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Business Angels and Firm Performance: First Evidence from Population Data*

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Abstract

Business angels dominate early-stage investment in firms, but research on their investment effects is scarce and is limited by sample selection. Therefore, we propose an algorithm for identifying business angel investments from total population data. We apply the algorithm to study business angels' effects on firm performance, using detailed and longitudinal total population data for individuals and firms in Sweden. Employing these data and a quasi-experimental estimator, we find that business angels invest in firms that already perform above par. There is also a positive effect on subsequent growth compared with control firms. Firms with business angel investments perform better in terms of sales growth, employment growth and the likelihood of becoming a high-growth firm. However, contrary to previous research, we cannot find any impact on firm survival. Overall, our results underline the need to address sample selection issues both in identifying business angels and in evaluating their effects on firm performance.

Keywords: business angels; firm performance; sample selection; population data

JEL Codes: G24, 32, L25, C23.

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1. Introduction

Business angels are instrumental for entrepreneurs in closing the gap between early-stage funding that entrepreneurs need and what is currently available (Wetzel, 1983, Sohl, 2003). They account for the major part of early-stage investments in both Europe and the United States, with venture capital and crowd-funding investments accounting for the remainder (EBAN, 2017, Gregson *et al.*, 2017). Despite their importance, rigorous research is scarce on the returns of business angels and the firms they invest in (Levratto *et al.*, 2018, Gregson *et al.*, 2017). Overall, research on business angels is dominated by small-sample and often industry-specific studies, where angels typically are part of a business angel network. This introduces sample selection bias issues and affects the external validity of the research.[1] A pertinent issue is thus to carry out large-sample or population-based studies of the effects of business angels on firm performance.

This paper develops an algorithm for identifying business angels using total population data of individuals and firms. We then meticulously employ a matching and difference-in-difference estimator on data from Sweden to estimate the effect of business angel investment on firm performance. We analyse the effects on firm growth (jobs and sales), firm survival and the likelihood of becoming a high-growth firm (a so-called gazelle).

We contribute to the literature in three ways. To start with, we are first to set out to identify business angel investment using administrative population registers rather than surveys or information from business angel associations. Our algorithm may be applied in other countries with access to micro-level data on individuals and firms. This opens up a novel avenue for research on business angels. Second, when matching firms that have received business angel investment (treated) with very similar firms without such investment (controls), we match on a wide range of key firm characteristics. Notably, we match on firm growth trajectories, which we use as revealed measures for growth ambition. Finally, we study the effect

[1] Generally, research on business angels is on the retreat. One reason is the difficulty of identifying angels and the resulting reliance on small and non-representative samples (Landström and Sörheim, 2019).

of angel investments not only on jobs and sales but also on firm survival as well as on the probability of becoming a gazelle.

Employing our matching and difference-in-difference estimator, we find that firms with business angel involvement show increased sales, employment and the likelihood of becoming a gazelle. Our finding of a pro-growth effect confirms two recent studies and refutes one that did not find a growth effect. However, contrary to recent studies, we do not find that business angel investment affects firm survival. Overall, our findings point to the importance of considering both sample selection and omitted variable bias in business angel research.

The remainder of the paper is organised as follows. In Section 2., we provide a primer on business angel investment and briefly review the literature on the effects of angels on firm performance. In Section 3., we present our population-based strategies for identifying business angels and their effects as well as descriptive statistics. In Section 4., we report and discuss the econometric results. In Section 5., we make concluding remarks.

2. A primer and literature review

Business angels are private individuals who invest resources in new or smaller firms out of their own funds to yield a return (Mason, 2007). To be called a business angel investor, the investor must not have family ties to any of the firms' owners in which they invest (Mason and Harrison, 1995, 2002, Maula *et al.*, 2005). Business angels may invest varying amounts of capital and other resources. They can accordingly be classified as micro, knowledge-oriented, capital-oriented or classic business angels (Avdeitchikova, 2008).[2] As business angels mature, they can move on from being micro or knowledge-oriented investors to becoming more capital-oriented or classic business angel investors.

[2] The four types differ in terms of the capital invested and the level of engagement in the firms (Avdeitchikova, 2008). A micro investor invests a minor amount of capital and takes an active, but minor, role in the firm. If the angel becomes more active, the business angel becomes a more knowledge-oriented angel. A capital-oriented business angel invests a larger sum of money but only takes a minor active role in the firm. If the business angel takes a more active stance, the investment becomes more similar to a classic business angel investment.

By investing their own funds in entrepreneurs' endeavours, business angels reduce the equity funding gap. Business angels usually invest in firms that require more capital for future development than the owners can raise themselves. Compared to venture capital (VC) funds, business angels often invest a smaller amount than VC funds would (Sohl, 2003). As business angels invest their own capital, the principal-agent problem is attenuated, as there is no need to consider other stakeholders or investors, which can be a problem with VC funding (Chung *et al.*, 2012). Business angels are often believed to be more risk-averse than VC investors due to their limited financial assets, which reduces their ability to diversify risk (Lerner *et al.*, 2018). Instead, their risk strategy is only to invest a minor part of their personal capital per investment, which delimits the risk of a potential negative outcome (Johnson and Sohl, 2012).

By investing non-pecuniary resources in entrepreneurial firms, business angels also contribute to the firm more generally. Business angels commonly take on an advisory or other responsible role, such as by joining the board of directors. In this way, business angels may share their experience, market knowledge and networks. Such involvement may generate additional advantages at a later stage, for example, by increasing the ability to attract capital from VC funds (Huang and Knight, 2017, Becker-Blease and Sohl, 2015). Business angel involvement may also promote the survival of firms. Finally, in exchange for shares, business angel investment strengthens firms' balance sheets (Avdeitchikova and Landström, 2016).

Despite the fairly large literature on business angel investment, few studies rigorously analyse the effects of business angel investment (Gregson *et al.*, 2017). Instead, the focus is typically on returns to investors rather than to the firms they invest in.[3] Much of this literature on entrepreneurial funding suffers from methodological issues that severely limit the possibility of identifying causal relationships (Cumming and Vismara, 2017, Kerr *et al.*, 2014). First,

[3] After reviewing the literature, Levratto *et al.* (2018) conclude that there is mixed evidence on business angels' performance. For example, Heukamp *et al.* (2007) compared business angels' investments with joint investments by business angels and VC funds in German-speaking countries and found that business angels did not receive higher returns compared with the joint investments.

it is difficult to identify business angel involvement. Commonly, researchers turn to already available information from business angel networks. However, this introduces a sample selection problem related to the business angels (only some business angels are selected) (Mason and Harrison, 2008). Second, it is a profound challenge to decide on the counterfactual case with which to compare the business angel investment. How do we assess whether a business angel promotes firm growth or merely picks the "winner"? This introduces sample selection issues in estimation (only the successful firms are selected). Below, we highlight three recent studies that contribute by paying attention to firm selection in terms of receiving business angel investment.

One study uses data from two business angel networks, consisting of approximately 370 US-based business angels in the years 2001-2006. A regression discontinuity approach is used to compare the year 2010 outcome for firms that barely received business angel funding with those that almost did (but ultimately did not) (Kerr *et al.*, 2014). The authors find funded firms to be more likely to survive and to perform better in job growth, patenting and attracting website traffic. A subsequent study adopts a similar estimation approach using a data set for business angel investment in 21 countries. It finds business angel investment to be positively associated with job growth, the likelihood of firm survival and with firms subsequently obtaining additional funding (Lerner *et al.*, 2018).

Another study uses data from a French business angel network to study the effects of investments on 432 firms in the years 2008-2011, using a difference-in-difference estimator that compared random and matched (size, age, industry, region and capital structure) samples (Levratto *et al.*, 2018). When comparing firms that received business angel investments with a random group of firms, firms with business angel investments exhibited significantly higher growth. However, in comparison with matched firms, there was no significantly higher growth for firms with business angel investment.

We conclude that recent studies considerably contribute to providing empirical, yet mixed, evidence on the effects of business angel investment. Key challenges in this literature are still the reliance on small-sample data, such as that from business angel networks and industries. We address these issues by exploiting population data. Finally, for identification, we employ unusually detailed data to carefully implement a quasi-experimental estimator, and in doing so, also address the important issue of parallel trends.

3. Identification and descriptive statistics

To identify business angel investment, we propose an algorithm based on administrative data from statistical agencies. To demonstrate the algorithm's usefulness, we have ensured access to detailed longitudinal individual and firm-level data from Sweden for the period 2009 to 2015. The data encompass every individual in Sweden from 15 years of age and every limited company. Using our algorithm and these data, we identify business angel investments in firms and then provide descriptive statistics for business angels, the firms being invested in and control firms.

3.1. Identification of business angel investment

Our algorithm for identifying business angel investment necessitates administrative information on individuals (stock market portfolios, board memberships and general characteristics), firms (boards, board chairs, performances and general firm characteristics) and the presence of unique identifiers for individuals and firms. We have accessed such data to identify prospective angels - individuals who both have business experience and capital - and then matched them with potential targets for angel investment. Our algorithm enables us to confidently capture a large share of all business angel investments while recognising that it is likely there is both some under- and over-coverage.[4] In the following, we present the

[4]Our approach is contingent upon a potential business angel investor having exited from a board, received a relatively large capital dividend, and then entered the board of another firm. The approach ensures that those identified as business angels have actual experience running a company, thereby bringing both capital and experience to another firm. However, under-coverage may occur for individuals who invest in a new firm without having exited the board of another firm, or who exited without receiving a substantial dividend.

details of our algorithm in four steps.

First, we identify shareholders and board members who have left a firm. Based on Statistics Sweden's Job Register,[5] we identify individuals who previously were shareholders in a closely held limited company.[6] In this way, we identified 35,845 individuals who were shareholders in closely held limited companies in 2010,[7] but were no longer shareholders in 2012 or 2013. To ensure that the individuals left the companies, we added the restriction that they no longer were on the board of directors; this reduced the number of individuals to 28,248. To address under-coverage of the number of shareholders in closely held limited companies, we identified individuals who were board members in 2010 but ceased to be board members or chairs of limited companies by 2012, using the Board Members Register and the Job Register.[8] In this way, we identified 95,630 individuals who previously were on the board of directors of companies but were not any longer.[9] These individuals were also not shareholders of limited companies in 2012, according to the Job Register. Summing up, and after removing duplicate individuals included both as previous shareholders and board members, we arrived at 117,221 unique individuals who ceased representing limited companies in the period 2010–2012.

Second, we require that the individuals who have ceased to represent limited companies also left with substantial funds, enabling them to invest in other firms. We operationalise this by requiring that the individuals must have declared a dividend of at least SEK 1.0 million (USD

Over-coverage may occur if an individual joins the board of a firm without investing capital in the firm. Addressing potential under- and over-coverage is challenging, e.g., in the absence of a shareholder register for non-listed firms.

[5]The Job Register is the cornerstone of the register-based labour market statistics (RAMS).

[6]To be included as a shareholder in RAMS, the individuals must have received a salary from the limited company, and the company must have filed the required form (K10/KU31) to the Swedish Tax Authority.

[7]This implies that they were also board members.

[8]Passive shareholders, who declare their capital dividend on form K12, are never classified as shareholders in RAMS. Moreover, not all companies pay dividends. This creates under-coverage of the number of shareholders of close limited companies in RAMS. In RAMS in 2015, 60 percent of limited companies were linked to at least one shareholder of a close limited company. To include board members from the remaining enterprises, we use the Swedish Companies Registration Office's Register of Board Members and the Job Register.

[9]According to the Register of Board Members, approximately 18 percent and 11 percent were also board chairs or managing directors, respectively.

102,753).[10] This reduced the number of individuals to 7,294. Thus, we identified a group of individuals who previously were associated with a closely held firm and who subsequently had the potential to invest capital in other firms, that is, prospective business angels.

In the third step, we identified firms in which the prospective business angels may have invested. To capture the effects of business angels, we need the firms to exist as potential investment objects in the initial years and remain for the following years. Consequently, we added the restriction that the firms potentially invested in still had to exist in 2011-2012. We examined this aspect using data from the Dynamics of Firms and Workplaces register (FAD). To identify the effects of business angels from other major changes in the firms, we also required that the firms did not replace their entire board of directors.[11] We also formally required that the firms did not merge or split in the years 2011-2012, as indicated by the FAD register.[12]

Fourth, we identified actual engagement in firms by matching prospective business angels with prospective investment objects. Using the Swedish Companies Registration Office's Register of Board Members, we searched for individuals who were appointed as new board members in the abovementioned limited companies. We arrived at 297 prospective business angels who recently were appointed as board members of 357 prospective investment objects.

Using our algorithm for total population data, we identified novel and active engagement of carefully identified prospective business angels in likewise carefully identified prospective objects for investment. Henceforth, these individuals and firms are considered "business angels" and "firms with angel investment".

Having been appointed to the boards of directors, these business angels are expected to

[10] We also require that they did not change their official postal address (2011-2012) to better ensure that the capital windfall came from a successful firm exit rather than a house sale.

[11] Replacement of the entire board could indicate that the company has been acquired.

[12] We also required the limited companies to have at least one gainfully employed person, which is equal to being part of the firm population in RAMS.

participate and assist in the firms' strategic work. Presumably, the angels were approached by firms not only for pecuniary investment but also for their business knowledge, contacts, and corporate management experience. Such assets are likely valuable to these firms, for example, when working with their business plans. Accordingly, they meet a key criterion of Avdeitchikova (2008) for knowledge-oriented business angels. Nevertheless, in the absence of a shareholder register, our algorithm cannot ascertain that the individuals actually used their recently received capital to invest in these firms. Therefore, our identified business angel investment in firms is an approximation.

Finally, we make two adjustments to the data set.[13] First, we are wary of capturing professional board member engagement – individuals engaged in a large number of firms – rather than typical business angels. Analysing the data, we find that our algorithm identifies a relatively large number of individuals engaging in firms in the industrial activities of head offices (NACE 7010), as well as in business and other management consultancies (NACE 7022). We recognise that these individuals are more likely to be professional board members than business angels. Therefore, we exclude these two 4-digit industries in the subsequent analysis. This reduces the number of individuals to 247 and leaves us with 300 unique firms. Second, we limited the analysis to SME firms, here defined as firms with less than 250 employees in 2011. To conclude, we, therefore, arrived at 156 firms and 134 individuals.[14]

3.2. Identification of effects on firm performance

We now turn to our strategy for identifying the effects of business angel investment on firm performance. As mentioned, a fundamental problem is potential selection bias from business angels "cherry-picking" their target firms. This is a problem in all evaluation studies of business angel investment, where firms do not simultaneously receive and not receive such investment. Ideally, we would like to obtain data on the unobserved outcomes, that is, on

[13] Our results are robust without making these adjustments, with results available upon request.

[14] To limit the influence of outliers on the results, we have excluded firms in the 1st and 99th percentiles of historical sales growth. We have also removed five observations with extreme growth in sales or employment from all estimations with a continuous response variable.

the counterfactual, to estimate unbiased causal effects from angel investment.

More formally, let y_{di} denote firm i's outcome with treatment being indicated by the variable $d_i = \{0, 1\}$:

$$y_i = y_{0i} + d_i(y_{1i} - y_{0i}) \tag{1}$$

As we are interested in the effect of the treatment we can estimate the average treatment effect on the treated (ATT):

$$\hat{\delta}_{ATT} = E([y_{1i} - y_{0i}]|d_i = 1) = E(y_{1i}|d_i = 1) - E(y_{0i}|d_i = 1) \tag{2}$$

where $E(\cdot)$ denotes the mathematical expectation operator, that is, the population average of a random variable. In reality, we can only observe the first term on the right-hand side; that is, the average performance of firms with business angel investment. The second term - the average performance of the counterfactual for non-treated firms, that is, the performance if they had received treatment - cannot be observed. However, we may still be able to construct a control group that enables us to provide a consistent estimate of the ATT. Put differently, we can estimate the change in the response variable as:

$$\Delta = E(y_{1i} - y_{0i}|d_i = 1) + [E(y_{0i}|d_i = 1) - E(y_{0i}|d_i = 0)] \tag{3}$$

The expression is the sum of two components, the ATT plus a selection bias component. The selection bias component is included to account for the fact that the average firm performance of non-treated firms $E(y_{0i} \mid d_i = 0)$ is not necessarily a good representation of the counterfactual case for firms that business angels chose to invest in $E(y_{0i} \mid d_i = 1)$. The selection bias is zero if the outcomes firms from the treatment and comparison group would not differ in the absence of treatment. Therefore, d should ideally be randomly assigned among firms.

In the absence of randomisation, our strategy is to minimise selection bias by using a difference-in-difference (DD) propensity score matching (PSM) estimator (DD-PSM) (Rosenbaum and Rubin, 1983, 1984, 1985, Heckman *et al.*, 1997). In this way, we may draw an inference based on reconstructing the counterfactual, exploiting the rich observational data we have access to ensure conditional independence between the assignment of treatment and the control firms' responses. A '*propensity score*' is defined as the probability of a firm receiving treatment - business angel investment - and it is based on a vector of firm characteristics $\mathbf{x}$, including the firm's growth trajectories, and additionally controlling for industry-specific effects.[15] We also impose a common support requirement, to ensure that firms with $\mathbf{x}$-values have a positive and equal opportunity of being assigned to the treated and control groups (Becker and Ichino, 2002). We then estimate the ATT by first selecting two firms with the same propensity score $Pr(d_i = 1 \mid \mathbf{x}) = p(\mathbf{x})$, where one firm receives business angel investment, and the other does not, and then comparing the mean changes in performance for the treated and controls, that is:

$$\hat{\delta}_{ATT} = E(y_{1i}|p(\mathbf{x})) - E(y_{0i}|p(\mathbf{x})) \tag{4}$$

where the treatment effect on the treated is conditional on the propensity score.

In our vector of firm characteristics $\mathbf{x}$, we include a range of important variables for business angel investment according to the literature (MacMillan *et al.*, 1985, Köhn, 2017). We control for the values of these variables in the year preceding business angel investment. The variables included are firm size (sales and employment), physical and human capital (tangible assets and the wage bill for skilled workers),[16] operating returns (turnover ratio), solvency, leverage and whether the operating leader has a university degree and previous

[15]Industry specific effects are at the NACE-group level, i.e., slightly more granular than the two-digit industry level. For the classification used, see A2.

[16]We include the wage bill for workers with post-secondary education as a proxy for research and development in the firm.

experience in that capacity.[17] Most of these variables are related to the firm's features while the last two focus on the skills and track record of the firm's manager.

3.3. Descriptive statistics

We now apply our algorithm for identifying business angel investment to study its association with firm performance in Sweden, using total population data. (Definitions and sources of our variables as well as their pair-wise correlations are provided in Tables A1 and A4 in the Appendix.)

In Table 1, we present cross-sectional summary statistics for the two groups of control and treatment, before the nearest-neighbour matching takes place. As expected, before matching, the two groups of firms are rather similar but not identical. On average, the treated firms are more well-endowed in terms of size (sales and workforce), tangible assets, human capital (education), while being more leveraged and displaying a lower turnover ratio. In terms of industries, the treated firms are more strongly represented in manufacturing, mining and quarrying, and in information and communication industries than control firms.[18] In addition, the control firms are more heavily represented in the construction and hospitality industries.

Before turning to the econometric results, we provide a snapshot of the firms being invested in and the angels investing.[19]

In Table 2, we note that the firms range from micro to relatively large firms, with up to 247 employees. On average, they are small-sized firms, and approximately a third of their workforce is female, and a quarter has post-secondary education.

Turning to the angels, in Table 3, an overwhelming majority of them are male and middle-

[17] We also control for parallel trends, by including growth in variables.

[18] See appendix Table A3.

[19] Results from the propensity score matching are available in Appendix Tables A4-A6. Based on the scores, we have chosen the nearest neighbours. Comfortingly, the bias in matching is low both overall and across variables, and it is never statistically significant at conventional levels.

Table 1

Summary statistics for firms, 2011-2012

	Control firms					Treated firms				
Variables	N	Mean	S.D.	Min	Max	N	Mean	S.D.	Min	Max
Ln Sales 2011	96,098	8.76	1.45	0.00	17.06	156	10.81	1.64	6.39	15.06
Ln Tangible assets 2011	96,098	5.89	2.73	0.00	17.17	156	8.70	2.70	0.00	17.28
Ln Wage highly edu 2011	96,098	5.59	6.45	0.00	18.63	156	12.50	5.29	0.00	18.22
Solvency ratio 2011	96,098	42.22	23.56	0.00	100.00	156	40.02	25.87	0.00	100.00
Turnover ratio 2011	96,096	2.36	2.62	-413.33	249.86	156	2.01	1.48	0.00	9.40
Leverage ratio 2011	96,098	3.51	9.02	0.00	100.00	156	7.26	17.95	0.00	100.00
Ln Workforce size 2011	96,098	1.57	1.18	0.00	5.52	156	3.14	1.28	0.00	5.51
Opf university degree	94,909	0.18	0.39	0.00	1.00	152	0.39	0.49	0.00	1.00
Opf experience of other Opf	94,909	0.18	0.39	0.00	1.00	152	0.38	0.49	0.00	1.00
Δ Sales	96,098	0.14	0.47	-8.98	4.86	156	0.31	0.51	-0.80	3.79
Δ Tangible assets	96,098	-0.03	1.35	-11.96	16.25	156	0.18	1.02	-3.36	4.97
Δ Wage highly edu	96,098	0.76	2.75	-7.03	16.40	156	1.03	3.18	-1.20	13.26
Δ Solvency ratio	96,098	0.78	17.39	-100.00	100.00	156	-3.18	22.81	-98.00	95.00
Δ Turnover ratio	96,096	-0.03	3.82	-918.65	244.58	156	0.11	0.77	-1.95	4.40
Δ Leverage ratio	96,098	-2.56	16.61	-100.00	100.00	156	-6.81	26.92	-99.80	80.70
Δ Workforce size	96,098	0.06	0.41	-4.06	4.54	156	0.15	0.38	-1.10	1.95

Notes: The table presents cross-sectional statistics for the control and treatment firms, before matching takes place.

Table 2

Characteristics of the firms being invested in

Variable	Mean	S.D.	Min	Max
Employees	45.0	57.2	1	247
Post-secondary education	28.5	29.0	0	100
Female	32.5	24.5	0	100

Notes: The table presents statistics for the firms being invested in by business angels, with variables in percent, except for workforce size, which is in number of employees.

aged. Most of them hold a post-secondary degree, commonly in the social sciences.

Table 3
Characteristics of the business angels

Variable	Mean	S.D.	Min	Max
Female	3.6	18.8	0	1
Age	54.3	9.2	34	74
Post-secondary education	65.7	47.6	0	1
Social sciences degree	48.9	50.2	0	1
Natural sciences/Engineering degree	35.8	48.1	0	1
Health and welfare degree	2.9	16.9	0	1

Notes: The table present statistics on the business angels, with variables in percent, except for age, which is in years.

4. Econometric results

Our estimates of the effects of business angel investment on firms are presented in Table 4, with the panels corresponding to the four response variables. For each variable, we present results from: a simple test for any difference between the two groups before firm-to-firm matching; an OLS regression, also before such matching; and then from employing four DD matching estimators. Our preferred estimator is the first nearest-neighbour estimator, which aims to minimise bias.

In Panels (A) and (B), we analyse the employment and sales growth of firms that receive business angel investment (treated) and those who do not (controls). We find that treated firms experience substantially higher employment and sales growth than do control firms. Overall, the results are statistically significant at conventional levels and across estimators. Firms with business angel investment grow almost 10-13 percent more than similar firms without such investment.

Next, in Panel (C), we analyse if firms' stronger growth performance with angel investment also translates into them having a higher likelihood of becoming high-growth firms (so-called gazelles). In recent years, gazelle firms have both received a great deal of attention from policy-makers and in research. The presence of gazelles has been associated with substantial

Table 4

Effects of business angel investment on firm performance

	Treated (1)	Controls (2)	ATT (3)	S.E. (4)	t-stat (5)	Obs. (6)
(A) *Change in employment*						
All firms	14.21	4.38	9.83	3.68	2.67	96,254
OLS			10.87	4.33	2.51	95,059
First Nearest Neighbour	14.27	0.73	13.22	5.09	2.59	152
Four Nearest Neighbour	14.27	5.96	8.31	4.45	1.87	152
Weighted Nearest Neighbour			12.30	5.86	2.10	152
Kernel matching			10.27	4.48	2.29	152
(B) *Change in sales*						
All firms	18.76	6.58	12.18	3.45	3.53	96,254
OLS			8.59	3.84	2.24	95,059
First Nearest Neighbour	18.44	7.76	9.96	4.41	2.26	152
Four Nearest Neighbour	18.44	9.99	8.45	3.89	2.17	152
Weighted Nearest Neighbour			12.70	5.18	2.45	152
Kernel matching			8.66	3.98	2.18	152
(C) *(0,1) Gazell*						
All firms	0.08	0.02	0.06	0.01	5.98	96,254
Logit (odds ratio)			2.13	0.68	2.38	95,024
First Nearest Neighbour	0.09	0.02	0.07	0.02	2.77	152
Four Nearest Neighbour	0.09	0.03	0.05	0.02	2.38	152
Weighted Nearest Neighbour			0.06	0.03	2.22	152
Kernel matching			0.05	0.02	2.46	152
(D) *(0,1) Survival*						
All firms	0.84	0.83	0.01	0.03	0.41	121,560
Logit (odds ratio)			0.94	0.56	-0.10	105,771
First Nearest Neighbour	0.98	0.97	0.01	0.02	0.71	166
Four Nearest Neighbour	0.98	0.98	0.00	0.01	0.38	166
Weighted Nearest Neighbour			0.06	0.02	2.55	166
Kernel matching			0.00	0.01	0.11	166

Notes: The table presents a simple comparison between treated and control firms and then average treatment effects on the treated. We use five estimators, i.e., an OLS estimator and four DD matching estimators, the latter with replacement (except when four nearest-neighbour matches are used). The response is measured as the difference in outcomes between 2012 and 2015. The estimator's control for industry-specific effects. A common support restriction has also been imposed. Robust standard errors are used when employing OLS and the first two DD matching estimators, while bootstrapped standard errors (with 500 replications) are used when employing the last two estimators. The response variable is binary in panels (C)-(D).

job creation (Henrekson and Johansson, 2010). Gazelle firms are in the OECD statistics defined as firms annually growing by 20 percent over three years, following Ahmad (2006).[20] We find that few firms are likely to become gazelles, irrespective of any business angel investment. However, the likelihood of becoming a gazelle is higher for firms with business angel investment. Moreover, the difference is non-trivial and statistically significant across estimators.

Finally, in Panel (D), we focus on whether business angel investment helps firms survive. Descriptively, we have noted that high-growth firms are associated with somewhat lower survival rates, suggesting ambition coming together with a higher risk of failure. It would, therefore, be advantageous for ambitious firms if business angel engagement would assist them in surviving. According to previous studies on samples from business angel networks, business angel investment does attenuate the risk of failure. We, therefore, revisit this issue, using population data. In line with the previous studies, we find that business angel investment is associated with a higher probability of survival. However, contrary to those studies, the association to survival is economically trivial and statistically insignificant. Therefore, we conclude that we cannot establish any particular association between the investment by business angels and the survival rates of the firms they invest in, compared with similar firms without such investment.

We conclude that the presented results confirm those of two recent studies, which suggest that business angel investment spurs growth while refuting the results of another study, which does not find such a pattern (Lerner *et al.*, 2018, Kerr *et al.*, 2014, Levratto *et al.*, 2018). In contrast to the recent studies, we cannot find any impact on subsequent firm survival, whether positive or negative. We argue that such an impact is not necessarily expected since business angel investment could be associated with both ambitions and riskier behaviour. An absence of such an effect in tandem with a pro-growth effect would suggest that business angel

[20] We operationalise the concept by applying the OECD definition of employment, while using an alternative definition for the micro-sized firms' subset (growing with seven or more employees), to heed the issues and recommendation of Poldahl *et al.* (2011)

investment is advantageous for firms subject to it - promoting growth while simultaneously avoiding to raise the risk of firm exit.

5. Concluding remarks

Business angels have an instrumental role in reducing the equity funding gap. They may become especially important in the aftermath of the COVID-19 crisis. In the crisis, financing has been squeezed, and bankruptcies, as well as layoffs, have multiplied, and this could stimulate a post-crisis increase in entrepreneurship.

Previous research on the effects of business angel investment has faced difficulties in providing representative findings due to the lack of population-based data on business angels. Relying on data samples from business angel networks and specific industries, the existing evidence for a positive effect of business angels on firm performance is mixed.

This paper proposes exploiting administrative and population-based registers to identify and match prospective business angels and investment objects. We present an algorithm to this end and then employ it to study the effects of business angels on firm performance, carefully using a matching and difference-in-difference estimator. Our results confirm a pro-growth effect on firms but cannot confirm any substantial effect on firm survival.

To conclude, this paper lays out and applies a novel way of addressing sample selection when studying business angels and their subjects. We hope the paper will initiate population-based research to improve the identification of business angels and their effects on firm performance.

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Appendix: Descriptive Information and Statistics

TABLE A1

Variable definitions and data sources

Control variables	*Definitions*	*Sources*
Ln Sales 2011	Ln (firms' net sales, 2011)	SBS
Ln Tangible assets 2011	Ln (firm's tangible assets 2011)	SBS
Ln Wage highly edu 2011	Ln (firm's wage bill for workers with post-secondary education)	RAMS
Solvency ratio 2011	Shareholders' equity over total assets, in percent, 2011	SBS
Turnover ratio 2011	Net turnover over total assets, in percent, 2011	SBS
Leverage ratio 2011	Total debt over total assets, in percent, 2011	SBS
Ln Workforce size 2011	Ln (firm's number of employees)	RAMS
Opf university degree (0,1)	Operating leader (OPF) has university degree (1,0), 2011	RAMS
Opf experience (0,1)	OPF has been OPF in another firm (1,0) in 2009-2011	RAMS
Δ Sales	Ln Sales 2011 - Ln Sales 2009	SBS
Δ Tangible assets	Ln Tangible assets 2011 - Ln Tangible assets 2009	SBS
Δ Wage highly edu	Ln Wage bill highly edu 2011 - Ln Wage bill highly edu 2009	RAMS
Δ Solvency ratio	Solvency ratio 2011 - Solvency 2009	SBS
Δ Turnover ratio	Sales over total assets 2011 - Sales over total assets 2009	SBS
Δ Leverage ratio	Leverage ratio 2011 - Leverage ratio 2009	SBS
Δ Workforce size	Ln Workforce size 2011 - Ln Workforce size 2009	RAMS
Outcome variables	*Definitions*	*Sources*
Change in employment	Change in employment, 2012-2015	SBS
Change in sales	Change in sales, 2012-2015	SBS
Gazelle (0,1)	Annual employment growth $\geq$ 20 percent, over the 2012-2015 period; except for micro-firms, see text	SBS
Survival (0,1)	Firm remaining in the FDB, in year 2015	FDB

Notes: The table presents variable definitions and sources. The sources from Statistics Sweden are Structural Business Statistics, SBS; Register-based Labour Market Statistics, RAMS; and Business Register, FDB.

Table A2
Industrial definitions

NACE-codes	Industry description
01	Ariculture, forestry and fishing
02	Mining and quarrying
02	Manufacturing
03	Electricity, gas, steam and air conditioning supply
04	Water supply; sewerage, waste management and remediation activities
04	Construction
05	Wholesale and retail trade; repair of motor vehicles and motorcycles
06	Transportation and storage
07	Accommodation and food service activities
08	Information and communication
09	Financial and insurance activities
10	Real estate activities
11	Professional, scientific and technical activities
11	Administrative and support service activities
12	Public administration and defence; compulsory social security
13	Education
14	Human health and social work activities
15	Arts, entertainment and recreation
15	Other service activities
15	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use
15	Activities of extraterritorial organisations and bodies

Notes: The table presents our industrial aggregation and is based on the NACE (Rev.2), which is the statistical classification of economic activities in the EU.

Table A3
The distribution of firms across industries

	Control firms		Treated firms	
Industry	No.	Percent	No.	Percent
01	3,166	3.29	1	0.64
02	12,364	12.87	33	21.15
03	581	0.60	4	2.56
04	15,431	16.06	8	5.13
05	22,525	23.44	30	19.23
06	6,761	7.04	8	5.13
07	4,067	4.23	2	1.28
08	5,33	5.55	19	12.18
09	33	0.03	2	1.28
10	2,965	3.09	6	3.85
11	14,708	15.31	22	14.10
12	0	0	0	0
13	1,505	1.57	3	1.92
14	3,468	3.61	7	4.49
15	3,194	3.32	11	7.05

Notes: The table presents the distribution of control and treatment firms across the industries of table A2., aggregated to the two-digit level.

Table A4
Pairwise correlations

Variable	No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Ln Sales 2011	1	1.000															
Δ Sales	2	0.189	1.000														
Ln Tangible assets 2011	3	0.511	0.034	1.000													
Δ Tangible assets	4	0.068	0.150	0.362	1.000												
Ln Wage highly edu 2011	5	0.369	0.058	0.169	0.037	1.000											
Δ wage highly edu	6	0.066	0.116	0.028	0.039	0.258	1.000										
Solvency ratio 2011	7	-0.203	-0.106	-0.094	-0.024	-0.027	-0.049	1.000									
Δ Solvency ratio	8	-0.047	-0.057	-0.049	-0.077	-0.024	-0.008	0.296	1.000								
Turnover ratio 2011	9	0.122	0.068	-0.214	-0.075	0.001	0.030	-0.187	-0.001	1.000							
Δ turnover ratio	10	0.014	0.108	0.001	-0.047	0.005	0.006	-0.006	0.008	0.401	1.000						
Leverage ratio 2011	11	0.106	0.015	0.098	0.016	0.060	0.017	-0.359	-0.126	0.010	-0.002	1.000					
Δ leverage ratio	12	-0.05	-0.029	-0.026	0.013	-0.038	0.005	-0.001	0.343	-0.007	-0.013	0.217	1.000				
Ln Work force size 2011	13	0.839	0.132	0.467	0.061	0.413	0.090	-0.231	-0.061	0.104	0.009	0.107	-0.039	1.000			
Δ work force size	14	0.103	0.413	0.042	0.129	0.072	0.163	-0.077	-0.06	0.027	0.024	0.024	-0.006	0.229	1.000		
Opf university degree	15	0.035	0.005	0.006	0.014	0.542	-0.048	0.063	-0.002	-0.065	0.000	0.027	-0.017	0.029	0.002	1.000	
Opf experience of other Opf	16	0.174	0.030	0.146	0.023	0.114	0.045	-0.116	-0.017	-0.017	0.005	0.097	-0.02	0.167	0.032	0.060	1.000

Notes: The table displays pair-wise correlations between key variables.

Table A5
Logit estimates and mean characteristics for the sales and employment growth models

	Logit coefficient (1)	S.E. (2)	Treated firms (3)	Control firms (4)	Percent bias (5)	t-stat (6)	$p > \|t\|$ (7)
Ln Sales 2011	**0.440**	0.111	10.78	10.67	7.20	0.59	0.55
Ln Tangible assets 2011	0.118	0.053	8.66	8.59	2.70	0.24	0.81
Ln Wage highly edu 2011	**0.081**	0.023	12.44	12.68	-4.10	-0.43	0.67
Solvency ratio 2011	0.002	0.004	40.01	40.66	-2.60	-0.23	0.82
Turnover ratio 2011	-0.117	0.071	2.03	2.08	-2.50	-0.30	0.76
Leverage ratio 2011	0.002	0.006	7.27	7.52	-1.70	-0.12	0.91
Ln Workforce size 2011	0.063	0.122	3.12	3.07	3.40	0.28	0.78
Opf university degree	-0.054	0.192	0.39	0.39	-1.50	-0.12	0.91
Opf experience	0.345	0.173	0.38	0.36	6.00	0.47	0.64
Δ Sales	0.311	0.191	0.29	0.26	6.10	0.48	0.63
Δ Tangible assets	-0.011	0.077	0.17	0.13	3.40	0.35	0.73
Δ Wage highly edu	0.006	0.03	0.97	1.21	-8.40	-0.66	0.51
Δ Solvency ratio	-0.003	0.005	-3.34	-3.72	1.90	0.14	0.89
Δ Turnover ratio	0.105	0.072	0.11	0.12	-0.10	-0.02	0.99
Δ Leverage ratio	0.00	0.004	-6.40	-5.50	-4.10	-0.29	0.77
Δ Workforce size	-0.029	0.237	0.14	0.16	-5.40	-0.49	0.62
Observations	94,989		152	152			

Notes: The table displays estimates of the propensity to receive business angel investment for the sales and employment growth DD matching estimations. We use logit estimation and condition on the pretreatment characteristics. Our DD matching estimator employs one nearest-neighbour matching without replacement. A common support restriction is also imposed. We control for industry specific effects. The average mean bias and median bias per variable is 4.7 percent and 4.0 percent, , respectively. Pseudo-R^2 is 0.1615. For coefficients in bold, $p < 0.01$.

TABLE A6

Logit estimates and mean characteristics for the firm survival models

	Logit coefficient (1)	S.E. (2)	Treated firms (3)	Control firms (4)	Percent bias (5)	t-stat (6)	$p > \|t\|$ (7)
Ln Sales 2011	**0.490**	0.103	10.82	10.84	-1.30	-0.11	0.91
Ln Tangible assets 2011	0.092	0.049	8.62	8.36	9.30	0.84	0.40
Ln Wage highly edu 2011	**0.082**	0.022	12.51	12.79	-4.90	-0.54	0.59
Solvency ratio 2011	0.001	0.004	39.78	39.83	-0.20	-0.02	0.98
Turnover ratio 2011	-0.099	0.066	2.08	2.47	-19.10	-1.73	0.08
Leverage ratio 2011	0.001	0.005	6.95	7.74	-5.70	-0.39	0.70
Ln Workforce size 2011	0.041	0.113	3.10	3.14	-2.80	-0.24	0.81
Opf university degree	0.066	0.182	0.41	0.33	17.60	1.48	0.14
Opf experience	0.326	0.166	0.38	0.45	-15.00	-1.23	0.22
Δ Sales	0.219	0.183	0.28	0.26	3.50	0.29	0.77
Δ Tangible assets	0.019	0.071	0.19	0.22	-3,00	-0.28	0.78
Δ Wage highly edu	0.019	0.027	1.06	1.54	-16.00	-1.25	0.21
Δ Solvency ratio	0.000	0.000	-2.89	-2.37	-2.50	-0.22	0.82
Δ Turnover ratio	0.088	0.067	0.10	0.08	1.40	0.23	0.82
Δ Leverage ratio	-0.002	0.004	-6.72	-5.21	-6.90	-0.55	0.58
Δ Workforce size	-0.013	0.225	0.13	0.12	3.70	0.34	0.74
Observations	105,692		166	166			

Notes: The table displays estimates of the propensity to receive business angel investment for the firm survival DD matching estimations. We use logit estimation and condition on the pretreatment characteristics. Our DD matching estimator employs four nearest-neighbour matching without replacement. We control for industry specific effects. A common support restriction is also imposed. We control for industry specific effects. The average mean bias and median bias per variable is 5.8 percent and 3.5 percent, , respectively. Pseudo-R^2 is 0.1618. For coefficients in bold, $p < 0.01$.