Belgium microStart targets low-educated, unemployed, first-time entrepreneurs. Since 2010, the European Commission has provided financial support to such initiatives through the "European progress microfinance facility."[2]

All over the world, MFIs supply financial services to vulnerable individuals, mostly micro-entrepreneurs. Microfinance activities in developing countries were largely publicized by Nobel Prize laureate Muhammad Yunus, while the microcredit movement more discreetly reached high-income countries, especially Europe, in the late 1980s (Cozarenco & Szafarz, 2020). In developed economies, loans are individual, as opposed to group loans, which are common practice in developing countries (Armendariz & Morduch, 2010). These MFIs are subsidized and usually offer attractive loan terms; some also provide business guidance (Bendig et al., 2014); they can attract clients who have access to bank debt. Another key difference between developed and developing countries relates to the segmentation of the credit market. In developing countries, segmentation between banks and MFIs is strong and co-financing is not

[1] For instance, Diriker et al. (2018) mention that the overall gross loan portfolio of European microfinance increased by 16% between 2016 and 2017.
[2] For more information on cited MFIs and on the policy of the European Commission, please visit the following websites: https://www.permicro.it/chi-siamo/impatto-sociale/, https://microstart.be/en, https://ec.europa.eu/social/main.jsp?langId=en&catId=836

an option. In contrast, in Europe, some banks have climbed on the microfinance bandwagon by setting up MFIs or collaborating with them. MFIs may enter into co-financing arrangements with banks, and thereby combine efforts as regards information collection and sharing (Brown & Zehnder, 2007). The prevalence of such arrangements is still understudied, probably because they require no formal contract between the financial institutions involved. In practice, loan applicants attracted by preferential terms tend to approach MFIs first. Ceiling-constrained MFIs are, however, forced to direct applicants with above-ceiling requests toward a bank to start the process.

Our contribution to the social finance literature relates to mission drift. Mission drift is a constant threat to the achievement of social goals that are logically expected by subsidy providers (Wry & York, 2017). In theoretical works, mission drift in prosocial lending is commonly understood as a shift toward serving better-off, and therefore more profitable, clients (Armendariz & Szafarz, 2011; Grimes et al., 2019; Varendh-Mansson et al., 2020). The empirical literature proposes two different approaches: multi-firm studies and case studies. The mechanisms assessed by multi-firm studies are usually linked to the evolution of the trade-off between social and financial goals associated with commercialization, growth, and change of legal status (Cull et al., 2007; Mersland & Strøm, 2010). By contrast, case studies allow for the unpacking of specific mechanisms, such as changes in governance, leadership style, employee incentivization, and product differentiation. By nature, the case-study approach allows a closer, more granular scrutiny of mission fulfilment/drift (D'Espallier et al., 2017a; Ramus & Vaccaro, 2017). Inevitably, however, results run the risk of idiosyncrasy and a subsequent lack of external validity.

Identifying the unintended perverse effects of regulatory rules will help us design appropriate frameworks. Indeed, the need for effective regulation goes beyond prosocial lending. As Beck et al. (2010) pointed out, credit market regulation can adversely affect access to credit for some.[3] Both the theoretical and empirical findings presented in this paper validate this general statement. The mechanism that we unpack involves co-financing arrangements between a prosocial lender and a commercial bank. In a ceiling-free environment, the risk of adverse selection would prevent banks from entering into co-financing arrangements proposed by prosocial lenders. In contrast, if a loan ceiling is enforced, then co-financing is the only possible path for social lenders eager to serve clients who require above-ceiling loans; it is also

[3] Beck et al. (2010) showed that US bank deregulation in the 1970s had a positive impact: helping the poor without harming the rich. In contrast, Lilienfeld-Toal et al. (2012) found that in the 1990s, the Indian reform enforcing lenders' recovery in the event of default shifted credit from poor to wealthier borrowers.

a cost-reduction strategy because banks will screen loan applicants more rigorously than prosocial institutions. This rationale suggests that loan caps can trigger co-financing arrangements by aligning the objectives of the two institutions involved. But at the same time, co-financing arrangements may crowd out those social loan applicants who need below-ceiling loans, i.e., precisely those targeted by the regulators. This path toward mission drift is the gist of our theoretical model.

We also contribute as regards the impact of regulation on financial inclusion. The regulatory framework for MFIs is usually separate from banking regulation because unlike banks MFIs are subsidized institutions pursuing a social mission, and the regulator is concerned with its proper accomplishment. Thus, investigating the impact of microfinance loan ceilings on the depth of outreach makes perfect sense. Strikingly, despite the importance of the loan ceiling rule for the development of MFIs in high-income countries, its impacts have hardly been explored so far. Mixed evidence from low-income countries shows, however, that regulating microfinance activities is a challenging task. Armendariz and Morduch (2010) have argued that current financial regulation, such as minimum capital requirements, interest rate limits, and rules aiming to protect consumers and prevent fraud, is sometimes ill-suited to the microfinance industry.[4] Our theoretical model shows that a restrictive loan ceiling may prompt prosocial lenders (on considerations of cost) to prefer serving better-off borrowers who also have access to bank loans. These clients benefit from favorable loan terms offered by subsidized MFIs while receiving the incremental loan amount from a commercial bank.

In sum, our model shows that a ceiling on MFI loans can incentivize bank-MFI co-financing arrangements and thus trigger mission drift. To test the model's implications, we used an identification strategy based on a regulatory shock. We scrutinized the transition of a French MFI from unregulated to regulated status, whereby a large share of the loans granted by the unregulated institution had exceeded the ceiling. The case of France is particularly revealing, since the regulator imposed a low (by international standards) ceiling, thereby expressing their special concern for MFIs serving people in need. To investigate the impacts of the regulatory ceiling, we hand-collected data on loan applicants and borrowers of Créa-Sol, a French NGO

[4] This has to do both with additional costs and the lack of flexibility toward poorly documented clients. Cull et al. (2011) emphasize that complying with regulation is costly for MFIs and may lead them to exclude vulnerable borrowers, such as disadvantaged women (see also Cozarenco & Szafarz, 2018). In contrast, Hartarska and Nadolnyak (2007) have found that regulation in general does not directly affect operational self-sustainability and outreach. It is possible that the negative impact of constraining rules—such as ceilings on interest and loan size—is outweighed by the benefits brought by a barrier to entry.

providing microcredit that was compelled to abide by a regulatory framework and, thus, a loan ceiling. The data cover both the pre-regulated period and the period under regulation.

This study raises the problem of endogeneity on the supply side and of sample selection on the demand side. On the supply side, we were confronted with potential biases stemming from omitted variables since the MFI had to deal with the 2008 financial crisis around the time of its change of status, which might have affected the institution's business model and the screening of new applicants. Likewise, the MFI's change of status gave it access to loanable funds, which might have interacted with the development of co-financing arrangements in a way that is unobservable to us. On the demand side, applicants seeking financing from the MFI after the loan ceiling was introduced might be structurally different from those who applied when there was none. We will address all these threats to endogeneity successively. First, we will show that the impact of the financial crisis was minimal, which is in line with existing evidence that the early microfinance sector in developing countries was insensitive to the financial crises in the 1990s (Wagner, 2012).[5] Second, we will rule out a change in business model taking place after the regulatory change by referring to interviews with staff members and checking that the MFI's level of altruism stayed the same during the entire period. Last, we will address the sample selection issue by estimating a difference-in-differences (diff-in-diff) model with propensity score matching. This matching also mitigates potential endogeneity stemming from functional form misspecification (Shipman et al., 2017).

Compared with the pre-regulated period, loan approval rates during the regulated period decreased by 11% for small projects and increased by 30% for large ones, suggesting that the MFI became less socially efficient when regulated. Our results also reveal that the MFI, which acted as a genuinely altruistic institution when unregulated, managed to overcome the shock thanks to co-financing arrangements with commercial banks. All in all, the empirical analysis suggests that the loan ceiling triggered mission drift and that the causal relationship was mediated by the emergence of co-financing.

The fact that loan ceilings may have perverse effects has policy implications. Wrong incentives to prosocial lenders can make them disregard, at least partly, their core market, which is made up of start-ups launched by disadvantaged and unemployed people, including migrants, women, and people with disabilities. Impeding the social action of MFIs through inappropriate regulation can also diminish their societal relevance and endanger their subsidization, thereby compromising their very existence in an already dense credit market.

[5] This was, however, no longer the case during the 2008 crisis (Brière & Szafarz, 2015).

The rest of this paper is structured as follows. Section 2 describes the microfinance market in Europe, with a special emphasis on France. Section 3 develops our theoretical framework. Section 4 presents the context of the case study and introduces the dataset. Section 5 describes the methods used to address identification and endogeneity issues, and reports on the empirical results. Section 6 provides robustness checks. Section 7 presents our conclusions.

2. Microfinance in Europe

Microcredit in Europe is a nascent, yet growing market, which involves over 500 MFIs (Bendig et al., 2014). MFIs not only differ from regular banks, but also from savings banks, cooperative banks, and social banks, particularly as regards their objectives and target clientele.[6] Subsidized European MFIs supply only short-to-medium-term microcredit. Their highly standardized loans target small firms and self-employed individuals.

Detailed information on European microfinance is scarce. In 2018, the European Microfinance Network (EMN) and the Microfinance Center combined their efforts to survey 138 MFIs operating in Eastern and Western Europe—including five French institutions—serving altogether 988,457 active borrowers (Diriker et al., 2018).

To highlight the similarities and differences within the microfinance sector (world, Europe, Western Europe, and France), Table 1 displays the usual microfinance indicators for these four zones (Hermes & Hudon, 2018; Cull et al., 2018). The variables are broken down into three categories: social performance, financial performance, and products. For Europe, we used both the results of Diriker et al. (2018) and our own computations based on the raw data of the EMN survey. The worldwide figures in Table 1 were retrieved from two sources: the 2019 Microfinance Barometer[7] and Cull et al. (2018), who used the MixMarket dataset.[8]

Social performance was assessed by four indicators: the breadth of outreach measured by the number of active borrowers, the average loan size (ALS) divided by gross national income (GNI) per capita, the percentage of female borrowers (Hermes et al., 2011; Strøm et al., 2014),[9] and the interest rate charged to the client (D'Espallier et al., 2017b). The first section of Table 1 shows that worldwide MFIs served 127.8 million borrowers in 2017, with a gross loan

[6] Savings banks and financial cooperatives provide financial services and focus on deposits, rewarding their members with higher returns on deposits and lower interest rates on loans (Ferri et al., 2014). Social banks are hybrid organizations whose mission is to finance social enterprises (of any size), which need cheap loans because they are usually less profitable than for-profit firms (Cornée et al., 2020).

[7] http://www.convergences.org/wp-content/uploads/2019/09/Microfinance-Barometer-2019_web-1.pdf

[8] Microfinance Information Exchange (MIX) is a nonprofit organization that facilitates access to reliable data in the microfinance sector—now available in the World Bank's Data Catalog.

[9] ALS/GNI per capita and the percentage of female borrowers are the most common proxies for depth of outreach.

portfolio amounting to EUR 114.4 billion. In contrast, in the same year, surveyed European MFIs served 988,000 clients, with a gross loan portfolio amounting to EUR 3.2 billion. France ranks second in Europe (after Spain) with 18% of the European gross loan portfolio. The French market is dominated by a major player, ADIE, set up at the end of the 1980s, whose gross loan portfolio represents 23% of the French total.

A low ALS/GNI per capita is evidence that the MFI grants small loans, which are typically requested by poor and disadvantaged applicants. Table 1 shows a low 39% for Europe, suggesting that European MFIs do target the poorer segments of the population. In contrast, the percentage of female borrowers (37%) in Europe is low compared with a global 80%. Compared with the rest of Europe, France has a remarkably strong social orientation, with an ALS/GNI per capita of 12% and an above-average share of female borrowers of 43%.

The trade-off between social and financial performance is key to examining the impact of regulatory loan ceilings. Some MFIs—with a low degree of altruism or with tight financial constraints—might be tempted to target clients requesting larger loans because fixed costs and credit risk make small loans proportionally more costly than larger ones (Armendariz & Morduch, 2010; Zamore et al., 2019). Table 1 shows an average 30-day portfolio at risk (PaR30)[10] of 6% for the World. Although portfolio quality in Western Europe (19%) is worse than in Europe as a whole (14%), France performs relatively well (8%). The lack of profitability of microfinance in Western Europe is attested by a negative average return on equity (ROE) (-13%) associated with low interest rates charged to clients, low portfolio quality, and high operating expenses. Akin to portfolio quality, French MFIs perform better, with a positive ROE of 1%. The average operating expense ratio computed for Europe (26%) is high compared with developing countries (11%). Again, French MFIs are best in class, reporting the lowest ratio (19%). They also achieve the largest economies of scale, with 26,500 active borrowers per MFI—the European average is 5,000— which, however, is still well below the World standards of 152,700 active borrowers per MFI.

To assess subsidization levels, we have no choice but to use different proxies for the World and Europe. The World datasets record donated equity and the EMN survey collects subsidies per unit lent, i.e., grants plus public guarantees,[11] divided by the gross loan portfolio. The subsidization rate of European MFIs (17%) lies above the worldwide level (13%), but such a

[10] PaR30 is the outstanding balance of loans for which installments are more than 30 days overdue, expressed as a percentage of the total value of loans outstanding.
[11] Public guarantees are partial backstops in the event of default (up to 80%) granted by the European Commission and national governments (See https://www.eif.org/what_we_do/microfinance/easi/easi-guarantee-instrument/index.htm).

comparison is problematical owing to measurement differences. Within Europe, the comparison is on safer ground. With a 39% subsidization rate, Western European MFIs appear to be heavily dependent on subsidies. This dependency confers significant weight to the public authority when it embarks on regulating the industry, which may explain why regulators in Western Europe tend to impose loan ceilings. Ceilings are less needed in developing countries where microfinance is mostly insulated from the banking sector. These ceilings might even be counterproductive if cross-subsidization opportunities exist (i.e., covering losses incurred by serving poor clients with profits earned from better-off ones).

Table 1. The microfinance industry in 2017

	World	Europe	Western Europe	France
Social Performance				
Number of active borrowers (thousand)	127,800	988	494	133
Gross loan portfolio (EUR billion)	114.4	3.2	2.3	0.6
Average ALS/GNI per capita (%)	240	39	25	12
Percentage of female borrowers (%)	80	39	37	43
Financial performance				
Average portfolio at risk 30 days (%)	6	14	19	8
Average return on equity (ROE) (%)	12	5	-13	1
Average operating expense ratio (%)	11	26	39	19
Average number of active borrowers per MFI (thousand)	152.7	5.0	3.4	26.5
Subsidization (%)	13	17	39	12
Products				
Share of MFIs providing business loans (%)	N.A.	81	94	83
Share of MFIs providing business loans above EUR 25,000 (%)	N.A.	37	40	33

The statistics for Europe and France are based on the EMN dataset collected in 2017 (see Diriker et al., 2018). World statistics were retrieved from the Microfinance Barometer, except for the average ALS/GNI per capita and subsidization, which were retrieved from Cull et al. (2018).

In terms of products, Table 1 shows that European MFIs predominantly supply business loans as opposed to personal loans. World statistics do not include this piece of information. In developing countries, the combination of informal businesses and informal financial arrangements makes it hard to assess the purpose of microloans (Guérin et al., 2011; Labie et al., 2017). European MFIs confine themselves to microcredit, probably because savings accounts are considered a bank monopoly (Ruesta & Benaglio, 2020). In Western Europe, microcredit is primarily viewed as a tool to fight unemployment through self-employment and address the credit rationing of start-ups. A relatively large proportion (37%) of European MFIs provide loans higher than the threshold of EUR 25,000 used by EMN to define SME loans. This threshold is also the ceiling recommended by the EU for regulated microcredit. The prevalence of loans above EUR 25,000 shows that the recommended cap would impose a significant constraint on many MFIs. The compulsory French ceiling, set at EUR 10,000 over our sample period, has been even more restrictive.

Overall, the financial performance of MFIs in Europe is systematically lower than that of their developing-country counterparts; but it is better in France than in the rest of Western Europe, probably because the industry is more mature and operates on a larger scale. Figures also reveal that loans supplied by European MFIs are far removed from the tiny loans that conventional wisdom associates with microcredit. As Table 1 shows, more than one-third of European MFIs provide loans to SMEs. Both banks and MFIs provide funding to small firms, which are habitually opaque (Berger et al., 2001) and hence risky borrowers. There is an overlap between the size ranges of loans granted by MFIs and banks; this is a necessary, but not sufficient, condition for the emergence of co-financing arrangements.

The boundary between SMEs served by banks and microbusinesses served by MFIs is thus blurred, and setting up partnerships can represent an attractive opportunity for risk sharing.[12] MFIs will screen micro-entrepreneurial projects less formally but monitor their clients more closely than banks (Armendariz & Morduch, 2000). To mitigate their high operating costs, MFIs favor cost-reducing lending methodologies based on standardized products (Banerjee & Duflo, 2010). In contrast, mainstream banks provide tailor-made loan agreements to SMEs. Their lending technologies combine soft screening with hard quantitative information such as financial ratios, payment histories, and other accounting information, preferably certified by third parties (Berger & Udell, 2006), for banks operating in competitive markets have little incentive to serve new, risky borrowers (Alesina et al., 2013). In addition, physical or cultural distances between lender and borrower may explain why microbusinesses and low-income individuals are underserved by banks (Beck et al., 2019; Mian, 2006).

Differences between banks and MFIs in Europe help explain why the regulatory framework for MFIs is normally separate from banking regulation: The regulator is concerned that prosocial lenders fulfill their mission, namely, providing loans to vulnerable borrowers. As a result, loan ceilings are key features of the prevailing regulatory framework. In practice, the European Union recommends a EUR 25,000 ceiling on microloans, but national authorities may set their own rules (see the full list in Cozarenco & Szafarz, 2019). France has Europe's lowest

[12] Examples of bank-MFI partnerships include MFIs borrowing from, or being subsidized by banks, banks taking equity ownership in MFIs and/or sitting on their boards of directors, as well as MFIs sharing front-office, back-office, offices, ATM facilities, and/or IT systems with banks (Cozarenco, 2015). ADIE, the French MFI that pioneered European microfinance, has stated that 29% of its clients complement microloans with regular bank loans (Brabant et al., 2009). Still, banks and MFIs pursue separate objectives: commercial and social, respectively; and they also differ in the ways they address agency and asymmetric information problems.

microcredit loan ceiling (EUR 10,000 in 2005, increased to EUR 12,000 in 2016). By comparison, the United States enforce a compulsory USD 50,000 cap on microcredit (Lieberman et al., 2012).

Co-financing by MFIs and banks may sound surprising. How can MFIs agree to such arrangements while sticking to their social mission? Or, alternatively, how can banks make it profitable to serve disadvantaged entrepreneurs? In fact, the two types of institutions are compatible for at least four reasons. First, MFIs in high-income economies are usually constrained by loan ceilings. A low ceiling can be a barrier to reaching out to target clients in need of relatively large loans, such as entrepreneurs with business plans requiring a significant investment. Second, co-financing arrangements enable banks and MFIs to exploit screening complementarities, thus leveraging the competitive advantages of each. In practice the collection of hard information is left to the bank, while the MFI focuses on soft information and close monitoring (Cornée et al., 2012). Many MFI applicants are start-ups, so credit risk can be high, and the use of soft information is vital for screening risky borrowers (Iyer et al., 2015). Third, co-financing helps seize risk-sharing opportunities. Clients with dual loans from a bank and an MFI run small businesses that banks normally consider too risky for the full requested amount. In addition, MFI loans cover expenses that are unacceptable to banks, such as liquidity provision and working capital. Last, co-financing helps banks develop early-stage relationships with SMEs, and so improve their access to the medium-sized credit market.

However, misaligned incentives are the main obstacle to co-financing. Loan applicants who can borrow both from a bank and an MFI will usually prefer full financing from a prosocial lender because it offers below-market conditions, whereas banks operate at market rates. Moreover, a ceiling-free prosocial lender can easily keep the best borrowers for itself and only consider the co-financing option to mitigate its risk exposure. This adverse selection issue will drive banks to refuse co-financing arrangements. In contrast, a loan ceiling that is binding on the MFI mitigates the risk of adverse selection. If the MFI is not authorized to grant above-ceiling loans on its own, its only option for attracting applicants pursuing large projects is to engage in co-financing with commercial banks. To these banks, in turn, co-financing appears as a contractual feature that helps them overcome an informational disadvantage (Beck et al., 2017b). In sum, binding loan ceilings provide fertile ground for the emergence of co-financing. The next section proposes a theoretical model based on this intuition.

3. The model

We examine the influence that a regulatory loan ceiling may exert on the allocation of prosocial lending. In our one-period setting, the pool of applicants is composed of two groups: those with small (and micro)businesses who request small loans (Type 1) and those with larger businesses needing medium-sized loans (Type 2). Subsidies allow the lender to supply loans at below-market conditions. Both loan types are costly to the social lender, but Type 1 loans are proportionately costlier owing to higher operating costs and, possibly, higher default rates. Three important features of our model are derived from the facts presented in Section 2. First, we rule out cross-subsidization opportunities. In our setting, cross-subsidization would mean that Type 2 borrowers are profitable and help fund Type 1 borrowers. While cross-subsidization makes sense in poorly competitive environments where profitable borrowers lack any outside options, it is unrealistic in the competitive environment of developed credit markets. Second, the stylized facts reported in Section 2 confirmed that subsidies were indispensable to microfinance activity in Europe. Government bodies therefore have the duty to ensure that MFIs deliver social value for money and thus contribute to the public good. We will assume that this is the purpose of the regulatory ceiling. Third, Section 2 explained why misaligned incentives would make co-financing by a bank and an *unregulated* MFI unlikely to happen. In our model, we assume that co-financing can only occur if the prosocial lender is regulated.

The objective function of prosocial lenders is controversial. The mantra of most microfinance actors combines poverty alleviation with financial inclusion. The breadth and depth of outreach denote the number of clients served and their poverty level, respectively. These two value metrics are commonly used as proxies for financial inclusion. In line with the literature (Armendariz & Szafarz, 2011; Ghosh & Van Tassel, 2008), we assume that the prosocial lender maximizes its weighted outreach $(n_1 + \lambda\, n_2)$, where $0 \leq \lambda \leq 1$; n_1 and n_2 are the numbers of granted loans of Type 1 and Type 2, respectively. To represent (inversely) the lender's level of altruism, we use the weighting coefficient λ attached to Type 2 loans.

Our model will determine and compare the numbers and sizes of loans granted in equilibrium by unregulated and regulated prosocial lenders. In order to focus on loan ceilings, we will simplify the rest of the model. We proceed in four steps. First, we define mission drift. Second, we present and solve the model for an unregulated lender. Third, we add a regulatory loan ceiling and co-financing opportunities to the picture and solve the model again. Last, we discuss the impact of the ceiling on the social lender’s mission and build testable hypotheses for the empirical analysis.

3.1. The definition of mission drift

In our model, applicants are entrepreneurs characterized by the sizes of their projects and the sizes of the loans that they request from the prosocial lender. Applicant *j* has a project of size $P_j \in [0, \mathrm{P}]$ and requests a loan of size l_j, with $l_j \leq P_j$. To simplify the analysis, we assume that only two loan sizes are available, L_1 and L_2 $(L_2 > L_1)$, and that there is a project threshold $\tilde{S} \in [0, \mathrm{P}]$ such that:

$$\forall\, j\colon\ P_j < \tilde{S} \Longrightarrow l_j = L_1, \text{and } P_j \geq \tilde{S} \Longrightarrow l_j = L_2. \tag{1}$$

Type 1 applicants request a small loan L_1 and Type 2 ones request a medium-sized loan L_2. Granting loan $L_i, i \in \{1,2\}$, entails expected cash flows with total present value γ_i, which adds up the (positive) principal repayment and present value of the interest differential (loan rate minus financing rate), and the (negative) costs and expected default loss.[13] In line with Labie et al. (2015), we assume that the γ_is are constant because all borrowers in one group have the same expected creditworthiness. The signs of γ_1 and γ_2 are not imposed, but we assume that $L_1 > \gamma_1$ and $L_2 > \gamma_2$ to acknowledge that social lending is costly and cross-subsidization is impossible. In line with the microfinance literature, we assume that granting (smaller) Type 1 loans is costlier than granting Type 2 loans owing to high fixed operating costs (Armendariz & Morduch, 2010), i.e., $L_1 - \gamma_1 > L_2 - \gamma_2$. At the same time, granting small loans entails a better social performance (depth of outreach), and therefore requires a higher level of altruism from the lender.

The lender is characterized by parameter $\lambda \in [0,1]$, which inversely captures the level of altruism. If λ is zero, the purely altruistic lender is interested in Type 1 clients only. As λ increases, the lender pays greater importance to Type 2 clients and is thus less altruistic. A regulator maximizing social welfare has the same objective as a purely altruistic lender. Consequently, if all prosocial lenders were purely altruistic, there would be no need for regulation since the objectives of lenders and regulator would be spontaneously aligned. The (exogenous) policy instrument is a loan ceiling, which can make a difference by imposing social discipline on lenders with a large λ. These lenders can indeed be tempted to serve a high proportion of Type 2 borrowers, and so use their subsidies to address the better-off segment of their pool of borrowers.

The impact of the regulation on a given MFI can be measured by the difference between the pre- and post-regulation outreach to Type 1 borrowers. A well-functioning ceiling should

[13] The γ_is also account for any other borrower-specific cash flows. For instance, if the lender receives specific subsidies to, say, serve poorer Type 1 applicants, this additional income is interpreted as a positive component of γ_1.

trigger an increase in the number of Type 1 borrowers while an ill-functioning cap has the opposite and counterproductive effect, which corresponds to the notion of mission drift in the microfinance literature (Mersland & Strøm, 2010; Armendariz & Szafarz, 2011). Definition 1 formalizes this classification.

Definition 1. The regulatory loan ceiling is:

- *efficient* and leads to *mission alignment* if the number of Type 1 borrowers is higher in the post-regulation period than in the pre-regulation period,
- *counterproductive* and triggers *mission drift* if the number of Type 1 borrowers is lower in the post-regulation period than in the pre-regulation period,
- *ineffective* if the numbers of Type 1 borrowers are the same in the pre- and post-regulation periods.

The gist of this definition goes beyond loan ceilings. It could be used to assess the efficiency of any regulatory constraint imposed on prosocial lenders. In our setting, the main challenge stems from the unobservability of parameter λ, which will be addressed in the empirical section. In the next subsections, we derive the optimal loan allocations of the prosocial lender in each period. The only difference between the two periods is the non-enforcement/enforcement of a loan ceiling.

3.2. *Prosocial lending without any loan ceiling*

The prosocial lender receives subsidy K. There are N_1 Type 1 applicants and N_2 Type 2 applicants and the unregulated lender's program writes:

$$\max_{0\le n_1\le N_1, 0\le n_2\le N_2} \{n_1 + \lambda n_2\} \qquad s.t. \quad K = (L_1 - \gamma_1)n_1 + (L_2 - \gamma_2)n_2 \tag{2}$$

We assume that the constraint $n_i \le N_i\,(i = 1, 2)$ is not binding, which is a reasonable assumption for the standard credit market, where credit rationing prevails (Stiglitz & Weiss, 1981), and even more so for the prosocial credit market, which supplies loans with below-market interest rates (Cornée et al., 2020). To make the optimal solution easily interpretable, we use the following denominations.

Definition 2. The lender's level of altruism is:

- *high* if $\lambda < \frac{L_2-\gamma_2}{L_1-\gamma_1}$;
- *low* if $\lambda \ge \frac{L_2-\gamma_2}{L_1-\gamma_1}$

In our simple linear setup, the optimal loan allocation is a corner solution. The optimal solution is given by:[14]

$$n_1^{Unreg} = \begin{cases} \frac{K}{L_1-\gamma_1} & if\ the\ level\ of\ altruism\ is\ high \\ 0 & if\ the\ level\ of\ altruism\ is\ low \end{cases} \tag{3}$$

$$n_2^{Unreg} = \begin{cases} 0 & if\ the\ level\ of\ altruism\ is\ high \\ \frac{K}{L_2-\gamma_2} & if\ the\ level\ of\ altruism\ is\ low \end{cases} \tag{4}$$

Lenders with a high level of altruism choose Type 1 borrowers exclusively. This is the typical situation applying to non-profit MFIs worldwide. In contrast, lenders with a low level of altruism turn to Type 2 and so disregard the so-called "bottom of the pyramid", as do most commercially oriented MFIs active in developing countries (Prahalad, 2012; Harper & Arora, 2005). The approval rates corresponding to Eqs. (3) and (4) are $\frac{n_1^{Unreg}}{N_1}$ and $\frac{n_2^{Unreg}}{N_2}$ for Type 1 and Type 2 projects, respectively.

3.3. *Prosocial lending with loan ceiling*

The loan ceiling S, where $L_1 < S < L_2$, prevents prosocial lenders from providing full financing to Type 2 applicants. Co-financing arrangements are then the only way to offer them loans. The banks involved in co-financing use their own screening methods, leading to a limitation in the number of admissible Type 2 applicants. $N_2' < N_2$ is the number of Type 2 applicants surviving the bank screening process; the others are rejected by the bank and disappear from the market. The lender can still serve Type 1 applicants in full, but the rigorousness of bank screening makes constraint $n_2 \leq N_2'$ potentially binding. Even though Type 2 applicants would prefer full financing from the (cheaper) prosocial lender, this option is no longer available to them owing to the loan ceiling. The best way for them to obtain a loan in the amount of L_2 is to combine a (maximal) loan of S from the prosocial lender and a complementary loan amounting to $L_2 - S$ from a bank. For simplicity's sake, the model leaves aside the bank's action, except for the spillover on the prosocial lender's granting strategy.

The number N_1 of Type 1 applicants is unaffected by the ceiling. Type 2 applicants who survived bank screening are equally or less costly to the social lender than unscreened Type 2 applicants to the lender's unregulated counterpart.[15] Let us denote γ_2' ($\geq \gamma_2$) the total present

[14] The level of altruism λ determines the group of optimal borrowers taking out a loan from the unregulated lender (exclusively Type 1 or Type 2 projects). It does not, however, appear as such in the optimal numbers of loans granted, which are derived from the budget constraint independently from λ.

[15] Experimental evidence by Becchetti and Conzo (2011) shows that, under asymmetric information, a loan from a commercial lender can signal trustworthiness, thereby increasing the likelihood of receiving a complementary loan from a social lender.

value of the cash flows associated with pre-screened Type 2 applicants. We rule out cross-subsidization by assuming that $S > \gamma_2'$. The program of the ceiling-constrained lender writes:

$$\max_{0\leq n_1 \leq N_1, 0 \leq n_2 \leq N_2'} \{n_1 + \lambda n_2\} \qquad s.t. \quad K = (L_1 - \gamma_1)n_1 + (S - \gamma_2')n_2 \tag{5}$$

If $\lambda > \frac{S-\gamma_2'}{L_1-\gamma_1}$, the optimal numbers of loans granted are:

$$n_1^{Reg} = \max\left\{0, \frac{K-(S-\gamma_2')N_2'}{L_1-\gamma_1}\right\} \tag{6}$$

$$n_2^{Reg} = \min\left\{\frac{K}{S-\gamma_2'}, N_2'\right\} \tag{7}$$

The regulated lender's optimum depends on both the ceiling S and the rigorousness of the bank's screening process. If the constraint on the number of pre-screened Type 2 applicants ($n_2 \leq N_2'$) bites, the lender serves the N_2' available ones and supplies loans from the remaining budget to Type 1 borrowers. Alternatively, if the constraint does not bite, the lender serves Type 2 borrowers only. The impact of Eqs. (6) and (7) on the lender depends on its level of altruism.

Overall, five cases are possible: The first four are implied by Eqs. (6) and (7) while the fifth one corresponds to the situation where these two equations do not apply. First, if the level of altruism is low ($\lambda > \frac{L_2-\gamma_2}{L_1-\gamma_1}$) and $N_2' \geq \frac{K}{S-\gamma_2'}$, the constraint $n_2 \leq N_2'$ does not bite and the lender serves only Type 2 borrowers and $n_2^{Reg} = \frac{K}{S-\gamma_2'}$. There is, however, a noticeable change for the lender. Under regulation, co-financing is incentive-compatible and the cost of lending to Type 2 borrowers is reduced thanks to co-financing. As a result, the number of Type 2 borrowers increases. Regulation is therefore beneficial to the lender because it increases its outreach.

Second, if the level of altruism is low ($\lambda > \frac{L_2-\gamma_2}{L_1-\gamma_1}$) and $N_2' < \frac{K}{S-\gamma_2'}$, the constraint $n_2 \leq N_2'$ bites and the lender faces rationing of its preferred clients; it has to turn to Type 1 borrowers for the remainder of its budget, so that $n_1^{Reg} = \frac{K-(S-\gamma_2')N_2'}{L_1-\gamma_1} > 0$.

Third, if $\frac{S-\gamma_2'}{L_1-\gamma_1} < \lambda \leq \frac{L_2-\gamma_2}{L_1-\gamma_1}$ and $0 < N_2'$, Eqs. (6) and (7) show that the regulation encourages a lender with a high level of altruism to grant loans to Type 2 borrowers, which inevitably decreases the budget left for Type 1 applicants.

Fourth, if the bank's screening is extremely rigorous ($N_2' = 0$), regardless of λ the lender will serve Type 1 borrowers only.

Last, if the level of altruism is very high ($\lambda \leq \frac{S-\gamma_2'}{L_1-\gamma_1}$), the incentive associated with lower costs is insufficient to encourage the regulated lender to enter into co-financing arrangements, implying that the optimal numbers of loans granted are the same as in the unregulated period $n_1^{Reg} = n_1^{Unreg}$ and $n_2^{Reg} = n_2^{Unreg}$. Table 2 summarizes the results.

Table 2. Theoretical impact of the loan-ceiling regulation

Case		Unregulated lender's optimum		Regulated lender's optimum		Breadth of outreach		Impact of regulation
						Unregulated lender	Regulated lender	
		n_1^{Unreg}	n_2^{Unreg}	n_1^{Reg}	n_2^{Reg}	Type 1 borrowers	Type 2 borrowers	
I	Low level of altruism: $\lambda > \frac{L_2-\gamma_2}{L_1-\gamma_1}$							
I. a	$N_2' < \frac{K}{S-\gamma_2'}$	0	$\frac{K}{L_2-\gamma_2}$	$\frac{K-(S-\gamma_2')N_2'}{L_1-\gamma_1}$	N_2'	$n_1^{Reg} > n_1^{Unreg}$	$n_2^{Reg} \lesseqgtr n_2^{Unreg}$	**Mission alignment**
I. b	$N_2' \geq \frac{K}{S-\gamma_2'}$	0	$\frac{K}{L_2-\gamma_2}$	0	$\frac{K}{S-\gamma_2'}$	$n_1^{Reg} = n_1^{Unreg}$	$n_2^{Reg} > n_2^{Unreg}$	**Ineffective regulation**
II	High level of altruism: $\lambda \leq \frac{L_2-\gamma_2}{L_1-\gamma_1}$							
II. a	$\lambda \leq \frac{S-\gamma_2'}{L_1-\gamma_1}$ or $N_2' = 0$	$\frac{K}{L_1-\gamma_1}$	0	$\frac{K}{L_1-\gamma_1}$	0	$n_1^{Reg} = n_1^{Unreg}$	$n_2^{Reg} = n_2^{Unreg}$	**Ineffective regulation**
II. b	$\lambda > \frac{S-\gamma_2'}{L_1-\gamma_1}$ and $0 < N_2'$	$\frac{K}{L_1-\gamma_1}$	0	$\max\left\{0, \frac{K-(S-\gamma_2')N_2'}{L_1-\gamma_1}\right\}$	$\min\left\{\frac{K}{S-\gamma_2'}, N_2'\right\}$	$n_1^{Reg} < n_1^{Unreg}$	$n_2^{Reg} > n_2^{Unreg}$	**Mission drift**

This table summarizes the optimal loan allocations of social lenders with low and high levels of altruism. The unregulated regime ($Unreg$) is contrasted with the regulated regime (Reg), which entails loan ceiling S; n_i^x is the optimal number of type-i borrowers (i = 1 for small projects, i = 2 for medium-sized ones) in regime $x \in \{Unreg, Reg\}$. The impact of the regulation is determined by comparing the numbers of Type 1 loans granted by a given social lender under the two regulatory regimes.

3.4. *Social impact of a regulatory loan ceiling*

We use Definition 1 to assess the effectiveness of the regulatory ceiling S and compare the numbers of Type 1 borrowers financed by the prosocial lender at a level of altruism $\lambda \in [0,1]$, with and without loan ceiling (n_1^{Reg} and n_1^{Unreg}). Evidently, the regulator wishes to enforce efficient regulation leading to mission alignment, which would correspond to: $n_1^{Reg} > n_1^{Unreg}$. Yet the mission-drift scenario stemming from a counterproductive regulation, where $n_1^{Reg} < n_1^{Unreg}$, cannot be ruled out because the prosocial lender can legally circumvent the regulation by co-financing Type 2 loans with a bank. Additionally, the regulation can be ineffective ($n_1^{Reg} = n_1^{Unreg}$) because the loan cap makes no difference.

Table 2 shows that the model outcome depends on the prosocial lender's level of altruism and the number N_2' of Type 2 applicants surviving bank screening. In Case I (a and b), the lender's level of altruism is low and the unregulated lender finances Type 2 projects only. Introducing a ceiling cannot make the situation worse for Type 1 applicants. Regulation brings the lender closer to the social-welfare optimum when bank screening is rigorous enough to make constraint $n_2 \leq N_2'$ bite so that bank-driven rationing makes the regulated lender serve some Type 1 borrowers even though Type 2 ones have become less costly (Case I.a). This is probably the situation that regulators have in mind when they impose loan ceilings.[16] In contrast, in Case I.b bank screening is soft, the rationing effect eventually disappears, and the lender serves Type 2 only, like its unregulated counterpart.

In Case II (a and b), the lender has a high level of altruism and its ceiling-free optimal strategy is to serve Type 1 borrowers only, which is in line with the regulator's optimum. In this context, a loan ceiling is ineffective at best (Case II.a) and induces mission drift at worst (Case II.b). In Case II.b, together with co-financing opportunities, the regulation has tipped the balance in the trade-off between the lower cost of serving Type 2 clients and the higher social value of serving Type 1 clients— in favor of Type 2 applicants.

In sum, our model shows that the occurrence of mission drift is more likely if 1) the lender is genuinely altruistic, and 2) the loan ceiling is low. The figures in Section 2 suggest that these two conditions are met in many European countries.

Predicting the precise reaction of a given prosocial lender to a given loan ceiling is complicated for several reasons. First, same-jurisdiction lenders exhibit heterogeneity in levels of altruism and attract different groups of applicants. Second, for a given level of altruism, the impact of a loan ceiling will depend on the interaction between three parameters: the level of the ceiling, the cost reduction associated with bank screening, and the rigorousness of this screening. Possibly, any reasonable loan ceiling may have the desired impact on some social lenders but a perverse effect on others. In addition, a bank's rigorousness might depend on the level of the loan ceiling. The lower the ceiling, the higher the bank's exposure to credit risk. For regulators, therefore, identifying the ceiling that best fits their purpose is difficult.

On the basis of Table 2, we will formulate the hypotheses that will guide the econometric investigation in Section 5. But to begin with, let us proceed to two technical adjustments to meet the needs of the empirical analysis. First, we use loan approval rates rather than numbers of granted loans to acknowledge that the number of applicants will vary through time. Replacing the numbers of granted loans with approval rates has no impact on the conclusions reported in Table 2. Second, the level of altruism is unobservable. To address this issue, we proxy altruism with the sign of the marginal effect of project size on the approval rate, estimated in the pre-regulation period. A positive value means that the unregulated lender has more

[16] In the limit case of I.a, where bank screening attains maximal rigorousness ($N_2' = 0$), all Type 2 applicants are rejected and the regulated lender serves Type 1 applicants only. Even though this solution is the social-welfare optimum, it entails a severe market failure: Type 2 applicants fail to obtain loans from any source. Banks find them too risky, while the loans they request are too large for regulated social lenders.

appetite for financing large projects, and therefore signals a low degree of altruism. Likewise, a negative marginal effect corresponds to a preference for small projects, which indicates a high altruism level. With these practical adjustments and the results in Table 2, we can build three complementary tests for mission drift.

H_1: If the prosocial lender exhibits a high degree of altruism, mission drift will occur if the pre-regulation approval rate of Type 1 projects is higher than the post-regulation one.

H_2: If the prosocial lender exhibits a high degree of altruism, mission drift will occur if the pre-regulation approval rate of Type 2 projects is lower than the post-regulation one.

H_3: If the prosocial lender exhibits a high degree of altruism, mission drift will occur if the post-regulation approval rate of Type 2 projects is higher than the post-regulation approval rate of Type 1 projects.

The first test (H_1) compares the pre-regulation and post-regulation approval rates of type-1 projects. The second test (H_2) makes the reverse statement for Type 2 projects. The last test (H_3) concerns the post-regulation period only; it assesses mission drift by comparing the post-regulation approval rates of Type 1 and Type 2 applicants, i.e., $\frac{n_1^{Reg}}{N_1}$ and $\frac{n_2^{Reg}}{N_2'}$, respectively. Table 2 shows that there are two possible outcomes under the mission-drift scenario: 1) $n_1^{Reg} = 0, n_2^{Reg} = \frac{K}{S-\gamma_2'}$, and 2) $n_1^{Reg} = \frac{K-(S-\gamma_2')N_2'}{L_1-\gamma_1}$, $n_2^{Reg} = N_2'$. In both cases, $\frac{n_1^{Reg}}{N_1} < \frac{n_2^{Reg}}{N_2'}$, implying that, in the post-regulation period, the approval rate of Type 2 projects is higher than the approval rate of Type 1 projects.

4. Context and data

4.1. Institutional background

To investigate the impacts of a regulatory ceiling, we hand-collected data on loan applicants and borrowers at *Contraction de Crédit Accompagnement Solidarité* (Créa-Sol), a French MFI. The data covers the period from April 2008 to June 2012.[17] Créa-Sol was set up in 2006 by *Caisse d'Epargne*, a savings bank active in the Provence-Alpes-Côte d'Azur region, to comply with the legal framework for the pursuit of social and local economy projects (*projets d'économie locale et sociale, PELS*). The law required that savings banks dedicate a given share

[17] At the end of our sample period, France had three licensed MFIs. The largest, ADIE, had been regulated since 2003. In 2013, it supplied 12,339 business microloans, and its year-end outstanding amount was EUR 73.7 million. The second-largest licensed MFI was Créa-Sol. In 2013, Créa-Sol supplied 648 business microloans for a year-end outstanding amount of EUR 4.5 million. The third licensed MFI, Caisse Sociale de Développement Local (CSDL), became regulated in 2008; in 2013, it supplied 197 business microloans for a total outstanding amount of EUR 0.7 million.

of their operating income to subsidizing social initiatives (Law on Savings and Financial Security, voted in 1999 and repealed in 2009). As a non-regulated MFI, Créa-Sol had no access to funding other than subsidies from its parent bank, while benefiting from loan guarantees provided by the French government. The board of the legally independent NGO included the CEO, the executive director, members of the parent bank, and independent members. In April 2009, following the repeal of the legal *PELS* obligation that incentivized *Caisse d'Epargne* to finance Créa-Sol, subsidies were substantially reduced. Créa-Sol had to turn into a regulated MFI in order to gain access to new sources of funding at preferential rates, including a loan from *Caisse des Dépôts et Consignations*—the investment arm of the French government—in 2009, a loan from *Caisse d'Epargne* in 2010, and a loan from the European Investment Fund in 2012. As a regulated MFI, Créa-Sol was now able to secure alternative funding sources that had been inaccessible when it was unregulated. The time span of our dataset makes it possible to observe loan allocation under Créa-Sol's two successive business structures.

This change in status, triggered by an external regulatory shock, is a unique opportunity to scrutinize the impact of a loan ceiling. Nevertheless, it should be borne in mind that complying with the regulation resulted in a shift in funding sources, from (mainly) subsidies to a larger share of loanable funds, albeit at preferential interest rates. This raises the issue of endogeneity stemming from potentially omitted variables that resulted from supply-side changes, which is addressed extensively in Section 5.2.

Créa-Sol's target clientele primarily comprises unemployed individuals seeking self-employment and start-ups lacking collateral. Loans are repaid in monthly instalments over an average term of 51 months. Since its inception, Créa-Sol has operated in line with the microcredit tradition, charging all clients the same interest rate, which is adjusted to market conditions every two years. Over the sample period, it ranged between 4% and 5%, which is low considering the credit risks associated with financing start-ups. Borrowers who obtained co-financing from Créa-Sol and a bank were charged a lower rate by the former than the latter.

Créa-Sol's screening process focuses first on the borrower's profile, encompassing factors such as education, occupation (or cause of unemployment), motivation, and business acumen. In the next step, the project is discussed, often with the help of a business plan (84% of all projects are start-ups). The loan officer requests financial ratios but uses them flexibly. Overall, personality assessment takes precedence over financial analysis,[18] in contrast to the tougher screening process used by commercial banks. The final step is only taken if the loan officer

[18] According to a Créa-Sol senior loan officer, personality is a major decision criterion, accounting for up to 90% of the overall assessment.

finds the project mature enough. In this case, a financial plan is set up, including all the funding sources of the applicant. Ultimately, the loan officer makes a recommendation to the lending committee, which generally follows it, but has the final say. In most cases, the decision boils down to approval or rejection of the loan request.

How has regulation affected Créa-Sol's screening process? In the first period, the unregulated MFI used to screen both small and medium-sized projects on its own. In the second period, starting in April 2009, loan applications were capped at EUR 10,000. Applicants who requested larger amounts had to come up with secured partial funding from a bank. During informal interviews, loan officers acknowledged that recipients of bank loans very easily received loans from the regulated MFI. Two arguments can explain the MFI's confidence in the bank's screening. First, the bank's stake in a co-financing arrangement is generally higher than the MFI's, its average loaned amount being EUR 43,000 (see Table 3), against no more than EUR 10,000 for the MFI. Second, the two screening methods are complementary since MFIs favor relationship lending based on soft information, while most commercial banks are transaction lenders using hard information (see Berger & Udell, 2002). Importantly, co-financing implies no debt seniority. Both lenders therefore have an incentive to monitor their common borrowers on their own. Hence, bank-MFI co-financing arrangements are restricted to screening complementarities and risk-sharing opportunities. The MFI exploits its comparative advantage in collecting soft information, while the bank can make use of soft as well as hard information when lending to informationally opaque SMEs (Berger & Udell, 2006).

4.2. Data and descriptive statistics

Our database contains exhaustive information on 1,016 loan applicants. During the first sub-period (April 2008–March 2009), Créa-Sol was an *unregulated* MFI operating in a ceiling-free environment. It processed 193 applications. During the second sub-period (April 2009–June 2012), Créa-Sol was a *regulated* MFI constrained by a EUR 10,000 loan ceiling. It received 823 loan applications. Table 3 summarizes the characteristics of applicants (Panel A) and borrowers (Panel B), before and after the loan ceiling was enforced. Their characteristics have been split into three categories: financial, business-related, and individual. Financial characteristics include project size, requested loan size, actual loan size,[19] and existing sources of funds.[20] The average project size did not vary across periods, at slightly above EUR 30,000.

[19] Although Créa-Sol typically grants the requested amount to approved applicants, loan officers may sometimes adjust loan size, either according to their perception of the project or to the client's repayment capacity.

[20] To address moral hazard and adverse selection issues, lenders favor entrepreneurial projects having already secured partial funding through own capital or funds provided by friends and family (Berger & Udell, 1998).

This suggests that a critical amount of cash is needed to start a microbusiness in France and that the EUR 25,000 ceiling proposed by the European Commission is more suitable than the French upper limit of EUR 10,000.

Despite the lack of variation in project sizes in Panel A (applicants), we could observe a significant increase in project sizes of actual borrowers in Panel B, which rose from EUR 26,910 when the MFI was unregulated to EUR 35,010 when it was regulated. One inevitable consequence of the loan ceiling was that requested loan size plummeted, from EUR 18,620 to EUR 6,970, as Panel A shows. Likewise, the average loan size fell from EUR 15,760 to EUR 6,860 (see Panel B).

In the ceiling-free context, 70% of requested loans exceeded EUR 10,000. This is additional evidence that the French ceiling is very low in view of the needs of micro-entrepreneurs. However, in the regulated MFI context, only 28% of requested loans were equal to the ceiling value. This sharp drop in demand for large loans gives credence to the hypothesis that the bank's screening process skimmed off applications for financing. This explanation is also consistent with the fact that 28% of applicants to the regulated MFI had previously secured a bank loan. In fact, 54% of applicants requesting EUR 10,000 had taken out such a loan. For applicants to the regulated MFI, having a bank loan is apparently an asset.[21]

According to Table 3, the regulatory context seems to have had no influence on the proportion of applicants/borrowers with personal investment (approximately 85%). However, compliance with the loan ceiling regulation is associated with a significant rise in the size of borrowers' personal investment (from EUR 5,930 to EUR 8,170 on average), suggesting that the regulated MFI leans toward applicants with higher personal investments. The proportion of borrowers with funds from other sources also increased significantly (from 51% to 71%) after the loan ceiling regulation was introduced. The ceiling may have encouraged small entrepreneurs to seek additional funds rather than downsize their projects. Section 5.2 will address this potential selection bias by using propensity score matching.

Fig. 1 depicts the average financial plans submitted to Créa-Sol under the two regimes. The share of project size to be financed by Créa-Sol dropped from 67% to 41% after the regulation was implemented. In contrast, the share to be financed by bank loan rose from 1% to 14%. Possibly, the loan ceiling is considered an attractive signal by applicants exhibiting diversified

[21] We ran a probit regression to confirm this intuition. The results (available upon request) show that the probability of being approved by the MFI is significantly higher for applicants who have secured a bank loan, all else equal (personal investment, funds from other sources, business and personal characteristics). During the unregulated MFI period, the five applicants with bank loans were all denied a loan from the MFI. However, their average project size (EUR 114,000) makes them potential outliers.

funding sources, but perhaps it also coincides with the withdrawal of some applicants who needed above-ceiling loans from Créa-Sol but failed to secure bank loans.

Table 3. Descriptive statistics for applicants and borrowers

	Panel A: Applicants			**Panel B: Borrowers**		
Variables	**Unregulated MFI (n=193)**	**Regulated MFI (n=823)**	**t-test/Chi2**	**Unregulated MFI (n=90)**	**Regulated MFI (n=511)**	**t-test/Chi2**
Approval rate (%)				46.63	62.09	15.461***
Financial characteristics						
Project size (EURk)	31.33	30.81	0.182	26.91	35.01	1.824*
Requested loan size (EURk)	18.62	6.97	25.465***	16.73	7.01	17.237***
Requested loan size ≥ EUR 10,000 (%)	70.47	28.31[a]	120.122***	64.44	30.53	38.391***
Granted loan size (EURk)				15.76	6.86	15.875***
Co-financing (%)	2.59	27.95	56.531***	0	32.88	41.069***
Bank loan (EURk)[b]	40.69	50.44	0.547	0	42.73	
With personal investment (%)	85.49	84.33	0.163	83.33	87.08	0.923
Personal investment (EURk)[b]	6.99	7.16	0.204	5.93	8.17	1.787*
With funds from other sources (%)	56.48	69.26	11.523***	51.11	71.04	13.975***
Funds from other sources (EURk)[b]	7.90	8.99	1.629	7.50	9.38	1.641
Business characteristics						
Start-up (%)	81.35	84.20	0.934	81.11	81.60	0.012
Services (%)	27.46	29.89	0.444	27.78	30.33	0.238
Trade (%)	20.73	30.98	7.985***	24.44	29.16	0.835
Food and accommodation (%)	16.58	12.15	2.714*	12.22	11.35	0.057
Construction (%)	9.84	11.30	0.338	11.11	11.35	0.004
Arts, entertainment and recreation (%)	6.74	3.89	2.995*	5.56	3.91	0.517
Other sectors (%)	18.65	11.79	6.479**	18.89	13.89	1.527
Individual characteristics						
Unemployed for over six months (%)	55.44	59.17	0.897	46.67	55.38	2.340
Female applicant (%)	37.82	40.83	0.586	35.56	40.90	0.910
Single (%)	61.66	50.55	7.742***	64.44	45.60	10.884***
Education (# educational qualifications)	2.79	2.78	0.031	2.93	2.901	0.175
Average monthly household income (EURk)	1.08	1.50	4.749***	1.17	1.64	3.554***
MFI branches						
Bouches-du-Rhône (%) (old branch)	74.61	61.73	11.291***	81.11	57.93	17.356***
Vaucluse (%) (old branch)	25.39	9.72	34.623***	18.89	10.18	5.716**
Var (%) (new branch)	0	6.8	13.899***	0	7.05	6.745***
Alpes-Maritimes (%) (new branch)	0	21.75	50.954***	0	24.85	28.361***

Panel A and Panel B give the mean values and significance levels of the t-test for equal means between the two regimes for Créa-Sol's loan applicants and. borrowers, respectively. *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

[a] This figure means that 28.31% of regulated MFI applicants requested exactly EUR 10,000.

[b] The mean value was computed by using only non-zero data points.

The business characteristics in Table 3 show that start-ups make up the lion's share of Créa-Sol's loan portfolio. Their proportion has remained stable over time, at approximately 81%. Likewise, there is no substantial change between the two regimes in sector representation, except for the trade sector, which gained 10 percentage points in the regulated period among applicants, but not among borrowers. As regards individual characteristics, the two significant changes—possibly interlinked—are an increase in average household income and a decrease in the proportion of single applicants.

Before the new regime, Créa-Sol had two branches, one in the Bouches-du-Rhône area and the other in the Vaucluse area. Two new branches (Var and Alpes-Maritimes) opened in 2010 after the regulatory change. Given that the enforcement of a new pro-business orientation imposes significant modifications to screening and loan allocation processes, the theories of habit formation (Pollak, 1970) and routine workplace resistance (Prasad & Prasad, 2000) predict that new processes would be implemented more swiftly in new branches than in old ones. We will address this issue in two ways: First, the baseline estimation model will include branch fixed effects; second, the robustness of the results will be assessed by restricting the sample to the old branches (see Section 6).

Figure 1. Applicants' project financing under the two regimes

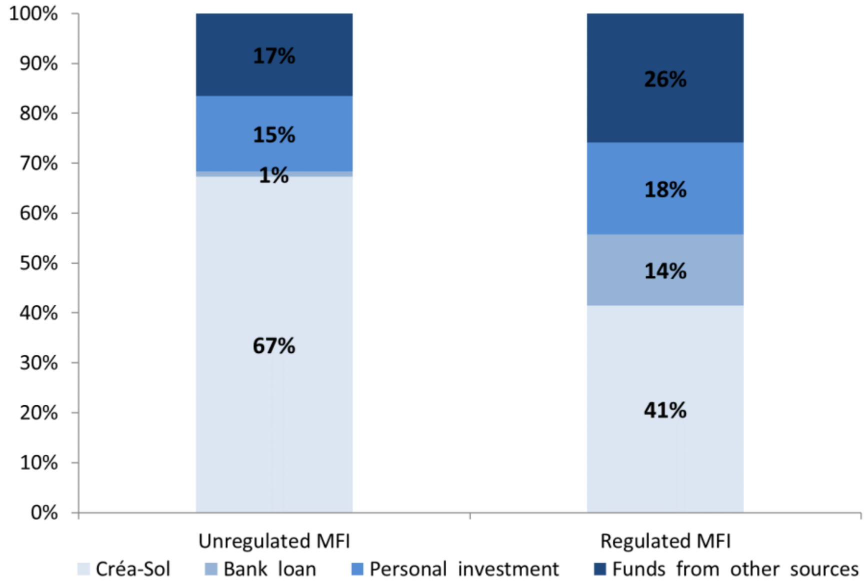
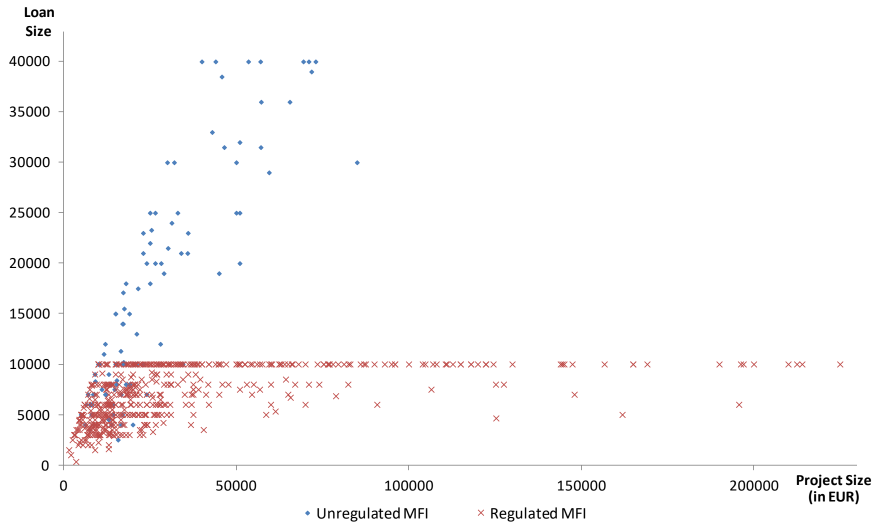


Fig. 2 features the relationship between project size and loan size. We represent the two regime-specific scatter plots. Once it was regulated, Créa-Sol financed larger projects than when it was unregulated. Moreover, under the regulated regime, there is an accumulation of points hitting the upper limit (EUR 10,000 loan size). When project size increases, the share financed by Créa-Sol decreases automatically because of the ceiling. In Section 3, our theoretical model showed how loan ceilings combined with co-financing opportunities could trigger mission drift in a regulated MFI.

Figure 2. Loan size as a function of project size



5. Regression analysis

In this section we present our empirical strategy and findings. First, we focus on splitting the sample into small and medium-sized projects. Second, we address the potential endogeneity stemming from supply-side changes and sample selection biases by using propensity score matching to control for potential demand-side changes. Third, we introduce our econometric diff-in-diff linear probability model. Finally, we present our findings, which allow us to assess the degree of altruism of the MFI under study and test for the mission-drift scenario (Case II.b in Table 2).

5.1. Splitting projects into "small" and "medium-sized"

The first step consists in dividing loan applicants into small and medium-sized businesses. In principle, we have two observable variables that can be used for this purpose: project size and the loan amount requested from the MFI. However, the requested amount is sensitive to the ceiling, which makes it unfit to be used as an exogenous variable for explaining loan allocation. We are thus left with project size to identify the empirical counterpart of S, the threshold for categorizing projects as "small" or "medium." Finding a workable proxy for S raises two additional problems. First, we cannot use the loan ceiling (EUR 10,000) since entrepreneurs seek partial debt financing only (see Table 3) and the ceiling does not cap project size. Second, defining medium-sized projects as those associated with a conditionally approved bank loan is not feasible because bank loans cannot be used as an identification device for project size in the first period.

We addressed this problem through a pragmatic two-step approach. In the first step, we exploited the theoretical assumption that small projects could be fully funded by a combination of all means of financing except bank loans. The idea was to determine the average size of projects proposed by applicants who secured project financing without any bank loan and with a microcredit not greater than EUR 10,000. Following this argument, for each application, we computed the amount of money collected from all sources excluding the MFI and banks. The average amount, computed over the entire sample, was added to the loan ceiling to obtain a first proxy of project size threshold *S* equal to EUR 22,048.

Table 4. Project size and bank loan: Regulated MFI only

Project size range (EUR)	With bank loan # Applicants	With bank loan # Borrowers	Without bank loan # Applicants	Without bank loan # Borrowers	% applicants with bank loan	% borrowers with bank loan
0-10,000	2	1	161	94	1%	1%
10,000-15,000	7	4	166	91	4%	4%
15,000-20,000	7	5	105	53	6%	9%
20,000-25,000	17	8	74	48	19%	14%
25,000-30,000	14	12	45	30	**24% (Last below 50%)**	**29% (Last below 50%)**
30,000-40,000	38	28	28	18	58%	61%
40,000-60,000	41	28	10	6	80%	82%
60,000-80,000	38	28	3	3	93%	90%
80,000-291,400	66	54	1	0	99%	100%
Total	**230**	**168**	**593**	**343**	**28%**	**33%**

This table shows the project size of the regulated MFI's applicants/borrowers with and without a bank loan. The objective is to determine the empirical counterpart of S, the size threshold for categorizing projects as "small" or "medium."

In the second step, we refined this first proxy by using data from the regulated MFI only. We determined the project size threshold at which fewer than 50% of applicants had taken out a bank loan. Table 4 places this threshold between EUR 25,000 and EUR 30,000. Finally, we decided to use the middle-of-the-road EUR 25,000 proxy for *S* in the baseline regressions, while keeping other possibilities in mind for robustness checks (see Section 6).

5.2. Addressing supply and demand-side changes

Before presenting the regression method, we address the potential endogeneity and sample selection problems stemming from Créa-Sol's change of status. We consider both the supply-side changes that might have impacted the MFI's selection of loan applicants, and the demand-side changes that might have altered applicant behavior. We show that: 1) supply-side changes are unlikely to trigger mission drift, and 2) demand-side changes can be addressed satisfactorily through the propensity score matching (PSM) approach.

From the supply-side perspective, endogeneity may occur because Créa-Sol's change of status had several side effects leading to omitted variables. A notable change concerns first-time access to loanable funds, which may have increased the MFI's emphasis on financial performance at the expense of social outreach (Hermes & Lensink, 2007; Reichert, 2018). This possibility cannot be ruled out econometrically since the change in funding is confounded with the regulatory status change.

However, the facts speak against a deterioration of the MFI's level of altruism. The new funders of Créa-Sol comprise a public partner, the European Investment Fund, and its parent bank. All of them have explicitly supplied loans at preferential interest rates to back the MFI's commitment to its mission. Accordingly, public statements by Créa-Sol (including on its website) were not modified after the regime shift. Informal interviews with staff members confirmed the primacy of the financial sustainability concern over the growth opportunity provided by loanable funds, suggesting that the MFI remained faithful to its social identity during the entire period despite the regulatory change.

What about changes in incentives driving loan allocation? The regime that came into effect in April 2009 brought regulatory constraints, but also new opportunities. The loan ceiling aside, the only change that might have affected Créa-Sol significantly was access to additional resources, because the unregulated lender already complied with the other—relatively mild—restrictions. Yet relaxing the regulated lender's budget constraint can only increase (or leave unchanged) the proportion of poor applicants receiving a loan, since the bank-driven threshold (N_2' in our model) is more likely to be binding. The available pool of medium-sized loan applications is exhausted more easily when more capital is available, leaving greater resources for financing small businesses. Thus, a large budget cannot lead to mission drift.

Another concern might be that the MFI makes changes to its supply and becomes 'softer' on larger loans under its new regulatory status because it anticipates changes in demand, rather than because co-financing opportunities arise. Actually, following the enforcement of a loan ceiling, the change in demand that can be expected is a decrease in the number of applicants pursuing large projects. For a highly altruistic MFI, this change would be an opportunity to focus even more on its social mission, i.e., favoring small projects. And since highly altruistic MFIs are the only ones for which mission drift is a possible outcome (see Table 2), the anticipation of changes in demand cannot trigger mission drift.

Our last supply-side concern relates to the impact of the 2008 financial crisis, which was at its height around the time of the change in status. To address this issue, we replicated our analysis by including a dummy variable accounting for the crisis as a robustness exercise (results available upon request). The crisis dummy had no significant impact on approval probability and the other coefficients were similar to those in the baseline model.

Demand-side changes may also threaten identification. In our context, two such changes can be expected: discouragement and downscaling. Discouragement refers to entrepreneurs with medium-sized businesses who abandon their projects for fear of rejection by commercial banks, either owing to the poor quality of their project or to high information asymmetry (Han et al., 2009). Downscaling is a softer reaction, whereby entrepreneurs wishing to avoid bank screening put forward below-ceiling projects, which are smaller than those that they would spontaneously have presented to the unregulated MFI. The self-selection implied by these rational reactions to the ceiling works against the mission-drift outcome since it increases the frequency and quality of applications for small loans.

To mitigate the effect of demand-side changes and control for the subsequent risk of sample selection bias, we used propensity score matching (PSM) (Rosenbaum & Rubin, 1983; Bennouri et al., 2018). PSM creates similar groups of treated and control observations and so minimizes the correlation between assignment to treatment and observable characteristics. Therefore, PSM alleviates the endogeneity concern of functional form misspecification.[22] However, since PSM relies on observables, it only addresses selection biases that are caused by observable differences between the treatment and control groups (Dehejia & Wahba, 2002).

We constructed comparable first and second-period samples by matching each applicant to the unregulated lender (pseudo-control group) with an applicant to the regulated one (pseudo-treated group), conditional on observed characteristics. PSM is typically used to assess the impact of treatments involving participants prone to (self-)selection biases that are due to observable differences. Intuitively, PSM matches untreated (or first-period) individuals with treated (or second-period) ones that are as similar as possible. Similarity is measured by the propensity score, here the predicted probability to be an applicant from the first period. Propensity scores are estimated from a probit model (see Table A1 in Appendix A) where the dependent variable is the dummy that takes the value of 1 in the first period with all available characteristics, except branch dummies, since two out of four branches did not exist during the first period.[23] Next, each first-period applicant is matched with their propensity-score nearest neighbor second-period counterpart.

To confer robustness on our results, we performed two different matching methods, with and without replacement run on the common support area. Matching with replacement minimizes

[22] If the linear relationship between the dependent and independent variables is misspecified, then the assumption of zero conditional mean for the error term does not hold. Hence, PSM mitigates endogeneity by reducing the correlation between "assignment to treatment" and "observable characteristics" (Shipman et al., 2017).

[23] We used the approach presented in Shipman et al. (2017) and Bennouri et al. (2018). These authors recommend including as many control variables as possible in the estimation of propensity scores in order to minimize the risk that our choice of variables might influence the main regression and to avoid the criticism of post hoc research design. Therefore, we used the same variables (except the branch dummies unavailable for the first period) for the matching and the main regression.

the propensity score distance between the two groups: Each first-period applicant is matched with its nearest second-period applicant without any restriction, so that some second-period applicants can end up being chosen several times. Therefore, matched couples have the closest possible propensity scores. This flexibility helps minimize selection bias.

In contrast, when matching without replacement, each second-period applicant can be used once at most, leading to potentially dissimilar matched couples. Statistically, the increased selection bias is traded-off against a larger sample—that has the same number of treated and untreated individuals—yielding higher precision for the subsequent regression estimates (Dehejia & Wahba, 2002). For this reason, we used PSM without replacement in our baseline model. Appendix B shows that PSM with replacement yields similar results.

Table 5. Descriptive statistics for applicants: Matching without replacement

	Matched sample without replacement		
Variables	Unregulated MFI (n=190)	Regulated MFI (n=190)	t-test/Chi[2a]
Mean propensity score	0.249	0.249	0.054
Financial characteristics			
Medium project	0.484	0.495	0.042
With personal investment	0.853	0.868	0.197
With funds from other sources	0.568	0.547	0.171
Business characteristics			
Start-up	0.811	0.789	0.263
Services	0.274	0.284	0.052
Trade	0.211	0.237	0.379
Food and accommodation	0.168	0.153	0.176
Construction	0.100	0.0737	0.830
Arts and entertainment	0.0632	0.0789	0.359
Individual characteristics			
Unemployed for over 6 months	0.558	0.589	0.387
Female	0.384	0.358	0.282
Single	0.616	0.642	0.282
Education (# educational qualifications)	2.774	2.668	0.649
Household income	1.041	1.098	0.624

This table reports descriptive statistics concerning the control variables for the matched sample of applicants to the MFI. In the matched sample, applicants to the unregulated MFI are matched with applicants to the regulated MFI by using a propensity score matching procedure (Rosenbaum & Rubin, 1983). Matching without replacement yields a sample of 380 applicants, where 190 applicants to the unregulated MFI are matched with 190 applicants to the regulated MFI.

*, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

[a] t-values are reported for continuous variables and Chi-square values for dummy variables.

Table 5 reports descriptive statistics for PSM without replacement, which leads to a sample of 380: the 190 original applicants to the unregulated MFI and the 190 matched applicants to the regulated MFI. In contrast to the full sample, the matched sample shows no significant differences between the first and second-period summary statistics, suggesting that PSM satisfactorily addresses the potential demand-side biases stemming from sample selection.

Table 6 shows detailed statistics for project size and approval rate computed from the matched sample. The approval rates over the two periods are broken down by project size and compared using Chi-squared tests. The overall approval rate is significantly higher for the regulated MFI than for its unregulated counterpart (61% vs 47%) but variation across project sizes is not uniform. While the approval rate of medium projects increased significantly after the regulation came into force, the approval rate of small projects decreased (54% vs 50%), but the difference is insignificant, probably owing to the relatively small sample.

Table 6. Project size and approval rate

Project size	Unregulated MFI			Regulated MFI		
range (EUR)	**Applicants**	**Borrowers**	**Approval rate**	**Applicants**	**Borrowers**	**Approval rate**
0-10,000	25	13	52%	34	19	56%
10,000-15,000	25	12	48%	32	15	47%
15,000-20,000	26	18	69%	20	9	45%*
20,000-25,000	19	8	42%	10	5	50%
Small projects	**95**	**51**	**54%**	**96**	**48**	**50%**
25,000-30,000	19	10	50%	23	18	78%*
30,000-40,000	23	9	39%	25	18	72%**
40,000-60,000	36	14	39%	15	12	80%***
60,000-80,000	10	4	40%	12	6	50%
80,000-291,400	7	1	14%	19	14	74%***
Medium projects	**95**	**38**	**40%**	**94**	**68**	**72%*** **
Total	**190**	**89**	**47%**	**190**	**116**	**61%*** **

This table reports approval rates broken down by project size for the matched sample without replacement, which is used in our baseline regressions. Approval rates over the two periods are compared using Chi-squared test. Stars report the significance levels of the Chi-squared test for identical approval rates by the unregulated and regulated MFI.
*, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

Overall, Table 6 suggests that enforcement of the regulation was followed by a more favorable treatment of larger loans, an outcome consistent with mission drift in the theoretical model. To further test the model's predictions while controlling for applicant characteristics, we turn to regression analysis.

5.3. Regression methods

Once the sample was adjusted by using PSM, we tested the theoretical predictions presented in Section 3. To explain the probability of loan approval before and after the introduction of the loan ceiling, we estimated a diff-in-diff linear probability model (LPM).[24] The model explains loan approval by project type, regulatory status, and control variables. Project type is captured by the dummy variable *Medium Project*, which takes the value of 1 for projects above EUR 25,000 (see Section 5.1), and 0 otherwise. The regulatory status is represented by the dummy variable *Reg*, which takes the value of 1 during the month of April 2009 and afterwards, and 0 during the month of March 2009 and earlier. The LPM is written:

[24] The results of the probit model are reported in Appendix C. Diff-in-diff LPM and diff-in-diff probit models each have their advantages and drawbacks (Greene, 2012; Angrist & Pischke, 2008). LPM produces easily interpretable marginal effects, but its predictions can lie outside the 0–1 interval, which is meaningless for a probability. Probit estimation is designed to explain probabilities, and its predictions always lie in the 0–1 interval, but interpreting marginal effects is harder. In our case, both approaches gave similar results.

$$E[Approval|Medium\ Project, Reg, \boldsymbol{X}]$$
$$= \lambda\ Medium\ Project + \delta\ Reg + \mu\ Reg * Medium\ Project + \theta\ \boldsymbol{X} + \epsilon \quad (8)$$

where $\boldsymbol{X}$ is a vector of control variables including the constant term, and ϵ is the error term; λ, δ, μ and vector θ represent the parameters to be estimated. The marginal effect of *Medium Project* for the unregulated MFI is λ, the sign of which assesses the MFI's level of altruism (see Section 3). If $\lambda < 0$, the level of altruism is high because the chances that a medium-sized project will receive a loan from the unregulated MFI are low (Case II in Table 2). In contrast, if $\lambda > 0$, the unregulated MFI favors medium-sized projects over small ones, which testifies to its low level of altruism (Case I in Table 2). The first task of the empirical analysis will be to determine the sign of λ, since mission drift can only occur if $\lambda < 0$.

Table 7. Testing for mission drift when lender exhibits a high degree of altruism

Theoretical hypothesis	Empirical test
H_1: The pre-regulation approval rate of small projects is higher than the post-regulation one.	$\delta < 0$
H_2: The pre-regulation approval rate of medium projects is lower than the post-regulation one.	$\delta + \mu > 0$
H_3: The post-regulation approval rate of medium projects is higher than the post-regulation approval rate of small projects.	$\lambda + \mu > 0$

The next step will consist in determining whether the regulation triggers mission drift. Eq. (8) enables us to test the three hypotheses derived from the theoretical model for prosocial lenders who exhibit a high degree of altruism. The relevant parameters are: δ, the impact of the regulation on the probability of approval of small projects; $\delta + \mu$, the impact of the regulation on the probability of approval of medium-sized projects, and $\lambda + \mu$, the marginal effect of *Medium Project* on the probability of approval by the regulated MFI. The marginal effects captured by δ and $\delta + \mu$ are not redundant since approval rates can increase simultaneously for medium-sized and small projects, as in the mission alignment situation (Case I.b in Table 2). Table 7 provides the empirical tests for each of the three hypotheses in the theoretical model's mission-drift scenario.

5.4. How altruistic is the MFI?

Parameter λ captures the marginal effect of project size on the unregulated MFI loan approval rate. The first line of Table 8 shows that the coefficient of the *Medium Project* dummy is significantly negative, and this result is remarkably consistent across specifications. Panel A suggests that under the unregulated regime a medium-sized project is around 20% less likely to receive a loan than a small project, all else equal. The marginal effects of the diff-in-diff probit model are qualitatively similar (see Table C1 in Appendix C). These results show that the MFI is highly altruistic. As Case II in Table 2 shows, imposing any regulatory loan ceiling on a lender with a high level of altruism is bound to be ineffective at best, and counterproductive at worst. This is because the lender's level of altruism is sufficiently high to self-enforce social discipline, so that the regulator cannot do better than the lender itself.

Table 8. Linear probability model for loan approval: Matching without replacement

	Panel A: Coefficient estimates					
Variables	(1)		(2)		(3)	
Medium project ($\hat{\lambda}$)	-0.18***	(0.06)	-0.18***	(0.06)	-0.22***	(0.06)
Regulated ($\hat{\delta}$)	-0.11**	(0.05)	-0.12**	(0.05)	-0.11**	(0.05)
Regulated* medium project ($\hat{\mu}$)	0.39***	(0.07)	0.40***	(0.07)	0.41***	(0.06)
With personal investment			0.06	(0.08)	0.08	(0.07)
With funds from other sources			-0.02	(0.06)	0.02	(0.06)
Start-up			-0.18***	(0.06)	-0.15***	(0.05)
Services			-0.10	(0.07)	-0.10	(0.08)
Trade			-0.09	(0.07)	-0.06	(0.08)
Food and accommodation			-0.24***	(0.08)	-0.20**	(0.09)
Construction			-0.06	(0.07)	-0.06	(0.07)
Arts and entertainment			-0.12	(0.08)	-0.11	(0.09)
Unemployed for over 6 months					-0.15***	(0.04)
Female					-0.03	(0.05)
Single					0.03	(0.04)
Education (# educational qualifications)					0.04**	(0.01)
Household income					0.01	(0.03)
Vaucluse area (old branch)	-0.09	(0.08)	-0.08	(0.09)	-0.08	(0.09)
Var area (new branch)	0.17***	(0.06)	0.18**	(0.06)	0.15**	(0.07)
Alpes-Maritimes area (new branch)	0.28***	(0.09)	0.27***	(0.08)	0.26***	(0.06)
Constant	0.58***	(0.03)	0.78***	(0.09)	0.70***	(0.10)
Observations	380		380		380	
R-squared	0.080		0.108		0.141	
	Panel B: Testing for mission drift					
	(1)		(2)		(3)	
$\hat{\delta}$	-0.11**	(0.04)	-0.12**	(0.05)	-0.11**	(0.04)
$\hat{\delta} + \hat{\mu}$	0.28***	(0.05)	0.28***	(0.06)	0.30***	(0.06)
$\hat{\lambda} + \hat{\mu}$	0.21***	(0.03)	0.21***	(0.06)	0.18**	(0.06)

This table presents the results of a linear probability model estimate of the nearest neighbor matched sample using the propensity score matching procedure (Rosenbaum & Rubin, 1983) without replacement, including the control variables successively. The dependent variable is the dummy for loan secured from the MFI. Panel A reports coefficient estimates and, in parentheses, standard errors clustered by sector of activity. Panel B reports the results of the test for mission drift. *Medium Project* is an indicator for projects over EUR 25,000. *Regulated* is the indicator for the period after the introduction of the loan ceiling (April 2009).
*, **, *** represent significance at the 10%, 5% and 1% levels, respectively.

Worse still, the ceiling-induced market distortion may make it optimal for the lender to seek co-financing arrangements with commercial banks while protecting these banks from adverse selection. As a result, the highly altruistic lender becomes less socially-minded than it would naturally have been in a regulation-free environment. The next section seeks to establish whether our data bears witness to an actual mission drift.

5.5. *Testing for mission drift*

Our empirical design (featured in Table 7) entails three testable impacts of mission drift. Panel B in Table 8 shows that all tests lead us to conclude in favor of the mission drift hypothesis. The marginal effects of the diff-in-diff probit model are qualitatively similar (see Table C1, Panel B in Appendix C). With respect to H_1, the first line of Panel B suggests that small projects are 11% less likely to be approved under the regulation than under the unconstrained regime. H_2 is tested in the second line of Panel B. The highly significant marginal effect is around 0.30, meaning that the approval rate of medium projects gained 30% under the regulation. The last line in Panel B shows that, under the regulation, the likelihood of medium-sized projects being approved is 18% higher than that of small projects.

We know from the previous subsection that our unregulated lender is altruistic enough to favor small projects over medium-sized ones. But the third test in this subsection suggests that a loan ceiling is sufficient to reverse this preference. Bank-MFI co-financing opportunities have two concurring perverse effects: They allow the regulated MFI to continue funding medium-sized projects and reduce the cost of doing so. By making co-financing indispensable for medium-sized projects, the regulation eliminates the adverse selection problem that formerly prevented banks from sharing credit risks with the MFI. Regardless of the underlying mechanism, our results confirm that, under the regulation, the MFI prefers to finance larger projects. This is the stigma of mission drift, whereby applicants proposing small projects have endured more stringent loan approval procedures since the ceiling was enforced.

The marginal effects of control variables provide additional insights. Start-ups (as opposed to buy-outs and existing firms), businesses in the food and accommodation industries, and long-term unemployed entrepreneurs are less likely to receive a loan, whereas the applicant's education level has a positive impact on loan approval. Table 8 also shows that branch fixed effects are significant, suggesting that the new branches do depart from the old ones. This result speaks in favor of the discontinuity and heterogeneity of operations under the new regulation. Changes to operations are therefore likely to be a potential driver of mission drift. The following section checks the robustness of our results.

6. Supplementary analysis

Although PSM allows us to control for sample selection biases, we are left with alternative mechanisms and facts that might have affected Créa-Sol's loan allocation from April 2009 onwards. This section addresses these facts and mechanisms along three dimensions.

The first check acknowledges the possibility that changes in loan approval detected in the baseline regressions are due, at least partly, to the opening of new branches. We run the regressions for old branches only. The reduced sample is made up of 190 observations for the unregulated MFI and 139 observations for the regulated MFI. Table 9 features the estimated results. Apart from some lower significance levels attributable to the smaller sample size, the figures appear to be remarkably close to those of the Table 8 regressions. Overall, the results suggest that the mission-drift outcome is driven not only by the new branches, but also by those predating the change of status.

Table 9. Linear probability model for loan approval: Old branches

	Panel A: Coefficient estimates					
Variables	(1)		(2)		(3)	
Medium project ($\hat{\lambda}$)	-0.18***	(0.06)	-0.17***	(0.06)	-0.21***	(0.06)
Regulated ($\hat{\delta}$)	-0.10*	(0.05)	-0.11**	(0.05)	-0.10**	(0.05)
Regulated* medium project ($\hat{\mu}$)	0.37***	(0.08)	0.38***	(0.08)	0.38***	(0.08)
With personal investment			0.03	(0.08)	0.06	(0.07)
With funds from other sources			-0.03	(0.07)	-0.00	(0.07)
Start-up			-0.16**	(0.07)	-0.13**	(0.06)
Services			-0.09	(0.08)	-0.09	(0.08)
Trade			-0.06	(0.08)	-0.03	(0.08)
Food and accommodation			-0.23**	(0.09)	-0.19*	(0.09)
Construction			-0.04	(0.08)	-0.03	(0.08)
Arts and entertainment			-0.04	(0.09)	-0.05	(0.09)
Unemployed for over 6 months					-0.15***	(0.04)
Female					-0.02	(0.05)
Single					0.05	(0.04)
Education (# educational qualifications)					0.03*	(0.02)
Household income					0.03	(0.03)
Vaucluse area (old branch)	-0.08	(0.08)	-0.09	(0.09)	-0.09	(0.08)
Constant	0.58***	(0.03)	0.77***	(0.10)	0.66***	(0.12)
Observations	329		329		329	
R-squared	0.043		0.068		0.104	
	Panel B: Testing for mission drift					
	(1)		(2)		(3)	
$\hat{\delta}$	-0.10*	(0.04)	-0.11**	(0.05)	-0.10**	(0.05)
$\hat{\delta} + \hat{\mu}$	0.27***	(0.04)	0.26***	(0.07)	0.28***	(0.07)
$\hat{\lambda} + \hat{\mu}$	0.19**	(0.04)	0.21***	(0.07)	0.17**	(0.07)

This table presents the results of estimating a linear probability model for the nearest neighbor matched sample using the propensity score matching procedure (Rosenbaum & Rubin, 1983) without replacement, including the control variables successively. The sample is limited to branches existing before ceiling enforcement. Panel A reports coefficient estimates and, in parentheses, standard errors clustered by sector of activity. Panel B reports the results of the test for mission drift. *Medium Project* is an indicator for projects over EUR 25,000. *Regulated* is the indicator for the period after the introduction of the loan ceiling (April 2009).
*, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

Second, we tested whether our results would resist changes to the EUR 25,000 threshold. To split our sample into small and medium projects, we identified the cut-off value of EUR 25,000 for project size statistically (see Section 5.1). We assess the robustness of our empirical findings by using the following cut-offs to define the *Medium Project* dummy variable (in EUR): 20,000;

25,000 (reference); and 30,000. Table 10 presents the estimates for specification (8) using these thresholds. To save space, we report only the estimated coefficients of interest.

Table 10. Linear probability model for loan approval with different thresholds for project size

Project size threshold (EUR)	20,000		25,000		30,000	
	Panel A: Coefficient estimates					
	(1)		(2)		(3)	
Medium project ($\hat{\lambda}$)	-0.20**	(0.07)	-0.22***	(0.06)	-0.20***	(0.07)
Regulated ($\hat{\delta}$)	-0.02	(0.06)	-0.11**	(0.05)	-0.00	(0.04)
Regulated* medium project ($\hat{\mu}$)	0.32***	(0.08)	0.41***	(0.06)	0.33***	(0.04)
	Panel B: Testing for mission drift					
	(1)		(2)		(3)	
$\hat{\delta}$	-0.02	(0.06)	-0.11**	(0.05)	-0.00	(0.04)
$\hat{\delta}+\hat{\mu}$	0.29***	(0.07)	0.30***	(0.06)	0.32***	(0.05)
$\hat{\lambda}+\hat{\mu}$	0.11*	(0.06)	0.18***	(0.06)	0.13*	(0.06)
Observations	378		380		382	
R-squared	0.097		0.141		0.122	

This table presents the results of estimating a linear probability model with propensity score matching procedure (Rosenbaum & Rubin, 1983) in which the dependent variable is the dummy for loan secured from the MFI and the definition of *Medium Project* varies according to the project size threshold used in each column. Panel A reports coefficient estimates and, in parentheses, standard errors clustered by sector of activity. All estimates include control variables; however, only the main coefficients of interest are reported. Columns (1)–(3) report the results for nearest neighbor matched sample without replacement, using 20,000, 25,000, and 30,000 euros for project size thresholds, respectively.
*, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

The first line in Panel A confirms that the MFI is highly altruistic since λ is significantly negative for any threshold. Regarding the impact of the regulation, the tests of significance reported in Panel B show that two tests (H2 and H3) out of three confirm the mission-drift scenario for project thresholds equal to EUR 20,000 and 30,000. The test statistic for H1 is insignificant for these two thresholds. Hypothesis H1 assumes a decrease in the approval rate of small projects in the second period. The sensitivity of H1 to project downsizing can have separate reasons for each threshold. First, using the EUR 20,000 threshold results in a notable decrease in the number of small projects in both periods, thereby creating a potential small-sample issue. Second, the EUR 30,000 cut-off can be problematic since, as Table 6 shows, the approval rates of projects between EUR 25,000 and 30,000 are systematically higher in the second period than in the first, suggesting that these projects share the fate of their medium, rather than small, counterparts; hence the EUR 30,000 cut-off value is unfitting.

Finally, we added the *Co-Financing* dummy to assess its importance in the mechanism driving mission drift. Our baseline regression captures the impact of the ceiling on loan allocation through the lens of co-financing. Here we aim to control for any additional impact of co-financing arrangements. We did not include the *Co-Financing* dummy in the baseline regression because it has a high correlation (0.68) with the *Regulated*Medium Project* interaction term. Regardless, Column (1) in Table 11 combines the two correlated variables. Co-financing is not significant, probably because of multicollinearity. Specification (2) refers to the same regression without the *Regulated*Medium Project* interaction, where the loading of the *Co-Financing* dummy is strongly significant. This suggests that co-financing is an undeniable channel for the mission-drift scenario uncovered in our empirical analysis. These findings are consistent with our baseline results.

Table 11. Linear probability model for loan approval with co-financing

Variables	(1)		(2)	
Regulated	-0.11**	(0.05)	-0.00	(0.05)
Medium project	-0.20***	(0.07)	-0.08	(0.05)
Regulated* medium project	0.35**	(0.13)		
Co-financing	**0.05**	**(0.10)**	**0.23*** **	**(0.04)**
With personal investment	0.08	(0.07)	0.07	(0.07)
With funds from other sources	0.02	(0.06)	0.02	(0.05)
Start-up	-0.13**	(0.05)	-0.11**	(0.05)
Services	-0.11	(0.07)	-0.11	(0.07)
Trade	-0.06	(0.07)	-0.04	(0.07)
Food and accommodation	-0.20**	(0.08)	-0.22**	(0.08)
Construction	-0.06	(0.07)	-0.07	(0.07)
Arts and entertainment	-0.12	(0.09)	-0.15	(0.09)
Unemployed for over 6 months	-0.16***	(0.04)	-0.15***	(0.04)
Female	-0.03	(0.05)	-0.04	(0.05)
Single	0.01	(0.04)	0.01	(0.04)
Education (# educational qualifications)	0.04***	(0.01)	0.04***	(0.01)
Household income	0.01	(0.03)	0.01	(0.03)
Vaucluse area (old branch)	-0.08	(0.09)	-0.07	(0.09)
Var area (new branch)	0.14*	(0.07)	0.13*	(0.07)
Alpes-Maritimes area (new branch)	0.25***	(0.06)	0.23***	(0.06)
Constant	0.70***	(0.10)	0.62***	(0.11)
Observations	375		375	
R-squared	0.139		0.120	

This table presents the results of estimating a linear probability model with propensity score matching procedure (Rosenbaum & Rubin, 1983) without replacement. The dependent variable is the dummy for loan secured from the MFI. The model includes the C*o-Financing* dummy, which takes the value of one for loans co-financed by the MFI and a commercial bank. The table reports coefficient estimates and, in parentheses, standard errors clustered by sector of activity. Columns (1) and (2) report the results with and without the interaction term *Regulated* Medium Project*, respectively.
*, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

Overall, the robustness check results suggest that both the mission drift outcome and the underlying co-financing mechanism in our theoretical model are robust.

7. Conclusions

Our results contain a warning against imposing loan ceilings on prosocial lenders in developed economies. A ceiling on social loans can trigger bank-MFI co-financing strategies and mission drift. It makes co-financing arrangements not only attractive to MFIs and their better-off borrowers, but also incentive-compatible to banks because it reduces the threat of adverse selection. In addition, statistical evidence concerning the European microcredit market suggests that the conditions for the emergence of mission drift are present. Regulators should therefore realize that low loan ceilings may crowd out disadvantaged borrowers failing to put forward projects whose sizes are large enough to be attractive to banks. Such mission drift defeats both the regulator's objective—social welfare—and the very spirit of prosocial lending.

Microfinance mission drift has macroeconomic implications. It can increase unemployment and dependency on social safety nets among disadvantaged people who could otherwise become micro-entrepreneurs. The deprived segments of the population targeted by MFIs include the unemployed, women, and migrants seeking financial empowerment through self-employment (Agier & Szafarz, 2013; Bendig et al., 2014). Mission drift adversely impacts public resources and diverts subsidies to social action. It also reinforces the credit rationing endured by micro-entrepreneurs, and therefore compromises the *raison d'être* of the microfinance sector. More generally, overregulating prosocial lending is costly to credit providers and therefore socially undesirable.[25]

But social mission aside, co-financing schemes have advantages, too. The existence of prosocial lending is an opportunity for mainstream banks to find partners with whom to share risks. This is particularly relevant for start-ups that would otherwise be denied access to the credit market. The European financial market is characterized by hierarchical banks that are often large and distant, and co-financing provides access to credit for otherwise rationed firms. Partnerships between banks and MFIs facilitate the "graduation" of MFI clients to traditional banking. By repaying a first loan sponsored by an MFI in a timely manner, micro-enterprises can build up a good credit history and lessen their informational opacity while developing their businesses.

Our stylized model shows with few assumptions that a loan ceiling can lead to mission drift. However, it suffers from some limitations. First, there are reasons to believe that the objective of prosocial lenders is institution-specific (Hudon & Sandberg, 2013). Second, the simplified assumption that the social-welfare optimum is characterized by serving as many poor borrowers as possible fails to account for the rich ongoing conversation on the fundaments of the notion of social welfare (Sen, 2017; Marti & Scherer, 2016). Third, our model disregards financing sources other than loans issued by MFIs and banks. In contrast, the empirical analysis shows that the applicants' personal investment matters. One attractive challenge for the future will be

[25] This point is confirmed by the "concerns of overregulation imposing unnecessary costs on financial service providers, reducing their efficiency and ultimately undermining economic growth" (Beck et al., 2017a).

to develop a general model of the credit market with banks and prosocial lenders having distinct objectives and screening devices but overlapping pools of applicants. Adding regulatory options to the picture will likely provide further insights into optimizing the use of subsidies in social finance.

Our database is remarkably detailed but nevertheless limited to a single institution, thus raising doubts about the external validity of our results. Yet a single case study is sufficient to make our point that loan ceilings can have unexpected, perverse effects on prosocial lending. Admittedly, our empirical results are contingent on the French ceiling, which is particularly low by developed-country standards, and therefore easily leads to mission drift. Loan ceilings are, however, ubiquitous within the regulatory frameworks of high-income countries. The European Union recommends a EUR 25,000 cap to its member states. As our descriptive statistics showed, 37% of European MFIs supply loans above this threshold, which is considerable given that many MFIs are constrained by compulsory ceilings. Arguably, several of these ceilings are unrealistic in view of the amount of capital needed to start a small business. In this regard, the US ceiling of USD 50,000 seems more reasonable than the European one, while potentially playing a useful role to prevent blatant abuse.

The pervasive diversity within the social lending sector makes it difficult, if not impossible, to find a loan ceiling low enough to make a difference but high enough to avoid mission drift. Moreover, regardless of the ceiling level, regulating loan size is questionable because borrowers may easily combine several loans. Capping the size of a single leg of a multiple-leg funding arrangement makes little sense. If two applicants propose projects of similar sizes, the one asking for the larger loan is likely to be the poorer one, i.e., with less personal capital to plough into the project.

In view of this problem, other regulatory blueprints could be envisioned. One could frame the regulation of prosocial lending in a larger picture and design simple rules that would both fulfil the needs of vulnerable borrowers and prevent mission drift by the lender. Prosocial loans could be provided to businesses belonging to specific sectors (Bach, 2014). People who borrow from subsidized institutions are habitually redlined by purely commercial lenders, which makes them suitable targets for welfare-improving lending (Gale, 1990). For instance, poor women and discriminated-against minorities could be targeted more specifically, which would stress the original affirmative-action principle of microcredit. Whichever way the regulators go, they will play a key role in shaping prosocial lending.

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Appendix A. First stage for propensity score matching

Table A1. First stage and balance test for propensity score matching

	Coefficient	Standard error
Medium project	0.45***	(0.11)
With personal investment	0.12	(0.15)
With funds from other sources	-0.39***	(0.10)
Start-up	-0.03	(0.14)
Services	-0.30**	(0.15)
Trade	-0.52***	(0.16)
Food and accommodation	-0.30*	(0.18)
Construction	-0.31	(0.20)
Arts and entertainment	-0.07	(0.24)
Unemployed for over 6 months	-0.06	(0.10)
Female	-0.02	(0.10)
Single	0.10	(0.11)
Education (# educational qualifications)	0.01	(0.03)
Household income	-0.21***	(0.05)
Constant	-0.35	(0.23)
Observations	1,016	
Pseudo R-squared	0.07	

This table reports the results of estimating the first stage probit model of the propensity score matching procedure, in which the dependent variable is a binary variable taking the value of 1 for the unregulated period.

*, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

Appendix B. Matching with replacement

Matching with replacement (see Section 5.2) yields a final sample made up of 337 observations: the 190 original applicants to the unregulated MFI and 147 matched applicants to the regulated MFI. Table B1 shows the descriptive statistics relating to this sample while Table B2 reports on the estimation of the baseline model. The results are similar to those reported in Table 8.

Table B1. Descriptive statistics for applicants: Matching with replacement

	Full sample			**Matched sample with replacement**		
Variables	Unregulated MFI (n=193)	Regulated MFI (n=823)	t-test/Chi2[a]	Unregulated MFI (n=190)	Regulated MFI (n=147)	t-test/Chi2[a]
Mean propensity score				0.249	0.235	1.207
Financial characteristics						
Medium project	0.492	0.341	15.249***	0.484	0.469	0.073
With personal investment	0.855	0.843	0.163	0.853	0.871	0.227
With funds from other sources	0.565	0.693	11.523***	0.568	0.578	0.033
Business characteristics						
Start-up	0.813	0.842	0.934	0.811	0.796	0.112
Services	0.245	0.299	0.444	0.274	0.286	0.060
Trade	0.207	0.310	7.985***	0.211	0.279	2.123
Food and accommodation	0.166	0.121	2.714*	0.168	0.136	0.665
Construction	0.098	0.113	0.338	0.100	0.0748	0.648
Arts and entertainment	0.067	0.039	2.995*	0.0632	0.0816	0.428
Individual characteristics						
Unemployed for over 6 months	0.554	0.592	0.897	0.558	0.619	1.276
Female	0.378	0.408	0.586	0.384	0.354	0.330
Single	0.617	0.505	7.742***	0.616	0.639	0.198
Education (# educational qualifications)	2.788	2.784	0.031	2.774	2.687	0.497
Household income	1.077	1.504	4.749***	1.041	1.116	0.747

This table reports descriptive statistics concerning the control variables for the full sample and for the matched sample with replacement of applicants to the MFI. In the matched sample, applicants to the unregulated MFI are matched with applicants to the regulated MFI by using a propensity score matching procedure (Rosenbaum & Rubin, 1983). Matching with replacement yields a sample of 337 applicants, where 190 applicants to the unregulated MFI are matched with 147 applicants to the regulated MFI.

*, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

[a] t-values are reported for continuous variables and Chi-square values for dummy variables.

Table B2. Linear probability model for loan approval: Matching with replacement

Panel A: Coefficient estimates

Variables	(1)		(2)		(3)	
Medium project ($\hat{\lambda}$)	-0.18***	(0.06)	-0.19***	(0.06)	-0.24***	(0.07)
Regulated ($\hat{\delta}$)	-0.10**	(0.04)	-0.10**	(0.04)	-0.09**	(0.04)
Regulated*medium project ($\hat{\mu}$)	0.35***	(0.06)	0.36***	(0.06)	0.38***	(0.05)
With personal investment			0.05	(0.07)	0.09	(0.06)
With funds from other sources			-0.03	(0.06)	0.02	(0.06)
Start-up			-0.17**	(0.07)	-0.16**	(0.06)
Services			-0.07	(0.08)	-0.07	(0.09)
Trade			-0.07	(0.08)	-0.04	(0.09)
Food and accommodation			-0.18**	(0.09)	-0.15	(0.10)
Construction			-0.05	(0.09)	-0.07	(0.09)
Arts and entertainment			-0.10	(0.09)	-0.10	(0.10)
Unemployed for over 6 months					-0.19***	(0.04)
Female					-0.05	(0.04)
Single					0.05	(0.05)
Education (# educational qualifications)					0.04**	(0.01)
Household income					-0.00	(0.03)
Vaucluse area (old branch)	-0.10	(0.08)	-0.09	(0.09)	-0.10	(0.09)
Var area (new branch)	0.19**	(0.07)	0.19**	(0.07)	0.14*	(0.07)
Alpes-Maritimes area (new branch)	0.23**	(0.11)	0.20*	(0.11)	0.14	(0.09)
Constant	0.58***	(0.04)	0.77***	(0.10)	0.72***	(0.12)
Observations	337		337		337	
R-squared	0.067		0.089		0.134	

Panel B: Testing for mission drift

	(1)		(2)		(3)	
$\hat{\delta}$	-0.10**	(0.04)	-0.10**	(0.05)	-0.09**	(0.04)
$\hat{\delta} + \hat{\mu}$	0.26***	(0.05)	0.26***	(0.06)	0.29***	(0.06)
$\hat{\lambda} + \hat{\mu}$	0.18***	(0.03)	0.18***	(0.06)	0.14**	(0.06)

This table presents the results of estimating a linear probability model for the nearest neighbor matched sample using the propensity score matching procedure (Rosenbaum & Rubin, 1983) with replacement. The dependent variable is the dummy for loan secured from the MFI. Panel A reports coefficient estimates and, in parentheses, standard errors clustered by sector of activity. Panel B reports the results of the test for mission drift. Medium Project is an indicator for projects over EUR 25,000. *Regulated* is the indicator for the period after the introduction of the loan ceiling (April 2009).
*, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

Appendix C. Probit model

Table C1. Probit model for loan approval: Matching without replacement

	Panel A: Coefficient estimates and marginal effects											
	(1)		**(2)**		**(3)**		**(4)**		**(5)**		**(6)**	
	Coef.	**SE**	**Marginal effect**	**SE**	**Coef.**	**SE**	**Marginal effect**	**SE**	**Coef.**	**SE**	**Marginal effect**	**SE**
Medium project ($\hat{\lambda}$)	-0.45***	(0.15)	-0.17***	(0.05)	-0.48***	(0.16)	-0.17***	(0.06)	-0.61***	(0.18)	-0.21***	(0.06)
Regulated ($\hat{\delta}$)	-0.30**	(0.13)	-0.11**	(0.05)	-0.34**	(0.13)	-0.12***	(0.05)	-0.33**	(0.14)	-0.11**	(0.05)
Regulated*medium project ($\hat{\mu}$)	1.04***	(0.19)	0.39***	(0.06)	1.10***	(0.19)	0.40***	(0.06)	1.16***	(0.19)	0.41***	(0.06)
With personal investment					0.17	(0.22)	0.06	(0.08)	0.24	(0.21)	0.08	(0.07)
With funds from other sources					-0.05	(0.17)	-0.02	(0.06)	0.06	(0.17)	0.02	(0.06)
Start-up					-0.52***	(0.17)	-0.19***	(0.06)	-0.47***	(0.15)	-0.16***	(0.05)
Services					-0.29	(0.20)	-0.10	(0.07)	-0.31	(0.22)	-0.11	(0.08)
Trade					-0.24	(0.21)	-0.09	(0.07)	-0.19	(0.23)	-0.07	(0.08)
Food and accommodation					-0.66***	(0.22)	-0.24***	(0.08)	-0.62**	(0.25)	-0.22**	(0.09)
Construction					-0.18	(0.20)	-0.06	(0.07)	-0.18	(0.21)	-0.06	(0.07)
Arts and entertainment					-0.33	(0.23)	-0.12	(0.08)	-0.33	(0.25)	-0.11	(0.09)
Unemployed for over 6 months									-0.44***	(0.11)	-0.15***	(0.03)
Female									-0.07	(0.13)	-0.02	(0.04)
Single									0.09	(0.11)	0.03	(0.04)
Education (# educational qualifications)									0.10***	(0.04)	0.03***	(0.01)
Household income									0.02	(0.08)	0.01	(0.03)
Vaucluse area (old branch)	-0.22	(0.22)	-0.08	(0.08)	-0.20	(0.24)	-0.07	(0.09)	-0.22	(0.24)	-0.08	(0.08)
Var area (new branch)	0.98**	(0.43)	0.36**	(0.16)	0.98**	(0.42)	0.35**	(0.15)	0.98***	(0.35)	0.34***	(0.12)
Alpes-Maritimes area (new branch)	0.49***	(0.17)	0.18***	(0.06)	0.56***	(0.18)	0.20***	(0.06)	0.50***	(0.19)	0.18**	(0.07)
Constant	0.19**	(0.09)			0.79***	(0.25)			0.60*	(0.31)		
Observations	380		380		380		380		380		380	
Pseudo R-squared	0.062				0.085				0.113			
	Panel B: Testing for mission drift with total marginal effects											
	(1)		(2)		(3)		(4)		(5)		(6)	
$\hat{\delta}$			-0.11**	(0.05)			-0.12***	(0.05)			-0.11**	(0.05)
$\hat{\delta}+\hat{\mu}$			0.27***	(0.05)			0.27***	(0.06)			0.29***	(0.06)
$\hat{\lambda}+\hat{\mu}$			0.22***	(0.07)			0.22***	(0.06)			0.19***	(0.06)

This table presents the results of estimating a probit model for the nearest neighbor matched sample, using the propensity score matching procedure (Rosenbaum & Rubin, 1983) without replacement, including the control variables successively. The dependent variable is the dummy for loan secured from the MFI. Panel A reports coefficient estimates, marginal effects, and the standard errors clustered by sector of activity in parentheses. Panel B reports the results of the test for mission drift using total marginal effects. *Medium Project* is an indicator for projects over EUR 25,000. *Regulated* is the indicator for the period after the introduction of the loan ceiling (April 2009).

*, **, *** represent significance at the 10%, 5% and 1% levels, respectively.