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Insider Trading Networks in Brazil

Redes de Insider Trading no Brasil

Eduardo Sanchez Astorino

Orientador: Prof. Dr. Bruno Cara Giovannetti

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Prof. Dr. Marco Antonio Zago

Reitor da Universidade de São Paulo

Prof. Dr. Adalberto Américo Fischmann

Diretor da Faculdade de Economia, Administração e Contabilidade

Prof. Dr. Hélio Nogueira da Cruz

Chefe do Departamento de Economia

Prof. Dr. Bruno Cara Giovannetti

Coordenador do Programa de Pós-Graduação em Economia

EDUARDO SANCHEZ ASTORINO

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Orientador: Prof. Dr. Bruno Cara Giovannetti

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Resumo

A presença de insider trading em um mercado financeiro é prejudicial ao seu funcionamento. Investidores com informação pública sempre estão em desvantagem quando negociam com agentes que detêm informação privilegiada. Portanto, insider trading aumenta o risco e diminui a participação em mercados financeiros. Neste estudo nós investigamos um possível canal através do qual a informação interna à firma é potencialmente transferida para participantes do mercado: conexões sociais baseadas em uma educação comum. Nós coletamos manualmente uma base de dados inédita sobre a experiência educacional de dois grupos de agentes: membros do conselho de diretores de empresas brasileiras e gestores de carteiras de fundos de ações. Os membros do conselho possuem informação privilegiada sobre suas firmas que seria valiosa para os gestores de fundos. Nós propomos que esses agentes podem engajar em contato social ativo se eles 1) frequentaram a mesma instituição de ensino, 2) em janelas de tempo sobrepostas e 3) obtiveram o mesmo diploma. A partir daí, estudamos se tais conexões influenciam as decisões de investimento dos gestores de carteiras. Nós descobrimos que gerentes de fundos tendem a alocar posições maiores em companhias com as quais eles possuem esta conexão educacional. Nós também descobrimos que tais conexões são valiosas: gerentes tendem a realizar grandes compras de ações conectadas em antecipação a aumentos em seu retorno e tendem a vender essas ações antes de quedas. Finalmente, nós estudamos se participantes do mercado veem aumentos na conectividade de uma empresa como aumentos no risco da empresa. Nós descobrimos que aumentos na conectividade são seguidos de aumentos no retorno esperado. Nós também encontramos que o retorno de um portfólio comprado em ações de alta conectividade e vendido em ações de baixa conectividade não pode ser explicado pelos fatores de risco tradicionais. Esses dois resultados indicam que o mercado vê a conectividade como uma forma de risco. Este é, ao nosso conhecimento, o primeiro trabalho de seu tipo para o Brasil.

Palavras-chaves: Finanças, Insider Trading, Informação Privilegiada.

Abstract

The presence of insider trading in a financial market is detrimental to its functioning. Traders with public information are always at a disadvantage when negotiating with agents in possession of inside information. Thus insider trading should increase risk and should lower participation in financial markets. In this study we investigate a channel through which inside information may be transferred to market participants: social connections based on common education. We hand-collect a novel data set of the educational background of members of the board of directors of Brazilian firms and portfolio managers of stock funds. Board members hold inside information on their firms that is valuable to fund managers. We propose that these agents may engage in active social interactions if they 1) attended the same educational institution, 2) within an overlapping time window, and 3) obtained the same degree. We study if such connections influence fund managers' portfolio decisions. We find that fund managers tend to place larger bets in companies with which they possess this sort of educational connection. We also find that these connections are economically valuable: managers tend to conduct large purchases of connected stocks prior to large increases in their return, and also tend to sell them prior to downfalls. Finally, we study if market participants view increases in a company's connectivity as an increase in its risk. We find that increases in connectivity are followed by increases in expected returns. We also determine that the return of holding a portfolio long in highly connected stocks and short on stocks with few connections cannot be explained by the traditional risk factors. These two results indicate that the market does indeed see connectivity as a form of risk. This is, to our knowledge, the first study of its kind for Brazil.

Key-words: Finance, Insider Trading, Inside Information.

Sumário

1 Introduction

Most economies with a stock market have some sort of regulation in place that aims at preventing insider trading[1]. This concern is justified by the negative effects that this practice entails. These can range from increasing firm's cost of capital (Bhattacharya and Daouk (2002), Easley and O'hara (2004)) and the bid-ask spread (Glosten and Milgrom (1985), Easley, Hvidkjaer and O'hara (2002)), to deterring other traders from participating in the market (Fishman and Hagerty (1992)) and increasing market volatility (Du and Wei (2004)), just to name a few.

It is thus essential for financial regulation enforcers to understand the channels through which inside information flows in order to be able to detect this sort of practice. In recent years a considerable number of studies have looked at how the flow of information between the participants of financial markets can influence security prices. In this work we contribute to this literature by proposing that a common educational background can be a basis for the transference of valuable information between financial agents. We adapt the methodology of Cohen, Frazzini and Malloy (2008) and construct a network between Brazilian mutual fund managers and members of the board of directors of publicly traded companies in order to study if market outcomes can be explained by the potential information flow between these agents.

We link these two groups of agents by defining an educational connection that may lead to active social contact between agents. We say that mutual fund manager A is connected with company insider B if they attended the same educational institution, at an overlapping time period, and obtained the same diploma. If this common education does indeed imply that agents exchange information through social interaction, then it is obvious how this information should flow between them: company insider B possesses private information on the quality of his company that would be valuable for fund manager A. Thus, it would be natural to test the flow of information between these two agents by testing if the outcomes of $A's$ portfolio choices are responsive to this connection.

1 As of 2002, according to Bhattacharya and Daouk (2002), from the 103 countries that have stock markets, 87 of them have insider trading laws.

We perform this test by measuring the impact of these connections on two outcomes: fund's portfolio allocations and its performance on their connected stock. We seek to answer the following questions: do fund managers place larger bets on companies with which they share an educational connection? And do they obtain abnormal returns on connected versus unconnected holdings? After controlling for other factors that might influence portfolio decisions, we find that mutual fund managers do place larger bets on their connected holdings. Additionally, we find that fund managers tend to gain from buying and selling connected stocks in different situations: the risk-adjusted returns of connected stocks tends to be larger than those of unconnected stocks after large purchases, while the opposite happens for small sales. These findings indicate that educational connections indeed serve as a basis for social ties that transmit economically valuable information.

Following this result, we then investigate if this measure of connectivity is being priced by the market. If insider trading is harmful to financial markets, and educational connections can lead to information leaks, then agents should respond to an increase in a firm's connectivity by demanding higher returns. In other words, market connectivity could be seen as a risk factor. We follow the Fama and French (1992) methodology in order to assess if Brazilian investors are indeed pricing the connectivity risk. We find that the return of a strategy that invests according to this connectivity risk cannot be explained by the more traditional risk factors of market, size, book-to-market and momentum. This indicates that there is indeed a risk that is associated with the social connections of firm's insiders.

Our work directly communicates with the literature on the impact of social connections on economic outcomes. There are a number of studies in finance which explore the effects of different types of social connections on firm behavior, such as links between members of the board of directors (Larcker et al. (2005), Hwang and Kim (2009), Cai and Sevilir (2012)), links between board members and politicians or political parties (Acemoglu et al. (2016), Faccio (2006), Goldman, Rocholl and So (2009), Fisman (2001), Gao and Huang (2016)) and more broad social connections (Hochberg, Ljungqvist and Lu (2007), Engelberg, Gao and Parsons (2013), Lerner and Malmendier (2013), Hochberg, Ljungqvist and Lu (2007), Shue (2013), Cohen, Frazzini and Malloy (2010), Conyon and Muldoon (2006)). Of special note is the literature that focuses on the effects of social connections on the mutual fund industry, such as Cohen, Frazzini and Malloy (2008), Gao and Huang (2016), Kuhnen (2009) and Ding and Wermers (2012).

We also interact with the literature on the effects of trading by privately-informed agents on financial markets. Perhaps the most important earlier paper in this area is Glosten and Milgrom (1985), where the authors study how the presence of traders with superior information affects market outcomes. They demonstrate that specialists have to set a positive bid-ask spread in order to avoid losses when dealing with privately-informed agents, thus decreasing market liquidity. Other papers reach similar conclusions as to the negative effects of insider trading, such as Easley and O'hara (2004), Cornell and Sirri (1992), Fishe and Robe (2004), Meulbroek (1992) and Du and Wei (2004). We also find papers that document country-level evidence of the negative impact of insider trading. Bhattacharya and Daouk (2002) finds that countries with a financial market suffer a significant drop in their cost of capital following the first prosecution of an insider trading case, while Du and Wei (2004) finds a connection between market volatility and the opinion of market participants on the prevalence of insider trading (according to the Global Competitiveness Report, which includes a survey of a country's corporate officers on the subjects of insider trading and legal corruption). Despite some controversy (as pointed by Bhattacharya (2014)), there seems to be a consensus in the economic literature that the practice of insider trading is indeed harmful to financial markets, by increasing risk and decreasing market participation.

The rest of this study is organized as follows. In Chapter 2 we present the methodology of our data collection, as well as summary statistics of our data. Due to the nature of our data set, it is important to dedicate an entire chapter to explaining the collection process, the assumptions that were made during our work, and the general features of the educational data base. The focus of Chapter 3 is in answering if funds seem to perform differently in their connected holdings in comparison to their performance on stocks with which they have no form of connection. We study if educational connections influence fund manager's behavior, as well as their return. As mentioned above, the answer is positive for both questions: funds tend to show larger holdings of connected stock as opposed to unconnected stock. In addition, they seem to change their holdings of connected stock in anticipation of future risk-adjusted returns, which implies that connectivity transmits valuable information to fund managers. In Chapter 4 we examine if changes in a firm's connectivity with the mutual funds industry affect the market as a whole in a negative way. More specifically, we find evidence that such connections are indeed priced as a risk factor. Finally, we present a conclusion in Chapter 5.

2 Data Set

2.1 Introduction

The data set used in this study was hand-collected from different sources. There are companies in the US that collect and make available the work history and educational background of mutual fund managers and high ranking company officials, presumably in order to help investors infer about managerial competence and possible conflicts of interest. Unfortunately there are no such pre-constructed data sets for Brazil, however we do find that it is possible to collect this data from social websites such as LinkedIn and Facebook, as well as from official forms that are filed by publicly-traded companies.

The objective of this Chapter is to detail how this hand-collected data set was constructed. Our study will encompass the period from 2010 to 2015, so the data on educational backgrounds, portfolio allocations, stock returns and risk factors will all be from this six-year period. We begin in Section 2.2 by defining the filters that we applied to the universe of Brazilian funds and companies. These filters will determine the composition of our sample, and thus the companies and funds that will focus our data scrapping. We filter companies based on their liquidity, and funds based on their size and performance.

In Section 2.3 we present the methodology and results of our data collection, detailing what were our main data sources and how we dealt with partial and missing results. As we will see, the publicly available data sources that we explore provide us with usable data on the background for most of our sample.

Finally, in Section 2.4 we show the results of the merge between the educational backgrounds of company insiders and fund managers.

2.2 Liquidity and Relevance Filters

Before starting our data scrapping we apply a filter to both publicly traded companies and mutual funds. Our company filter aims at selecting firms based on their liquidity, while funds are selected based on their size and past performance. The data on stock prices and daily volume, as well as fund's daily net asset value, comes from Economatica. In order to filter publicly traded Brazilian companies, we adopt the liquidity criteria defined by the Brazilian Center for Research in Financial Economics of the University of São Paulo (Nefin)[1]. The Nefin methodology aims to create a market portfolio of stocks that is reevaluated at the beginning of each year. A stock traded in BOVESPA is considered eligible for year t if it meets 3 criteria:

- The stock is the most traded stock of the firm (the one with the highest traded volume during last year);
- The stock was traded in more than 80% of the days in year $t-1$ with volume greater than 500.000,00 Reais per day. In case the stock was listed in year $t-1$, the period considered goes from the listing day to the last day of the year;
- The stock was initially listed prior to December of year $t-1$.

According to the Nefin methodology stocks are evaluated once a year in order to assess their eligibility, and the resulting market portfolio will potentially have a different composition after each evaluation. In order to avoid gaps and discontinuities in our data set (due to stocks entering and leaving the market portfolio), we do not drop a company's stock if it becomes ineligible. More specifically, if a company is eligible according to the Nefin criteria for any year t, we choose to keep it in our sample for every year from 2010 to 2015, even if the Nefin criteria would reject this company as illiquid for one of those years. In Table 1 we present summary statistics on eligible companies.

For the Brazilian mutual funds industry we limit our sample to stock funds, which are obligated to maintain 67% of their portfolios in the form of stocks. We also choose to limit our sample by only selecting funds that seem to have displayed an ability for selecting stocks in the past, as well as a large asset value. For a fund to be considered eligible for our sample, it has to respect the following criteria:

[1] These criteria, as well as other relevant information, can be found at <http://www.nefin.com.br/>.

Table 1 – Summary Statistics - Selected Companies

In this table we present summary statistics for the companies whose stocks were considered eligible according to the Nefin liquidity criteria. We present the average, median and standard deviation for returns, market value of equity and volume. We calculate returns for companies with more than one type of stock as the value-weighted returns of each stock, while the volume for such companies is the sum of the volume of each individual stock. All variables are presented in a monthly frequency. Market value of equity and volume are measured in billions of Reais.

	Mean	Median	Std. Dev.
Return	-0.17%	0.00%	9.74%
Market Value of Equity	13.4	3.88	35.6
Volume	0.59	0.14	1.57

- The fund has to present average net assets that are larger than 100 million Reais since its creation;
- The fund has to present cumulative returns that are larger than the cumulative IBOVESPA return for the period studied (2010-2015).

The data on fund portfolio allocations is publicly available with, at most, a three month lag, since Brazilian investment funds are required to divulge their end-of-month portfolios to the Brazilian financial regulatory agency, the "Comissão de Valores Mobiliários" (CVM). We access this information through Economatica, which collects and consolidates this public information. The data on fund net assets and cumulative returns also comes from Economatica.

In addition to selecting funds based on performance and size, we must also aggregate all information concerning assets and portfolio choices at the asset management firm level. As we will see below, we cannot link individual funds directly with publicly traded companies because fund managers do not detail the exact fund in which they work, they merely state that they hold the position of portfolio managers at an asset management firm that manages several different funds. Since we cannot link funds and companies directly, we aggregate all funds to the asset management firm level. In Table 2 we present summary statistics for the asset management firms.

Table 2 – Summary Statistics - Selected Asset Management Firms

In this table we present summary statistics for the holdings of our sample of asset management firms. We present the mean, median, standard deviation, minimum and maximum for the following variables: number of funds belonging to each asset management firm, the number of stocks held in each firm's portfolio, the value of each position that the firms choose to hold and the total value of the firm's portfolio of held stock. The last two are presented in billions of Reais.

	Mean	Median	Std. Dev.	Minimum	Maximum
Number of Funds	3.83	2	4.48	1	28
Number of Stocks Held	6.03	0	15.48	0	72
Billions of Reais In Each Position	0.24	0.19	0.49	-	32.30
Billions of Reais Held In Stock	1.05	0.29	4.68	-	48.80

We now present the results of our data scraping of educational backgrounds for the companies and funds that were selected. As we will see, the selection described above does not seem to affect the sample properties with regards to the educational background of insiders and fund managers, therefore leaving us with a fairly representative sample for our study.

2.3 The Educational Background of Brazilian Fund Managers and Insiders

2.3.1 The Population of Fund Managers and Insiders

After selecting the publicly-traded companies and asset management firms via the criteria above, we then need to find, for each company, the composition of its board of directors over time, and for each asset management firm, its portfolio managers. Thanks to the support of the Brazilian financial regulation agency, the "Comissão de Valores Mobiliários" (CVM), we obtained access to the composition of the boards of publicly traded companies. This information is publicly available in a class of official forms known as the "formulários de referência", which are equivalent in content to the SEC 10-k filings, however CVM compiled this information on our request.

We have to adopt a different approach for the population of Brazilian fund managers, since funds in Brazil do not have an obligation to divulge information on the background and education of their employees. We cross the information available in three public data sources. The first and most important source of information in our study is LinkedIn. Many companies make use of LinkedIn by making official public profiles to which all employees with an account must subscribe, thus it is possible to discover an asset management firm's composition by searching for its name and then extracting the information of all users that claim to work or to have worked in the past for the firm.

The second main source of information for fund composition are the Annual Funds Reports released by the "Associação Brasileira das Entidades dos Mercados Financeiro e de Capitais" (ANBIMA). These reports contain information at the asset management firms level about total asset holdings, the list of funds under their management and also a list of high ranking officials and partners, including their function. However unfortunately these reports are no longer being published as of 2015 (when it contained data on the funds industry for 2014).

Finally, some asset management firms divulge their composition at their company website, however this is a rare occurrence, and additionally the company website only gives us a snapshot of the firm's current composition, thus making it impossible to explore this source to reconstruct the firm's employment history.

A final concern before collecting the educational information is that LinkedIn users sometimes misreport their own current and past functions in their profile. We adopt a conservative approach and filter out any agent that does not explicitly report that their function is "portfolio management". We also include agents that describe themselves as "partners" or "founders" of the asset management firm, since it seems to us that these agents would hold some power over portfolio decisions and would be interested in obtaining insider information in order to increase their profits.

In Table 3 we briefly present summary statistics for the population of company insiders and fund managers. Our final sample will be composed of the agents for which we

In this table we present summary statistics for the number of insiders and fund managers that compose our universe of agents. We count the number of insiders and portfolio managers for each year of our sample and present summary statistics. The universe of company insiders was provided to us by CVM, and corresponds to the aggregation of information contained in forms that were issued between 2010 and 2015. These are called "formulários de referência", and correspond to the SEC 10-k filings. The universe of fund managers is determined by crossing the information found in Linkedin, the Anbima Annual Fund Reports and at the fund's official website. In addition, we filter out fund employees that don't seem to be in a position to take portfolio decisions, such as middle office, IT and risk.

Table 3 – Insiders and Fund Managers

	Mean	Median	Std. Dev.	Minimum	Maximum
Insiders per Year	2,709.5	3,006.5	875.4	1,000	3,376
Managers per Year	466.8	479.5	49.7	388	512

were able to collect usable information regarding their educational background and work history.

2.3.2 Educational Data

We now present the results of our data collection. All our educational data sources are publicly available, and accessible via the Internet.

The educational background of company insiders comes mainly from the official forms described above, the "formulários de referência". These forms contain the composition of the board of directors, as well as a brief text detailing their work history. The main focus of the form is to detail possible conflicts of interest relating to the fact that directors sometimes serve on several different boards at the same time. In fact, CVM does not demand that board members disclose information regarding their educational background. However, when examining the forms we find that most often than not they do contain a very extensive set of educational information for each board member. It is thus interesting to note that board members frequently divulge this information, even though they are not required by law to do so. Whenever these forms present any incomplete information, we rely on Google searches to attempt to fill in the lacking information. Most Google searches end up redirecting us to the official forms themselves, however sometimes we find the information we need on alumni pages or business news websites.

For fund managers, the main source of educational information is LinkedIn. LinkedIn users usually divulge their entire work history on their profiles, as well as all the undergraduate and post-graduate degrees that they hold. Users also establish connections among themselves that facilitate the work of finding all agents who claim to work or to have worked in the past at an asset management firm. However, one negative aspect is that managers sometimes are not as exact as we require when describing their function. Since we are interested in only collecting information regarding agents that have the power to mold portfolio decisions, we have to apply a filter based on agent's self-described function. Our goal is to keep only agents who explicitly define themselves as "managers", "partners" or "founders", while excluding the rest. By excluding agents that do not fall in this category, we are being conservative in our approach to data collection.

We classify the degrees obtained by agents into five categories: undergraduate, masters, Ph.D, MBA and Post-Graduate. This last category is only used when we cannot determine to which of the other four categories a degree should belong to. Unfortunately our data collection will sometimes result in an incomplete set of information. In our study we are interested in defining different levels of connectivity, with the deepest form of connection being the one in which insider and fund manager attended the same educational institution, in overlapping time intervals, and obtained the same diploma. We are particularly interested in this sort of educational connection because it carries the highest probability of active social interaction. We will only be able to connect an agent in this manner if we have the institution which they attended, the degree obtained and the starting and ending dates of their studies. We classify an agent's degree as unusable if any of these three types of information is lacking. Our data collection revealed that the starting and ending dates information is the one that is most often lacking in public LinkedIn profiles and official forms, with agents often only divulging their graduation year. In order to be able to use these agents in our study, we assume a fixed duration for each type of degree. We assume that undergraduate degrees require 5 years of study, while masters last 2 years, PhDs last 4 and MBAs last 1. Since our Post-Graduate category is prone to errors, we do not assume a duration for post-graduate degrees, and only use this information if it is complete.

In Table 4 we present the results of our data collection. Overall, we were able to obtain usable information for 70.3% of all the fund managers in our population, and 78.5% of all company insiders. In other words, there is the potential for at least 535 fund managers and for $2,546$ insiders to generate some sort of connection with each other.

Table 4 – Results of Data Collection

This table presents the overall results of our data collection of the educational background of company insiders and fund managers. We present the size of the population of both types of agents, as well as the number of fund managers and insiders for which we were able to obtain some sort of usable educational information, that is, the type of information that could generate some sort of educational connection. We also show what this number represents as a percentage of its respective population.

Agents	Total Size of Population	Percentage with Usable Information	Final Size of Sample
Fund Managers	761	70.3%	535
Company Insiders	3,244	78.5%	2,546

In Tables 5 and 6 we present summary statistics on the results of our data collection. We present the five most common courses and institutions for both insiders and fund managers, separated in each of the five degree categories.

Table 5 – Top Five Institutions and Courses For Company Insiders

In this table we present the five most common institutions and courses for company insiders. We separate this information according to 5 levels of higher education: Undergraduate, Masters, PhD, MBA and general Post-Graduate Degree. The latter category is used when we cannot determine the exact post-graduate degree held by the insider. The number of insiders which attended each course and institution is displayed in parenthesis.

Courses	Undergraduate	Masters	PhD	MBA	Post-Graduate
(1)	Business (555)	Economics (64)	Economics (38)	Undefined (71)	Business (87)
(2)	Economics (463)	Business (42)	Accounting (11)	Finance (69)	Finance (40)
(3)	Law (354)	Law (29)	Law (11)	Business (39)	Marketing (18)
(4)	Civil Engineering (227)	Accounting (14)	Industrial Engineering (6)	Executive MBA (15)	Law (14)
(5)	Accounting (219)	Industrial Engineering (12)	Business (5)	Business Management (14)	Financial Management (11)
Institutions	Undergraduate	Masters	PhD	MBA	Post-Graduate
(1)	University of São Paulo (281)	University of São Paulo (42)	University of São Paulo (33)	Insper (34)	FGV-SP (62)
(2)	UFRJ (171)	UFRJ (30)	UnB (5)	University of São Paulo (26)	Dom Cabral Foundation (25)
(3)	FGV-SP (120)	PUC-Rio (24)	UFRJ (5)	UFRJ (17)	University of São Paulo (22)
(4)	PUC-Rio (109)	UnB (12)	PUC-SP (3)	FGV-RJ (17)	FGV-RJ (21)
(5)	PUC-SP (94)	FGV-RJ (12)	Unicamp (3)	FGV-SP (16)	Harvard Business School (17)

Tables 5 and 6 show that there is considerable homogeneity for undergraduate studies, with funds being more skewed towards professionals with a technical background. Also of note is the fact that São Paulo shares its importance in the mutual funds industry with Rio de Janeiro, which is still an important financial center in Brazil.

Finally, we now turn our attention to establishing educational connections between insiders and fund managers. In the next section we present the results of the merge between the two data sets.

2.4 The Connectivity Between Insiders and Fund Managers

Our methodology for merging the two data sets follows certain rules that determine when we will be able to say that two agents are indeed connected. First, we do not allow any sort of connectivity between two different categories of higher education. In other words, we only allow for undergraduates to connect with other undergraduates, and so on. In addition, when connecting agents through the degrees that they obtained, we only allow for connections between agents with the exact same degree. For instance, an insider

Table 6 – Top Five Institutions and Courses For Fund Managers

In this table we present the five most common institutions and courses for fund managers. We separate this information according to 5 levels of higher education: Undergraduate, Masters, PhD., MBA and general Post-Graduate Degree. This latter category is used when we cannot determine the exact post-graduate degree held by the fund manager. The number of fund managers which attended each course and institution is displayed in parenthesis.

Courses	Undergraduate	Masters	PhD	MBA	Post-Graduate
(1)	Business (159)	Economics (39)	Economics (10)	Finance (69)	Finance (7)
(2)	Economics (156)	Finance (25)	Finance (3)	Undefined (32)	Business (7)
(3)	Industrial Engineering (57)	Business (19)	Political Science (1)	Business (12)	Financial Engineering (4)
(4)	Law (21)	Law (4)	Engineering (1)	Executive MBA (3)	Economics (3)
(5)	Mechanical Engineering (21)	Finance and Economics (4)	Law (1)	Corporate Finance (2)	Business Management (2)
Institutions	**Undergraduate**	**Masters**	**PhD**	**MBA**	**Post-Graduate**
(1)	University of São Paulo (98)	FGV-SP (23)	University of São Paulo (4)	Ibmec-RJ (26)	Harvard Business School (13)
(2)	PUC-Rio (94)	FGV-RJ (21)	PUC-Rio (2)	Insper (16)	FGV-SP (11)
(3)	FGV-SP (55)	PUC-Rio (17)	UC Berkeley (1)	FGV-RJ (8)	Insper (7)
(4)	UFRJ (54)	University of São Paulo (9)	IUPERJ (1)	University of São Paulo (7)	PUC-Rio (6)
(5)	PUC-SP (21)	Insper (7)	University of Colorado at Boulder (1)	Harvard Business School (7)	Harvard (6)

with an undergraduate degree in mechanical engineering will not be considered as having the same degree as a fund manager with a civil engineering undergraduate degree, even if they attended the same educational institution in their undergraduate studies. This is a significant point of departure in comparison to Cohen, Frazzini and Malloy (2008), since the authors aggregate different degrees in categories such as business school, medical school etc. We feel that this is a necessary adaptation in order to avoid spurious results, for Brazilian universities tend to be more rigid than US institutions with regards to curricula.

We define four levels of connectivity between agents. The weakest form of connection is when insider and fund manager attended the same educational institution. The second type of connection is when insider and fund manager attended the same institution and obtained the same degree. The third type of connection is defined when both agents attended the same institution within an overlapping time period. Finally, the strongest type of connection is when both agents attended the same institution, in an overlapping time period, and obtained the same degree. We will also refer to these connections as CONNECTED1, CONNECTED2, CONNECTED3 and CONNECTED4 in what follows. We understand that the last type of connectivity is the strongest, since it implies in a large probability of active social interaction between agents. In Table 7 we present the number of insiders and fund managers that showed some form of connection with each other as a percentage of the total amount of each agent with usable educational information.

Table 7 – Types of Connections

In this table we present the types of educational connections that we discovered between company insiders and fund managers. We define four levels of connectivity: when agents attended the same school; when agents attended the same school and obtained the same degree; when agents attended the same school within overlapping time periods; and when agents attended the same school, within an overlapping time period, and obtained the same degree. The table gives us the percentage of our sample of company insiders and fund managers that connected with at least one other agent in some way.

Agents	Same School	Same School and Degree	Same School and Overlapping Time Period	Same School, Degree and Overlapping Time Period
Company Insiders	65%	43%	40%	20%
Fund Managers	96%	80%	77%	61%

As we can see, it is relatively rare for agents to have no connections whatsoever. 65% of insiders have the weakest form of connection with at least one fund manager, while 96% of fund managers have a weak connection with at least one insider. For the deepest type of connection we have that these numbers are 20% for insiders and 61% for fund managers.

With this we conclude the presentation of our data. Our next step is to analyze if the portfolio decisions of fund managers are being influenced by educational connections, and if fund managers are earning higher returns from their connected holdings. We perform this study in the next Chapter, while in Chapter 4 we analyze if markets become riskier and less liquid as a response to an increase in connectivity.

3 Do Educational Connections Influence Portfolio Selection and Returns?

3.1 Introduction

After presenting our data set, we proceed to testing if educational connections are indeed channels for the transmission of inside information. Our objective in this Chapter is to answer if Brazilian mutual fund managers are influenced by their educational connections when making portfolio decisions. In addition, we want to determine if these connected managers do indeed earn higher returns as a function of their connections. We will answer both questions positively: not only fund managers place larger bets on companies with which they share a connection, but they also make large purchases and small sales in anticipation of positive and negative changes in returns, respectively. Overall our results support the idea that educational connections serve as a channel for the transmission of valuable information.

There is considerable evidence that social connections indeed influence economic outcomes. Hwang and Kim (2009) finds that companies in which directors have some sort of social connection with the CEO tend to have significantly higher levels of compensation and lower pay-performance and turnover-performance sensibility in comparison to firms in which the board of directors and the CEO are socially independent[1]. In Engelberg, Gao and Parsons (2013) the authors find that CEOs with large networks tend to earn more than those with smaller networks, and that this increase in compensation seems to have an efficient contracting explanation. In this case, the authors make use of the BoardEx database in order to link CEOs by examining former work experience (including boards in which the CEOs has served), past universities attended and past or current business relationships. Gao and Huang (2016) finds that hedge fund managers gain an informational advantage when trading through their connections with lobbyists. The paper proposes that hedge funds actually employ lobbyists to influence political decisions, and the latter's

[1] The authors focus on social ties as measured by regional origin, as well as mutual *alma mater*, military service, discipline and industry.

contact with politicians gives them access to valuable information that is then passed to hedge fund managers.

Many papers also specifically attest to the importance of educational connections for financial outcomes. In Cohen, Frazzini and Malloy (2010) the authors find that sell-side analysts outperform by up to 6.60% per year on their stock recommendations when they have an educational link to the company. In other words, sell side analysts are better able to assess the quality of a firm with which they share an educational connection. In Ahern (2015) the author hand-collects the legal documents pertaining insider trading cases, which provide accounts of the person-to-person communication of inside information. Of all the available pairs of insiders, the study finds that 64% first met before college, while 16% met in college or graduate school. In Shue (2013) the author studies the consequences of random assignment of MBA students to sections at the Harvard Business School, and finds that this common education can explain factors such as executive compensation and acquisition strategy. The study also finds that these peer effects become more than twice as strong following staggered alumni reunions.

These findings are also verified in Cohen, Frazzini and Malloy (2008), the most important reference for our study. The paper explores the educational connections between mutual fund managers and company board members in the US, and finds that managers tend to place larger bets on companies with which they share a connection. In addition, mutual fund managers obtain larger gains in these stocks than in their unconnected holdings, which suggests that these connections have economic value. The authors keep an open mind as to the nature of the information flow between insiders and fund managers, however their results are less consistent with a story based on fund managers having a comparative advantage in assessing the managerial quality of company officials in their network. Our paper diverges from this study in two main points. First, we conduct an event study of movements in portfolio composition in order to test if connections generate abnormal returns for portfolio managers, while the original paper investigates this possibility by constructing a portfolio that replicates the aggregate holdings of the entire US fund industry in connected and unconnected stock. In contrast, our approach asks the following question from the data: when a manager purchases or sells stock, will the return of said stock vary significantly over the following months depending of its connectivity? In other words, do connected portfolio changes predict future returns? Our approach points to the same direction that the replicating portfolio of the original paper, however it allows us to better characterize the gains of connected portfolio managers.

The second main point in which this study differs from Cohen, Frazzini and Malloy (2008) is on the nature of the data used. We need to adopt a different approach to data collection in order to account for the lack of preexisting databases on the educational backgrounds of Brazilian fund managers and company insiders. The original paper benefited from the existence of financial services that collected information on the background of portfolio managers and corporate officers. More specifically, the authors obtained information on mutual fund managers' educational background from Morningstar, which collects all the undergraduate and graduate degrees received by U.S. portfolio managers, the year in which they were granted, and the educational institution attended. The biographical information on board of directors and senior company officers was provided by BoardEx of Management Diagnostics Limited, a private research company specialized in social network data on company officials of U.S. and European public and private companies. These services unfortunately do not have this sort of data for Brazilian companies and funds, and there are no local equivalents that could be exploited in order to create a similar database. Our solution was to explore the publicly available information on social networks such as LinkedIn, as well as the official public company filings that are demanded by Brazilian financial regulators. As shown in Chapter 2, our manual approach yielded a very good success rate, as we were able to obtain usable information for 70% of fund managers and for 79% of insiders in our sample. It is interesting to note that the current prevalence of social networking services such as Facebook and LinkedIn facilitates the work of economists interested in studying the effects of social connections.

In the next Section we present our methodology for testing if portfolio choices are responsive to educational connectivity between fund managers and company insiders. We then present the results of our tests.

3.2 Results: Impact of Connections on Portfolio Choices

In this Section we study if the educational connections detailed above can influence the portfolio decisions of fund managers. We merge our database on connections with the data on the aggregate portfolios of asset management companies. Using the connection data, we can construct a set of dummy variables that indicate the depth of connectivity between asset management companies and publicly traded firms. Following Cohen, Frazzini and Malloy (2008) we define four measures of connectivity, based on whether the portfolio manager and the insider attended the same school (CONNECTED1), attended the same school and obtained the same degree (CONNECTED2), attended the same school at an overlapping time window (CONNECTED3), and attended the same school at an overlapping time window and obtained the same degree (CONNECTED4). We are mainly interested in CONNECTED4, since it is the strongest measure among the four, giving us the highest likelihood of social interaction between fund manager and insider. Measures 1 through 3 are important in order to assess if the detected effects are being driven by other factors, such as common education, as opposed to active social contact.

In order to study the effects of connections on portfolio choices we run pooled OLS regressions of the portfolio weights of asset management firms on the connectivity dummies we describe above. Since portfolio managers' decisions could also be driven by exposure to some type of risk, we also include a set of controls aimed at replicating the size, book-to-market and momentum factors, as presented in Carhart (1997). We include firms book-to-market, market value of equity and 12-month cumulative returns as controls in our regressions. Finally, we include a full set of time, fund and firm fixed effects through all our specifications. All regressions are based on monthly observations.

In Table 8 we present the results of the regressions of portfolio weights on the connection variables. We measure portfolio weights in basis points. We first regress portfolio weights on each connection variable separately, and finally on both CONNECTED1 and CONNECTED4. This last regression allows us to isolate the effect of deeper connections from the effects of more superficial links. Despite the negative effect of CONNECTED1

Table 8 – OLS Regression: Portfolio Weights in Connected vs. Unconnected Stock

This table shows the results of the pooled OLS regressions of asset management firm's portfolio shares on the connectivity dummies. All regressions are based on monthly observations, and portfolio shares are measured at the end of the month. We define $CONNECTEDX_{ijt}$ as a dummy indicating that, in the month t, the asset management company i shares an educational connection of type X with firm j, where X indicates the level of connectivity between firms and asset management companies: $X = 1$ indicates that at least one portfolio manager working at asset management company j attended the same school as at least one director working at firm i; $X = 2$ indicates that both agents attended the same school and obtained the same degree; $X = 3$ indicates that both agents attended the same school in an overlapping time window; finally, $X = 4$ indicates that both agents attended the same school, in an overlapping time window, and obtained the same degree. Portfolio shares are in basis points. We present the results of five regressions, the first four on the connection variables CONNECTED1 through CONNECTED4, and the last one on both CONNECTED1 and CONNECTED4. For all five regressions we use a full set of time, firm and asset management company fixed effects. We also control for firm book-to-market, market value of equity and 12-month cumulative returns on all regressions. The standard errors are reported in parentheses, and are corrected for possible clustering at the month level. $*$, $**$ and $***$ indicate significance at the 10%, 5% and 1% level.

$$Share_{ijt} = \beta_0 + \beta_1 CONNECTEDX_{ijt} + \beta_2 BM_{jt} + \beta_3 ME_{jt} + \beta_4 12MReturn_{jt} + FE + \varepsilon_{ijt}$$

	(1)	(2)	(3)	(4)	(5)
Constant	23.65***	22.60***	22.87***	22.71***	24.08***
	(5.35)	(5.38)	(5.42)	(5.42)	(5.36)
CONNECTED1	−4.20***				−5.34***
	(1.43)				(1.36)
CONNECTED2		−0.32			
		(0.83)			
CONNECTED3			5.89***		
			(1.11)		
CONNECTED4				9.62***	10.63***
				(2.41)	(2.33)
Adjusted R^2	0.131	0.131	0.131	0.131	0.131

as shown in Columns 1 and 5, the other regressions support the selection of educational connections as a proxy for social interaction. As we move to deeper connection variables, we detect stronger effects of connections on portfolio weights. According to our results, fund managers place an additional 9.62 basis points on stocks with which they share the closest connection, roughly 42% more than on unconnected stocks.

In addition to measuring how managers change portfolio weights in response to an educational connection, we are also interested in analyzing how their investment decisions differ from the rest of the market. In order to study this question we construct a market portfolio based on the aggregate investments of the funds in our sample. Based on this variable, we can calculate how the portfolio decisions of each individual asset management company differs from this market portfolio. This measure is simply the difference between the portfolio weight of asset management company i on stock j at time t minus the market portfolio weight on the same stock and at the same period. The interpretation of this measure is straightforward: if, for example, a fund manager places 3% of its net assets on stock j at time t, while our sample of funds places 2% of its net assets at the same stock at the same time, we conclude that this manager is placing larger bets on stock j than the rest of the market.

In Table 9 we run regressions of this difference on the four connection variables separately, and on both CONNECTED1 and CONNECTED4 simultaneously. Our results corroborate our interpretation of Table 8: as connections become deeper, its effects on portfolio decisions become stronger. As we can see in Column 4, in comparison with the market portfolio, a fund manager places an additional 8.73 basis points in a stock if he attended the same school, at the same time, and received the same diploma as an insider. We obtain a similar result if we additionally control for the weakest connection, as can be seen in Column 5.

Overall, our results indicate that social connections affect the portfolio decisions of fund managers, and that the strength of this effect is increasing in the depth of the connection. It is also important to note that the magnitude of the effects of the CONNECTED4 variable are similar to those found in Cohen, Frazzini and Malloy (2008). In the next Section we turn our attention to analyzing if these insider connections can also generate abnormal returns.

Table 9 – OLS Regression: Relative Portfolio Weights in Connected vs. Unconnected Stock

This table shows the results of the pooled OLS regressions of asset management firm's portfolio shares minus market portfolio shares on the connectivity dummies, where the market portfolio share of firm j at time t is the sum of all value invested in firm j by our sample of funds, divided by the sum of all value invested in stocks by those funds. All regressions are based on monthly observations, and portfolio shares are measured at the end of the month. We define $CONNECTEDX_{ijt}$ as a dummy indicating that, in the month t, the asset management company i shares an educational connection of type X with firm j, where X indicates the level of connectivity between firms and asset management companies: $X = 1$ indicates that at least one portfolio manager working at asset management company j attended the same school as at least one director working at firm i; $X = 2$ indicates that both agents attended the same school and obtained the same degree; $X = 3$ indicates that both agents attended the same school in an overlapping time window; finally, $X = 4$ indicates that both agents attended the same school, in an overlapping time window, and obtained the same degree. Portfolio shares are in basis points. We present the results of five regressions, the first four on the connection variables CONNECTED1 through CONNECTED4, and the last one on both CONNECTED1 and CONNECTED4. For all five regressions we use a full set of time, firm and asset management company fixed effects. We also control for firm book-to-market, market value of equity and 12-month cumulative returns on all regressions. The standard errors are reported in parentheses, and are corrected for possible clustering at the month level. $*$, $**$ and $***$ indicate significance at the 10%, 5% and 1% level.

$$(Share_{ijt} - MarketShare_{jt}) = \beta_0 + \beta_1 CONNECTEDX_{ijt} + \beta_2 BM_{jt} + \beta_3 ME_{jt} + \beta_4 12MReturn_{jt} + FE + \varepsilon_{ijt}$$

	(1)	(2)	(3)	(4)	(5)
Constant	-7.34^{***}	-6.64^{***}	-6.20^{***}	-6.40^{***}	-7.01^{***}
	(2.29)	(2.17)	(2.17)	(2.17)	(2.30)
CONNECTED1	3.24^{**}				2.35^{***}
	(1.54)				(1.51)
CONNECTED2		2.25^{**}			
		(0.70)			
CONNECTED3			6.52^{***}		
			(1.12)		
CONNECTED4				8.73^{***}	8.29^{***}
				(2.22)	(2.19)
Adjusted R^2	0.138	0.138	0.138	0.138	0.138

3.3 Results: Returns on Connected Holdings

The second question we address is if mutual fund managers obtain abnormal returns from their connected holdings. In order to answer this question we conduct an event study of stock returns following a change in their holdings. We compare the average return of connected holdings following purchases and sales with the average return of unconnected holdings. If fund managers indeed use educational connections to obtain economically valuable information, we would expect a positive difference between the return of connected versus unconnected stock following a purchase, and a negative difference following a sale.

We define an event as the decision to purchase or sell a stock. Since we have the monetary value of the investment in each stock j for each fund in our database, we can decompose the change in this value from time t to $t+1$ into two parts. The first is the result of a deliberate decision to buy or sell stocks, while the second is given simply by the fact that j delivered a return $r_{j,t+1}$, thus constituting a passive change in its holdings. We can thus define an event as the deliberate decision to increase or decrease the exposure to a stock. Additionally, we also experiment with restricting our definition of an event to changes greater than a certain amount.

Finally, we define the response variable of our event study. In order to compare stock returns over time and the cross-section of Brazilian firms, we construct a measure of risk-adjusted returns at the firm level[2]. For each firm in our sample we run the following regression of its daily excess return on the market, size, book-to-market, momentum and illiquidity risk factors available at the Nefin website[3]:

$$(R_{j,t} - R_{ft}) = \alpha_j + \beta_1 Market_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 WML_t + \beta_5 IML_t + \epsilon_{j,t} \quad (3.1)$$

Thus, the risk-adjusted return of stock j at time t is given by $\alpha_j + \epsilon_{j,t}$. For each firm j, the regression constant α_j gives us the return that is consistent over time and

[2] Since many firms in Brazil issue both preferred and ordinary stock, our measure of firm return is the value-weighted return of all the stocks issued by the firm.

[3] These risk factors are updated monthly and can be downloaded at <http://www.nefin.com.br/risk_factors.html>. This URL also contains information on the construction of these risk factors.

cannot be explained by our measures of risk, while the error term $\epsilon_{j,t}$ is the part of this unexplained return that varies over time. We believe that our measure of risk-adjusted returns should take both these factors into account, since an investor becomes exposed to both when acquiring equity.

In Table 10 we see the results of our event study. We examine the cumulative average risk-adjusted return of stocks for five months following a purchase or sale, and test if the mean return after an event is different between connected and unconnected stock. In the case of a purchase, we expect that connected stocks present higher risk-adjusted returns than unconnected stocks on average, while the opposite should hold after a sale. We define a connection in the same way as we defined the variable CONNECTED4 above, that is, as a fund manager that attended the same institution, at the same time, and obtained the same degree as a firm insider.

On Panel 1 we consider all purchases and sales regardless of their value. For the former we actually find the opposite result that was expected. The average return on connected holdings following a purchase is lower than unconnected holdings, and this effect is significant even at the 1% level, for all 5 periods after a purchase. The same holds for sales, however in this case this is the result that was expected. A different pattern begins to emerge on Panels 2 through 4, where we restrict our events to purchases and sales over $500,00$, $1,000,000$ and $5,000,000$ reais. As we increase the value of our cutoff point for portfolio changes, we begin to find statistical significance for purchases, while sales become less significant. Overall, our findings suggest that fund managers with access to insiders tend to gain on high value purchases and low value sales of connected stock.

One way of interpreting findings of our event study is that connected managers seem to move before the rest of the market to adjust their portfolios. Suppose, for instance, that one of the fund managers of our sample has an educational connection with firm j, while another does not. Since j is a connected stock to one fund manager but not to the other, its return will contribute to the average returns following both a connected and an unconnected purchase. Thus, the difference in average risk-adjusted returns between connected and unconnected events arises because both managers are buying stock j, but at different times. Since our event study shows that fund managers tend to conduct their connected portfolio changes in the same direction as the changes in risk-adjusted returns, it would seem that they are able to predict future returns on their connected stock. This is consistent with the hypothesis that educational connections are indeed serving as conduits to inside information. Since managers are buying and selling their connected stocks in response to future movements in risk-adjusted returns, it is less likely that educational connections are merely helping managers to assess the managerial skill of board members.

Table 10 – Event Study - Risk-Adjusted Returns on Connected versus Unconnected Holdings

The four tables below show the results of the event study for portfolio changes. We conduct four types of event studies: the first one defines purchase and sale events as portfolio changes of any value, while the next three only look at portfolio changes of more than 500,000, 1,000,000 and 5,000,000 reais, respectively. We report the mean and standard error of cumulative risk-adjusted returns for up to five periods after the event, for both connected and unconnected portfolio changes. We also report the mean and standard error for the difference between the connected and unconnected means. The p-value refers to the one-tailed t-test that is relevant to our hypothesis that educational connections generate abnormal returns: for purchases we test if the mean of connected returns is larger than unconnected returns; for sales we test if the mean of connected returns is smaller than unconnected returns. We use *, ** and *** to denote statistical significance at the 10%, 5% and 1% levels, respectively.

All Purchases

	Connected		Unconnected		Difference		
	Mean	SE	Mean	SE	Mean	SE	p-value
t_1	0.31	0.09	0.44	0.05	−0.13	0.11	0.893
t_2	0.23	0.07	0.19	0.04	0.04	0.08	0.293
t_3	0.14	0.06	0.23	0.03	−0.09	0.06	0.923
t_4	0.09	0.05	0.17	0.03	−0.08	0.06	0.919
t_5	0.03	0.05	0.37	0.02	−0.33	0.05	1.000

All Sales

	Connected		Unconnected		Difference		
	Mean	SE	Mean	SE	Mean	SE	p-value
t_1	0.05	0.09	0.37	0.06	-0.32^{***}	0.11	0.002
t_2	−0.12	0.06	0.30	0.04	-0.41^{***}	0.08	0.000
t_3	−0.15	0.05	0.25	0.04	-0.40^{***}	0.07	0.000
t_4	−0.19	0.05	0.21	0.03	-0.40^{***}	0.06	0.000
t_5	−0.22	0.04	0.13	0.03	-0.34^{***}	0.05	0.000

Purchases > R$ 500,000

	Connected		Unconnected		Difference		
	Mean	SE	Mean	SE	Mean	SE	p-value
t_1	0.44	0.11	0.38	0.06	0.06	0.13	0.308
t_2	0.39	0.08	0.11	0.04	0.28^{***}	0.09	0.001
t_3	0.38	0.07	0.22	0.03	0.16^{**}	0.08	0.019
t_4	0.32	0.06	0.13	0.03	0.19^{***}	0.07	0.004
t_5	0.28	0.06	0.50	0.03	−0.21	0.06	1.000

Sales >R$ 500,000

	Connected		Unconnected		Difference		
	Mean	SE	Mean	SE	Mean	SE	p-value
t_1	0.20	0.11	0.32	0.08	−0.12	0.14	0.205
t_2	0.07	0.08	0.26	0.06	-0.19^{**}	0.10	0.031
t_3	0.03	0.07	0.18	0.05	-0.15^{**}	0.09	0.038
t_4	0.02	0.06	0.18	0.05	-0.16^{**}	0.07	0.016
t_5	0.01	0.05	0.10	0.04	−0.08	0.07	0.113

Purchases > R$ 1,000,000

	Connected		Unconnected		Difference		
	Mean	SE	Mean	SE	Mean	SE	p-value
t_1	0.51	0.12	0.35	0.06	0.16	0.14	0.125
t_2	0.41	0.09	0.08	0.04	0.33^{***}	0.10	0.000
t_3	0.42	0.07	0.22	0.04	0.20^{***}	0.08	0.007
t_4	0.38	0.07	0.13	0.03	0.25^{***}	0.07	0.000
t_5	0.34	0.06	0.55	0.03	−0.21	0.07	0.999

Sales >R$ 1,000,000

	Connected		Unconnected		Difference		
	Mean	SE	Mean	SE	Mean	SE	p-value
t_1	0.18	0.13	0.36	0.10	−0.17	0.16	0.138
t_2	0.08	0.09	0.29	0.07	-0.20^{**}	0.11	0.037
t_3	0.05	0.07	0.18	0.06	-0.13^{*}	0.09	0.080
t_4	0.05	0.06	0.18	0.05	-0.13^{*}	0.08	0.053
t_5	0.01	0.06	0.09	0.05	−0.08	0.08	0.135

Purchases > R$ 5,000,000

	Connected		Unconnected		Difference		
	Mean	SE	Mean	SE	Mean	SE	p-value
t_1	0.60	0.18	0.28	0.07	0.32^{**}	0.19	0.047
t_2	0.46	0.12	−0.07	0.05	0.53^{***}	0.13	0.000
t_3	0.46	0.10	0.13	0.04	0.32^{***}	0.11	0.002
t_4	0.47	0.09	0.06	0.04	0.41^{***}	0.10	0.000
t_5	0.49	0.08	0.69	0.03	−0.19	0.09	0.984

Sales >R$ 5,000,000

	Connected		Unconnected		Difference		
	Mean	SE	Mean	SE	Mean	SE	p-value
t_1	0.28	0.17	0.44	0.15	−0.16	0.23	0.240
t_2	0.23	0.13	0.31	0.11	−0.08	0.17	0.305
t_3	0.25	0.11	0.20	0.09	0.05	0.14	0.643
t_4	0.29	0.09	0.17	0.08	0.12	0.12	0.858
t_5	0.24	0.08	0.11	0.07	0.14	0.11	0.899

3.4 Conclusion

This Chapter suggests that social connections are relevant in determining how information travels from firms to financial agents. We collect publicly available educational data on Brazilian mutual fund managers and board members of publicly traded firms in order to infer if these individuals share a social connection generated by common educational experience. We use these educational connections as proxies for social interaction between both groups. This allows us to investigate the flow of information between company insiders and fund managers, since the natural flow of information in this network would be from the former, who possesses private information on the quality of their firm, to the latter, who has an economic incentive to acquire this private information. We find that mutual fund managers tend to place larger bets on connected stock, both in comparison to other assets in their portfolio and in comparison to the aggregate market portfolio of equity funds. We also conduct an event study around purchases and sales of stock and find that connected managers tend to move their portfolios in the same direction as future returns. They tend to conduct large purchases of connected stock months before an increase in their risk-adjusted return, and small sales prior to decreases in this return. We interpret this as an indication that their connections allow them to access private information on the quality of firms before the rest of the market.

4 Market Effects of Educational Connections

4.1 Introduction

In Chapter 3 we analyzed the effects of educational connections on the portfolio allocations of fund managers, and reached the conclusion that such connections (serving as a proxy for active social contact between agents) are indeed relevant. We also found that manager's risk-adjusted returns are affected by our measure of social connections, in such a way that connected managers tend to buy and sell in anticipation of positive and negative shifts in risk-adjusted returns, respectively. We argue that these results arise because educational connections are potential channels for the flow of inside information.

Additionally, if educational connections can indeed transmit inside information, then we should also observe certain market-wide results. This occurs because inside information negatively affects the functioning of financial markets. As mentioned above, the finance literature detects several negative effects associated with insider trading, ranging from an increased cost of capital to lower stock liquidity. Thus, it could be argued that another way to infer if educational connections transmit inside information is by studying if such connections are associated with the above mentioned market effects. One interesting way of thinking about this problem is in relation to Easley, Hvidkjaer and O'hara (2002), where the authors propose that inside information could affect financial markets through the liquidity channel. More specifically, since market makers are required to hold an inventory of certain stocks, they should thus respond to an increase in the probability of trading with better-informed agents by also increasing the bid-ask spread (since they risk losing their inventory by not adequately adjusting their buy and sell prices), thus decreasing market liquidity. According to our assumptions, the probability of informed trading for the stocks of a certain company should thus respond to how many educational connections said company shares with the rest of the market.

We thus propose that an increase in the number of connections between company insiders and portfolio managers should increase the perceived risk of a security, as well as decrease its traded volume (our measure of liquidity). All things equal, investors would demand higher returns in order to be compensated for holding the stocks of a company with more educational connections, since these connections imply a higher chance of information leak, while some investors would abandon the market for a stock altogether for fear of conducting trades with informed agents. We believe that it is plausible to propose that market participants are sensitive to our measure of connectivity, since the educational information that we use is publicly available on the Internet.

In order to test this hypothesis we define the connectivity of a company as the number of asset management firms with which it shares at least one case of the deepest form of connection that we studied in Chapter 3 (that is, when an insider and a fund manager attended the same institution, in an overlapping time interval, and obtained the same diploma), divided by the total number of asset management firms in our sample. In other words, it is the percentage of asset management firms with which a company shares a deep connection. We view this measure as a proxy for the probability of valuable inside information being transferred from company insiders to fund managers, and argue that market participants should be sensitive to this information. We find that an increase of company connectivity is associated with an immediate drop in return, while future returns respond positively. We also find that traded volume relates to connectivity in a counter-intuitive way, by increasing instead of decreasing. This result is also found by Cornell and Sirri (1992), in which authors study a particular case of insider trading that generated a prosecution by the Securities and Exchange Commission, however they attempt to explain this contradictory result by indicating that noise traders could be falsely interpreting insider purchases as a positive change in company fundamentals, which would characterize them as "falsely-informed traders". While we do not believe that this answer could be applied to our case, this would be an interesting venue of research for the future.

Additionally, it would be interesting to analyze if the risk of purchasing securities with a larger probability of insider trading is being priced by Brazilian investors. We apply the standard Fama and French (1992) methodology in order to study if company connectivity is a risk factor. However our results are inconclusive due to the short time period for which we were able to construct our educational database. We do find that there is still a significant risk premium in the connectivity portfolio even after we control for the market, size, book-to-market and momentum factors, which indicates that there is relevant variation in returns that is not being explained by the more traditional risk factors.

Overall, our results in this chapter give further indication that the educational connections studied in this work are indeed a plausible channel through which information is being transferred from insiders to market participants. Since connectivity seems to predict expected returns, and since the more traditional risk factors cannot fully explain the return of the portfolios sorted by connectivity, we have further indication that educational connections can serve as conductors to inside information.

The rest of this Chapter is organized as follows. In Section 4.2 we contextualize our contribution by offering a brief summary of previous work on identifying the impacts of insider trading. In Section 4.3 we present our data set, methodology and results, and finally in Section 4.4 we present a conclusion.

4.2 Literature Review

The literature on insider trading has produced a significant number of insights on the mechanism through which insiders affect market outcomes, as well as estimates to this effect. Here we present a brief summary of the studies that we believe to be most relevant for the analysis we undertake.

The first point that we believe must be stressed is that the general opinion on insider trading is that it is indeed a detrimental practice for financial markets. Some papers do find that information-based trading seems to increase market efficiency by allowing insider information to be transmitted to prices (such as Ahern (2015)), however we interpret this as very tenuous evidence to the benefits of this practice. A complete liberalization of insider trading would more likely lead to an increase in risk, as mentioned in the preceding section. In Bhattacharya and Daouk (2002) the authors produce evidence regarding the importance of insider trading laws. By compiling a data base of international laws, they find that countries show a drop in their cost of capital after prosecuting a case of insider trading[1]. The paper is innovative in comparing several countries with a financial market, and produces one of the strongest cases for the adoption and enforcement of insider trading legislature. A theoretical paper that links insider trading with the cost of capital is Easley and O'hara (2004), in which the authors investigate the role of private information in market outcomes. They find that uninformed investors will demand higher returns in order to hold stocks with greater private information, since they are less able to shift their portfolios in order to incorporate new information. Firms with greater private information will thus present a larger cost of capital.

Most papers in this literature reference Glosten and Milgrom (1985) as the seminal theoretical paper on insider trading. In it, the authors establish that the presence of traders with superior information leads to a positive bid-ask spread, thus decreasing market liquidity. The mechanism proposed in the paper is that market makers need to maintain an inventory of stocks in order to quote bid and ask prices for the rest of the market. Thus the presence of traders with insider information posits an adverse selection problem to the market maker, since the former possesses information that the latter does not. In this case, market makers have to increase the bid-ask spread in order to recoup the losses suffered when negotiating with these agents. Most models in the literature owe their basic framework to Glosten and Milgrom (1985), and this is perhaps the most fundamental paper in the literature. In Amihud and Mendelson (1986) we find another important contribution, linking market micro-structure with market outcomes. In this paper the authors posit that liquidity is priced by investors, who maximize their expected return net of transactions costs and thus expect larger returns from securities that present lower liquidity. Since a measure of these transaction costs is the bid-ask spread, the results in Glosten and Milgrom (1985) and Amihud and Mendelson (1986) can thus be linked together in order

[1] Their study suggests that the mere adoption of insider trading legislature is not enough to cause this drop. They believe that a successful prosecution is important in signaling a commitment by financial regulators to the enforcement of insider trading laws.

to present a case as to the importance of limiting insider trading in a financial market. Du and Wei (2004) associates the existence of insider trading with market volatility. They use an innovative measure of insider trading prevalence, the Global Competitiveness Report from 1997 and 1998. The Report presented a survey in which 3.000 corporate officers from around the world were asked to respond if they considered that insider trading was common in their domestic stock market. According to the paper's results, countries with more prevalent insider trading have more volatile stock markets, even after controlling for the volatility of macroeconomic fundamentals, such as the volatility of real output and of the monetary and fiscal policies. Fishe and Robe (2004) identifies traders in possession of inside information through a natural experiment. In 1999 the SEC charged five stockbrokers with insider trading when they gained access to an early release of the *Business Week's* "Inside Wall Street" column, which they then used to purchase some of the recommended stocks. The paper finds that informed trading decreases market liquidity due to the fact that market makers increase the bid-ask spread when they detect signs of informed trading.

Finally, one of the most relevant papers for our study attempts to solve this problem by showing that the presence of insiders drives the bid-ask spread to increase. Our attempt to create a measure of the probability of insider trading is mainly inspired by Easley, Hvidkjaer and O'hara (2002), where the authors use high frequency trade data from NYSE-listed stocks to estimate a measure of the probability of information-based trading, which they abbreviate as PIN. They propose a market micro-structure model in which market makers infer the probability of negotiating with informed traders by comparing the arrival rate of trades with their historical values. If, for instance, more purchase requests are arriving than usual, the market maker infers that he must be trading with agents in possession of more information than him, and responds by increasing the ask price[2], thus increasing the bid-ask spread and diminishing market liquidity. They estimate the probability of informed trading for each asset in their sample and then follow Fama and French (1992) in constructing portfolios ordered by this variable in order to investigate if

[2] As mentioned above, the market maker is obligated to quote bid and ask prices for a security, so the increase in the amount of informed traders presents an inventory risk for him.

it could explain the portion of asset returns that the more traditional risk factors based on market, size and book-to-market cannot explain. They conclude that a difference of ten percentage points in the probability of information-based trading between two stocks leads to a difference in their expected return of 2.5 percent per year.

In our study we view the share of the funds market with which companies share a deep connection as a proxy for the PIN, since we associate our measure to the probability of information leaks from insiders to fund managers. The main difference between Easley, Hvidkjaer and O'hara (2002) and our paper is that our measure is not derived from an analysis of the behavior of traders, but in fact from our assumption that educational connections are indeed a good approximation for social connectivity, and that this implies that there is an active flow of valuable information between company insider and fund manager.

4.3 Results

4.3.1 Data Sets

Our data on the connectivity of individual companies is derived from our own data base of educational connections. The variable is constructed as follows:

- For each company i and each month t in our sample, we count the number of asset management firms j with which company i shared at least a single case of what we defined as CONNECTED4 in Chapter 1, that is, when an insider at company i studied at the same institution, in an overlapping time interval, and obtained the same diploma as a portfolio manager working for asset management firm j;
- We then divide this number by the total number of asset management firms that are active in our sample at month t. This gives us what we call the connectivity variable, a measure of how connected a company is with the funds market. A value of 1 would indicate that the company presents at least one case of the deepest connection studied in this work with every asset management firm in our sample.

Note that this construction does not take into account the fact that some companies will have multiple deep connections with the same asset management firm. We choose to give no extra weight to these occurrences, although the case could be made that the probability of information transmission would be larger between insiders and fund managers in these cases.

The resulting connectivity variable is summarized in Table 11:

Table 11 – Connectivity of Companies in Sample

In this table we present summary statistics for the connectivity of companies. We calculate this information over all companies and all months in our sample.

Mean	Median	Std. Deviation	Minimum	Maximum
9.41%	4.76%	10.94%	0%	58.82%

As we can see, companies show a relatively small connectivity each month, with a monthly average of 9.41% and a median of 4.76%. The maximum connectivity achieved by a company in our sample is 58.82%.

The data on asset returns and traded volume comes from Economatica. Asset returns are calculated taking into account that companies sometimes issue ordinary and preferred stocks. For each company that is considered eligible according to Nefin's liquidity criteria, we calculate daily returns of each issued stock. We then calculate the daily value-weighted returns of the company, using the market value of equity which also comes from Economatica. Finally, we compound this daily variable for each month in our sample to get monthly returns. A company's monthly traded volume is the sum of monthly traded volume for all the stocks issued by the company. We use this volume as a measure of a company's liquidity.

4.3.2 Impact of Connectivity on Current and Future Returns and Volume

The first test we wish to run is if a company's connectivity impacts its returns and liquidity. We first run a pooled OLS regression of returns on the connectivity variable and a set of company fixed effects. We are also interested in learning if the connectivity variable influences future returns, so we also run this regression for 1-, 6- and 12-month cumulative forward returns, our measure of expected returns. The results are on Table 12.

Table 12 – Effects of Connectivity on Current and Future Returns

In this table we present the results of the OLS predictability regressions of current and future returns on company connectivity. All returns are monthly, and forward returns are cumulative. If a company has multiple types of stock in the market we calculate the value-weighted return of all its stock. Both returns and connectivity are measured in percentage points. Every specification also controls for company fixed effects. We correct for clusters at the time variable. (*), (**) and (***) indicate significance at the 10%, 5% and 1% level.

	$returns_t$	$returns_{t+1}$	$returns_{t+6}$	$returns_{t+12}$
Constant	0.97	-0.94	-1.18^{***}	-1.54^{***}
	(0.81)	(0.61)	(0.25)	(0.17)
Connectivity	-0.06^{*}	0.06^{**}	0.07^{***}	0.09^{***}
	(0.03)	(0.03)	(0.01)	(0.01)
N	7,965	7,955	7,851	7,708
R^2	.03	.07	.21	.28

As we can see an increase of one percentage point in the connectivity of a company leads to a decrease of 0.06 percentage points in the company's return. This immediate response of returns to an increase in connectivity represents a drop in the company's market value as a result of the increase in connectivity, and thus in the probability of valuable information being transmitted from insiders to fund managers. Since privately-informed agents trade at an advantage with publicly-informed traders, the latter will demand higher returns in order to carry the security in question. The implication is that the company will suffer a drop in its market value in order to adjust market returns.

This interpretation is supported by the results of the 1-, 6- and 12-month forward regressions. According to our results, an increase of one percentage point in connectivity will lead to increases in expected returns for all the horizons considered. The largest increase occurs 12 months after the change in connectivity, when returns rise by 0.09 percentage points.

The overall results corroborate our hypothesis that the market responds to an increase in educational connections by understanding that information leakage becomes more common. This implies in an increase in expected return, since publicly-informed agents trade at a disadvantage with holders of inside information, and thus demand higher returns to hold the security in question. One implication of this line of reasoning is that we should also see a decrease in market liquidity following an increase in connections, however as we see in Table 13, this does not occur.

Table 13 – Effects of Connectivity on Current and Future Volume

In this table we present the results of the OLS predictability regressions of current and future traded volume on company connectivity. We present monthly volumes, measured in millions. If a company has multiple types of stock in the market we calculate the monthly sum of traded volume of all its stock. Connectivity is measured in percentage points. Every specification also controls for company fixed effects. We correct for clusters at the time variable. (*), (**) and (***) indicate significance at the 10%, 5% and 1% level.

	$volume_t$	$volume_{t+1}$	$volume_{t+6}$	$volume_{t+12}$
Constant	26.40***	26.51***	25.29***	21.70***
	(1.98)	(2.00)	(2.49)	(3.07)
Connectivity	0.95***	0.90***	0.82***	0.95***
	(0.12)	(0.12)	(0.14)	(0.13)
N	$8,424$	$8,424$	$8,424$	$8,424$
R^2	.85	.85	0.84	0.85

Table 13 shows us that volume responds positively to an increase in company connectivity, across all time horizons considered. An increase of one percentage point in connectivity leads to an increase of 0.95 million reais in contemporaneous traded volume, while future volume responds by roughly the same amount. This result contradicts economic intuition, since we expect that an increase in the amount of information-based trading would lead to a drop in an asset's liquidity. This replicates the results of Cornell and Sirri (1992), where the authors find that traded volume net of insider purchases also rose due to insider activity. Their explanation is that this could be generated by the presence of noise traders (a term owed to Black (1986) and Long et al. (1990)), agents that wrongfully believe that they are in possession of superior information. However Cornell and Sirri (1992) do not propose a way to test this explanation. It could be argued that this explanation is applicable to the case that the authors study, which consists of the purchase of Campbell Taggart by Anheuser-Busch in 1982. According to their study, Campbell Taggart showed a relatively small average daily trading volume, of less than 50 thousand US dollars on most days leading to the announcement of the tender offer by Anheuser-Busch. It would seem to us that noise traders should be more active in markets with a small level of liquidity to begin with, which would lead them to be overly sensitive to changes in traded volume, thus misinterpreting the entrance of insiders in the market as a change in fundamentals. However it would still be interesting to study this matter in the future.

We thus close this investigation with mixed results. The return regressions indicate that connectivity is influencing current and future returns in the direction that we expected if educational connections are indeed a channel through which information flows in the financial market. However agents do not seem to respond by refusing to carry the security in question, as the volume regressions point out.

We now conduct a more deep investigation of the impact of educational connections and insider trading in financial agent's expected return. We do this by applying the Fama and French (1992) methodology to study if this information risk is being priced by the market.

4.3.3 Do Investors Price Connectivity?

In order to answer if agents see insider trading as a risk factor we adapt the Fama and French (1992) methodology to Brazilian data. As mentioned above, if educational connections do indeed transmit inside information we expect that agents would respond to an increase in the connectivity of a company by demanding higher returns in order to hold said company's stock. This implies that connectivity would behave as a risk factor, and should be priced by agents as a risk that is orthogonal to the more traditional factors. In this section we explore this question by constructing portfolios sorted by company connectivity and then studying if their returns are fully explained by market, size, book-to-market and momentum risk factors.

Our methodology for constructing the connectivity portfolios is as follows. For each month t we (ascending) sort the companies in our sample according to their connectivity with the funds market (as defined in the previous section). We then separate the companies at the terciles of the connectivity distribution on month t, and calculate the equally-weighted returns of each portfolio. In Table 14 we present summary statistics for our

Table 14 – Connectivity Portfolios

The table contains summary statistics for 3 portfolios sorted by company connectivity. For each month in our sample we sort the companies according to their connectivity and separate them into 3 quantiles. We present monthly averages of the return, number of companies and connectivity of the three portfolios.

	Avg. Excess Return	Avg.Number of Companies	Average Connectivity
Low Connectivity	-0.71	48.51	0.43%
Medium Connectivity	-0.99	36.64	6.74%
High Connectivity	-0.60	37.44	21.90%

portfolios.

Table 14 shows that the portfolios present an ordering in their excess return, with the high connectivity portfolio paying a larger return than the low-connectivity portfolio. This indicates that an investor holding a portfolio that is long on highly connected companies and short on companies with low connectivity would earn a premium. This is the first indication that Brazilian investors are pricing the information risk presented by insider trading.

However we cannot conclude that the information risk is being priced just yet. It could be the case that, by selecting companies according to their connectivity, we simply replicated another risk factor. This would be the same as saying that the connectivity factor contains no information about expected returns that is not in other, more traditional, risk factors. We now run the regressions of each portfolio on the market, size, book-to-market and momentum risk factors. If the alphas of these regressions continue to present an ordering after controlling for other risk factors, we will have a stronger indication that the risk of purchasing securities with a high probability of insider trading is being priced.

In this exercise we use the risk factors for the Brazilian market that are calculated by Nefin[3]. The Nefin portfolios are constructed by ordering eligible stocks according to different variables, such as size, book-to-market and 12-month cumulative returns. For each of these variable Nefin establishes cutoff points at the terciles of the distribution, and

[3] Data on the risk factors is freely available at <http://www.nefin.com.br/risk_factors.html>. All stocks were selected according to the liquidity criteria presented in Chapter 2.

calculates value- and equal-weighted returns for each of the three resulting portfolios[4].

The market factor is the difference between the return of a value-weighted portfolio composed of all eligible stocks and the risk free rate. The risk free rate is computed from the 30-day DI Swap. The size factor is the difference between the equal-weighted returns of the small and big portfolios, while the book-to-market factor is the difference between the equal-weighted returns of the high book-to-market and low book-to-market portfolios. Finally the momentum factor is the difference between the equal-weighted returns of the high past returns (winners) and low past returns (losers) portfolios[5].

In Table 15 we present summary statistics for the Nefin risk factors used in this work, as well as a connectivity risk factor. The latter is simply the difference between the equal-weighted returns of the high connectivity and low connectivity portfolios. The main methodological difference between the connectivity factor and the Nefin risk factors is that the latter are constructed in such a way as to be possibly replicated by investors in the Brazilian financial market. The Nefin portfolios thus need only be re-calibrated once per year, while our connectivity portfolios are possibly re-calibrated every month. As such, stocks could potentially transition between the low and high connectivity portfolios every month. This guarantees our exposure to the connectivity factor.

In Table 15 we can see that the properties of the more traditional risk factors change considerably when we limit the sampling period to the period studied in this work. In this matter we cite Filho (2016) as a reference for the topic of robustness of risk factors. The author investigates the problems of estimating significant risk factors for the Brazilian market, and finds that this is not caused by the relatively small number of assets, but by the short time interval of available data. In fact, the author estimates that even the US risk factors would face similar problems of statistical significance if they were estimated within the short time windows available for Brazil.

This indicates that we will not be able to replicate all the steps of the Fama and

4 All portfolios can be downloaded at <http://www.nefin.com.br/portfolios.html>.

5 Nefin also calculates a risk factor based on illiquidity, as defined by Amihud (2002). We choose not to use this risk factor in our study, since it presents difficulties in its validity even for the entire 2001-2015 sample.

Table 15 – Risk Factors

The table contains summary statistics for the Brazilian risk factors as calculated by Nefin, as well as the connectivity factor. We present monthly summary statistics for both the entire time series as well as the period analyzed in our study, from 2010 to 2015. The Nefin methodology is available at <http://www.nefin.com.br/Metodologia/Methodology.pdf>. The Connectivity factor is the return of a portfolio that is long on the most connected companies in our sample and short on the least connected. We measure the connectivity of a company by calculating the number of asset management firms with which they share at least one case of the deepest connection that we study (that is, when a firm insider and a fund manager studied at the same institution, at an overlapping time interval, and obtained the same diploma). We then divide this quantity by the total amount of asset management firms in our sample, to arrive at a number that could be interpreted as the percentage of the funds market with which they share a deep connection. This percentage is then used to order companies from most to least connected. We construct equally-weighted portfolios consisting of the most and least connected thirds of our sample, and define our Connectivity factor as the difference between the return of the most connected portfolio and the least connected.

Source: Nefin - <http://www.nefin.com.br/risk_factors.html>

	2001-2016			2010-2015		
Risk Factors	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
Market	0.19	-0.02	6.22	-0.82	-0.57	4.51
Size	-0.04	-0.12	5.00	-1.21	-1.10	3.79
Book-to-Market	0.53	0.06	4.93	-0.91	-1.40	3.15
Momentum	1.19	1.57	6.03	2.55	2.64	4.22
Connectivity	-	-	-	0.09	-0.02	1.98

French (1992) methodology to investigate our connectivity factor. More specifically, we will not be able to run the cross-section regressions of asset returns on estimated betas in order to find the risk premium for our connectivity factor, since these regressions would reject even the market, size, book-to-market and momentum factors. However we are able to run the time series regression of each connectivity portfolio on the risk factors. The results of these regressions are presented in Table 16.

The most important feature of this table is that there is still an ordering between the low and high connectivity portfolios, even when we control for the set of risk factors. The constant for the low connectivity portfolio is 0.004, and presents no statistical significance, while the constant for the high connectivity portfolio is 0.007, which is significant at the 1% level. We interpret these results as indicating that the risk of holding a connectivity portfolio is not explained by the usual risk factors, which lends further support to the idea that investors are aware that a company's connectivity increases its risk, and should be rewarded with larger expected returns.

Table 16 – Time Series Regressions of Portfolio Returns on Risk Factors

This table presents the results of the time series regressions of the excess returns of each connectivity portfolio on the Nefin risk factors. We present parameter estimates for the market, size, book-to-market and momentum portfolios. Standard errors are in parenthesis. (*), (**) and (***) indicates significance at the 10%, 5% and 1% level, respectively. Regressions are at the month level, and the period used is from 2010 to 2015. The excess returns of the connectivity portfolios are the equal-weighted returns minus the risk free rate, which we compute from the 30-day DI Swap rate. The Market factor is the difference between the value-weighted daily return of the market portfolio (using all the eligible stocks) and the risk-free rate. The Size factor is the return of a portfolio long on stocks with low market capitalization (small) and short on stocks with high market capitalization (big). The Book-to-Market factor is the return of a portfolio long on stocks with high book-to-market ratio and short on stocks with low book-to-market ratio. Finally, the momentum factor is the return of a portfolio long on stocks with high past returns and short on stocks with low past returns. Nefin risk factors can be downloaded at <http://nefin.com.br/risk_factors.html>.

Risk Factors	Low Connectivity	Medium Connectivity	High Connectivity
Constant	0.004	0.002	0.007***
	(0.003)	(0.003)	(0.003)
Market	0.789***	0.880***	0.950***
	(0.063)	(0.058)	(0.052)
Size	0.363***	0.254***	0.434***
	(0.078)	(0.076)	(0.065)
Book-to-Market	−0.037	−0.057	−0.136*
	(0.097)	(0.081)	(0.080)
Momentum	−0.014	0.002	−0.038
	(0.0748)	(0.071)	(0.062)
Adjusted R^2	.76	.85	.87

The rest of Table 16 gives us what the literature refers to as “factor loadings”, the relative importance of each risk factor in explaining the returns of the sorted portfolios. Our results indicate that the market and size factors are the most relevant, presenting a high level of statistical significance across all portfolios. Meanwhile book-to-market and momentum are almost never statistically significant.

As mentioned before, the final step when applying the Fama and French (1992) methodology is then analyzing the properties of the risk premium associated with the connectivity factor. This would be done by running the regression of the excess return of all eligible stocks on the Nefin risk factors, in addition to the connectivity factor. We would save the resulting factor loadings and then run a set of cross-section regressions of excess returns at time t on these regression coefficients. Following the Fama-Macbeth methodology (as presented in Fama and MacBeth (1973)) we would then calculate the mean and standard deviation of the coefficients of the set of T cross-section regressions in order to investigate if the market indeed pays a risk premium for the connectivity factor. However this last step suffers from the small time window of our study, in which we would not find a risk premium for any of the risk factors. We finish this part of the study by concluding that there is convincing evidence that educational connections are channels through which information flows from company insiders to market participants, and that the risk of negotiating with such informed traders cannot be explained by other systemic risks.

4.4 Conclusion

In this paper we studied the effects of insider trading on the Brazilian financial market. We propose a measure of the probability of trading with individuals who hold inside information that is based on social connections acquired through common education. We assume that investors will be attentive to these connections since they increase the risk of trading with better informed agents, which would cause losses for investors with strictly public information. We test the validity of this measure by studying if its predicted effects on returns and liquidity are verified. We find that an increase in the connectivity of a company leads to an immediate drop in its returns and an increase in future returns, which is consistent with the assumption that investors respond to insider trading by demanding larger returns in order to hold a company's stock. However the effects on volume, our measure of liquidity, do not go in the expected direction, with an increase in connectivity being associated with an increase in volume for all the time horizons considered. We find similar cases in the insider trading literature, however we do not believe that their answer to this puzzle applies in our case.

Finally we apply the Fama and French (1992) methodology to investigate if this insider trading risk is being priced by investors. We find that the Brazilian market pays a premium for holding a portfolio that is long on high connectivity stocks and short on low connectivity, and that this premium is not explained by the market, size, book-to-market and momentum risk factors. However we are unable to carry forward with the Fama and French (1992) methodology due to the short time periods available for the Brazilian market, which keeps us from estimating the connectivity risk premium.

Overall our results indicate that educational connections impact the functioning of financial markets. Agents understand that school ties are venues for the transfer of information, and respond by demanding larger returns from companies that present more connections with the funds market. One possible future research idea would be to attempt an estimation of the probability of informed trading as in Easley, Hvidkjaer and O'hara (2002) for the Brazilian market. Since we have a time series constraint that keeps us from concluding the study of educational connections as a risk factor, it would be interesting to attempt to bypass this problem by comparing our probability of insider trading with the PIN, which was found to be priced as a risk factor in the US market.

5 Conclusion

The main objective of this study is to analyze if educational connections are a plausible channel for information to flow through the financial market. We believe that the evidence presented here gives a good indication that this seems likely. Not only fund managers place larger bets on their connected stocks, but they also tend to earn high returns in their connected positions. We also find that market participants seem to detect an increase in a company's connectivity, and associate it with an increase in risk. We find that the return to connectivity cannot be explained by the market, size, book-to-market and momentum risk factors, which indicates that connectivity could indeed be a risk factor. These findings are consistent with the literature on the relevance of social ties for economic outcomes and also with studies on the negative market effects of insider trading.

In summary, our findings support the idea that educational connections serve as possible channels for the flow of inside information. As mentioned earlier our work is the first of its kind applied to Brazil. One of its possible applications would be in helping to guide the local regulatory institutions in detecting and monitoring possible cases of insider trading. If a common educational background between two agents indeed implies in a higher chance of social interactions, then it would be in the interest of regulators to make a systematic effort to collect this information. In Brazil a part of the infrastructure needed to support this data collection is already in place, since CVM already demands from board members that they divulge possible conflicts of interest arising from their assignment to multiple boards simultaneously. Also, as mentioned above, many board members already detail their educational background in the official forms, so we argue that the true challenge of implementing this policy lies in the monitoring of mutual funds.

Another important point to take into account is that the Brazilian financial market is still relatively young and small in comparison to other developing countries. The recent years have seen a considerable increase in market participation, especially by individual, non-institutional investors. It could be argued that these new investors will demand a larger level of protection as they invest for the first time in financial markets, since they are likely to reject this investment opportunity if their first experience with trading in stocks is negative.

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