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Are business angel-backed companies truly different?

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Abstract

This paper investigates the impact of Business Angels on the financial structure of backed firms using several matching methods applied to a unique individual dataset of French companies over the 2010-2015 period. It shows that the signal effect of Business angel investment, improving access to external finance by the reduction of information asymmetry from another investor is limited. This paper contributes to the corporate finance literature by investigating the validity of corporate finance theories. It also brings an insight into the understanding of value added of BAN on backed firms bu focusing on certification effect of angels.

Keywords: Business angels, Financial Structure, Informal venture capital, Matching techniques

JEL classification: G24, L25, L26, M13, O16

1. Introduction

Recent advances in the dynamics of financing instruments for entrepreneurship (Drover et al., 2017; Wallmeroth et al., 2017) have highlighted Business Angels[1] (BAs hereafter) as prominent investors in the early stages for young and innovative firms (European Commission, 2016 and Lanstrom and Mason, 2016 and Witz et al., 2015). This point of view, however, does not find a univocal academic support. Despite the growing interest for this market segment (Edelman et al., 2017), results from both theoretical and empirical analysis on angels' activity still differ according to the methodological choices made and dataset used. The informational opacity due to the positioning of angels in early stage financing (Kraemer-Eis et al., 2018), their willingness to remain anonymous (Mason and Harrison, 2004) and the lack of tangibles and comparable data from an early stage makes this promising field of research as yet not undertaken. Debate is thus still open on the influence of the business angels networks[2] (BANs hereafter) on backed-companies (White and Dumay, 2017) especially in bank-based economies such as the French one (Bonini and Capizzi, 2019).

This paper seeks to shed some light empirically on the BANs' capacity to reduce information asymmetry and increase external financing conditions of backed firms thanks to several financial structure indicators. The investigation undertaken uses a unique dataset made up of French firms funded by French BANs 2010-2014 to compare BAN-backed to non-BAN-backed firms, using propensity score methods and panel data analysis[3]. Our results show that the angels' influence on firm

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[1] Following Mason and Harrison (2008), a Business angel is: a high net worth individual, acting alone or in a formal or informal syndicate, who invests his or her own money directly in an unquoted business in which there is no family connection and who, after making the investment, generally takes an active involvement in the business, for example, as an advisor or member of the board of directors. (Mason and Harrison (2008) p.309). For BAN characteristics, one can refer to Politis (2008), Capizzi (2015) or Landström and Mason (2016).

[2] Since the 1990s (Mason and Harisson, 1997) angels tends to regroup into a network that facilitates decision making and monitoring while reducing risk sharing and increasing diversification. The structuration of angels' market in the wake of the 2000s leads to a visibility of the angels' financing process and market and improves the mechanisms of agency cost reduction (Witz et al., 2015).

[3] This paper investigates two areas around angels' intervention (Bonnini et al., 2019). This first research field lies on the influence of angels as advisors and mentors and the second is the certification effect induced by the presence of angels. Research questions need separate analysis since to test the value-added hypothesis of angels' no equity counterparts' firms are needed. Indeed, by comparing equity-financed firms with non-equity-financed firms we isolate the influence of angels

financial structure is marginal. They do not radically reduce the information asymmetry either toward banking and financial systems, or toward stakeholders in the firm environment. Moreover, we also clarify the relationship between bank and trade credit and find marginal support of substitutability between these two prominent financing instruments to SMEs.

Our paper is distinguished from previous literature by the uniqueness of dataset uses that encompasses a total of 371 companies invested in by BANs 2001-2014. Moreover, the length and homogeneity of the period under review also mark a difference from previous empirical papers that either use one-shot surveys and cross-section analysis or reduced panel datasets.[4] By covering the wake of the global and financial crisis, we are considering angels' impact in a recovery context (Mason and Harison, 2015). Moreover, the length of the covered period enables us to distinguish between a short- and medium-term effect of angel financing on the capital structure of invested firms which is an under-researched question (Collewaert, 2016). Finally, the novelty of our research comes from the consideration of angels' certification effect compared to any other equity investment. To this end, we pay attention to several aspects of the financial structure to encompass the multinomial dimension of angels' intervention on backed-firms' financial decision making which is to our knowledge new in the literature (Landström and Sørheim, 2019). We notably focus on the leverage ratio and interest charges to explore external finance availability from banking institutions following BANs' funding, reflecting certification effect. We also investigate the angel's certification effect by studying the terms of the use of trade debt. While the two first indicators lead to exploring long-term relationship with financial systems, the latter two ratios allow the short-term financial environment that backed firms construct with stakeholders to be explored. Taken together, these aspects offer a new

on capital structure. However, this counterpart's dataset no longer suits the second research question since, to isolate the certification effect of angel compared to others financial sources, we must control for an external finance demand and for equity increases. By including equity-financed firms we can isolate a certification effect linked to angels compared to any other equity intervention.

[4] See Landstrom and Sorheim (2019) for a survey.

framework from which we draw fresh insight on angels' contribution to firms' development and growth compared to previous works.

Our research contributes to the entrepreneurship literature in a twofold way. From a theoretical perspective, our paper goes beyond the issue of the dilemma between the trade-off and the pecking order theories which admit the existence of an ideal capital structure but disagree on how it is established (Daskalakis et al., 2017; Fama & French, 2002). Considering firm and environment specific characteristics influence firms' financial decisions (Myers, 2001), we focus on the role played by BANs to determine to what extend their presence can shape the financial structure of the companies in which they invest. This aspect is to our knowledge under-researched in angel's literature (Landström and Sorheim, 2019). The second contribution to the entrepreneurial literature is related to the signalling theory (Leland and Pyle, 1977; Ross, 1977) since we show that the presence of BAN among the pool of investors is not neutral but, on the contrary, signals information to outside investors. In the vein of the signal theory, we show that angels' presence can be beneficial to backed firms considering the reduction of information asymmetry between insiders and outsiders although not in a systemic way.

The remainder of the paper is structured as follows: Section 2 reviews the literature and proposes hypotheses to be tested; Section 3 defines the econometric strategy; Section 4 presents and discusses the results obtained; Section 6 proposes robustness checks; and Section 6 concludes.

2. Literature review and hypotheses

2.1 Theoretical development for entrepreneurial finance

Given the important agency costs and information asymmetry in entrepreneurial financing decisions (Cassar, 2004), this paper uses traditional finance theory (Myers 1984, Myers and Majlouf, 1984) and signalling theory (Ross, 1977 and Spence, 2002) to investigate the financial structure of backed firms by business angels.

The traditional pecking order theory (POT) states that financing instruments follow a hierarchical order (Myers 1984, Myers and Majlouf, 1984). Internal funds would be preferred to bank debt that is itself preferred to external equity to avoid control rights.[5] Despite the theory having been built for larger and listed firms, recent research has extended, under conditions[6], prior findings to small, young and innovative firms (Epure and Guasch 2019 and Collewaert, Manigart and Aernoudt, 2010). Innovative and young firms often lack internal funds to finance investment opportunities and need outside financing to take investment opportunities (Vanacker and Manigart, 2010). However, their risk profile, implied by a high information asymmetry issue, limits recourse to bank debt. In turn, young and innovative businesses could be more likely to turn to private equity (like BANs) than banks, Indeed, while internal are still preferred to external funds, recent papers have highlighted a reversed order in the use of external finance (Minola et al., 2013) where equity can be preferred to bank debt[7].

The trade-off theory (TOT) states that capital structure is driven by a trade-off between the costs, like bankruptcy and agency costs, and the benefits, tax and agency conflicts associated with debt (Titman, 1984, Shyam-Sunder and Myers, 1999, Frank and Goyal, 2008). Given the entrepreneurial context, capital structure decisions are less affected by fiscal considerations than by information asymmetry and, therefore, we use the POT to explore BAN-backed companies financial structure (Cassar, 2004, Minola et al., 2013).[8]

Developed concomitantly with corporate finance and agency theories (Jensen and Meckling 1976), signal theory aims to depict how observables discriminatory and costly signals can reduce the

[5] In the case of the entrepreneurial market, information asymmetry leads to a “lemon” premium (Akerlof, 1970) that incentives opaque firms to prefer internal funds to any other financing instrument, reinforcing the POT according to internal fund preference.
[6] Vaznyte and Andries (2019) conclude that the POT is influenced by factors such as industry risk at the sectorial level and entrepreneurial orientation (EO) and break-even point at the firm level.
[7] The banking system is shown to be inefficient in screening and monitoring innovative projects (Paul et al., 2007). On the contrary, equity investors are better able to reveal the value of an innovative project (Colombo and Grilli, 2010). Moreover, BANs have human capital that can help innovative firms (Collewaert and Manigart, 2016)
[8] The recourse to the POT framework is empirically supported by recent research on French data by Van Hoang et al., (2018).

information gap between firms and outside investors (Spence, 2002). In an equity financing context with high information asymmetry, firms must signal their value to outside investors to obtain funding to finance future growth opportunities (Elitzur and Gavious, 2003). Signal theory can support and even supersede traditional corporate finance theories (Epure and Guasch 2019) to explain financing decision in an equity financing context for young and innovative firms (Hogan et al., 2017 and Mina and Lahr, 2018)

2.2 Review of the Influence of Angels investors

2.2.1 Business Angels' activity and networks

Measuring the influence of BANs[9] is a challenging though necessary task due to (i) the numerous contributions angels provide throughout the firm's life (Politis, 2008) and (ii) the tax advantages conceded by governments to this class of investors (Carpentier and Suret, 2013). Angels are characterized by a wide heterogeneity (Lahti, 2011), with strong national specificities that limits convergence of findings in both theoretical and empirical fields (Frid, 2009 and Savignac, 2007) especially given the high selection process inherent in the context of private equity financing (Dutta and Folta, 2016)[10] Unfortunately, despite the growth and employment potential of young and innovative firms there is a loss of interest on the part of the academic side because of data availability that discourages researchers and limits research developments (Landström and Sørheim, 2019).

Besides the opacity of the angels' market, the choice of unit of measurement of their contribution is also subject to debate. No ideal indicator(s) to measure the angels' network influence has been identified in the literature; the ratios proposed are determined by the nature of the research

[9] For a definition of angels see Mason and Harrison (1999)
[10] According to Riding et al. (2007), the rejection rate at the first stage in the investment decision process can go up to 90 percent of the business proposals. Their selectivity is confirmed by Croce et al. (2018) and Mason and Harrison (2015).

and must be taken carefully (Welch, 2011).[11] In this vein, we propose a set of indices resting upon the difference between *what angels have* (human capital) from *what angels are* (market certifier) following Bonini et al. (2019). We focus on *what angels* are, that is. market certifiers whose decisions send a signal on the quality of invested firms.

2.2.2 The multidimensional effect of BAN intervention

The literature present BAs as important economic players with a critical role in financing early stage firms with innovative orientation (Politis, 2008, 2016 and Witz et al., 2015). Although, their influence on financial structure still deserves investigation given the lack of empirical studies on this topic (Landström and Sørheim 2019).

When a BAN funds a firm, it sends a signal to the market indicating that the selected company has valuable innovative projects (Ko & McKelvie, 2018 and Elitzur and Gavious, 2003). Angels' investment act like a risk management mechanism that could elevate information asymmetry that weighs on financing constraints, limiting bank financing (Vanacker and Manigart, 2010, Bonini et al., 2019). In turn, backed firms with reduced agency problems would be more likely to obtain external debt financing after funding compared to their equity financed counterparts that can be materialized through an increase of financial debt differentials. This reasoning is summarized in the following hypothesis:

H1a: *BAN-backed firms should exhibit a higher level of debt following funding compared to their equity-financed counterparts, reflecting lower financing constraint due to the angels' certification effect.*

[11] The heterogeneity of indicators used is, at least, partly responsible for the contradictory results obtained (Landström and Mason, 2016). Since Angels' equity financing often goes to young and innovative companies, several papers focus on the influence of financial investment on patent filing (Kortum and Lerner, 2000; Bottazzi and Da Rin, 2002). Other scholars adopt an accounting perspective and, following, look at the gross added value or profits to measure firm performance whereas others use alternative indicators of firm growth (Levratto et al., 2017).

Besides the level of debt, the financing conditions under which loans are granted influence their use (Epure and Guasch 2015). POT stipulates that the level of information a firm is willing to disclose is strongly correlated to the financing instruments used. Prior to funding, both treated and control groups are characterized by a high information asymmetry that has motivated equity financing.[12] Consequently, both groups should record similar (and high) interest charges levels (Myers and Majlouf, 1984).[13] Following funding, BAN-backed firms benefit from angels' certification and presence on the board, allowing them to fund at better conditions or to renegotiate the terms of the contracts with banks. Hence, in subsequent years following funding, BAN-backed firms should record lower interest charges compared to their equity financed counterparts. This aspect constitutes our second hypothesis linked to the reduction of information asymmetry by BAN and their signal effect on external finance availability.

***H1b**: BAN-backed firms benefit from improved financial market conditions following funding compared to their counterparts, which is reflected in interest charges reduction.*

The scarcity of financing instruments for young and innovative firms (Bonini et al., 2018, Masiak et al., 2017) limits the capacity of firms to fund investments opportunities and ultimately weighs on the growth path (Levratto, 1996 and Psillaki and Eleftheriou, 2015). Among alternative instruments, trading debt appears to be the most prominent for entrepreneurial firms[14]. The use of trade credit in entrepreneurial firms is supported by both information asymmetry and transaction costs

[12] Opaqueness is not necessarily suffered by firms, it can answer to the will to maintain information about products for competitive proposes which is the case for innovative firms. Moreover, entrepreneurs' orientation may influence objectives that may differ from what corporate finance theory predicts. While some are engaged in profit maximisation, others could prefer a balance between work and family to growth and others might prefer to keep control right that can hampers the development of the firm. However, we argue that entrepreneurial orientation is not a concern since all the firms studied have agreed to open capital to increase growth opportunities and thus in profit maximisation mechanisms forcing them to adopt rational financing strategy to maximise firms' value Vaznyte and Andries (2019).

[13] The "lemon premium" (Akerlof, 1970) induced by information asymmetry problems for innovative firms operating in early stage financing increases the cost of banking debt both in absolute value and relatively to other financing sources (Vanakaert and Manignart, 2010)

[14] See (Cuñat and Garcia-Appendini, 2012) for a review on the use of trade credit. In addition to being an important source of funding from constrained firms (Masiak et al., 2017), trade credit offers buyers the capacity to build either a credit history or fixed asset to put as collateral to ensure quality when seeking bank loans. It also allows the relationship with customers and suppliers to be improved (Cuñat and Garcia-Appendini, 2012)

theories (Elliehausen and Wolken, 1993)[15]. In addition, the literature underlines two characteristics of trade debt to consider in this paper. First, companies operating in the high-tech sector in which intangible and specific assets are often hardly resalable make a frequent use of a trade debt instrument (Psillaki and Eleftheriou, 2015) Second, the trade debt is more often used in economic systems offering a weak creditor protection (Demirgüc-Kunt Maksimovic, 2001), an institutional feature corresponding to civil law countries (La Porta , Lopez-de-Silanes, Shleifer & Vishny, 1998).

The role of trade credit during and following the credit crunch received specific attention from both academics and policymakers (McGuiness and Hogan, 2016, Cabo-Valverde et al., 2016 and Psillaki and Eleftheriou (2015). In France, Psillaki and Eleftheriou (2015) empirically test trade credit theories using French manufacturing data. They confirm the redistribution view (Meltzer, 1960) of trade credit according to less credit constrained firms obtaining bank loans and redistributing to more constrained firms in the form of commercial debt during credit crunch periods. On the contrary, García-Teruel and Martinez-Solano (2010), using European data, support the substitution views according to which bank and commercial debts are substitutes for one another. Cabo-Valverde et al., (2016) also investigate the use of trade credit following a crisis. Although not being able to discriminate between alternative views of trade credit, they stress that the use may depend on the financial situation of firms. In this paper we go beyond the apparent contradiction between theories and, in the vein of Demirgüc-Kunt Maksimovic, (2001) argue that both theories may articulate into a financing continuum (Berger and Udell; 1998) according to financial situations. More precisely, at the beginning of the life cycle, more constrained firms will turn to trade credit as an alternative to bank loans (substitution effect). While they accumulate credit history from suppliers and thus become less informationally opaque, firms will tend to act like financial intermediaries and redistribute bank

[15] While adverse selection and moral hazard reduction are argued to be better achievable by suppliers than banks (Cuñat and Garcia-Appendini, 2012) justifying the recourse to trading debt for credit constrained firms, the latter also and most importantly use trade debt to reduce transaction costs to fund working and fixed capital needs (Elliehausen and Wolken, 1993). Empirically, (Masiak et al., 2017) provides evidence on the deep use of trade debt instruments for entrepreneurial firms.

financing to other firms in the form of short-term commercial debt (redistribution view)[16]. Consequently, prior to investment, backed firms should be characterized by a high level of information asymmetry that can be costly to reduce for banks limiting the use of bank loans. In addition, the reduction in information asymmetry can also be costly to acquire for other firms, resulting in expensive trade credit conditions for backed firms (Minola et al., 2013). The positive signal effect of angels' investment goes along with the reduction of agency costs that improve trade debt conditions in terms of payment, delay and late payment. Moreover, beyond the positive signal effect, angels open the doors of their network to entrepreneurs, helping them to find better financing conditions within the angels' network (Politis, 2008, Bonini et al., 2018, Collewaert el al., 2010). Hence, backed companies should record a higher trade credit reduction, reflecting reduced information asymmetry problems associated with BANs presence on board.

H2a: *Backed firms benefitting from the certification effect of angels would record a higher trade debt reduction reflecting a reduced information asymmetry issue.*

However, the theoretical literature is not univocal on the signal effect of equity investment on the use of trade debt that can depend on sectoral needs and risk, entrepreneurial orientation and strategic or personal goals pursued by entrepreneurs (Vaznyte and Andries, 2019).

Beyond the level of trade debt, the delay in payment of that commercial debt can be a sound indicator of the relationship with the stakeholders that angels are likely to improve. About this last aspect, we expect that angel-backed companies benefiting from the angels' network will find more favourable conditions which materialize in longer payment delays. Indeed, as stated above, suppliers take an

[16] The use of trade debt grants implicit equity stakes of the supplier equal to the amount of the net present value of future profits. In the case of bankruptcy on the customers' side, trade debt suppliers come after debt suppliers which motivates a higher "lemon premium" to compensate lower creditor protection of suppliers compared to bankers. This implies that a trade creditor is more likely to be conciliant towards financing issues of the customer like liquidity shortage while banks are likely to be more prone to pursue liquidation (Cole, 2010 and Huyghebaert et al., 2007).

implicit equity stake in firms that incentivates them to adopt a conciliant contract if firms are financially constrained, leading to longer payment delays.

H2b*: Backed firms will tend to have longer payment delay induced by improved relationship with suppliers.*

3. Empirical strategy and variable operationalization

Our empirical investigation rests upon an initial dataset of 370 firms invested in by BANs between 2010 and 2014 provided by France Angels, the national network of business angels. In addition, we have at our disposal two datasets, all provided by the French National Institute of Statistics.[17] Merging BAN-backed companies to these datasets enables us to compose an unbalanced panel of 370 BAN-backed companies over the 2010-2014 period to be compared to a reference group of equity financed firms.

3.1.Definition and measure of variables

The choice of indicators to properly highlight a firm's financial structure is determined by the context, by the objectives of the users and by data availability (Barnes, 1987). When looking at angels' and entrepreneurial literature, it appears that results obtained greatly depend on the indicators chosen to describe outcomes (Rauch et al., 2009 Runyan et al., 2008). Hence, to avoid partial and misleading conclusions, we consider several outcomes to capture the heterogeneous aspect of the certification effect of angels on the reduction of information asymmetry.

[17] The first dataset (FARE for Fichier Approché de Résultats d'Entreprises) contains the tax report, mainly composed of the balance sheet and the profit and loss statement of any taxable corporate company located in France. The second source (CLAP or Connaissance Locale de l'Appareil Productif) provides information on the location, the age and the legal status of the companies. The coverage and the homogeneity of datasets is ensured from 2009 (with also some limits in 2012 for some balance-sheet variables, limiting historical on pre-treatment data accumulation

The first ratio we use to describe the liabilities structure is a debt ratio, noted *DebtR*, defined as the amount of financial debt scaled by total debt. Table 4 in the appendix presents the definition of the explained variables used and the main descriptive statistics.

Another important aspect that concerns a firm's financial strategy is the costs of financial debt. This component of financial structure shapes the financing pattern (Kremp and Stöss, 2001), reflects companies' internal characteristic and disclosure quality (Anderson et al., 2004) and influences external finance availability (Ko &McKelvie, 2018). The cost of debt, noted *DebtCost* is defined by interest and similar charges, noted *interest,* scaled by the *gross operating profit* (GOP), which proxy the EBITDA, to control for scale effect.

The third ratio considered is the share of trade debt which reflects the capacity of a company to rely on its suppliers to finance its operating cycle. Trading debt is also a proxy for information asymmetry that increases credit constraints (Psillaki and Eleftheriou, 2015). The weight of the trade debt in the total of external resources is approximated by the ratio of the trade accounts payables and the total amount of debt.

The last ratio under consideration allows us to go beyond the level of trade debt that can be misinterpreted. We thus consider the days of payables outstanding that represent the average time a firm takes to pay its suppliers. Noted *DPO* this ratio allows studying in depth the multifaced character of trade debt (Cuñat and Garcia-Appendini, 2012).

3.2. Comparison strategy

3.2.1. Matching approach

Angels do not randomly invest in projects and companies but select them according various criteria (Maxwell et al., 2011). To circumvent the risk of selection bias resulting from the comparison between invested companies and the average firm, it is necessary to neutralize the difference between backed and non-backed companies by composing comparable samples through a matching procedure.

The aim of matching literature[18], initially theorized by Rubin (1973), Cochran and Rubin (1973), and Rosenbaum and Rubin (1983), is to balance the distribution of covariates of groups under research, named treated group (angel-backed companies) and the control group (non-angel-backed companies) to estimate properly the causal effect of a treatment via a scalar, named propensity score, summarizing the covariates used in regression. The propensity score defines the probability of receiving a treatment and is used to match observations. Applying this technique makes it possible to estimate the average angels' effect on backed-firms, namely the average treatment of treated (ATT) with a lower risk of sample bias due to selection effect. ATT is defined as:

$$ATT = \frac{1}{N}\sum_{i=1}^{N}(Y_i(1)|BA = 1, X = x) - (Y_i(0)|BA = 0, X = x)] \qquad (1)$$

where N is the number of treated firms and BAN a dummy variable equal to 1 for angels-backed firms and 0 otherwise.

Matching procedure is initiated with the estimation of a logistic equation that determines the probability of receiving a treatment based on observable characteristics and distance metric (step 1). The aim of the logistic equation is to compute the propensity score (step 2) that will be used to match observation based on observable financial characteristics. Once the matching is obtained, its balancing is assessed (step 3) to ensure efficient causal treatment effect estimations (step 4).[19]

3.2.2 *Model and variable operationalization*

Beyond selection bias, other types of distortion arise. One is driven by unobservable effects resulting from angels' decision making (Jeffrey et al., 2016, Maxwell et al., 2011). Bertrand et al. (2004) introduce a procedure to reduce this bias through the settlement of the double difference

[18] Austin (2011) Caliendo and Kopeinig (2008) present the various propensity score matching techniques. Table 3 in the appendix recalls the main different techniques.

[19] For further information about matching approach, see Rosenbaum and Rubin (1983) Stuart and Rubin (2007) and Stuart (2010)

estimator.[20] Hence, to capture angel influence of capital structure of a backed firm over years, net of selection bias and unobservable effects, we compute outcome differentials over the timeframe of the funding year. This method enables us to control for an unobservable time invariant, firm specific and business cycle effects occurring during the event window. It also allows angels' value added at different stages of its relationship with entrepreneurs to be explored (Kelly and Kim, 2018), through outcome variables expressed as follows:

$$Diff_{i,x}\, Y = Y_{i,t+x} - Y_{i,t} \qquad (2)$$

With $x \in \mathbb{N}, x = \{1, \ldots 6\}$ represents the number of years span used to calculate outcome variables. We computed outcome variables over 1 to 6 years intervals when available for both treated and control firms.

To determine the probability of getting funds from a BAN, we run the following logistic model, based on propensity score distance metric:

$$Pr\,(BA_{i,t}) = \alpha + \beta X_{i,t} + \varepsilon_{it} \qquad (3)$$

Where Y_{it} is a dummy variable indicating angel presence, it takes the value 1 if a firm *i* receives an angel investment and zero otherwise. $X_{i,t}$ is the full set of desired covariates for matching and ε_{it} is a standard error term. All variables used are winsorized at 5 and 95 percent level to reduce the impact of outliers. Matching is performed on a year-by-year basis and retained control units must record equity increase on the same year as treated units. The literature helps determine the appropriate proxies that capture the decision making criteria of angels, being organised or not in networks (Mason and Stark, 2004, Croce et al., 2017, 2018). While the first generation of studies about angels' activity

[20] A common trend assumption is required to perform efficient double difference matching estimators. According to this assumption a common time trend in outcomes before treatment is required between treated and control units to ensure efficiency of matching.

highlighted the heterogenous and informal nature of investment decisions[21] of individual angels, recent studies point out the professionalisation of angels' activity and decision-making process, especially within the angels' networks (Capizzi, 2015), which rely on more objective and comparable data between firms to reduce coordination and transaction costs (Carpentier and Suret, 2015 and Croce et al., 2017). Furthermore, Brush et al., (2012) and Mason and Botelho (2016) highlight the importance of tangible and objective criteria in the initial stage of investment while Paul et al. (2007) conclude with the importance of financial ratios for investment decision making. In addition, research on early stage financing highlights the low explanatory power of personal factors on financing decision making (Cassar, 2004 and Cole 2010). Based on this background and following Capizzi (2015) and Bonnini et al., (2019) we select a set of comparable financial indicators on which BANs might rely to make their decision.

We introduce a profitability ratio (*ROA)* (in logarithm) measured by the EBITDA scaled by total asset that takes account of the financial soundness of firms. We also include the stock of intangible assets (*intangibles)* in logarithm to account for innovative orientation (Landström and Mason 2016). The stock of tangibles asset expressed in logarithm is also included to capture the importance of collateral (Mason and Stark, 2004, Carpenter and Suret, 2002). To control for growth opportunities, we also include sales (*Sales*) in logarithm. Finally, the age of the firm since the foundation year (*age*) and the number of employees (*Employees*), both in logarithm, are also added to encompass the quality of the project and the capacity of firms to attract working forces. *Location* and *Industries* dummies are also included as control variables to control respectively for local conditions (Giot and Schwienbacher, 2007) and for preference of BAN for technological activities (Bonini et al., 2018, Politis, 2016 and Van Osnabrugge, 2000). Finally, for robustness purposes, we add to the

[21] See Croce et al., (2016) Landstrom and Sorheim (2019) for a review of angels' decision-making studies.

matching model a proxy of Tobin's Q to account for firm performance as well as the level of financial debt prior to funding to account for the level of information asymmetry.

4. Results

4.1. Investment process and firms' characteristics

This section aims to bring support to the funding decision-making process of BANs (Capizzi, 2015, Croce et al., 2017, Brush et al., 2012; Carpentier and Suret, 2015 Jeffrey et al., 2016, Maxwell et al., 2011 Riding et al., 2007).

The estimation of the probability of being financed by angels, given observable financial characteristics is achieved using a logistic model where the dependent variable is the dummy variable indicating angel investment. The results are available in Table 1.

Findings indicate a stable and significant positive influence of the *ROA* on angel funding suggesting that business angels are twice as likely to invest in firms with higher growth margin potential than others. Indeed, a high *ROA* is associated with the capacity to increase margins which is, although not the only one, an interesting financial aspect of angels' decision making (Capizzi, 2015, Mason and Bothelho, 2016). This result also finds support in Croce et al.(2017) who investigated Italian data from 2008 to 2014.

A negative relationship is found for *Sales* indicating that angels'-backed firms do not necessarily generate incomes at time of investing which is corroborated by the negative sign associated with the *Age*. The younger firms have a greater probability of being funded. Besides, higher levels of tangible assets are associated with a lower probability of being selected by a BAN as shown by the negative coefficient of the variable *tangible asset*. This finding reflects the importance of the stock of tangible assets in influencing treatment probability reflecting angels' preference for young and innovative firms. This result could also capture the lack of internal funds and assets to pledge as collateral that characterize BAN-backed companies (Lahti & Keinonen, 2016). On the contrary, we find a positive influence of *intangible assets* on the probability of being funded by a BAN. Indeed, results indicate that the probability of being financed by a BA strongly increases with the stock of intangible assets, confirming angels' preference for innovative activities (Politis, 2016). As in Croce et al. (2018) the firm size, proxied by number of employees, is shown to be an important driver influencing positively the probability of being financed by a BAN. The relatively high explanatory power of our model of BAN decision making (81 percent) highlights that the decision-making process by BAN is oriented towards comparable and observable aspects of firms (Carpentier and Suret, 2015 and Croce et al., 2017) suggesting a professionalization in the BANs decision-making process.

Table 1

Probability of being invested by Angels

Variable	Odds ratio
ROA	2.06 ***
	(16.40)
Intangibles	1.46 ***
	(-3.62)
Tangibles	0.84 ***
	(10.75)
Sales	0.86 ***
	(-5.91)
Age	0.009 ***
	(-45.30)
Employees	1.79***
	(7.37)

Intercept	37041 ***
	(11.07)
Fixed Effect	
Localisation	YES
Industries	YES
Observations	179142
Pseudo R^2	0.8180
Log Likelihood	-1470.90

*Notes: This table presents logistic regression of the dummy variable equal to 1 of backed firms and 0 otherwise. Variables are lagged to avoid the treatment assignment influencing covariates' level. Variables included are expressed in logarithm. * ** and *** respectively denotes 10, 5 and 1 percent significance*

One important concern about the matching procedure is the balancing of results which ensures the comparability of the multidimensional distribution of covariates in treated and in control groups (Stuart, 2010). Indeed, unlike regression-based methods, matching methods allow examination of the distribution of predictors and have a straightforward diagnosis resulting in an assessment of the effectiveness of a treatment. Table 6 in the appendix summarizes the balancing test before and after mahalanobis matching. The results indicate that balancing is achieved through a substantial bias reduction around 90 percent for almost all variables[22]. After matching, the two groups are not statistically different for almost all the dimensions of multivariate matching, ensuring a well-balanced procedure.

Another concern refers to event study research design related to the pre-trend assumption (PTA) according to which trends of outcomes variables should not exhibit different dynamics between both groups before treatment. To ensure that the pre-treatment outcomes trends are similar between groups,

[22] With the exception of the number of employees and the localisation of firms where matching only succeeds in reducing bias respectively by 67.3 percent and 49.3 percent

we compute the growth rates of the outcomes variables on a year-by-year basis and compare the growth rates of the outcomes variables through a mean test. Table 9 in the appendix displays the results of the PTA and shows that the trends of the outcomes variables do not show different dynamics ensuring a robust treatment effect analysis.

4.2. Assessment of BANs influence

This section presents the results of the investigation on the impact of BANs on the capital structure of backed firms when distortions resulting from the sample composition are eliminated. Table 2 records the results for the hypotheses posed. Baseline matching is performed using a mahalanobis distance metric. This technique allows us to control for interconnectedness between covariates as it includes the correlation matrix in the distance metric. Covariates being defined at the firm level, it allows one to take account of the owner-managers' financial orientation and behaviour leading to a better balance between groups.[23]

The upper part of table 2 shows that angel-backed companies record higher levels of financial debt compared to non-BAN-backed firms. Although the difference between the treated and control group hardly achieves a significant level, we can notice that the accumulation of financial debt is systematically higher for the treated group compared to the control group (regardless of the timeframe). This result indicates that angels-backed companies achieve financial debt accumulation in a higher proportion than control firms do, though not in a significant way. Consequently, we bring a weak support for *H1a* and conclude that angels have a limited influence on the accumulation of financial debt. The same conclusion holds for the hypothesis about debt cost. The coefficient of the equation determining the cost of the debt for the test group is not significantly lower than the one obtained for the reference group, regardless of the timeframe (Second part of table 2). Hence, *H2b* is

[23] Mahalanobis matching takes account of the idiosyncratic behaviour leading to a better matching adjustment of covariates distribution between groups compared to other parametric (nearest neighbours) or non-parametric (kernel) techniques.

not supported. One possible explanation is that grants certification effect of the angels, reduces information asymmetry and leads to better conditions of financial debt contracts (Elitzur and Gavious, 2003). However, this mechanism can be substantially offset by the nature of backed firms which are involved in innovative and risky activities (Edelman et al., 2017). The systemic effect is limited and underdetermined. It can depend on the prominence of angel signal effect in terms of amount invested and of quality of monitoring (Ko & McKelvie, 2018).

Overall, the results indicate a weak support for the certification effect of BAN to the financial system compared to any form of equity investment.

A similar conclusion can be transposed to the certification effect of BAN to stakeholders of the firms' environment. When comparing trade debt level differential, one can see that although not significant only for the higher time frame, differential is, above all, negative. This indicates a higher reduction of trade debt for backed companies reaching up to 10 percent five years after funding. Since trade debt is more often used by credit constrained firms (Huyghebaert et al., 2007) a higher decline of trade debt in angels-backed companies can be interpreted as a decrease in information asymmetry. Indeed, following the trade debt and agency costs literature, BAN investment would create a certification effect that would enhance firm visibility and strengthen entrepreneurs' networks making it possible to obtain more favourable financing conditions (Edelman et al., 2017). This interpretation is supported by prior studies (Politis, 2008, Ko & McKelvie, 2018) which considers that BANs are not only shareholders but also a pro-active stakeholder involved in the firm management (Wiltbank, 2005; Macht and Robinson, 2009).

Consequently, *H2a* is partially supported, indicating a limited certification effect on BAN compared to a certification effect of any other form of equity participation.

When regarding DPO, we notice, unlike previous indicators, that the differential does not exhibit any patterns and consequently *H2b* cannot find any empirical support. The capacity of angels to relax DPO is thus not confirmed.

The findings regarding the certification that BAN would grant to stakeholders only benefits marginally firms with high trade debts and do not change substantially the conditions under which trade debt contracts are expressed. The findings do not show a significant difference between both groups given the proximity of treated and control firms in their financing choices and due to the heterogenous nature of angels' value added (Collewert and Manigart, 2010), which is not covered by data at our disposal. Moreover, as suggested by Vaznyte and Andries (2019), other parameters such as entrepreneurial orientation and personal goals can influence external finance choices for entrepreneurial firms.

Finally, our results suggest a substitutability relationship between trade and financial debt. Indeed, our results indicate that the decrease in trade debt observed in backed companies goes along with an increase in the financial debt ratio. This suggests that (i) trade and financial debts are more used as substitutes than as complements for treated firms and that (ii) an information asymmetry reduction mechanism can be associated with angel financing.

Table 2

. Result of the ATT

Variable	Treated	Control	Difference	S. E	T-Stat	treated observations		Control observations
						Off support	On support	
Differential Financial DebtR (*H1*)								
1 Year differential	0.10	-0.06	0.16	0.07	2.30 **	113	241	26,288
2 Years differential	0.26	-0.06	0.32	0.26	1.22	221	35	15,056
3 Years differential	0.39	-0.01	0.40	0.30	1.34	201	32	12,089
4 Years differential	0.53	-0.08	0.61	0.34	1.78 *	109	28	8,921
5 Years differential	0.37	-0.07	0.44	0.35	1.25	9	29	3,869
Differential DebtCost (*H2*)								

1 Year differential	0.0004	0.0004	0.0001	0.0106	0.01	186	492	18,445
2 Years differential	0.0071	-0.0032	0.0103	0.0117	0.88	125	345	10,121
3 Years differential	0.0068	-0.0026	0.0094	0.0126	0.75	87	253	7,516
4 Years differential	0.0090	0.0156	-0.0066	0.0174	-0.38	25	114	4,578
5 Years differential	0.0316	0.0130	0.0186	0.0252	0.74	5	33	4,082
Differential Trading Debt (*H3*)								
1 Year differential	-0.02	-0.01	-0.01	0.01	-0.38	186	492	18,477
2 Years differential	-0.02	-0.02	0.00	0.02	-0.22	125	345	10,136
3 Years differential	-0.04	-0.02	-0.02	0.02	-0.85	87	253	7,524
4 Years differential	-0.03	0.00	-0.03	0.03	-0.94	25	114	4,584
5 Years differential	-0.07	0.02	-0.09	0.05	-1.73 *	5	33	4,089
Differential DPO (*H4*)								
1 Year differential	-1.08	-9.07	7.99	7.73	1.03	186	493	19,503
2 Years differential	3.25	-6.52	9.77	11.45	0.85	125	346	10,495
3 Years differential	5.57	0.21	5.36	11.12	0.48	25	114	7,773
4 Years differential	-13.39	7.08	-20.47	18.32	-1.12	25	114	4,714
5 Years differential	9.62	13.76	-4.14	14.14	-0.29	5	33	4,179

*Notes: This table present results from the outcome analysis provided by mahalanobis matching using 1 neighbours. S.E records the standard deviation of difference, T-Stat record the t-statistic of the equal mean test, N treated and N control represents respectively the number of treated and control observations under study.*and ** respectively represent 0.1 and 0.005 significance level.*

5. Robustness checks

Since the theoretical literature about matching does not provide a clear guidance to empirical researchers with some rare exceptions (Stuart, 2010), we apply an alternative matching technique to test the sensitivity of our results to the approach used and run alternative specifications to check for the robustness of our results.

This sub-section presents the results of robustness checks made using an alternative matching approach, namely *k*-nearest-neighbours (*k*-NN hereafter with k the number of neighbours selected) using Euclidian distance. The results are available in table 7. A balancing of this alternative method can be found in the appendix, in table 8. While the Kernel approach creates control groups using every information within bandwidth and excluding any observation outside of it; NN only consider the nearest (or the *k*-nearest) point(s) even if far away from a treated unit in terms of propensity score. Consequently, kernel matching can produce a smoother estimation of density function of the propensity score.

Table 7 shows that the results obtained with alternative specifications confirm the ones obtained with the baseline approach. Outcome analysis confirms the weak influence of angel on the reduction of information asymmetry regardless of the timeframe although information asymmetry reduction mechanisms seem to occur.

6. Conclusion and research agenda

This paper investigates whether the financial structure of angel-backed firms differs from the non-backed ones. The results of our empirical analysis partially support the theory according to angel's presence influencing financial structure. This research contributes to the literature on corporate finance, shedding some light on the role played by Business Angels as equity investors. Our results sustain the possibility of a certification effect since BAN-backed companies are less dependent on trade-debt than non-backed ones but tend to raise some doubt about the capacity of these investors to significantly influence the perception of a bank of the backed firms' risk. The advantage BANs provide to invested companies is thus marginal and may be heterogenous due to differences in human capital. The reliability of the results obtained is demonstrated thanks to the use of various matching methods, the use of parametric and non-parametric approaches and the use of alternative distance metrics to compute propensity scores. The findings may be partially explained by the fact that BANs are non-professional investors, with high heterogenous capacities. They also indicate that they are less called by entrepreneurs to benefit from their contacts in their role as certifiers than for their entrepreneurial capabilities.

The policy implications of our findings are potentially important. Indeed, our results provide new support for entrepreneurship policy in the informal capital market to strengthen the growth of recovery in a post-global crisis context. Whereas financial innovations tend to facilitate the entry of non-professional investors in the small firm financing market, it is important to question their capacity to radically and significantly change the firms' growth path. Shedding some light on this field, it is all the more important that we reveal a contradiction between the effectiveness of BANs and the qualities attributed to them, often presented as key partners with human and social capital skills. This central point should be kept in mind by entrepreneurs when starting a relationship with an angel. The deal should then concern not only the financial support but also the non-financial aspects of the relationship.

Despite the strength of our results granted by the uniqueness of our research setting, our study suffers from certain limitations that need to be addressed in future studies. First, the test group is only composed of firms funded by BANs members of the French federation of Business angels' networks. Even if they realize most of the deals registered in France, they can be specific and, consequently, different from unaffiliated BANs, resulting is a possible sample bias when estimating the treatment effect. Indeed, membership in an angel network provides a higher level of information and enables individuals to share experience and know-how with other members, making them more similar to professionals. Second, more qualitative information would be informative to characterise the relationship between entrepreneurs and angels since they might influence treatment effect. In this vein, the relationship between angel's finance and backed firms' developments should encompass the aspect related to entrepreneurial orientation and personal goals pursued by entrepreneurs. Finally, and linked to the previous caveat about the heterogenous nature of angels, the heterogenous determinants of financial structure of early stage companies should be considered to have more reliable evidence of BAN certifications effects compared to other equity investors.

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Appendix

Table 3

Road map of matching methods

Methods			Bias		Variance	
NN-matching *(Rubin, 1973)*	Radius		(-)	(+)	(+)	(-)
K-NN	Kernel Matching *(Becker & Ichino, 2002)*		(-)	(+)	(+)	(-)
K-NN	Mahalanobis matching (*Stuart and Rubin 2007)*		(-)	(+)	(+)	(-)
Parameters						
Number of nearest neighbours	Single	Multiple	(-)	(+)	(+)	(-)
Caliper threshold	With	Without	(-)	(+)	(+)	(-)
Replacement	With	Without	(-)	(+)	(+)	(-)
Bandwidth with KM	Small	Large	(-)	(+)	(+)	(-)

Note: This table indicates the advantages and the disadvantages of several matching methods and options. (+) increases and (-) decreases.

Table 4

Definitions and descriptive statistics

Variable	Definition	Source	Sample	Obs	Mean	Std. Dev.	Min	Max
Dependent Variables								
Financial Debt ratio	$\frac{Financial\ Debts_{i,t}}{Total\ \ Debts_{i,t}}$	FARE (Insee)	BAN	2160	0.33	0.27	0.00	0.79
			Non-BAN	276040	0.25	0.25	0.00	0.79
DebtCost	$\frac{Interest\ charges_{i,t}}{GOS_{i,t}}$	FARE (Insee)	BAN	2153	0.0	0.1	-0.2	0.2
			Non-BAN	296,240	0.03	0.06	-0.04	0.18

Trading Debt	$\frac{Suppliers\ debt}{Total\ Debt_{i,t}}$	FARE (Insee)	BAN	2151	0.3	0.2	0.0	0.7
			Non-BAN	296010	0.3	0.2	0.0	0.9
Day payable outstanding (DPO)	$\frac{Suppliers\ debt}{Total\ cost\ of\ purchase\ of\ goods\ sold\ _{i,t}}$ *365	FARE (Insee)	BAN	1944	92.2	67.3	1.0	316.4
			Non-BAN	368535	55.9	48.7	1.0	224.9
Independent Variables								
Age	Year between date t and the creation of the firm.	CLAP (Insee)	BAN	2160	1.8	0.6	0.7	4.1
			Non-BAN	536800	3.3	0.3	2.6	3.7
Effectives	Number of employees	CLAP (Insee)	BAN	2159	1.6	1.0	0.0	3.3
			Non-BAN	531150	1.3	1.1	0.0	2.9
Return on Asset (ROA)	$\frac{GOS_{i,t}}{Total\ Assets\ _{i,t}}$	FARE (Insee)	BAN	2153	0.8	0.3	0.3	1.3
			Non-BAN	296531	0.2	0.6	-17.0	19.4
Intangible Assets	Amount of intangible assets	FARE (Insee)	BAN	2160	3.64	1.84	0.00	5.25
			Non-BAN	536799	2.4	2.0	0.0	5.3
Sales	Total Sales on a given fiscal year	FARE (Insee)	BAN	2143	1.3	2.4	0.0	6.9
			Non-BAN	536800	2.9	3.2	0.0	7.7
Tangible	Amount of tangible assets.	FARE (Insee)	BAN	2160	3.3	1.9	0.0	6.6
			Non-BAN	536799	4.4	1.7	0.0	6.6
Sector	Categorical variable to classify industries	CLAP (Insee)	BAN					
			Non-BAN					
Location	Geographical categorical variable	CLAP (Insee)	BAN					
			Non-BAN					

Table 5

Correlation matrix

	ROA	***Sales***	***Age***	***Employees***	***Tangible***	***Intangibles***	***Interest Charge***	***Commercial Debt²***	***DPO***	***Financial Debt***
ROA	1									
Sales	-0.07	1.00								
Age	-0.05	0.07	1.00							
Employees	-0.16	0.12	-0.11	1.00						
Tangible	-0.10	0.15	0.04	**0.63**	1.00					
Intangibles			-							
	-0.14	0.27	0.05	0.40	0.37	1.00				
Interest										
Charge	-0.04	0.11	0.05	0.21	0.22	0.15	1.00			
Commercial										
Debt	0.03	0.22	0.06	-0.01	-0.03	-0.01	-0.06	1.00		
DPO			-							
	-0.07	-0.12	0.04	-0.01	-0.04	0.02	0.01	0.30	1.00	
Financial			-							
Debt	-0.05	0.05	0.02	0.01	0.17	0.13	0.18	-0.43	-0.06	1.00

Table 6

Smooth matching using Mahalanobis distance

Variable	Unmatched Matched	Mean Treated	Control	percent bias	percent reduction bias	t-test	t p>t
	U	0.8	0.2	182.7		54.7	0.00
ROA	M	0.8	0.9	-7.7	95.8	-2.8	0.01
Sales	U	1.2	3.4	-75.3		-24.3	0.00

	M	1.2	1.2	1.8	97.6	0.6	0.55
	U	1.8	3.4	-401.4		-247.1	0.00
Age	M	1.8	1.8	1.9	99.5	0.4	0.71
	U	1.7	1.3	41.9		14.5	0.00
Employees	M	1.7	1.5	13.7	67.3	3.9	0.00
	U	3.3	4.4	-65.4		-25.4	0.00
Tangibles	M	3.3	3.3	2.1	96.7	0.5	0.59
	U	3.7	2.5	64.3		22.7	0.00
Intangibles	M	3.7	3.6	7.7	88.0	2.1	0.04
	U	58.2	50.9	45.1		17.6	0.00
Industry	M	58.2	58.3	-0.4	99.1	-0.1	0.92
	U	42.1	50.4	-26.4		-10.1	0.00
Localisation	M	42.1	46.3	-13.4	49.3	-3.4	0.00

Notes : "U" refers to matched sample "M" to matched sample. percent bias represents the standard mean difference between both groups while "percent reduction bias" represents the reduction of bias following matching. The last two columns record respectively student statistics of equal mean test and associated decision rules.

Figure 1

Smooth matching using Mahalanobis distance

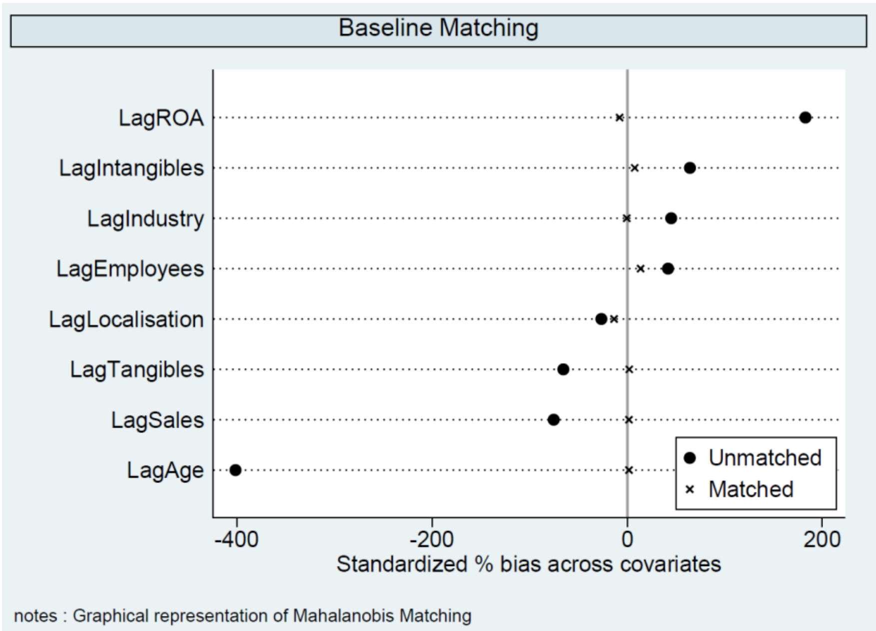

Table 7

Alternative matchings approaches

Technique	TimeFrame	Treated	Controls	Difference	S.E.	T	Treated observations: Off Support	Treated observations: On Support	Control observations
				Differential Financial Debt (*H1*)					
Kernel	*1 Year differential*	0.18	-0.02	0.19	0.18	1.07	236	116	26,288
	2 Years differential	0.26	-0.03	0.29	0.26	1.1	214	35	15,056
	3 Years differential	0.39	-0.03	0.42	0.30	1.4	201	32	12,089
	4 Years differential	0.53	0.02	0.51	0.34	1.49	109	28	8,921
	5 Years differential	0.47	-0.04	0.52	0.37	1.4	11	27	3,869
5-NN	*1 Year differential*	0.10	-0.02	0.12	0.07	1.62	111	241	26,288
	2 Years differential	0.26	-0.03	0.29	0.26	1.12	214	35	15,056

	3 Years differential	0.39	-0.03	0.42	0.30	1.41	201	32	12,089
	4 Years differential	0.53	0.02	0.51	0.34	1.51	109	28	8,921
	5 Years differential	0.37	-0.05	0.41	0.35	1.17	9	29	3,869
1-NN	*1 Year differential*	0.10	-0.03	0.12	0.12	1.04	111	241	26,288
	2 Years differential	0.26	-0.02	0.28	0.26	1.06	214	35	15,056
	3 Years differential	0.39	-0.03	0.42	0.30	1.4	201	32	12,089
	4 Years differential	0.53	0.04	0.49	0.34	1.42	109	28	8,921
	5 Years differential	0.37	-0.05	0.42	0.35	1.18	9	29	3,869
				Differential DebtCost (*H2*)					
Kernel	*1 Year differential*	0.00	0.00	0.00	0.01	-0.02	180	493	18,445
	2 Years differential	0.01	-0.01	0.02	0.02	1.03	117	346	10,121
	3 Years differential	0.01	0.00	0.01	0.02	0.66	86	253	7,516
	4 Years differential	0.01	-0.01	0.02	0.02	1.11	24	114	4,578
	5 Years differential	0.03	0.00	0.03	0.03	0.85	5	33	4,082
5-NN	*1 Year differential*	0.00	0.00	0.00	0.01	-0.19	180	493	18,445
	2 Years	0.01	-0.01	0.02	0.01	1.35	117	346	10,121

	differential								
	3 Years differential	0.01	0.00	0.01	0.02	0.47	86	253	7,516
	4 Years differential	0.01	-0.01	0.02	0.02	0.87	24	114	4,578
	5 Years differential	0.03	0.00	0.03	0.03	1	5	33	4,082
1-NN	*1 Year differential*	0.000	-0.001	0.001	0.012	0.12	180	493	18,445
	2 Years differential	0.007	-0.008	0.016	0.012	1.25	117	346	10,121
	3 Years differential	0.007	-0.005	0.011	0.018	0.62	86	253	7,516
	4 Years differential	0.009	-0.019	0.028	0.022	1.28	24	114	4,578
	5 Years differential	0.032	-0.009	0.041	0.044	0.93	5	33	4,082
Differential Trading Debt (*H3*)									
Kernel	*1 Year differential*	-0.02	0.02	-0.03	0.03	-1.19	180	492	18,477
	2 Years differential	-0.02	-0.02	0.00	0.04	-0.13	117	345	10,136
	3 Years differential	-0.04	-0.03	0.00	0.04	-0.1	86	253	7,524
	4 Years differential	-0.03	-0.07	0.04	0.04	0.88	24	114	4,584
	5 Years differential	-0.07	-0.02	-0.05	0.06	-0.86	5	33	4,089
5-NN	*1 Year differential*	-0.02	0.01	-0.03	0.03	-1.18	180	492	18,477

	2 Years differential	-0.02	-0.02	0.00	0.03	-0.13	117	345	10,136
	3 Years differential	-0.04	-0.03	-0.01	0.03	-0.38	86	253	7,524
	4 Years differential	-0.03	-0.07	0.03	0.04	0.89	24	114	4,584
	5 Years differential	-0.07	-0.05	-0.02	0.06	-0.39	5	33	4,089
1-NN	*1 Year differential*	-0.02	0.02	-0.03	0.03	-1.15	180	492	18,477
	2 Years differential	-0.02	-0.03	0.00	0.04	0.07	117	345	10,136
	3 Years differential	-0.04	-0.04	0.00	0.04	0.09	86	253	7,524
	4 Years differential	-0.03	-0.08	0.04	0.04	1.03	24	114	4,584
	5 Years differential	-0.07	-0.03	-0.04	0.07	-0.55	5	33	4,089
					Differential DPO (*H4*)				
Kernel	*1 Year differential*	-1.08	2.14	-3.21	7.10	-0.45	180	493	19,503
	2 Years differential	3.25	-5.25	8.49	8.87	0.96	117	346	10,495
	3 Years differential	5.57	2.75	2.82	9.65	0.29	86	253	7,773
	4 Years differential	9.62	-2.28	11.90	11.61	1.03	24	114	4,714
	5 Years differential	-13.39	6.24	-19.63	21.86	-0.9	5	33	4,179
5-NN	*1 Year*	-1.08	-2.62	1.54	7.88	0.2	180	493	19,503

	differential								
	2 Years differential	3.25	-9.56	12.81	12.32	1.04	117	346	10,495
	3 Years differential	5.57	5.73	-0.16	11.73	-0.01	86	253	7,773
	4 Years differential	9.62	-5.63	15.25	13.20	1.15	24	114	4,714
	5 Years differential	-13.39	0.99	-14.37	20.54	-0.7	5	33	4,179
1-NN	*1 Year differential*	-1.08	2.21	-3.29	9.67	-0.34	180	493	19,503
	2 Years differential	3.25	-7.08	10.33	13.57	0.76	117	346	10,495
	3 Years differential	5.57	8.85	-3.28	14.34	-0.23	86	253	7,773
	4 Years differential	9.62	8.32	1.30	14.91	0.09	24	114	4,714
	5 Years differential	-13.39	10.90	-24.29	24.89	-0.98	5	33	4,179

Table 8

Robusteness test for smooth matching using alternative methods

Methods	Variable	Unmatched Matched	Mean Treated	Mean Control	percent bias	percent reduct bias	t-test	t p>t
Kernel	ROA	U	0.83	0.16	186.9		56.2	0
		M	0.83	2.05	-343.1	-83.5	-11.16	0
N(5)		U	0.83	0.16	186.9		56.2	0
		M	0.83	2.07	-349.8	-87.1	-11.33	0

N(1)		U	0.83	0.16	186.9		56.2	0
		M	0.83	1.86	-291.1	-55.7	-10.29	0
Kernel	Sales	U	1.23	3.11	-66.4		-21.48	0
		M	1.23	1.20	0.9	98.6	0.31	0.76
N(5)		U	1.23	3.11	-66.4		-21.48	0
		M	1.23	1.14	3.2	95.2	1.05	0.295
N(1)		U	1.23	3.11	-66.4		-21.48	0
		M	1.23	1.25	-0.6	99.1	-0.19	0.846
Kernel	Age	U	1.81	3.38	-380.2		-212.33	0
		M	1.81	1.91	-23.3	93.9	-3.55	0
N(5)		U	1.81	3.38	-380.2		-212.33	0
		M	1.81	1.86	-11.9	96.9	-1.96	0.05
N(1)		U	1.81	3.38	-380.2		-212.33	0
		M	1.81	1.84	-6.8	98.2	-1.14	0.255
Kernel	Employees	U	1.68	1.29	39.6		13.69	0
		M	1.68	1.27	41.6	-5	11.2	0
N(5)		U	1.68	1.29	39.6		13.69	0
		M	1.68	1.33	35.6	10.3	9.39	0
N(1)		U	1.68	1.29	39.6		13.69	0
		M	1.68	1.31	37.9	4.3	10.13	0
Kernel	Tangibles	U	3.30	4.41	-64.5		-25.13	0
		M	3.30	3.06	14.1	78.2	3.38	0.001
N(5)		U	3.30	4.41	-64.5		-25.13	0
		M	3.30	3.06	14.1	78.2	3.37	0.001
N(1)		U	3.30	4.41	-64.5		-25.13	0
		M	3.30	3.01	16.5	74.4	3.99	0
Kernel	Intangibles	U	3.71	2.43	68.1		24.09	0
		M	3.71	2.76	50.6	25.8	12.79	0
N(5)		U	3.71	2.43	68.1		24.09	0
		M	3.71	2.84	46	32.4	11.69	0

N(1)		U	3.71	2.43	68.1		24.09	0
		M	3.71	2.99	38.3	43.8	9.85	0
Kernel		U	58.18	50.91	43.4		16.23	0
		M	58.21	57.73	2.9	93.4	0.74	0.46
N(5)	Industry	U	58.18	50.91	43.4		16.23	0
		M	58.21	57.77	2.6	94	0.67	0.502
N(1)		U	58.18	50.91	43.4		16.23	0
		M	58.21	58.24	-0.2	99.5	-0.06	0.955
Kernel		U	42.09	50.24	-26		-10.01	0
		M	42.06	45.76	-11.8	54.7	-2.98	0.003
N(5)	Localisation	U	42.09	50.24	-26		-10.01	0
		M	42.06	45.48	-10.9	58.1	-2.76	0.006
N(1)		U	42.09	50.24	-26		-10.01	0
		M	42.06	47.39	-17	34.7	-4.23	0

Table 9 Pre-trend Assumption (PTA)

Variables	Treated		control		Difference	T-test of equal pre-trend dynamics
	Mean	N	Mean	N	Mean	
Financial Debt	0.24	337	0.92	19560	0.68	0.50
	(1.43)		(0.13)		(1.02)	
DebtCost	0.16	190	-4,67	8652	-4.84	0.94
	(0.47)		(10,7)		(10.47)	
Trading Debt	0.23	385	0.84	24486	0.60	0.34
	(0.06)		(0.08)		(0.64)	
DPO	0.89	236	0.43	61870	-0.45	0.12
	(0.38)		(0.018)		(0.30)	

This table presents results of the PTA. Outcome variables are computed in growth rates to ensure that pre-treatment dynamics are not different between treated and control group. N represents the number of observations used to compute mean tests and depends on pre-treatment data availability.

Figure 2 Test of smooth matching Kernel, 5-NN matching and 1-NN matching