



Search Funds: analyzing location preferences through historical patterns

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Abstract

The study introduces the search fund model, provides descriptive statistics, deepens the discussion of the factors –search funds' relationship, investigate location and time trends and comparing research findings with the searchers' opinion. Panel data regression model of US search funds activity shows a positive relationship with average income, number of companies per capita, and population. Results show that most of the search fund activity exists in larger cities. US search funds differ from international ones, mostly in the acquired company's distance and valuations.

Keywords: Traditional Search Funds, Panel Data Regression, Acquisition Success Factors, VC&PE

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1 Introduction

A search fund is established to finance a search for a potential business to be acquired and managed. "Young professionals decide for a career as a search fund manager because it allows having a leadership role very early, 10 or 15 years earlier as someone else would climb on the career ladder within a company. It avoids a tremendous risk of starting a company from scratch and proving the working business model. Instead, searchers buy a proven business, and within a year or two, they properly function as entrepreneur CEO." (Ruback, 2017)

By definition, "a search fund is an entrepreneurial path undertaken by one or two individuals ("the searcher") who form an investment vehicle with a small group of aligned investors, some of whom become mentors, to search for, acquire and lead a privately held company, for the medium to long term, typically six to ten years" (Kelly & Heston, 2020). What are the conditions for a searcher to attract investors and then successfully acquire a company? The research focuses on search funds established by one or two first-time searches ("the searcher"), financed by two or more investors. This form is the so-called "traditional search funds" or only "search funds". Other forms include self-funded search funds or financed by one investor, not the searcher.

The study aims to analyze search fund patterns globally and quantitatively assess search funds' activity across US counties. Conducting interviews with searchers and investors and sending out questionnaires allowed us to analyze the model's standard business practices and determine essential factors used in the panel data regression analysis. The study measures the fund's activity, not the fund's profitability. Results may show that specific factors positively affect the search funds' activity, which does not directly mean it also affects a search fund's successful exit or profitability.

H. Irving Grousbeck created the model in 1984 and until today 532 first-time traditional search funds have been established. Of those, around 75% are based in the US (Kelly & Heston, 2020; Kolarova et al., 2020). The first search fund in Europe was established in 1992, and to this day, IESE business school has a strong influence on their development in continental Europe. From 1984 to 2019, approximately USD 1.4 billion of equity has been invested in traditional search funds that generated around USD 6.9 billion of equity for investors and USD 1.8 billion for entrepreneurs (Kelly & Heston, 2020).

To better understand the relationship of the searcher, the investors and the company; the model can be related/compared to a horse racing team. The trainer is the investor who supports and helps the jockey whose task is to search for the potential company/the horse on the market. Then the investor finances the acquisition, and the searcher manages the company to support its growth and increase the total value. Purchase of the company is a stepping-stone for success and requires attentive diligence since it is irreversible. "Even the best jockey cannot win with a sick or injured horse. On the flip side, if you have a good, stable horse, even a young, inexperienced jockey can excel." (Goerge Janković (TH), interviewee). It resembles the saying: "The best jockey in the world is never going to win races riding a lame horse." The quote emphasizes the importance of the first two steps of the search fund model for the investor and the searcher.

In most cases, a searcher finds investors. He proposes investor investment in a search fund based on Private Placement Memorandum (PPM). Based on the given information, the investor must assess the searcher's profile and the targeted region, where the searcher wants to acquire a business. Usually, more than ten investors are included in the search fund's cap table, who must also align interests. After agreement among the searcher and investors, he receives an initial fund that finances the search for a potential company to acquire. The searcher usually creates a fund first and then raise capital from investors. A next phase is a company search, a very time-

consuming process that represents a full-time job. This step might deviate between the US and international search funds since, in Europe, most of the search funds target companies in the same country of the search fund origin or the same language perimeter. Whereas in the US, their targeted region could be the whole US, but their search would be more specific regarding the targeted company's sector or similar. It can also be psychically exhausting since a day with only negative responses from business owners means failure for the searcher (Ruback and Yudkoff, 2017). Suppose a business owner is interested in the company sale. In that case, a searcher might sign a letter of intent (LOI), which shows both parties' interest, states disclosure agreement and allows the searcher to perform due diligence; an extensive process to assess the target's business and assets tax and legal obligations and financial performance.

As the business owner tries to lead a searcher's investigation away from shortfalls and the searcher struggles with the amount of information he can obtain in a short period, asymmetric information relationship exists between them. The purchasing process can be called off even on the final days before signing the business purchase agreement. The first wave of COVID-19 was an excellent test for deals with high information asymmetry. Gabriel Ronacher, a searcher from Brazil, cancelled the deal due to disagreement about the business valuation with the owner.

"Business response to COVID-19 was a good indicator for searchers if the business can survive the economic downturn and has implemented an effective strategy." (David Lescure (FR), interviewee) Five interviewees mentioned that business valuations had changed during the pandemic, predominantly decreasing their value. On the other side, searchers without the acquired company received a positive experience from COVID-19, since business owners were more approachable, using more virtual conversation tools. Similarly, a searcher-investor virtual relationship must exist. Funds may not acquire a company at the location of their investors. Due to capital concentration, one would assume that more of the search funds are located in the

Western world and, less in Latin America. Until today, more search funds acquired a company in Mexico than in the United Kingdom, in Colombia than in France and Italy than in the Dominican Republic (Kolarova et al., 2020). SME activity can be more significant in developing areas than developed ones. Numerous other factors enhance the activity of search funds. Spain has the most search funds in continental Europe, since IESE business school, the leading university concerned about search funds is located there.

	US Search Funds	International Search Funds	
Searcher			
Female	7%	4%	
Male	93%	96%	
Age at Start of Search	31	31	
Finished MBA	84%	92%	
Years of Experience	1	1	
Professional background of the searcher for both regions			
Management Consulting	IB/Finance*	PE**	General Management
12%	22%	14%	17%
Search Fund			
Initial Capital Raised (USD)	440,000	451,000	
No of Search Fund Investors	15.8	15.0	
No of Months Fundraising	3.5	5.5	
Length of the search (months)	21	19	
Descriptive statistics about acquired company (Median value in USD million, except %)			
Purchase Price	10.8	11.0	
Company revenues at purchase	8.0	8.0	
Company EBITDA at purchase	2.0	2.4	
Company EBITDA margin at purchase	22%	23%	
PP/EBITDA***	6.0x	5.6x	
PP/Revenue***	1.5x	1.3x	
Company Employees at Purchase	43	64	

*IB=investment banking, **PE=private equity, ***PP=purchasing price

Table 1: Main findings of the search funds from Stanford Graduate Business School and IESE Business School

Table 1 summarises the Stanford Graduate Business School and IESE Business School's main findings and compares the US and international search funds.

The rest of the paper introduces the reader to the topic and presents previous research in the field, explaining data collection and data analysis of the interview, questionnaire, and panel data regression. Furthermore, it presents the results and discusses the findings, limitations, potential research improvements and direction for further research.

2 Theoretical Background

Little academic research has been done about search funds, excluding Stanford and IESE Business Schools' studies. Most active in the research field were master students writing feasibility studies of a search fund model implemented in a specific country. Compared to venture capital (VC) or private equity (PE) activity, a search fund's is smaller. It is still in the process of being taught in many business schools and introduced to many investors. Venture capital focuses more on financing start-ups and supporting the creativity of young entrepreneurs. Having an established track record is not essential (Leong Kaiwen et al., 2014). On the other hand, PE literature explains the success of leveraged transactions through advanced financial instruments and, modern management techniques that create some interest in increasing personal income (Meyer, 2006). A search fund's target company requires both markets with growth expectations and access to debt finance for established businesses (Groh et al., 2010). However, both models experience significant changes in the target companies' alterations in how they are operated, increasing investor activeness, increasing CEO turnover, and improving earnings quality (Metrick & Yasuda, 2011). That means their transformations might well step into the field of search funds. Especially in Germany, many searches must compete with PE funds for companies of a higher valuation. One can intuit a search fund model is a mix of both; therefore,

VC/PE research findings can be, to some extent, transposed to a search fund industry and especially meaningful for us, since little existing research can be found about search funds. Lee and Peterson (2000) find evidence of a more friendly environment in the US than the UK for entrepreneurs, which leads to an explanation of loosening regulation for entrepreneurs and a higher number of SMEs relative to the GDP. They concluded that 38% of UK potential entrepreneurs feared a failure, whereas only 28% in the US. Importance of developed capital markets is essential, especially for financial engineering. Schertler (2003) researched the importance of stock market liquidity and found a significant positive impact on early VC investments. Cetorelli and Gambera (2001) provide evidence that bank concentration positively affects industries' growth, requiring more generous external financing, especially in young companies. Since those factors are hardly measured and compared over long periods and small regions, others also interested us.

Groh and Lichtenstein (2010) calculated European country attractiveness index for VC and PE funds. They found the importance of countries' economic power defined in access to debt, public equity market, investor protection, innovation degree, and initial start-up costs for both models. In PE, educational ties between the investors and CEOs of target companies play a positive role in successful deals, which might be reflected by the academic connections of a searcher with investors and the ability to acknowledge the existence of the investment model (Fuchs et al., 2020).

Groh and Liechtenstein (2010) concluded that government expenditure on education is essential for the VC, but not the PE model. In emerging markets, entrepreneurial education seems very important for family businesses' success (Soares et al., 2020). Moreover, a research study about the CEOs level of education showed a positive correlation with the efficient use of resources, environmental footprint (Amore et al., 2019) and successfulness of acquisitions, evaluated by the

size of the premium, completion rates and advantage in negotiation (Wang & Yin, 2018).

Percentage of higher education within the population and the number of higher education institutions are higher in urban rather than rural areas. Lee and Xu discovered that businesses grow faster in urban areas, explained by the agglomeration economies (Fujita et al., 1999). It describes costs savings and positive externalities arising from the concentration of households, factories, and companies within the city area. It concentrates skills in one place, so it is easier for companies to hire the right person. It decreases transportation costs and creates a more prominent local market. On the other side, agglomeration might cause congestion problems and lack of space, if inappropriate city management is in place (Fujita & Thisse, 2002). New firm formation rates are higher in industrial dense, populated areas with high-income growth (Spilling R. Olav, 1996). Benjamin Friedman (2006) discussed that higher average income allows a country to protect national interest abroad. However, it does not necessarily bring well-being and more growth opportunities. People must acknowledge more is better, but also different, limiting other pre-existing rights. However, he concludes that economic growth does raise living standards which helps strive for political development that gives more space for improvement. In the process, both average income and the number of companies should increase. Individual-level resources might be more critical for creating new businesses in a location with finance and educational support geared towards entrepreneurship (de Clercq et al., 2013).

The process of a search fund model requires specific conditions to be met. From the initial selection of 5,000 to 10,000 companies, a searcher wants to narrow down the selection to dozens of companies (Graduate School of Business, 2020). This process requires asking specific questions that ensure a high probability of a healthy and growing business after the acquisition. Still, at the filtering process, a searcher needs a high number of companies of a specific size.

On average, searchers targets companies with EBITDA higher than EUR 1 million and an EBITDA margin of at least 10% and the historical profitability of at least three years (Graduate School of Business, 2020).

Unknowns provide a strong reason to research further the correlation of search fund activity and success with the factors mentioned above. Research emphasizes the difficulty of including all the variables. Many of those are not measured over the extended period or across US county/metropolitan area. That is why interviews helped address factors expressed as necessary by the searchers, the PE/VC sector's findings, and the business activity. After collecting the data and excluding factors with high categorical correlation, we identified four factors: average income per capita, education rate, urban-rural classification, population, and the number of companies per location.

Accordingly, our study's primary goal was to perform fixed effect panel data regression on the historical data of location-specific factors and traditional US search funds activity to analyze any significant correlations, controlling for year and location differences. In other words, we analyze location preferences of existing US search funds by identifying essential business factors for search funds and their development over time. The research will test the following hypothesis:

- A wealth of the population within the location increases the number of search funds.
- The number of established search funds increases with the rate of people with the educational attainment of at least a bachelor's degree.
- Urban settlements offer better conditions to search funds; therefore, search fund activity is positively correlated.
- The number of companies per location increases the probability of successfully acquiring the company.

3 Research Method

Quantitative analysis was performed after thorough research about the industry, holding more than 30 interviews with searchers and investors and 57 out of 570 sent questionnaires answered by searchers, who already acquired a company. The study introduces the search fund model, provides descriptive statistics, deepens the discussion of the factors – search funds relationship, point out location and time trends and compare research findings with the searchers' opinion. Regression analysis does not include profitability measures due to the limited access to private data. Instead, the search funds' activity is measured, as the number of search funds established within a county that later successfully acquired a business. A more thorough analysis was made for the US model, rather than the International one, due to data availability. Additionally, some factors could not be included in the research, such as access to finance, due to the same reason.

3.1 Data Collection

The data was collected from September to October 2020. Interviewees were contacted by LinkedIn or with the help of the search fund community. In total, we interviewed 35 searchers and 6 investors. Interviews lasted for 30 to 60 min, and besides 17 questions, we included additional questions posed on the answers, interviewer shared with us. Part of the interview was focused on standardized questions, which were directed towards finding patterns across the model's use. The second part of the interview was focused on individual specific experiences that can be understood as anomalies or business culture specific to a location or stage of a country's economic cycle. Searchers were selected from various countries that represented the European, American, and the African continent.

Questionnaires were constructed based on the literature review and answers of the interviews. It was explicitly sent to traditional searchers that have already acquired a company, independent of

the geographical location. Approximately 570 searchers (all searchers registered on the Searchfunder.com website that already acquired a company) were contacted by email or LinkedIn, which resulted in 20% answered questionnaires of 50% responded invitations. The questionnaire was primarily used to examine each stage's patterns, which focuses on the investor – searcher relationship and the searcher – business relationship.

For the panel data regression analysis, data was collected from publicly available sources. Data about the search funds (year, location) were obtained from the website Searchfunder.com and data regarding the independent variables were obtained from statistical databases such as the US Census Bureau, FRED and similar. Searchfunder.com represents the central communication medium for the search fund community; therefore, it is assumed that its search fund database is the most accurate publicly available sample. It includes 274 search funds, compared to 401 search funds listed in the private database of Stanford Graduate School, which should be sufficient for a representative sample of the population. Datasets of economic and demographic factors were filtered, transformed, and restructured in one dataset. From cross-sectional to panel data, filtered by year, location, and factor, then bound together. The process was automated by formulas to avoid human error. Through the operation of the database creation, regular tests were performed, to ensure no data loss or errors. In the end, data were gathered in one long-format panel database, ranging from 1984 to 2019 and including 55 counties, defined by the US FIPS code. Location is time-invariant variable, and all other variables are time-specific.

Factors include income per capita (expressed in chained 2012 US dollars), education rate as % of the population older than 25 with a completed bachelor degree or higher, urban-rural classification of counties with the scale from 1 to 9, real gross domestic product (expressed in chained 2012 US dollars), unemployment rate, the number of registered companies per capita and population per county. Alongside these factors, the data set also includes the duration of the

search period and the distance from the search fund to the acquired company; both expressed as an average of all the search funds established in a particular year, within one county. The number of search funds variable was transformed to binary form, to avoid the effect of outliers (counties with a high number of search funds in a specific year, compared to others with only one in the whole period). The urban-rural classification with a 1-9 scale was transformed to binary form. Grade 1 for the biggest cities stayed 1 and 2-9 converted to zero.

3.2 Data Analysis

Interviews helped the researcher understand the recent patterns since most searchers interviewed established a fund in 2020 or 2019. Individual interviews were summarised, and its mean, median, mode, maximum and minimum are presented in a table. Personal experiences expressed in the interview were collected in one database and cited through the research paper.

Fifty-seven answers of questionnaires were automatically gathered in a standard table. We calculated descriptive statistics and found patterns of the profitability answers and others. Since only a few of the respondents answered questions about profitability measurements, findings can be a good indicator, but they do not provide a definite answer.

Unbalanced panel data is ordered by county from A-Z and by year, which details are given in appendix A. Unemployment and real GDP were excluded as independent variables due to the high correlation ($\text{Corr} > 0.5$) with other independent variables, evidenced in the appendix B correlation matrix. We structured data as balanced by changing the variables' period. Limiting the independent variable's maximum duration with the shortest time range and avoiding the unbalanced random effect term. Balanced panel data includes 29 time periods (t) for 54 individual counties (N) and 1566 total points (n) for each variable. It also categorizes as fixed panel data since the same individuals are observed for each period. The table structure is

evidenced in appendix C. Using the histograms in appendix E; we can estimate the independent variables' distribution, of which only education rate is normally distributed. Others are positively skewed with high kurtosis. Despite positive skewness, the number of establishments has many upper outliers. Therefore, log transformation is used for average income, the number of establishments per capita and population to improve the coefficients' distribution and avoid outliers.

The relationship was modelled first with OLS and then with, least squares dummy variables model (LSDV), to control any country and year fixed effects. Test of linear restriction was performed with restricted (OLS) and unrestricted (LSDV) model with a null hypothesis that the OLS model is better than the LSDV. An F-test (F=55) confirmed the unrestricted model's statistical significance, confirming differences over time and across locations. The conditional logit fixed effect regression model, and the fixed effect "within" model was used and compared with LSDV. All four are suitable for panel data and used before in similar research. We used the LSDV that fits the data better than the pooled OLS model. It avoids omitted variables bias, excluding county-specific characteristics or characteristics over time that could influence the dependent variable but are not included in the regression.

LSDV model has the following equation:

$$\begin{aligned}
 & \textit{search.fund.b}_{i,t} \\
 & = \beta_0 + \beta_1 \log(\textit{avg.income}_{i,t}) + \beta_2 \textit{education.rate}_{i,t} \\
 & + \beta_3 \log(\textit{no.establishments.capita}_{i,t}) + \beta_4 \textit{urban.id}_{i,t} + \beta_5 \textit{population}_{i,t} \\
 & + \gamma_1 \textit{location}_{i,t} + \gamma_2 \textit{year}_{i,t} + \varepsilon_{i,t}
 \end{aligned}
 \tag{1}$$

Where β_0 is the intercept, $\beta_1 \dots \beta_5$ are parameter estimates of coefficients, $\gamma_1 \dots \gamma_2$ are dummy coefficients and $\varepsilon_{i,t}$ are the residuals or the error term. As explained, the dependent variable and urban id are in binary form, to overcome the problem of linearity. Non-linear models, such as logit one did not show a better correlation than a linear model.

4 Results

Search fund model is very well described by the Search Fund Primer of Stanford Graduate School of Business. Recent search fund activity based on interviews identified with the model well since both show the same characteristics. Comparing the Private Placement Memorandum (PPM) of the Search Fund primer given as an example of the Stanford Graduate School and the PPM of searchers, one finds little variation. The median of interviewee answers targeted companies with a minimum EBITDA of EUR 1 million, EBITDA margin of 10%, and at least three years of profitable operations. The same as the example also mentioned in the introduction. On average, interviewees raised a fund with 12 investors, of which 30% represented local investors and one unit of raised capital represented EUR 30,000.

Surprisingly, answers about the effects of COVID-19 varied. Around 60% of interviewees in the search period agreed that pandemic was beneficial for them since it identified the strengths or weaknesses of specific companies. On the other side, 40% of searchers disagreed, since the pandemic forced parties to reevaluate the deals and many owners changed their decision about selling the company, or they could not negotiate the price. Some investors decided to postpone the new search fund activity.

Overall, European searchers exposed high competition of search funds and private equities in Germany, especially for the model's higher valued companies. Among international investors, France is known for their complex legal system and strong worker unions, discouraging them

from investing. On average, searchers exposed the importance of minimizing paperwork when establishing a fund and making it as simple as possible for the investor. "You want to avoid a need for investors to travel to your country, especially for US investors. The searcher does not want to include them in creating the search fund, which would require physical presence. Therefore, the searcher wants to establish a company and then create a capital raise, which is handled with the shareholder agreement." (Kirils Gerasimovic (LV), interviewee) Overall, the searchers and investors emphasized that the search fund model is a numbers game. The greater the number of companies in the selection process, the better the chances of success.

	Minimum	Median	Mode	Maximum
Searcher				
Age	26	31	30	45
Years of experience	2	8	5	20
Fund Establishment				
Number of Units Raised	5	13	12	30
Value of One Unit	€ 12,000	€ 30,938	€ 30,000	€ 75,000
% of Local Investors	0%	60%	80%	100%
Search Period				
Number of Interns	0	2	2	15
Companies assessed	3	1317	2000	10000
Number of Signed LOIs	1	3	3	12
Duration of the Search (months)	3	22	24	46
After Acquisition				
Revenue Growth	-5%	15%	15%	100%
Payback period (years)	1	4	3	10
IRR	0%	35%	40%	50%
ROI	0x	1.25x	1.20x	1.40x

Table 2: Main findings from the questionnaire

Table 2 summarises the quantitative answers given in the questionnaire about different stages of the search fund. Profitability measures have a relatively lower response rate than other questions. IRR and ROI are measured when the investors' investment is repaid. Based on categorical

answers, summarised in appendix F, 76% of searchers are 30 years old or older, when they establish a search fund and 30 is the most common age. 81% have an MBA degree, 5% a master's degree and 10% a bachelor's degree (appx. G). Only MBA students and one master student had a course that taught or introduced the search fund model; others did not (63.2%). Most of them (51%) established a search fund in partnership. After the acquisition, searchers communicate with an active investor daily (2%), weekly (28%), monthly (49%), quarterly (19%) or more seldom (2%) (appx. H).

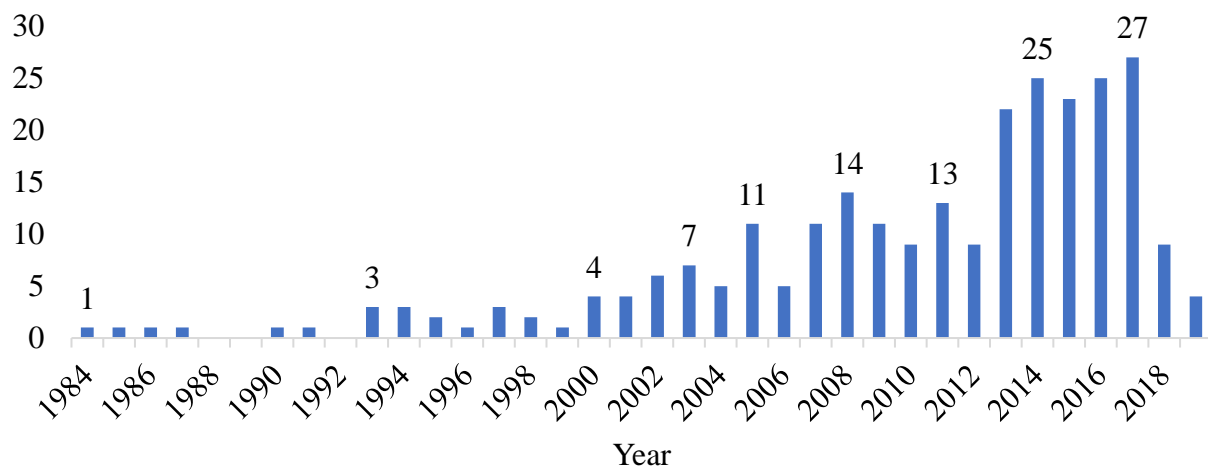


Figure 1: Number of established US search funds per year

Focusing only on US search funds, the number of established search funds per year had increased, from the year 1984, when there was only one, to the year 2017, with 27 search funds. Most of the search funds were established from the year 2000 and onwards. Before Millennium, $\frac{3}{4}$ of them were established in California. The number of newly established search funds decreased to 5 in 2006 but again increased to 11 in 2007 and 14 in 2008, indicating a lag or lead correlation between the search fund activity and financial crisis. A decline in 2018 and 2019 could also be due to the missing data from the source.

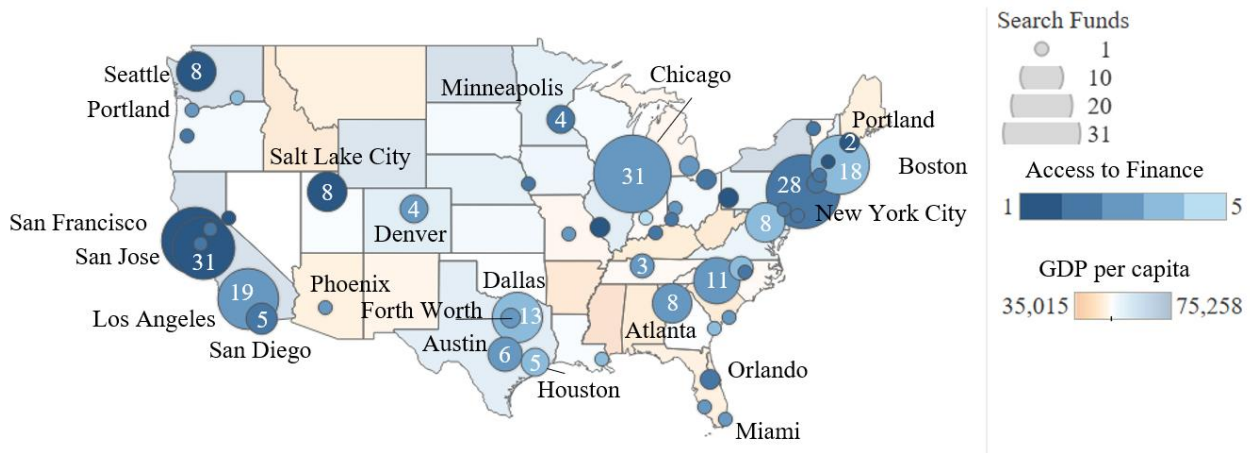


Figure 2: Location of US traditional search funds

Figure 2 depicts the distribution of search funds across the US. The only missing state is Alaska, where one search fund is operating. States with high GDP per capita are coloured blue, and ones with low are coloured orange. The circles' size represents the number of search funds at a specific area, and the colour represents access to finance index of Federal Reserve Bank of New York research. High access is coloured dark blue and low access light blue. Most search funds are based in states with higher GDP per capita and greater access to finance. Distance from a search fund to an acquired company is in 47% below 100 km but varies for the rest (Figure 3).

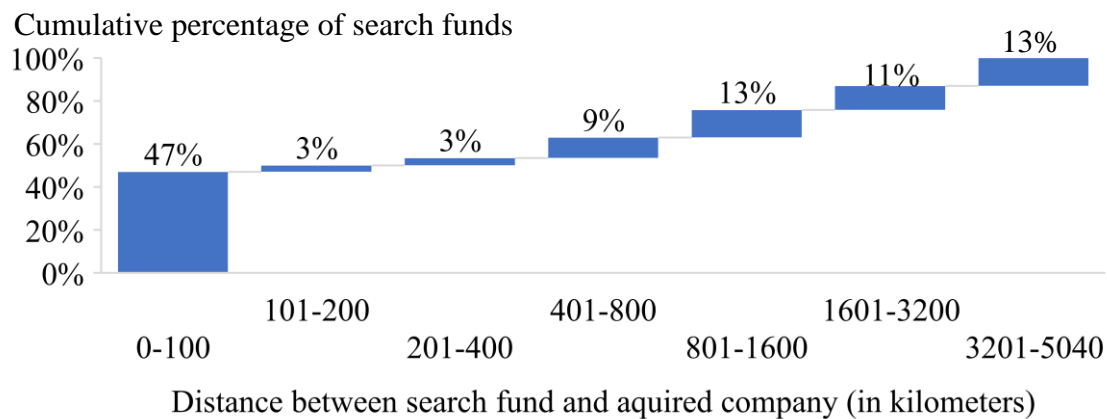


Figure 3: Cumulative percentage of search funds categorized by the distance between the search fund and the acquired company

		Min	Median	Max
Residuals		-0.774	-0.034	1.049
Coefficients	Estimate	Std. Error	Pr (> t)	
(intercept)	-4.604	1.921	0.0166	*
log(income.capita)	0.506	0.130	0.0001	***
education.rate	-0.011	0.005	0.0200	*
urban.id	0.070	0.041	0.0854	.
log(no.establishment.capita)	0.358	0.112	0.0014	**
log(population)	0.072	0.082	0.3267	
*** p < 0, ** p < 0.01, * p < 0.05				
Number of observations	1566			
F - value	6.833			
degrees of freedom	86 and 1479			
R ²	0.2843			
Adjusted R ²	0.2427			
p-value	2.20E-16			

Table 3: Results of least squared dummy variable regression

In Table 3 above, regression results indicate a significant relationship between the search fund activity factors, except urban id and population. However, estimated factors are relatively small, where change must be relatively large, to affect the search funds' activity.

With all independent variables being zero, and a confidence level of 95%, there will be no search fund activity. With 99.9% confidence, a one per cent increase of average income is expected to increase search funds activity by more than zero. With 95% confidence, a unit change in education rate is expected to decrease search fund activity. The sign of the coefficient is debatable since the literature review concludes different results. Urban id has shown significance only within a 90% confidence level, and it is positive. With 99% confidence, one per cent increase in the number of companies within the region will positively affect search fund activity by more than zero. Again, no strong significance with the population variable. Due to the dispersion of residuals, both R-squared and adjusted R-squared have values below 0.5. This

means the model accounts for only 28% of the total variance in search funds' activity. Although having a small R, the regression model has a minimal p-value. The model is significant in predicting the search fund activity. Fixed effect "within" regression model showed the same results for the variables' coefficients. The R-squared was smaller since the "within" total sum of squares is calculated on the demeaned outcome variable.

Appendix I shows intercept coefficients of the county and year. With a 99.9% significance, Austin, Boston, and Salt Lake City have higher intercept than the regression model. Formerly listed are the cities, instead of counties to point out that high significance exists in counties with big cities. With a 99% significance, Durham, Charlotte (NC), Philadelphia, New York City also have higher intercepts as even Chicago, Grand Rapids, San Francisco, Raleigh, and Montgomery, with 95% significance. With 99% significance, the year 1999 have lower intercepts and 1996, 1997, 1998, 2004, 2006, 2007, 2010, 2012 with 95% significance.

5 Results Discussion

Results of both the interviews and regression analysis have given insightful information that can help future professionals in the search fund field. The US and International search funds are similar to a certain degree. While all traditional searches closely follow the Stanford Graduate School model, the business environment seems different. Specifically, business owners in the US are less emotionally attached to the company. When asked to sell it, they think about the right price. Whereas in Europe, emotional attachments create a barrier to sell the company. Many have never considered selling the business, so the searcher must first convince the owner into selling the business, before starting a negotiation.

Furthermore, most experienced investors are in the US than in Europe, making a competitive advantage for US searchers. However, non-US searchers will also have some US investors on the

cap table. Less time needed to establish a fund and acquire a company recommends higher liquidity in the US than in Europe. Due to the higher liquidity, valuations are also higher in the US than internationally. Another reason could be many underperforming firms in Europe (Metrick & Yasuda, 2011). Operating in a capitalist society is still relatively new for many Eastern European companies, and their owners may not have completed any formal business education.

Search funds are still very male-dominated of MBA graduates. However, many searchers, being female, without an MBA or master's degree, coming from third world countries or rural areas, have proven the population structure can change in the following years. Searchers' ambition finds more opportunities in less liquid and standardized regions to create a search fund.

Fortunately, most of the investors in the search fund field are active investors that want to have an active role in the acquisition process and offer support in managing the company. Compared to the private equity model, which does not require active participation between the fund and the investors, the search fund community is more approachable, the same as their investors.

Regression results confirmed that average income and number of companies are essential for the search fund's activity. As the average income of a specific location increases, there will likely be more search funds. The same holds for the number of companies, which reinforces the importance of entrepreneurship and development of the small business sector, consequently increasing the search fund and later on private equity activity. A positive and significant relationship was expected based on the literature review, with which we also found a contradiction of results for education rate. Education rate has shown a negative correlation with it, which would mean that the fewer bachelor and higher graduates living at the location, the more likely it is a search fund will exist there. The explanation for unexpected results could be the structure of the dependent variable. If none of the search funds were created in a specific

county, the dependent variable would have a zero value for all the 29 years observed. If there is one search fund established over the observed period, there are 28 zero values and one positive value. Little change with one established search fund. Higher frequency of search funds can fix a problem of many zeroes in predicting the patterns. With low frequency, measurements are exposed to many random effects in a specific year or location affecting search funds. An example could be US elections, which are not related to the overall education rate or average income within the county but could change business sentiment, regulation, and expectations.

Education rate might have an unexpected sign, due to the difference in partial and normal correlation. Correlation between *search.fund.b_{i,t}* and *education.rate_{i,t}* is 0.235, which is positive, but not significant. There are also some other explanations. Some other variable might affect search fund activity regarding low R-squared, such as distance from financial centres, effective tax rate, agglomeration economics and distance from universities offering courses about entrepreneurship and search funds, which could be especially strong in cities with lower average education rate.

Education rate measured as a percentage of people with the bachelor's degree or higher, targets the question: "Are there enough graduates that could become searchers and increase the search fund activity?". The higher education might have a lower impact than overall education rate, including students with finished high school. Consequently, a different type of education rate could be used, including college and high school graduates.

Another reason could be omitted variable bias. The biggest US cities, such as New York City, Chicago, Los Angeles, and Boston, have the most search funds. However, not all of them have high education rates. For example, in Chicago, 30 search funds were established within the observed period, and 26% of the population have a bachelor's degree or higher. Whereas in a smaller city, such as Burlington (Chittenden, VT) there is only one search fund, but 38% of

residents have a bachelor's degree or higher. Unexpected results could be caused by an outlier effect of big cities, which have a lot of search fund activity. However, is this activity homogeneously dispersed across all boroughs? They could be very different, such as Manhattan and Queens, within New York City. One increases the average of search fund activity. The other lacks a higher percentage of educational rate. If both are analyzed together, results show an average of the variables and decrease the precision of results. Boroughs of the city could have been very different. Then, big cities should be segregated on boroughs and compared individually.

Another reason could be multicollinearity of education rate and average income, which is 0.47, a low positive correlation. Multicollinearity was tested with *vif* function in R studios, and education rate had a significant coefficient proving multicollinearity. An education rate could be expressed in other terms, as a ratio of another variable.

Despite the strong influence of big cities, urban id, transformed into a binary form, still shows indecisive results. No significance of the urban id coefficient, while larger cities have significant intercepts, confirming a positive relationship. A solution to a problem could be a different categorization of the cities with higher boundaries (population, size, GDP), creating more subgroups among bigger cities. Now, Chicago, New York City, Austin and Miami are all in the same subgroup, despite their differences.

Timewise, years before the global recessions have significantly lower intercepts. We can assume that search fund investors are good at predicting global financial crises and effectively stop investments before the financial crisis, which is another exciting topic.

6 Limitations

Qualitative observations presented in the research were obtained by interviewing professionals (investors, searchers, interns) in the field. Because conclusions from the interviews are drawn on personal experiences, we cannot create definitive conclusions. Many of the answers can be specific for the location or regulatory territory.

Although the US has the highest number of search funds, the number of transactions is still smaller than the PE or VC sector transactions. More annual transactions will increase data availability in the future and allow us to perform better analysis and come up with new, more precise conclusions. Interviews and literature review defined numerous essential factors to be included in the analysis, for which afterwards, little data was publicly available, even if the variable would be included in the analysis on the state level or for shorter periods.

Limitation of data existed for effective taxation, government investments in entrepreneurial education and overall support of entrepreneurs, agglomeration effect, access to finance, and a limitation of fund-specific information, such as the acquisition price, fund returns, exit valuations and annual reports. Most of the acquired businesses showed only revenue and profit information for the past five years in public databases, such as Orbis.

Since the capital for the search phase, and the acquisition comes from investors, their decision making has a strong implication on the activity. Suppose factors that affect search fund activity are the same as factors included in the investor's decision-making formula, our research can be a perfect tool to understand investors. However, subjective factors described by behavioural finance can affect investors' decision-making alongside the investment formula. Then the model loses its explanation power of search fund activity, and additional research is needed about investors.

Another bias that might affect our results is the limited time of the search process that puts pressure on the searcher in the final months, making him/her more inclined to accept the deal. Raising a fund takes approximately 2-6 months and searching for a company takes around 12-24 months. "Usually most of the acquisitions happen from month 15 to month 24." (Niel Wyma, South Africa, interviewee) Many searchers might accept the deal, because of the time pressure and fear of project abolishment, after much effort put in. Such decision making would be recorded as a search fund activity, alongside poor conditions, potentially distorting the model relationship between essential search fund conditions and activity. A problem would be bypassed by including the end profitability measures of search funds if as mentioned, they would be available.

7 Directions for future research

This paper is one of the first ones focusing on quantitative analysis of the search funds. It makes an example of quantitative analysis and recognizes some pitfalls and obstacles to overcome and to avoid in the future. We recommend introducing the subject to more entrepreneurial university courses to increase the topic's interest and brainstorm possible research directions.

As mentioned, behavioural finance and investor decision making also affect the search fund activity. Therefore, it is another essential direction to be researched. The search fund process includes much human interaction between investors and searcher and searcher and business owners, with a presence of adverse selection.

Investors supporting the deals in new regions should be compared to the investors focusing on established markets. The comparison would help determine if the new regions have improved/developed and now satisfy the search fund formula, or those investors pose different investment mindset and formula to accommodate the search fund model in new areas.

We would highly recommend researching the implications of agglomeration economics and access to finance on search fund activity. These are presumably some of the most decisive factors, but some measurability is missing on a large scale. The research might become even more interesting internationally, where both local and domestic investors participate in the capital raise. However, the cultural differences present a new challenge for investors, therefore posing a question: "Due to the cultural barriers, do investors properly assess risk and return in the foreign countries to invest in all viable opportunities?"

Finally, companies acquired by search funds are categorized as small to medium companies and put little management focus on ESG principles integration, which is becoming more critical to investors and business etiquette around the world. However, as a company grows, "when company transforms into a full-blown multi-market corporation, CEO should fully explore and execute on growth pathways", it must act responsibly and achieve higher ESG score (Weaver et al., 2020). Therefore; "Does integration of ESG principles distinguish exits with 10x return from 2x-5x or <2x return?"

This research can also be a basis for research about other types of search funds, such as self-funded search funds or one-investor financed search funds since all types of search funds target similar companies.

8 Conclusion

Search funds are a relatively new, but a prosperous model representing second-generation ownership for many smaller companies outside of the scope of private equities or within the owner's descendants' interest. It allows young professionals to stretch themselves and with the active participation of investors managerially, financially restructure the company. The study has researched existing patterns of the searcher, investors, acquired businesses and their location

characteristics, and the relationship between selected factors and search fund activity across locations and time. Search funds included in this study have already completed the first two stages of the search fund model, creating a search fund, and acquiring a business. Based on the Stanford Business School statistics, acquiring a business increased search funds' success rate to exit with positive returns from 67% to 75% in the US and Canada and 89% internationally. It means our research analyzes search funds with high success, for which data is still accessible. The US and international interpretation of the model are very similar. The former has a higher number of search funds, valuations of acquired businesses, access to finance for searchers, and the distance between the acquired company and the search fund's location for the US model. In Europe, searchers acquire a company in the same country or same language region, whereas the acquired company can be much further away in the US.

Based on the results, we confirmed the first, second, and fourth hypotheses, with additional research to verify the third hypothesis. Panel data regression of the least-squares dummy variables for a county and a year method has estimated a significant positive relationship of search fund activity with income per capita and the number of businesses per capita, also backed by literature review. Conversely, a negative correlation of search fund activity with educational rate contradicts the literature review. More research is needed to assess the relationship between the education rate and search fund activity. From the selected data, most search funds are established in bigger cities, such as Boston, Chicago, New York, San Francisco, and similar, as an outlier with double the number of search funds compared to other towns.

A significant part of the search fund activity variation is still unknown. We assume it comes from access to finance, agglomeration economics and behavioural economics, which is also our proposed direction for further researches in the following years.

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10 Appendix

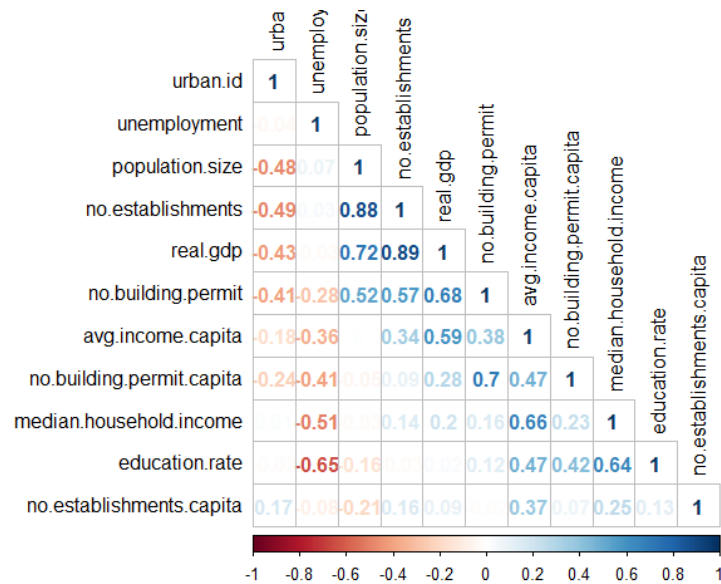
10.1 Appendix A – Panel data characteristics

Variable	Search fund .binary	Average income per capita	Real GDP	Unemployment	Education rate	Population size
Start year	1984	1984	2001	2001	1984	1984
End year	2019	2018	2018	2019	2018	2018
Expected corr. w DV		+	+	-	+	+
Unit of measurement	1 or 0	USD*	USD*	%	%	unit
Skewness	5.75	2.23	2.88	1.56	0.55	3.62
Kurtosis	49.23	10.46	9.13	3.76	0.27	15.90

Variable	Median household income	Urban ID .binary	No of establishments per capita	No of building permits per capita
Start year	2010	1984	1990	2003
End year	2019	2019	2019	2019
Expected corr. w DV	+	-	+	+
Unit of measurement	USD	1 or 0	units	units
Skewness	1.31	Categorical	3.15	2.56
Kurtosis	3.47	Categorical	10.87	10.83

*chained to USD value in 2012

10.2 Appendix B – Correlation matrix of independent variables



10.3 Appendix C – Panel data frame

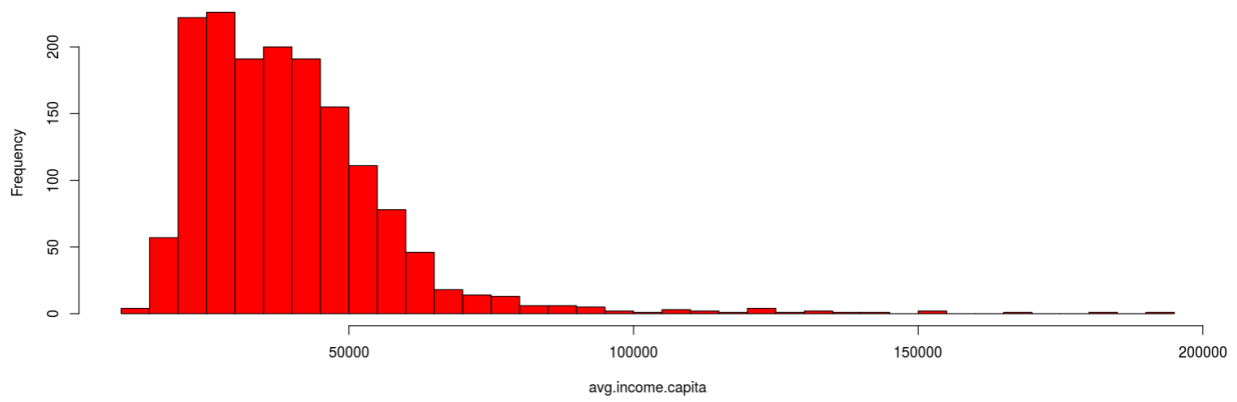
```
Classes 'data. Table' and 'data. Frame': 1566 obs. of 8 variables:
 $ location      : Factor w/ 54 levels "Alameda, CA",...: 1 1
1 1 1 1 1 1 1 1 ...
 $ year         : Factor w/ 29 levels "1990","1991",...: 1 2
3 4 5 6 7 8 9 10 ...
 $ search.fund.b : num 0 0 0 0 0 0 0 0 0 0 0 ...
 $ income.capita : num 22657 23169 24116 24739 25466 ...
 $ education.rate : num 28.8 28.8 28.8 28.8 28.8 28.8 28.8
28.8 28.8 28.8 ...
 $ urban.id.b   : Factor w/ 2 levels "0","1": 2 2 2 2 2 2 2
2 2 2 ...
 $ no.establishment.capita: num 0.0229 0.0263 0.0278 0.0287 0.028 ...
 $ population   : num 1306166 1318543 1332208 1339189
1341707 1346548 ...
```

10.4 Appendix D – Descriptive statistics

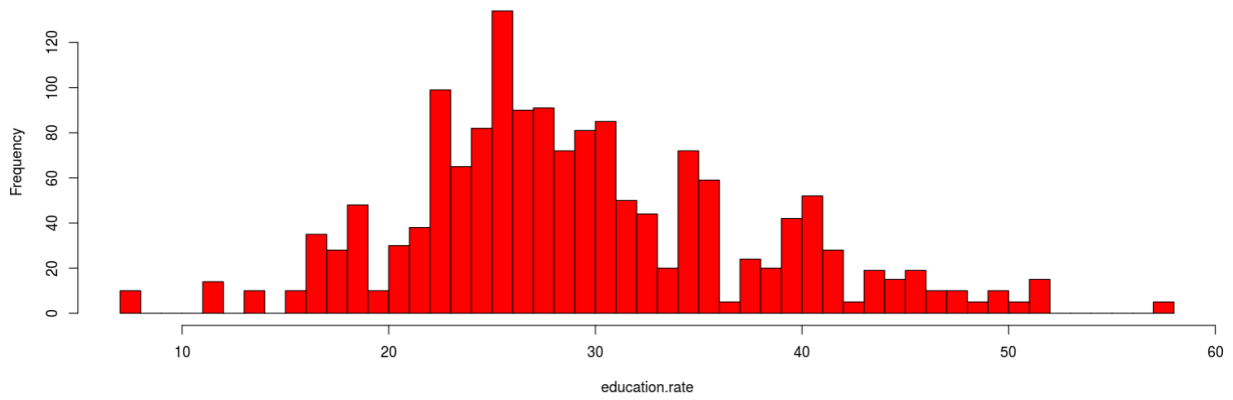
Variable	N	Mean	Std. dev.	Min.	25 %	Median	75 %	Max.
search.fund.b	1,566	0.119	0.324	0.000	0.000	0.000	0.000	1.000
avg.income.capita	1,566	39,829.331	17,908.295	12,898.000	27,493.250	37,218.500	47,675.000	193,940.000
education.rate	1,566	29.214	8.338	7.500	23.800	27.700	34.500	57.100
urban.id.b	1,566	0.973	0.162	0.000	1.000	1.000	1.000	1.000
no.establishments.capita	1,566	0.034	0.018	0.006	0.025	0.029	0.035	0.126

10.5 Appendix E – Histograms of independent variables

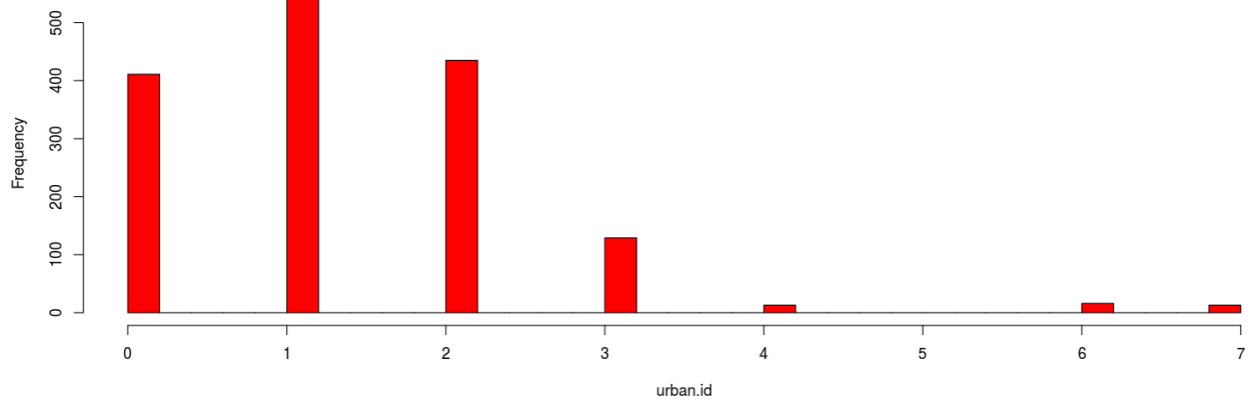
EI



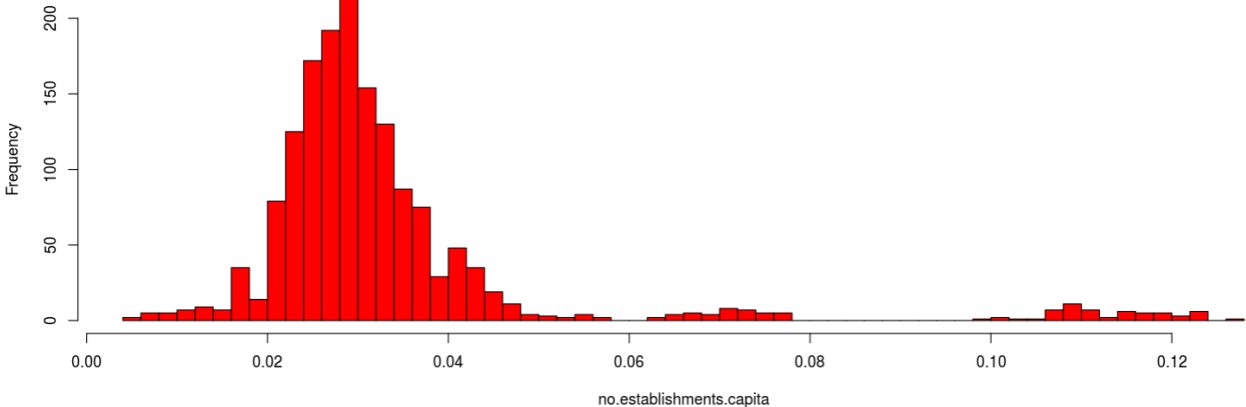
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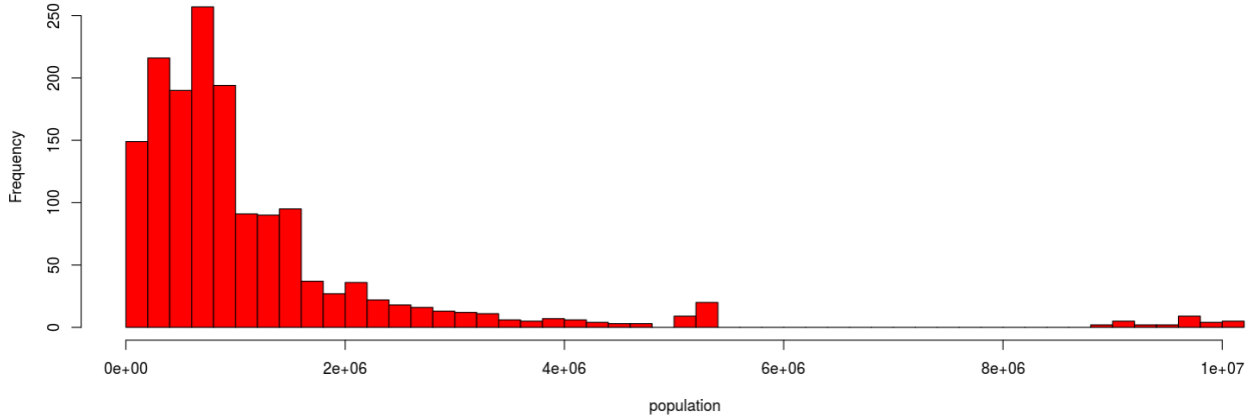
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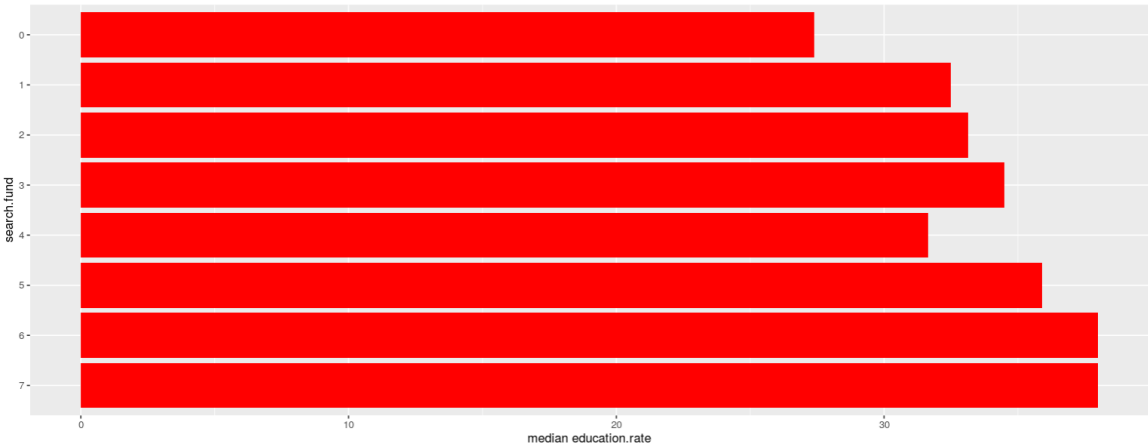
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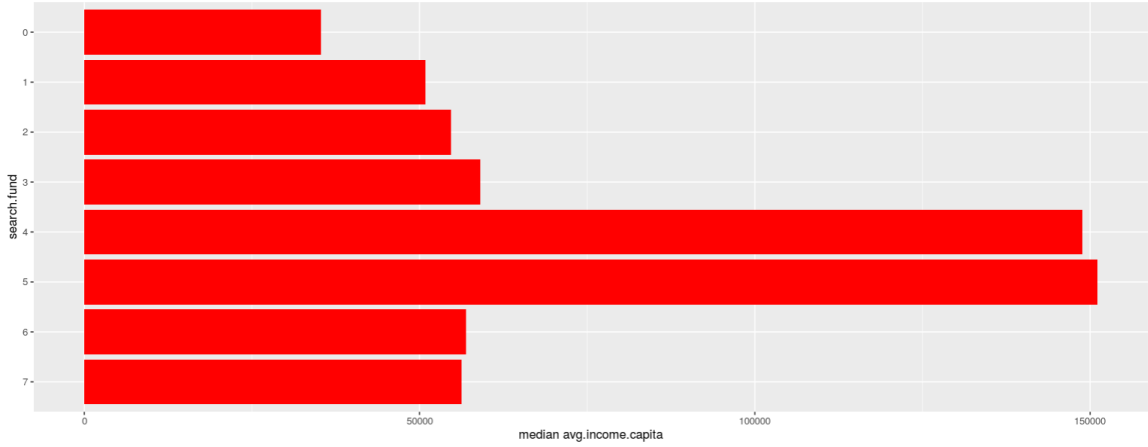
EV



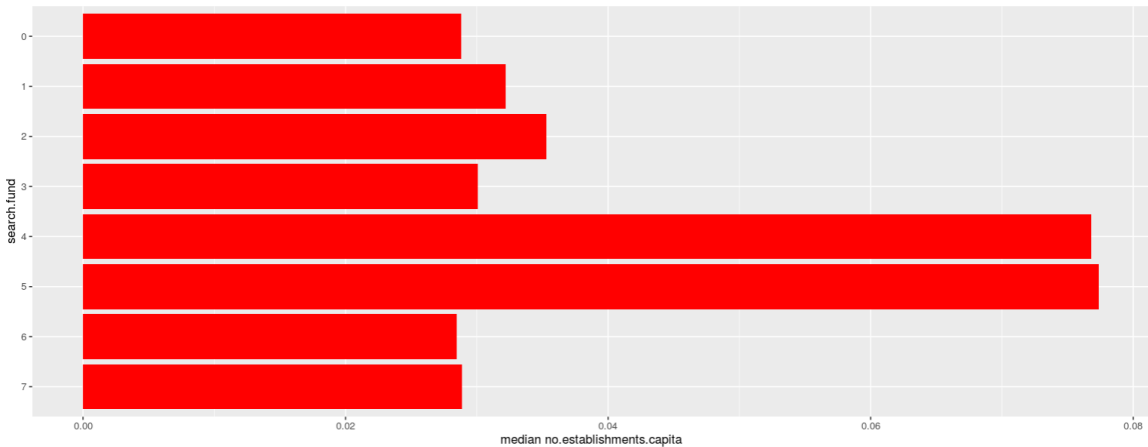
EVI



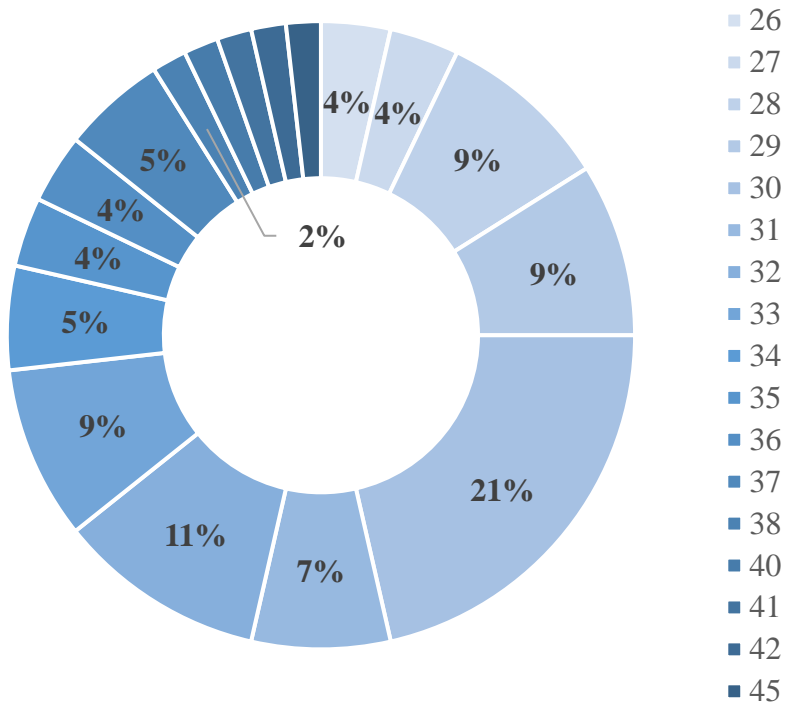
EVII



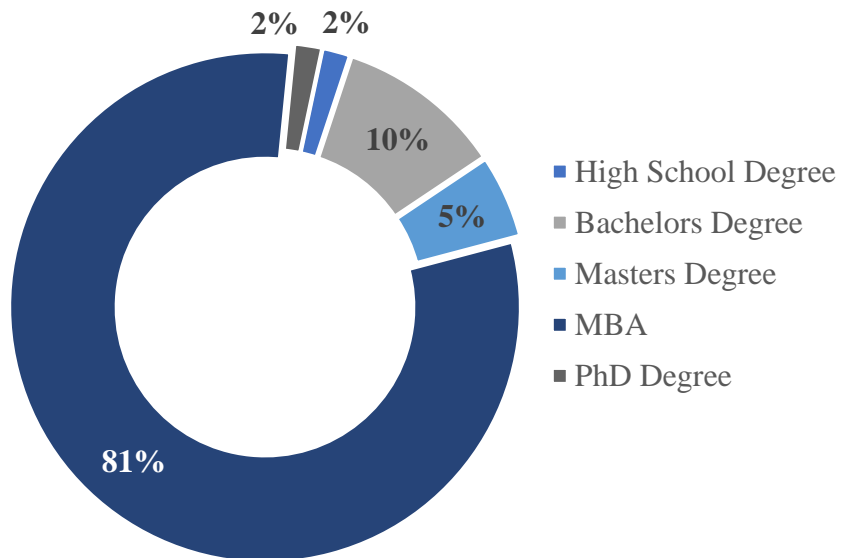
EVIII



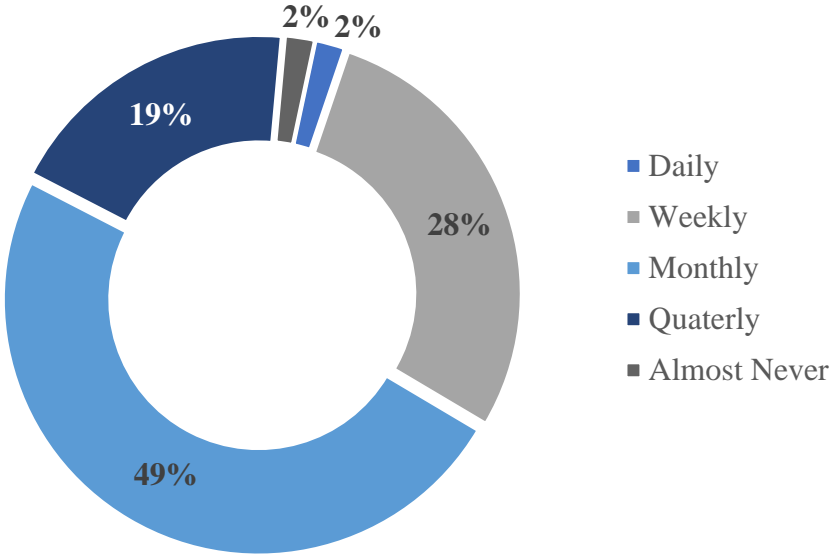
10.6 Appendix F – Age of searchers at the establishment



10.7 Appendix G – Level of searcher's education



10.8 Appendix H – Communication with investors



10.9 Appendix I – Regression results of the LSDV model

Call:

```
lm(formula = search.fund.b ~ log(avg.income.capita) + education.rate +
    urban.id.b + log(no.establishments.capita) + log(population) +
    factor(location) + factor(year), data = df_panel_19112020)
```

Residuals:

```
      Min       1Q   Median       3Q      Max
-0.77398 -0.13700 -0.03460  0.03634  1.04863
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	-4.60448	1.92075	-2.397	0.016643	*
log(avg.income.capita)	0.50576	0.13041	3.878	0.000110	***
education.rate	-0.01159	0.00498	-2.328	0.020047	*
urban.id.b	0.07036	0.04088	1.721	0.085406	.
log(no.establishments.capita)	0.35790	0.11187	3.199	0.001408	**
log(population)	0.07201	0.08662	0.831	0.405941	
factor(location)Allegheny, PA	0.08086	0.08241	0.981	0.326695	
factor(location)Anchorage, AK	-0.32916	0.20517	-1.604	0.108860	
factor(location)Atlantic, NJ	0.22048	0.18091	1.219	0.223145	
factor(location)Baltimore, MD	0.07470	0.09790	0.763	0.445593	
factor(location)Benton, WA	0.30546	0.21065	1.450	0.147247	
factor(location)Carson City, NV	0.22210	0.30153	0.737	0.461493	
factor(location)Charleston, SC	0.20107	0.15029	1.338	0.181121	
factor(location)Chatham, GA	0.26605	0.17674	1.505	0.132463	
factor(location)Chittenden, VT	0.29178	0.21371	1.365	0.172362	
factor(location)Cook, IL	0.33231	0.13858	2.398	0.016613	*
factor(location)Cumberland, ME	0.14418	0.16457	0.876	0.381119	
factor(location)Cuyahoga, OH	0.02054	0.08895	0.231	0.817441	
factor(location)Dallas, TX	0.17410	0.09005	1.933	0.053389	.
factor(location)Davidson, TN	0.13908	0.10869	1.280	0.200875	
factor(location)Denver, CO	0.01300	0.11258	0.115	0.908084	
factor(location)Douglas, NE	0.12312	0.12295	1.001	0.316811	
factor(location)Durham, NC	0.50866	0.18203	2.794	0.005268	**
factor(location)Fulton, GA	0.09685	0.09477	1.022	0.306969	
factor(location)Hamilton, OH	0.05073	0.09355	0.542	0.587675	
factor(location)Harris, TX	0.09695	0.11699	0.829	0.407435	
factor(location)Hartford, CT	0.01568	0.09116	0.172	0.863485	
factor(location)Hennepin, MN	0.07262	0.07958	0.913	0.361574	
factor(location)Jefferson, KY	0.08454	0.10715	0.789	0.430254	
factor(location)Kent, MI	0.24302	0.12306	1.975	0.048468	*
factor(location)King, WA	0.07250	0.08365	0.867	0.386260	
factor(location)Lane, OR	-0.22338	0.21820	-1.024	0.306135	
factor(location)Lee, FL	0.13777	0.13375	1.030	0.303145	
factor(location)Los Angeles, CA	0.26798	0.18749	1.429	0.153130	
factor(location)Maricopa, AZ	0.06951	0.11226	0.619	0.535860	
factor(location)Mecklenburg, NC	0.28258	0.09275	3.047	0.002354	**
factor(location)Miami-Dade, FL	-0.04943	0.10586	-0.467	0.640630	
factor(location)Miller, MO	0.49350	0.37808	1.305	0.191995	
factor(location)Monroe, IN	0.64711	0.23995	2.697	0.007080	**
factor(location)Montgomery, OH	0.26328	0.13182	1.997	0.045973	*
factor(location)Multnomah, OR	0.03060	0.10297	0.297	0.766367	
factor(location)New Castle, DE	0.06489	0.11805	0.550	0.582640	
factor(location)New Haven, CT	0.17589	0.10063	1.748	0.080678	.
factor(location)New York, NY	-0.43948	0.15926	-2.760	0.005860	**

factor(location)Orange, FL	0.16334	0.09530	1.714	0.086759	.
factor(location)Orleans, LA	0.15195	0.13785	1.102	0.270512	.
factor(location)Philadelphia, PA	0.34726	0.11519	3.015	0.002616	**
factor(location)Sacramento, CA	0.03310	0.08737	0.379	0.704892	.
factor(location)Salt Lake, UT	0.64279	0.15355	4.186	3.01e-05	***
factor(location)San Diego, CA	0.12301	0.09848	1.249	0.211811	.
factor(location)San Francisco, CA	0.26179	0.11402	2.296	0.021814	*
factor(location)San Mateo, CA	0.30150	0.10639	2.834	0.004660	**
factor(location)St. Louis, MO	-0.02480	0.08126	-0.305	0.760223	.
factor(location)Suffolk, MA	0.41086	0.09831	4.179	3.09e-05	***
factor(location)Tarrant, TX	0.15307	0.09237	1.657	0.097709	.
factor(location)Travis, TX	0.38352	0.09465	4.052	5.34e-05	***
factor(location)Wake, NC	0.23194	0.10913	2.125	0.033721	*
factor(location)Wayne, MI	0.21910	0.12729	1.721	0.085400	.
factor(location)Worcester, MA	0.17194	0.10377	1.657	0.097748	.
factor(year)1991	-0.02397	0.05452	-0.440	0.660306	.
factor(year)1992	-0.07288	0.05518	-1.321	0.186803	.
factor(year)1993	-0.04575	0.05620	-0.814	0.415718	.
factor(year)1994	-0.08685	0.05753	-1.510	0.131342	.
factor(year)1995	-0.11957	0.05991	-1.996	0.046126	*
factor(year)1996	-0.16667	0.06273	-2.657	0.007973	**
factor(year)1997	-0.17797	0.06608	-2.693	0.007158	**
factor(year)1998	-0.22028	0.07119	-3.094	0.002011	**
factor(year)1999	-0.26290	0.07483	-3.513	0.000456	***
factor(year)2000	-0.18505	0.07816	-2.368	0.018030	*
factor(year)2001	-0.19200	0.07936	-2.419	0.015669	*
factor(year)2002	-0.19828	0.07984	-2.483	0.013126	*
factor(year)2003	-0.16092	0.08224	-1.957	0.050564	.
factor(year)2004	-0.22373	0.08658	-2.584	0.009860	**
factor(year)2005	-0.15847	0.09119	-1.738	0.082460	.
factor(year)2006	-0.30057	0.09894	-3.038	0.002425	**
factor(year)2007	-0.26733	0.10311	-2.593	0.009621	**
factor(year)2008	-0.26088	0.10564	-2.470	0.013642	*
factor(year)2009	-0.23155	0.10161	-2.279	0.022825	*
factor(year)2010	-0.28154	0.10508	-2.679	0.007460	**
factor(year)2011	-0.25178	0.11075	-2.273	0.023141	*
factor(year)2012	-0.33010	0.11570	-2.853	0.004390	**
factor(year)2013	-0.20329	0.11587	-1.754	0.079569	.
factor(year)2014	-0.13820	0.12297	-1.124	0.261256	.
factor(year)2015	-0.18251	0.12713	-1.436	0.151321	.
factor(year)2016	-0.14293	0.12914	-1.107	0.268564	.
factor(year)2017	-0.13144	0.13345	-0.985	0.324832	.
factor(year)2018	-0.34786	0.13856	-2.511	0.012159	*

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2823 on 1479 degrees of freedom
Multiple R-squared: 0.2843, Adjusted R-squared: 0.2427
F-statistic: 6.833 on 86 and 1479 DF, p-value: < 2.2e-16