SIEPR Discussion Paper No. 16-014

Matching Prime Brokers and Hedge Funds

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JOB MARKET PAPER

December 23, 2015

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Abstract

Prime brokers and hedge funds form relationships in a matching market. What are the determinants of these matches? How did they change after the financial crisis? I estimate a matching model in which part of the profits of prime brokers and hedge funds depends on variables that are defined at the level of the entire portfolio of clients that a prime broker serves. I show that prime brokers and their client hedge funds choose to have trading relationships with each other in a manner that reflects the benefits of specialization. Moreover, prime brokers preferred risky clients before the crisis, while they were averse to risky clients after the crisis. Identification follows from pairwise matching stability. I analyze the potential underlying economic mechanisms, mainly the cost advantages to a prime broker of collateral re-use between hedge fund clients. This is known as internalization. I estimate that the value of internalization for major prime brokers, such as Goldman Sachs, is around $100-200 million annually.

Keywords: Prime brokers, Hedge funds, Matching, Internalization, Collateral re-use, Financial Networks

JEL Codes: G01, G23, G24, G28, C78

*I am deeply indebted to my advisors Pablo Kurlat, Darrell Duffie, Arvind Krishnamurthy and John Cochrane for invaluable suggestions, comments, criticism and guidance. I thank Nicola Pierri and Alp Şimşek for extremely helpful conversations in the early stages of the project. I also thank George Aragon, Vasiliki Fouka, Jeremy Fox, Jessica Jeffers, Bob Hall, Han Hong, Moritz Lenel, Michael Leung, Jessie Li, Hanno Lustig, Yiming Ma, Bobak Pakzad-Hurson, Lasse Pedersen, David Price, Pietro Tebaldi and the participants of the Macroeconomics Seminar at Stanford University for helpful discussions. I gratefully acknowledge the support for this research provided through the George P. Shultz Fellowship and the E.S. Shaw and B.F. Haley Fellowship for Economics by the Stanford Institute for Economic Policy Research. All errors are my own.

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1 Introduction

I show that prime brokers and their client hedge funds choose to have trading relationships with each other in a manner that reflects the benefits of specialization. Specifically, the client hedge funds of a given prime broker tend to have similar investment strategies. I explain that a likely source of benefit to specialization is internalization. Internalization allows the prime broker to more quickly and efficiently fill the orders of a given client or locate securities by exploiting the orders and securities obtained from another client.

Prime brokers are usually units of large, global investment banks that provide brokerage services to hedge funds. Prime brokers provide financing for hedge funds to take leveraged long positions and lend securities for short positions. The key related services provided by prime brokers are margin loans, securities lending and repurchase agreements. Prime brokers also act as a derivatives counterparty to their hedge fund clients. I discuss the institutional details in Appendix A.

The prime brokerage market played a central role during the financial crisis. Hedge funds caused a large-scale liquidity drain on prime brokers. For example, the prime brokerage units of Morgan Stanley suffered a liquidity loss of about $56 billion in just ten days, between September 12-22, 2008 (Duffie (2013)). Since the crisis, the prime brokerage market has been affected by Basel III banking regulations through capital, leverage and liquidity requirements (JPMorgan (2014)).

Prime brokers and hedge funds form relationships in a matching market. What are the determinants of these matches? How did they change after the financial crisis? The central idea in this paper is that part of the profits of prime brokers and hedge funds depends on variables that are defined at the level of the entire portfolio of clients a prime broker serves.

I document that hedge funds trading similar securities tend to be served by the same prime broker, which I refer to as specialization. To assess the relative benefits of specialization and diversification for a prime broker and the benefits that a hedge fund receives indirectly from other hedge funds served by the same prime broker, I estimate a matching model. I use data on prime broker and hedge fund relationships in September 2008, prior to Lehman Brothers' bankruptcy, and in October 2015 to evaluate the changes of the determinants of a match before and after the financial crisis.

I find that prime brokers benefited from specialization and hedge funds benefited from being served by a prime broker that specializes in both 2008 and in 2015. Prime brokers preferred risky clients in 2008, while they were averse to risky clients in 2015. The relative magnitudes of the impacts of specialization and hedge fund risk on prime brokerage profits changed between 2008 and 2015. In 2008, the benefits of client riskiness were of a magnitude comparable to the benefits of specialization. In 2015, the cost of client riskiness was outweighed by the benefits of specialization.

Identification of the parameters of interest follows from pairwise matching stability, without the need to impose the equilibrium conditions of a fully-specified model of competition using a methodology developed by Fox (2010). The usefulness of this methodology is that it can be implemented without observing profits or the monetary transfers, such as fees, commissions and interest on margin loans that hedge funds pay to prime brokers, on which there are no reliable data.

The economic mechanisms that I intend to capture in the estimation are the following: Specialization, through serving clients that trade similar securities, allows prime brokers to intermediate trades between clients more efficiently, by netting long and short positions that hedge funds request from the prime broker and by re-using the collateral obtained from one client to support the opposite positions of another. This practice is known as internalization. Internalization saves search costs and economizes on the use of the prime broker's balance sheet through netting benefits.

I construct two measures of specialization. The first is a portfolio Herfindahl index that measures the concentration of hedge funds with specific investment styles (such as long/short equity, fixed income, global macro etc.) of a prime broker's clientele. The second is the degree of co-movement of the prime broker's clients' returns. High values for both of these measures would signal that the client hedge funds of the given prime broker are likely to be trading similar securities. This would allow the prime broker to internalize, that is, to net long and short positions or to net buy orders against sell orders.

In a downturn, if similar hedge funds default at the same time, the prime broker might suffer credit losses through the price impact of fire sales of similar types of collateral, resulting in a motive for diversification. However, since this is a secured lending market and collateral protects the prime broker to some extent, the prime broker could prefer risky clients if the collateral obtained from risky clients is useful to the operations of market-making and proprietary trading desks in the bank-holding company. For example, if the market-making desk naturally has a long position in a security and riskier clients are the ones that short-sell more, bringing its own inventory to sale could provide balance sheet efficiencies to a dealer bank (Kirk, McAndrews, Sastry and Weed (2014)). I measure the riskiness of clients by the lower semi-deviation of returns, which is a commonly used measure of downside risk.

Finally, from the point of view of a given hedge fund, a broker that is a large player in its specific investment style can provide better immediacy in filling trade orders. I measure this benefit to the hedge fund by the market share of the prime broker in the hedge fund's investment style.

In order to assess the relative importance of these variables in generating a match surplus, I estimate a matching model taking a revealed-preference approach, imposing pairwise stability. Parameters are identified and consistently estimated even without data on monetary transfers (such as fees, commissions, interest on margin loans), profits or quotas (Fox (2010)).

For example, suppose that we observe that Goldman Sachs is matched with a hedge fund, Pure Epsilon, and Morgan Stanley is matched with a hedge fund, Pure Delta, but the opposite is not true. An implication of the pairwise stability requirement is that the joint surplus of the four agents must be higher this way than if the pairings were reversed. This results in one inequality where transfers drop out. The match-specific variables defined at the level of the entire portfolio of a prime broker's clients are different on each side of the inequality as Pure Epsilon and Pure Delta fit differently with all other clients of Goldman Sachs and Morgan Stanley. I construct such an inequality for all possible and meaningful two prime broker-hedge fund pair comparisons. Parameters are identified and estimated consistently assuming a rank order property (Fox (2010)).

There might be idiosyncratic drivers of a match that are observable to market participants, but unobservable to the econometrician. I use a global maximization algorithm, called "differential evolution," developed by Storn and Price (1997). This algorithm stochastically iterates over parameter values in order to find the set of parameters that globally maximizes the number of explained matches.

Because the estimation relies on inequalities, parameters are only identified up to scale. Thus, I cannot directly estimate a dollar amount for the degree to which the variables affect profits. In order to estimate the dollar benefit of internalization, I develop a stylized accounting framework which gives me a formula of the value of internalization that depends on accounting measures. I use accounting measures for Goldman Sachs and estimate that the value of internalization for Goldman Sachs is around 100 to 200 million dollars annually. This benefit was higher in 2015 than in 2008.

I attempt to attribute the changes between 2008 and 2015 to changes in the regulatory environment after the crisis. Tighter capital regulation in 2015 implies that internalization is valued more because of savings in balance sheet utilization. This effect cannot be captured in the matching estimation, since the results are not comparable across years. I show anecdotal evidence consistent with this explanation. Moreover, the desire to take downside risk in 2008 may have been due to the opportunities this created for market-making or proprietary trading, which is more constrained nowadays, making diversification motives more important in 2015.[1]

Using estimates of internalization in 2008 and 2015 and assuming that internalization is indeed what drives the preferences of a prime broker to specialize, I obtain an approximate value for the magnitude of the benefit. I estimate that a one percentage point increase in the market share of Goldman Sachs in prime brokerage of hedge funds within given style provides annual benefits for an average client hedge fund in that style of around $110,000 in 2008 and $80,000 in 2015.

Despite the systemic importance of the prime brokerage market, data limitations have inhibited research of this market.[2] This paper studies the prime brokerage market with the data that are available, using techniques developed in the industrial organization literature. This is the first paper to analyze the prime brokerage market as a matching market and to identify the match-specific effects in profits for prime brokers and hedge funds. This is also the first paper to empirically estimate the benefits of internalization. The paper benefits from and contributes to the literature on collateral re-use, financial networks, over-the-counter (OTC) markets, industrial organization of the financial services industry and estimation of matching games.

Kirk, McAndrews, Sastry and Weed (2014) qualitatively study the funding of dealer banks. They discuss the balance sheet treatment and the benefits of internalization. This paper complements Kirk, McAndrews, Sastry and Weed (2014) by introducing a simple model of internalization and empirically analyzing the benefits of internalization and tying internalization to the specialization of prime brokers.

Chung and Kang (2014) and Gerasimova (2014) show that the returns of hedge funds that are the clients of the same prime broker co-move with each other. Unlike in this paper, they control for factors such as style co-movement and several risk factors to isolate possible reasons for co-movement of hedge funds served by the same prime broker. They aim to answer whether hedge funds returns are affected by the identities of their prime brokers. They study a single sample period and attribute the results to a "common information hypothesis," by which returns of hedge funds co-move because their prime brokers give them information on profitable trades.

Aragon and Strahan (2012) show that when Lehman Brothers failed, Lehman Brothers' clients were more likely to fail compared to others. Furthermore, the loss in liquidity of the stock holdings of Lehman Brothers' client hedge funds were larger. They conclude that hedge funds are liquidity providers to public markets. In Section 9, I discuss financial stability and liquidity implications of the importance of internalization in light of the finding by Aragon and Strahan (2012), of hedge

[1] See CGFS (2014) for how market-making and proprietary trading activities of banks were affected after the crisis.

[2] See Adrian, Begalle, Copeland and Martin (2013), Kirk, McAndrews, Sastry and Weed (2014) and Baklanova (2015)

funds being liquidity providers to public markets.

This paper uses techniques developed by Fox (2010) to estimate the parameters of the many-to-many matching game between prime brokers and hedge funds. Fox (2010) uses the same techniques to study the car parts industry.

This paper also contributes to the growing literature on collateral re-use (Singh and Aitken (2010), Lee (2013), Dang, Gorton and Holmström (2013), Maurin (2014), Infante (2014), Eren (2014), Muley (2015), Kahn and Park (2015), Fuhrer, Guggenheim and Schumacher (2015), Kirk, McAndrews, Sastry and Weed (2014)). The main contribution of this paper to the literature on collateral re-use is the analysis of internalization as a form of collateral re-use.

There is a large literature on financial networks. The contribution of this paper to the literature on financial networks is the empirical analysis of relationship formation between prime brokers and hedge funds, two important classes of players in financial markets.[3]

The large literature on OTC markets studies search costs, information asymmetries and pricing in OTC markets. Internalization lowers search costs, which is a dominant friction in prior work on OTC markets.[4]

This paper also contributes to the literature on the relationships between prime brokers and hedge funds,[5] the literature on the estimation of matching games[6] and the literature on the industrial organization of the financial services industry.

In a speech at the Federal Reserve Board, Tarullo (2011) called for a new research agenda to investigate the financial services industry by applying tools from the industrial organization literature. This paper contributes to that agenda by studying the prime brokerage market which is systemically important, by using techniques developed in the industrial organization literature.

This paper also contributes to a relatively large literature on the value of concentration in the banking sector. Prior literature mostly focuses on the commercial banking sector. Acharya, Hasan and Saunders (2006) and Hayden, Porath and Westernhagen (2007) show that specialization in certain industries is accompanied by lower loan loss rates. Boeve, Duellman and Pfingsten (2010) find that banks exert more and better monitoring if they are specialized rather than diversified. In recent work, Paravisini, Rappoport and Schnabl (2014) use data on bank lending and exporting firms and use a revealed preference approach to show that bank specialization reflects a comparative advantage in lending.

The rest of the paper proceeds as follows. Section 2 describes the data. Section 3 presents the measurement of the key variables and shows descriptive statistics and motivating facts. Section 4

[3] Li and Schurhoff (2014), Allen and Babus (2009), Elliot, Golub and Jackson (2014), Acemoglu, Ozdaglar and Tahbaz-Salehi (2015), Babus (forthcoming), Cabrales, Gottardi and Vega-Redondo (2014), Farboodi (2015), Glasserman and Young (2015), Bloch and Jackson (2007), Gale and Kariv (2007), among others

[4] Duffie, Garleanu and Pedersen (2005), Duffie, Garleanu and Pedersen (2007), Babus (2012), Lagos and Rocheteau (2007), Lester, Rocheteau and Weill (2014), Glode and Opp (2015), Green, Hollifield and Schurhoff (2007), Kondor and Babus (2013), Lagos and Rocheteau (2009), Lagos and Weill (2011), Colliard and Demange (2015), Atkeson, Eisfeldt and Weill (2013), Acharya and Bisin (2014), among others.

[5] Duffie (2010), Aikman (2010), Klaus and Rzepkowski (2009), Boyson, Stahel and Stulz (2010), Sialm, Sun and Zheng (2014), Chung and Kang (2014), Aragon and Strahan (2012), Gerasimova (2014), Ang, Gorovyy and van Inwegen (2011)

[6] Sørensen (2007) studies venture capital markets in a matching framework. Akkus, Cookson and Hortacsu (2014), Park (2013) and Uetake and Watanabe (2013) study empirically mergers as a two-sided matching market. Other empirical matching papers that do not study financial markets include: Choo and Siow (2006), Agarwal (2015), Baccara, Imrohoroglu, Wilson and Yariv (2012), Fox (2010), Ahlin (2009), Fox and Bajari (2013).

introduces a conceptual framework for what the match surplus is in this market. Section 5 presents the empirical methodology used for the identification of the parameters of interest. Section 6 shows and discusses the estimation results. Section 7 provides a complementary model of internalization and quantifies the value of internalization using accounting measures. Section 8 presents the estimation results by value-weighting variables instead of equal-weighting. Section 9 discusses the issues related with financial stability arising from the new structure of the market. Section 10 concludes.

2 Data

This section describes my data and their limitations. Section 2.1 describes the data. Section 2.2 describes the limitations.

2.1 Data Description

My data source is the Lipper Hedge Fund database accessed through WRDS. This dataset contains information on hedge funds that voluntarily choose to report to the database. Hedge fund managers report to the database primarily to promote their funds to potential investors. The dataset contains information on monthly returns of hedge funds,[7] among other characteristics, such as the investment style (e.g. long/short equity hedge, fixed income arbitrage etc.), domicile, inception date, assets under management. The dataset also includes the prime brokers of each hedge fund.[8]

For the monthly returns, I use a sample period from January 1994 until September 2015.[9] For hedge funds that start reporting later than January 1994, their monthly returns start from the first date they report to the database. Other characteristics, such as the investment style are constant over the months, which might be true or a limitation of the data if any change in investment style is not reported.

I have two such snapshots containing the information on the links between hedge funds and prime brokers, one is a snapshot from September 2008, obtained from George Aragon,[10] which was used in Aragon and Strahan (2012). The second snapshot is obtained in October 2015. I match the information on the links with prime brokers with the hedge fund characteristics.

[7]The distribution of returns in each month sometimes features positive skewness. I winsorize the monthly returns that are above 100% to 100% in order to mitigate the effect of outliers. Therefore, in each month, monthly returns vary between -100% and 100% in my sample. I construct excess returns by using the risk-free rate as the one month Treasury bill rate.

[8]The assigned names for the same prime brokers could be different even though they indicate the same broker. For example, Goldman Sachs might be reported as *Goldman Sachs & Co* and *Goldman Sachs & Co (GSCO)* etc. In order to conduct the analysis, I clean the data such that all different name a prime broker is coded represent the same prime broker. Another issue with the raw data is that it may not always be current after a merger or acquisition. For example, some hedge funds that are currently reporting to the database could report their prime brokers as Bear Stearns, which I change to JP Morgan. Similarly, some hedge funds report their prime broker to be Bank of America, which I change to Bank of America Merrill Lynch etc. Another example is the Newedge Group. Newedge was formed as a result of a merger of FIMAT and Calyon Financial. Its parent bank is Societe Generale. Hence, I code all Newedge, FIMAT and Calyon Financial as Societe Generale.

[9]Some funds have a delay in reporting their returns, so for those I use it from January 1994 until the last month they reported returns.

[10]The data I obtain are not the raw data. Instead I obtained the cleaned version of the prime broker-hedge fund relationships used in Aragon and Strahan (2012). I am grateful to George Aragon for providing these data.

In the dataset, there are hedge funds that are Funds of Funds (FoFs). FoFs invest in a portfolio of hedge funds. In the paper, the main focus is on the services that the prime broker provides such as financing long positions or lending securities, providing leverage etc. Hence, FoFs are different from all other hedge funds since they do not receive those services from prime brokers. Therefore, I exclude FoFs from the dataset. Leaving out the FoFs, there are 11 investment styles Lipper classifies, which are convertible arbitrage, dedicated short-bias, emerging markets, equity market neutral, event-driven, fixed income arbitrage, global macro, long/short equity hedge, managed futures, multi-strategy and other. I do not drop hedge funds that are classified as other, but treat other as a separate investment style. The other eleven investment styles are broad enough to cover a large portion of alternative strategies. Therefore, I keep "other", since it contains information that the investment style is not one of the eleven broad styles.

Throughout the paper, I define the market that hedge funds and prime brokers interact as a single global market for prime brokerage services offered by prime brokerage units of large, global investment banks. In order to make the two snapshots comparable, I filter out most prime brokers with a few clients and only focus on prime brokers with large and global parent banks that appear in both snapshots. I end up with 13 prime brokers in 2008 and 12 prime brokers in 2015. In 2008, the prime brokers in the sample are Morgan Stanley, Goldman Sachs, JP Morgan (includes the clients of Bear Stearns after the acquisition), UBS, Citigroup, Bank of America, Credit Suisse, Deutsche Bank, Lehman Brothers, Societe Generale, Merrill Lynch, HSBC and Barclays. In 2015, the prime brokers in the sample are Morgan Stanley, Goldman Sachs, JP Morgan, UBS, Citigroup, Bank of America Merrill Lynch, Credit Suisse, Deutsche Bank, Societe Generale, HSBC, Barclays and BNP Paribas. As a result, I end up with a final dataset of 1,531 distinct hedge funds and 1,532 links in 2008 and 1,621 hedge funds and 2,225 links in 2015.[11]

Sometimes a fund might stop reporting to the database, or may report with delays. I assume all hedge funds that last reported returns in 2007 or earlier were liquidated and I do not include them in the 2008 snapshot. Similarly, I do not include any hedge fund that last reported returns in 2014 or in 2015 in the sample for the 2015 snapshot. Table 1 shows the number of prime brokers used by hedge funds that are operating in the October 2015 snapshot. A large majority of hedge funds report having one prime broker. The second most likely case is hedge funds reporting having two prime brokers. The maximum number of prime brokers reported is 7.

Table 2 shows the composition of the prime broker-hedge fund links in the final datasets in 2008 and in 2015. The main take-away is that the top players in 2008 have lost market share after the crisis, while hitherto small prime brokers gained business from hedge funds in 2015.

Table 3 documents the market shares (in the final sample) of the top 3 players in each investment style in 2008 and in 2015. The data disaggregated at the investment style level show that for some styles, such as emerging markets, event-driven, fixed income arbitrage, global macro, long/short equity hedge and multi-strategy, there has been increased competition, whereas for convertible arbitrage and managed futures, market players that were small in 2008, Barclays and Societe

[11]Note that the number of prime brokers that a hedge fund has is much larger in 2015 compared to 2008. This could be due to two reasons. First, actually a large majority of hedge funds were using a single prime broker and after the failure of Lehman Brothers, diversification motives led to having multiple brokers. Hence, the data reflects the reality. Second, it could be due to bad reporting. For example, hedge funds only report the prime broker that they use the most etc. There is no way of knowing that with the available data, hence I acknowledge any limitation this might cause.

Table 1: Number of Prime Brokers Hedge Funds Have in 2015

Number of PBs	**Percentage**
1	78.96%
2	9.81%
3	6.11%
4	2.53%
5	2.34%
7	0.25%
Total	1,621

Notes: Table shows the percentage of hedge funds that are in the 2015 sample with different number of prime brokers reported.

Table 2: Shares in 2008 and in 2015

Prime Broker	*Share in 2008*	*Share in 2015*
Morgan Stanley	25.91	19.73
Goldman Sachs	19.97	17.93
JP Morgan	15.47	8.54
UBS	9.46	11.64
Credit Suisse	4.63	10.79
Deutsche Bank	3.98	10.34
Citi	5.22	5.30
Societe Generale	3.20	4.63
Barclays	0.52	3.87
HSBC	0.26	1.08
Bank of America	4.77	-
Merrill Lynch	3.07	-
Lehman Brothers	3.52	-
BoA Merrill Lynch	-	5.57
BNP Paribas	-	0.58
Total	1,532	2,225

Notes: These data are constructed from the relationships observed in September 2008 and in October 2015. There are 1,532 links in 2008 and 2,225 links in 2015. Column 1 shows the prime broker. Column 2 shows what percentage of the links the prime broker has in 2008 and Column 3 shows what percentage of the links the prime broker has in 2015. A missing value means that the prime broker is not in the sample in the given year. In 2008, BoA Merrill Lynch and BNP Paribas are not in the sample. In 2015, Bank of America, Merrill Lynch are not in the sample, since they merged after the crisis. Lehman Brothers is not in the sample in 2015, since it went bankrupt in 2008.

Generale, respectively, came to dominate those styles in 2015.

Table 3: Top 3 Prime Brokers and Shares in Each Style in 2008 and 2015

Style	*Top 3 in 2008*	*Top 3 in 2015*
Convertible Arbitrage	JPM (28%),MS (26%),GS (15%)	Barclays (43%), MS (14%), GS (11%)
Emerging Markets	MS (29%), UBS (15%), Citi (14%)	GS (21%), DB (17%), MS (16%)
Equity Market Neutral	MS (33%), GS (20%), JPM (13%)	MS (31%), BoA ML (20%), GS (14%)
Event Driven	JPM (42%), GS (17%), MS (16%)	JPM (32 %), MS (16%), GS (13%)
Fixed Income Arbitrage	Citi (28%), JPM (21%), ML (10%)	Barclays (23%), JPM (20%), GS (16%)
Global Macro	GS (30%), LB (12%), SG (12%)	GS (21%), UBS (17%), Citi (13%)
Long/Short Equity Hedge	MS (32%), GS (23%), UBS (11%)	MS (27%), GS (20%), CS (11%)
Managed Futures	JPM (17%), MS (9%), UBS (6%)	SG (46%), UBS (20%), JPM (6%)
Multi-Strategy	GS (31%), MS (18%), LB (11%)	GS (21%), MS (17%), CS (15%)

Notes: (i) Table shows the shares of the Top 3 prime brokers in different hedge fund investment styles (investment style dedicated short-bias is excluded since there is only one observation.).
(ii) JPM: JP Morgan, GS: Goldman Sachs, MS: Morgan Stanley, BoA ML: Bank of America Merrill Lynch, SG: Societe Generale, CS: Credit Suisse, DB: Deutsche Bank LB: Lehman Brothers
(iii) For example, Morgan Stanley had 32% of total number of hedge funds that are in long/short equity in 2008, Goldman Sachs had 23% of those clients and UBS has 11% of those clients. In 2015, Morgan Stanley had 27% of the hedge funds in long/short equity that are in the 2015 sample, Goldman Sachs had 20% and Credit Suisse had 11%. For the composition of hedge funds across styles in both years, refer to the last columns of Table 4 and Table 5.

2.2 Data Limitations

Assets Under Management. The dataset has a limitation which is the data on assets under management is incomplete. Of the hedge funds in my final sample in 2015, only 1,023 report assets under management on the last reporting date, while that information is missing for 598. This creates a problem since it would not allow me to use value-weighted indices and I would not be able to identify any sorting on size. The total assets of hedge funds that report assets amount to $248 billion.[12] Extrapolating that to the whole sample, I get that the total assets under management of all hedge funds in my final sample in 2015 is $393 billion. According to BarclayHedge (2015), a hedge fund database, the total assets under management in the hedge fund industry is around $2.5 trillion in 2015 (which also includes hedge funds working with small prime brokerages that I do not include in my sample.). In the final sample in 2008, 1,279 of the hedge funds reported the assets under management, while data are missing for 252 hedge funds. For the hedge funds that report the total assets under management reported is $330 billion.[13] Extrapolating that to the whole sample, I get around $395 billion as the total assets under management in the sample.

[12] For hedge funds that report AUM in a currency other than the USD, I use the exchange rates on September 30, 2015 to convert the reported amount into USD.

[13] For hedge funds that report AUM in a currency other than the USD, I use the exchange rates on August 30, 2008 to convert the reported amount into USD.

According to BarclayHedge (2015), the total assets under management of the hedge fund industry was around \$1.5 trillions in 2008.

In the baseline results, I equally weigh all hedge funds when I construct the variables. Note that equal-weighting and value-weighting the measures both capture different aspects of the prime broker-hedge fund relationship. Equal-weighting contains information about the composition of the clientele, while value-weighting contains information about the size and composition. For the purposes of this paper, a comparison of these results contains potentially valuable information. After conducting the analysis by equally weighting hedge funds, I will report the results for value-weighted case in Section 8 and discuss the implications of the difference in the results.

Family Effects. Another issue with the data is some hedge funds which I use as observations belong to the same "family" of hedge funds. The problem is sometimes the family reports the same returns for individual hedge funds. In Appendix B.1, I define some hedge funds as "duplicates", where a hedge fund is a duplicate if it belongs to the same family and the same style as another one and it has the same reported rate of return at least once. In Appendix B.1, I show how the composition of the sample is different when duplicates are excluded, show the values of the measures and do the estimation without duplicates in the sample. The results are qualitatively similar when duplicates are taken out of the sample.

3 Key Measures and Motivating Facts

In this section, I document facts about the composition of client portfolios of prime brokers, introduce key measures that I use in the rest of the paper. Tables 4 and 5 document the shares of each investment style in prime broker portfolios of clients in 2008 and in 2015, respectively.

First thing to note is that the composition of hedge fund investment styles are different in the two years. The notable shifts are the decrease in the number of funds in long/short equity hedge and event-driven styles and the increase in multi-strategy funds.

The most important take-away is the apparent concentration of portfolios of different prime brokers in different styles. For example, in 2015, 37.5% of the sample are in long/short equity hedge and 53.3% of the portfolio of Morgan Stanley are in long/short equity hedge. Similarly, the total share of hedge funds in managed futures is 6.4%, while 65.0% of the funds in the portfolio of Societe Generale comprises of managed futures funds etc. I measure the portfolio concentration of prime brokers by a Herfindahl Index (HHI), a commonly used measure of concentration.

Herfindahl Index of the Prime Broker Portfolio. A Herfindahl index (HHI) is calculated as follows. After leaving out the FoFs, there are 11 investment styles that Lipper classifies. Denoting the styles as

Denoting all styles as $S_1, S_2, ...S_{11}$, I construct the measure as follows:

$$HHI_{PB} = \sum_{i=1}^{11} \left(\frac{\text{Number of Clients in } S_i}{\text{Total Number of Clients}} \right)^2 \tag{1}$$

Due to the fact that for a sizable part of the sample, data on assets under management are missing making it difficult to know the weight of each hedge fund in a prime broker's portfolio.

Table 4: Portfolio Weights of Each Investment Style for Prime Brokers in 2008

Style	**MS**	**GS**	**JPM**	**UBS**	**Citi**	**CS**	**DB**	**SG**	**HSBC**	**Barclays**	**BoA**	**ML**	**LB**	**HFs**
Convertible Arbitrage	3.5%	2.6%	6.3%	-	7.5%	7.0%	1.6%	-	-	12.5%	-	-	5.5%	3.4%
Dedicated SB	-	-	2.1%	1.3%	1.2%	-	-	-	-	-	1.3%	-	-	0.5%
Emerging Markets	10.0%	4.2%	5.4%	14.4%	25%	25.3%	6.5%	-	-	-	-	6.3%	7.4%	8.8%
Equity Mkt Neutral	9.3%	7.5%	6.3%	6.2%	2.5%	7.0%	6.5%	9.8%	-	-	8.2%	14.8%	3.7%	7.1%
Event-Driven	6.2%	8.8%	27.8%	9.6%	10.0%	1.4%	9.8%	2.0%	-	-	2.7%	4.2%	7.4%	10.1%
FI Arbitrage	0.5%	1.3%	4.2%	-	16.2%	1.4%	1.6%	2.0%	-	62.5%	-	10.6%	7.4%	3.0%
Global Macro	0.7%	6.5%	1.6%	4.8%	5.0%	8.4%	1.6%	16.3%	50.0%	-	-	6.3%	14.8%	4.3%
L-S Equities	61.4%	56.2%	26.5%	57.2%	13.7%	39.4%	72.1%	-	25%	-	83.5%	46.8%	31.4%	48.6%
Managed Futures	1.5%	0.6%	4.6%	2.7%	5.0%	1.4%	-	65.3%	-	12.5%	-	2.1%	3.7%	4.1%
Multi-Strategy	3.7%	8.1%	2.9%	3.4%	1.2%	5.6%	-	-	25.0%	12.5%	2.7%	8.5%	16.6%	5.2%
Other	2.7%	3.9%	11.8%	-	12.5%	2.8%	-	2.0%	-	-	1.3%	-	1.8%	4.3%
Total Clients	397	306	237	145	80	71	61	49	4	8	73	47	54	1,532

Notes: This table shows the composition of the investment style of the clientele of each prime broker in the sample. Note that the unit of observation is a link between a prime broker and a hedge fund. The last column shows the composition of the investment styles of each hedge fund in a prime broker-hedge fund link. The last row shows the total number of links every prime broker has in the sample in 2008. Dedicated SB is Dedicated Short-Bias.

Table 5: Portfolio Weights of Each Investment Style for Prime Brokers in 2015

Style	**MS**	**GS**	**JPM**	**UBS**	**Citi**	**CS**	**DB**	**SG**	**HSBC**	**Barclays**	**BoAML**	**BNP**	**HFs**
Convertible Arbitrage	2.9%	2.5%	2.6%	0.7%	4.2%	4.1%	1.7%	-	-	45.3%	0.8%	-	4.0%
Dedicated SB	-	-	-	0.3%	-	-	-	-	-	-	-	-	0.04%
Emerging Markets	7.5%	11.0%	8.4%	10.8%	17.8%	4.5%	15.6%	-	16.6%	6.9%	4.8%	-	9.2%
Equity Mkt Neutral	7.7%	4.0%	0.5%	2.7%	4.2%	2.0%	4.7%	1.9%	-	4.6%	17.7%	-	4.8%
Event-Driven	5.6%	5.0%	25.7%	6.1%	5.9%	5.0%	3.4%	6.8%	-	2.3%	0.8%	30.7%	6.7%
FI Arbitrage	0.4%	1.2%	3.1%	1.1%	2.5%	0.4%	0.8%	-	-	8.1%	0.8%	-	1.3%
Global Macro	2.0%	5.7%	4.2%	7.3%	11.8%	5.4%	2.6%	6.8%	-	3.4%	2.4%	15.3%	4.8%
L-S Equities	53.3%	43.6%	19.4%	35.9%	16.1%	39.5%	38.7%	9.7%	20.8%	5.8%	55.6%	46.1%	37.5%
Managed Futures	1.3%	1.2%	5.2%	11.5%	8.4%	1.2%	1.3%	65.0%	12.5%	4.6%	2.4%	-	6.4%
Multi-Strategy	16.1%	22.5%	11.5%	17.7%	12.7%	25.8%	25.6%	7.7%	50%	10.4%	12.9%	7.6%	18.4%
Other	2.7%	3.0%	18.9%	5.4%	16.1%	11.6%	5.2%	1.9%	-	8.1%	1.6%	-	6.4%
Total Clients	439	399	190	259	118	240	230	103	24	86	124	13	2,225

Notes: See Table 4 for details.

Therefore, I treat all hedge funds equally, for the construction of the HHI measure. If the HHI is measured to be 1, it would mean that the prime broker only has hedge fund clients in only one of the styles. On the other extreme, if each style constitutes an equal share in the portfolio, the HHI would be 0.09. A higher HHI corresponds to a more concentrated portfolio.

Table 6 reports the Herfindahl index for each prime broker in the samples in 2008 and in 2015. The HHI for all the hedge funds that were active was 0.2712 in 2008 and 0.2031 in 2015. This suggests that overall hedge funds have a wider variety of styles in 2015 compared to 2008. Given that, on average, prime brokers were holding a more concentrated portfolio compared to a random allocation of hedge funds, both in 2008 and in 2015, where the average HHI was 0.3577 in 2008 and 0.2756 in 2015.

In both years, prime brokers have more concentrated portfolios than a random allocation of hedge funds to prime brokers. However, since the composition of hedge funds that operate in both years is different and hence the composition of the portfolios of prime brokers is different. Therefore, this measure only suggests the prime brokers are specialized in both years, but cannot say much about the difference between the two years.

Table 6: Concentration of Prime Broker Portfolio - Herfindahl Index

Prime Broker	*HHI in 2008*	*HHI in 2015*
Morgan Stanley	0.4042	0.3274
Goldman Sachs	0.3445	0.2625
JP Morgan	0.1787	0.1670
UBS	0.3662	0.1986
Credit Suisse	0.2414	0.2469
Deutsche Bank	0.5393	0.2474
Citi	0.1450	0.1286
Societe Generale	0.4693	0.4485
HSBC	0.3750	0.3368
Barclays	0.4375	0.2441
Bank of America	0.7068	-
Merrill Lynch	0.2702	-
Lehman Brothers	0.1714	-
Boa Merrill	-	0.3617
BNP Paribas	-	0.3372
Average	**0.3577**	**0.2756**
All Hedge Funds	**0.2712**	**0.2031**

Notes: (i) HHI documents the values for Equation 1 in 2008 and in 2015 for the respective prime broker. (ii) "All Hedge Funds" measures the concentration of style of hedge funds alive in respective years. Average is the simple average of all the prime brokers in the sample in each year.

Comovement with the other Hedge Funds using the Same Prime Broker. In addition to portfolio concentration in investment styles, in this section I ask the question whether the returns of hedge funds that are the clients of the same prime broker co-move with each other. Moreover, I test whether there is any difference between this co-movement in the 2008 sample compared to the 2015 sample.

I proceed by constructing a two indices. One is the "market return index", which simply takes the average of returns of all the hedge funds, that are alive in a given month, regardless of whether they are alive in the time of the snapshot which I estimate the outcome of the matching game.[14] Second is a "prime broker return index", which I construct separately for all the prime brokers in my sample. I take the average of the returns of all the hedge funds that are clients of the prime broker when the snapshot was taken. The goal is to estimate how "similar" the returns of hedge funds in the portfolio of a prime broker at the time of the snapshot. To avoid getting results mechanically, for every hedge fund, I remove itself from the prime broker's portfolio and recalculate the bank return index without that hedge fund. Then I run time series regressions on the following specification for each hedge fund h and prime broker pair, regardless of whether the hedge fund is a client of the prime broker or not. I calculate a $\beta^{h,PB}$ for each hedge fund and prime broker pair.

$$R_{h,t} = \alpha_h + \beta_h^{MKT} R_t^{MKT} + \beta_h^{PB} R_t^{PB} + \epsilon_{h,t} \tag{2}$$

In Panel A, I define

$$\bar{\beta}^{ownPB} \equiv \frac{1}{H} \sum_{h=1}^{H} \beta_h^{ownPB} \tag{3}$$

$$\bar{\beta}^{MKT} \equiv \frac{1}{H} \sum_{h=1}^{H} \beta_h^{MKT} \tag{4}$$

where $\bar{\beta}^{ownPB}$ is the average of the coefficients on the return index on their own prime broker for all hedge funds in the sample. In order not to have mechanical correlations, I exclude the returns of the hedge fund itself from the prime broker return index, if the hedge fund is a client of the prime broker. $\bar{\beta}^{MKT}$ is the average of the coefficients on the market index when the prime broker return index is the one of their own prime broker. Note that the unit of observation here is a link instead of a hedge fund.

In Panel B, I define:

$$\bar{\beta}_p^{ownPB} \equiv \frac{1}{H_p} \sum_{h=1}^{H_p} \beta_h^{ownPB} \tag{5}$$

$$\bar{\beta}_p^{others} \equiv \frac{1}{H_p} \sum_{h=1}^{H_p} \Big(\frac{1}{P-1} \sum_{q \neq p} \beta_h^q \Big) \tag{6}$$

where H_p is the number of hedge fund clients of a prime broker p, P is the number of prime brokers in the sample in a given year.

Panel A of Table 7 shows the estimation results for the regression of each hedge fund's returns on the market index and the return index of their own prime proker. The first column uses time

[14] I include the returns of all hedge funds in the initial raw sample, regardless of whether their prime broker is included in the final sample, to get a better approximation of the "market return"

Table 7: Mean Comovement of Hedge Fund Client and the Average Comovement of those Hedge Funds with other Prime Brokers

Panel A: Regression Results			
	1994-2008	1994-2015	2008-2015
β^{OwnPB}	0.81	0.89	0.90
t-stat	[23.7]	[42.2]	[39.0]
β^{MKT}	1.03	0.89	1.10
t-stat	[39.7]	[34.0]	[36.1]

Panel B: Comparison across prime brokers						
Prime Broker	$\bar{\beta}_p^{ownPB}$	$\bar{\beta}_p^{others}$	$\bar{\beta}_p^{ownPB}$	$\bar{\beta}_p^{others}$	$\bar{\beta}_p^{ownPB}$	$\bar{\beta}_p^{others}$
Morgan Stanley	0.87	0.20	0.92	0.58	0.92	0.55
Goldman Sachs	0.86	0.27	0.85	0.56	0.88	0.55
JP Morgan	0.89	0.21	0.90	0.54	0.88	0.56
UBS	0.86	0.37	0.89	0.54	0.92	0.52
Credit Suisse	0.83	0.38	0.89	0.61	0.91	0.62
Deutsche Bank	0.58	0.24	0.93	0.54	0.96	0.58
Citi	0.85	0.30	0.87	0.53	0.84	0.50
Societe Generale	0.83	-0.62	0.89	-0.05	0.89	-0.17
HSBC	0.74	0.19	0.54	0.48	0.50	0.46
Barclays	-0.23	0.08	1.06	0.33	1.04	0.30
Bank of America	0.65	0.19	-	-	-	-
Merrill Lynch	0.50	0.20	-	-	-	-
Lehman Brothers	0.35	0.06	-	-	-	-
BoA ML	-	-	0.87	0.37	0.86	0.34
BNP Paribas	-	-	0.51	0.59	0.53	0.66

Notes: Panel A is constructed by the regression (16) for a hedge fund and its own prime broker. β^{ownPB} is defined as in (17), β^{MKT} is defined as in (18). Panel B is constructed by running the regression (16) for all possible hedge fund-prime broker pairs. $\bar{\beta}_p^{ownPB}$ is defined in (19). $\bar{\beta}_p^{others}$ is defined as in (20).

(ii) The first block uses returns from January 1994-August 2008 and matches from the 2008 snapshot. The second block uses returns from January 1994-September 2015 and matches from the 2015 snapshot. The third block restricts the returns from September 2008 until September 2015 and matches from the 2015 snapshot.

(iii) T-tests of the null hypotheses of $\bar{\beta}^{ownPB}_{1994-2008} = \bar{\beta}^{ownPB}_{1994-2015}$and $\bar{\beta}^{ownPB}_{1994-2008} = \bar{\beta}^{ownPB}_{2008-2015}$ are both rejected against the alternative hypotheses $\bar{\beta}^{ownPB}_{1994-2008} < \bar{\beta}^{ownPB}_{1994-2015}$and $\bar{\beta}^{ownPB}_{1994-2008} < \bar{\beta}^{ownPB}_{2008-2015}$ at 1% significance level.

series from January 1994 to August 2008 and the links from the September 2008 snapshot. The second column uses time series from January 1994 to September 2015 (or whenever the last report date is) and the links from the October 2015 snapshot. Finally, the third column uses time series from September 2008 to September 2015 (or whenever the last report date is) and the links from the October 2015 snapshot.

In Panel B, I report the comparison between the co-movement of a hedge fund with other clients of the same prime broker and the the average $\beta^{h,PB}$, with all prime brokers except own prime broker for the respective time periods. Statistical tests suggest that the co-movement with the own PB index has increased since the financial crisis. Furthermore, the co-movement with the own PB index is greater than the co-movement with the others on average. This suggests that hedge funds that are similar group together at the same prime broker and this has increased since the crisis.

The findings that prime broker portfolios of clients they serve are more concentrated than if hedge funds were allocated to prime brokers randomly and the co-movement with other hedge fund clients of the same prime broker, more than other prime brokers suggest that specialization is an important part of the business model of prime brokers. However, higher concentration of portfolios might also mean that since hedge funds are similar, in a downturn, this could cause stress for the prime broker due to fire sales, margin calls etc. In order to take that into account, in the next subsection, I define a measure for downside risk.

Downside Risk. I measure the downside risk of a prime broker's portfolio by the semideviation of the average returns of the portfolio of a prime broker, when the portfolio return is negative:

$$\sigma_{below\_zero} = \sqrt{\frac{1}{n}\sum_{r_t<0}^{n}\Big(0 - r_t\Big)^2} \tag{7}$$

where n is the total number of months where the equally-weighted portfolio of the prime broker had negative returns and r_t is the return on the portfolio in that month.

This means the following. I construct a portfolio return for a prime broker by averaging the returns of all of its clients in a given month. Lower semi-deviation measures the dispersion in the average monthly returns conditional on the average of the monthly returns of the portfolio becomes negative. This measures the downside risk of specialization for the prime brokers since it measures the dispersion in returns when enough hedge funds get negative returns, pushing the average returns to negative. In that case, the prime broker could face stress by having to liquidate collateral at fire sales prices or by having to issue margin calls. The upside risk of its clients is not an important factor for a prime broker since prime brokers only provide services to hedge funds and receive pre-agreed contractual fees. Hedge funds receive the upside of their trades, net of fixed fees they pay to prime brokers.

Table 8 reports the measures for the prime brokers in the sample in 2008 and in 2015. The downside risk of the average prime broker's portfolio seems to have increased after the crisis.

Table 8: Downside Risk - Lower Semideviation at 0

	1994-2008	1994-2015	2008-2015
Prime Broker	σ_{below_zero}	σ_{below_zero}	σ_{below_zero}
Morgan Stanley	0.0198	0.0212	0.0261
Goldman Sachs	0.0152	0.0215	0.0277
JP Morgan	0.0147	0.0175	0.0243
UBS	0.0221	0.0234	0.0252
Credit Suisse	0.0274	0.0212	0.0252
Deutsche Bank	0.0502	0.0179	0.0224
Citi	0.0181	0.0176	0.0230
Societe Generale	0.0341	0.0312	0.0193
HSBC	0.0433	0.0365	0.0266
Barclays	0.0082	0.0356	0.0216
Bank of America	0.0232	-	-
Merrill Lynch	0.0130	-	-
Lehman Brothers	0.0187	-	-
BoA ML	-	0.0191	0.0200
BNP Paribas	-	0.0368	0.0410
Average	**0.0237**	**0.0250**	**0.0252**

Notes: (i) σ_{below_zero} is measured as in equation (7).

(ii) The first block uses returns from January 1994-August 2008 and matches from the 2008 snapshot. The second block uses returns from January 1994-September 2015 and matches from the 2015 snapshot. The third block restricts the returns from September 2008 until September 2015 and matches from the 2015 snapshot.

4 Conceptual Framework: What is the Match Surplus?

In this section, I discuss the factors that affect the match surplus in the prime broker-hedge fund relationship.

4.1 The Value of the Match for the Prime Broker

In this part, I write down a framework to think about how a prime broker might be affected from the set of matches it has that does not involve the monetary transfers received from hedge funds.

4.1.1 Internalization

An important element of the prime broker-hedge fund relationship is the financing long positions of hedge funds and providing securities to cover the short positions of hedge funds. Suppose a hedge fund calls a prime broker and requests a margin loan from the prime broker in order to take a leveraged position in a stock, say AAPL, Apple Inc.. In a margin loan, the prime broker lends the hedge fund cash and the hedge fund takes a position in AAPL. For example, the hedge fund wishes to take a long position worth \$100 million and suppose the margin rate is 50%. In that case the hedge fund puts in \$50 million and borrows another \$50 million from the prime broker. The contract specifies a margin rate, interest rate on the loan, the tenor among other elements such as whether the prime broker could re-pledge or re-use the collateral.

Once the contract is in place, the prime broker has several options. First, it can do nothing, in that case the cash extended to the hedge fund would be locked up until the end of the contract, this would have a cost to the prime broker, which is the opportunity cost of these locked up funds, as well as balance sheet costs since the transaction inflates a broker's balance sheet.

Second, it could hold on to the securities, but borrows an unsecured loan to finance the position of the hedge fund and earn a spread. This is costly, since the prime broker would need to pay an interest rate on the unsecured loan, as well as the search and balance sheet costs.

Third, it could re-pledge the securities posted by the hedge fund to an external party and earn the spread between the interest rate it receives from the hedge fund and the interest rate it pays the external counterparty. This process is referred to as matched-book. In this case, there are search costs in order to find a counterparty that would want AAPL as collateral.[15]

Finally, it can internalize the positions between two clients (i.e. intermediate between the two clients). It could find a client that wishes to take a short position in AAPL.[16] It lends the security

[15] One might imagine this model to be a broader model of financial networks where the prime brokers incur these costs in search for other counterparties, such as other broker-dealers, money market funds or securities lenders in reduced form.

[16] This is almost costless since the prime broker could electronically solicit whether another hedge fund wants to take an opposite position in "microseconds." As Tabb and Morgan (2012) suggest: "Historically, trading desks were able to match buying and selling interest received concurrently on the desk. As technology now allows messages to be sent and responded to in microseconds, trading desks can send out messages to solicit the other side of the trade. If an order can't be found directly, it then moves into the firm's dark pool. If still unable to be matched, the dark pool sends messages to a wider array of market participants to trade. If still unexecuted, the order is sent to other dark pools that message a wider group of traders. If by the time the order went through two or three different dark pools and messaging cycles and the order remained unexecuted, it would then go to the exchanges. This all occurs in a fraction of a second, all managed by a series of electronic routing engines."

and receives cash collateral. As a result, the prime broker ends up with no exposure to the security. It merely intermediates between two hedge funds allowing the flow of securities from the long hedge fund to the short hedge fund and the flow of cash from the short hedge fund to the long hedge fund. At the end of the contracts, it receives interest rates from the long hedge fund and securities lending fees from the short hedge fund.[17]

Prime brokers that are able to internalize trades more frequently can save more costs and hence are more efficient. The chances of internalizing trades is the greatest if the prime broker serves a portfolio of clients that have similar strategies. That requires the prime broker to be specialized, with clients similar enough to each other so that they trade similar securities and load on similar factors, but have differences such that they sometimes take opposite positions to each other. In this case, the prime broker earns an interest payment from the long hedge fund r_L and earns securities lending fees r_S from the short hedge fund.

Hedge funds are long-biased in their investments. Therefore, it is reasonable to assume two hedge funds that trade similar strategies overall load on the same factors. The prime broker then internalizes trades that give rise to the idiosyncratic returns of hedge funds. For example, if a prime broker is specialized in commodities, the returns of hedge funds move with a commodities risk factor, however if there are disagreements about, say oil prices, the prime broker internalizes trades.

If the prime broker instead had two clients that did not take opposite positions in the same security, then the prime broker would have to incur a cost for each trade as in the following figure.

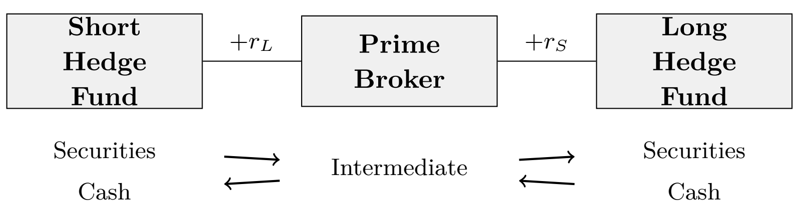

Figure 1: Internalization

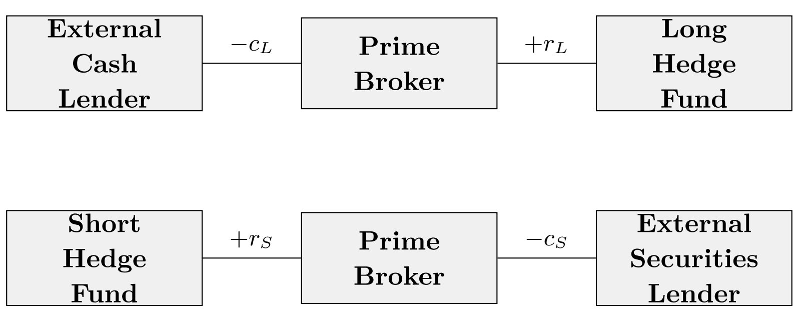

Figure 2: A long position and a short position that cannot be internalized.

Suppose the total order flow the prime broker receives is Q. Suppose that the prime broker could internalize a fraction $i_L + i_S$ of the total order flow. However, a fraction, $1 - i_L$ are long positions

[17] See Kirk, McAndrews, Sastry and Weed (2014) for additional balance sheet efficiency internalization provides compared to other forms of financing.

that were not internalized and a fraction $1 - i_S$ are short positions that were not internalized. For simplicity, suppose there are search and balance sheet costs, c per unit, for each non-internalized trade. Internalization reduces these costs to a fraction $f \in [0, 1]$. Therefore, internalization costs fc per unit of order flow internalized. For brevity, denote $i \equiv i_L + i_S$. Profits, net of other costs, could be written as:

$$\pi = Revenues - (1 - i) \times Q \times c - i \times Q \times (fc)$$

If the prime broker did not internalize any trade, then the profits would be:

$$\pi = Revenues - Q \times c$$

Per unit of internalized flow, the prime broker saves on costs net of the cost of internalization, that is $(1 - f)c$, since it would have to incur these costs both for the long and the short position. Therefore, the total realized value of internalization, V, is:[18]

$$V = i \times Q \times (1 - f) \times c$$

For a prime broker, being specialized increases the chances to internalize trades. i.e. $i(HHI, \bar{\beta}_p^{ownPB})$, where $\frac{\partial i}{\partial HHI} > 0$ and $\frac{\partial i}{\partial \bar{\beta}_p^{ownPB}} > 0$. Also note that, the marginal benefit of internalization is higher when c is higher, or f is lower.

Anecdotal Evidence. According to an article by Tabb and Morgan (2012), defining internalization as "the practice of brokers matching orders internally on their trading desk - before orders are either sent to dark pools or exchanges" suggest that nearly 33% of US equities trading in 2012 was either internalized or sent to dark pools. This figure was less than half in 2008, at 15% in 2008. According to an FTAlphaville (2010a) blog post "...there are stocks with internalization rates greater than 40 percent-outliers with rates reaching 50, 60 or even 70 percent." In another news article (FTAlphaville (2010b)), FT argues "...[w]hat can't be matched or offset internally is then re-directed onto exchanges. But what is internalised, captures the best market-making spreads of all." Cantor (2014) cites a study by Barclays and documents that "prime brokers obtain anywhere from 30-60% of their funding from internal efficiencies and 20-50% from short-term repo markets."

4.1.2 Expertise

The specialization of prime brokers could also be attributed to building expertise in certain asset classes. Having expertise could benefit the prime broker through informational advantages it entails as it is the case in most of the banking literature. It could provide better monitoring of the trades hedge fund clients make and evaluate the risks better.

[18]This is just to illustrate the value of internalization and through which mechanism it arises. In Section 7, I will pick up from here to do an accounting analysis of internalization.

4.1.3 Downside Risk

A prime broker serving a concentrated portfolio of similar clients might get benefits from internalization or expertise. However, it is also exposed to risk since it serves hedge funds that trade similar securities and have similar factor loadings. In a downturn, if hedge funds fail, the prime broker would be left with similar types of collateral to liquidate or would have to issue margin calls to many hedge funds. The lower semi-deviation at target rate zero captures this in the following way. It measures the dispersion in returns when enough hedge funds get negative returns, pushing the average returns to negative, which would be a likely outcome in terms of downside risk arising from specialization.

4.2 The Value of the Match for Hedge Funds

I measure how specialization of their prime brokers might affect hedge funds by the market share of the prime broker in the investment style of the hedge fund, excluding itself. In this part, I provide a conceptual framework for how hedge funds might benefit or be hurt by being matched with a specialized prime broker and therefore indirectly matched with the other clients of the same prime broker. The benefits arise from the increased ability of the prime broker to provide immediacy. On the other hand, if the prime broker is specialized, then there might be others that compete to borrow the same securities to take a short position. Which effect dominates is an empirical question that is answered by the estimation.

The benefits through immediacy are as follows: Hedge funds simultaneously take long positions in some securities and short positions in others. Most of the hedge funds are long-biased. They aim to find profitable trades whenever they find any mis-valuation in asset classes they specialize in. They trade frequently. Therefore, the value they receive from a relationship with a prime broker comes from the fee structure of the prime broker as well as immediacy in executing their trades. Hedge fund strategies often involve taking short positions in securities that are scarce, often called "hard-to-borrow" securities. Since other hedge funds might also be competing to borrow the same securities, timing of these trades are important.

When a hedge fund wishes to take a short a position in a security, they call their prime broker. If the prime broker has the security in its inventory or could easily match this short position with a long position of another client on the same security, it can provide the position fast. Hence, the hedge fund would be able to take the position it wants at the time and the price it wants.

If the prime broker does not have the security or cannot match the trade with another hedge fund in-house, it would need to search for it externally, for which the prime broker incurs a cost. The costs to a hedge fund of not having immediacy is different. Every second or maybe mili-second that the hedge fund waits to start the position, the price could move in an unwanted direction, resulting in reduction of profits for the hedge fund. In that sense, there is a value that hedge funds receive from the match that is different than the value that prime brokers receive pre-transfers. In a study of dealer networks in municipal bonds, Li and Schurhoff (2014) find the value of immediacy to be substantial. They estimate that it "costs investors up to 0.6-0.7% of transaction value to speed up execution by a day."

On the other hand, the specialization of their prime broker could lead to congestion by multiple hedge funds competing for similar securities to take short positions, instead of trading with each other through their prime broker. Hence, the market share of their prime broker in their investment style could be damaging.

In addition to the market share of the prime broker in a hedge fund's investment style, I would like to ask whether a hedge fund that is similar to others in the same style prefer the specialization of its prime broker more or less.

I create a new measure, which is the co-movement of a hedge with the others in the same style[19] for each hedge fund:

$$R_{h,t} = \alpha_h + \beta_h^{MKT} R_t^{MKT} + \beta_h^S R_t^S + \epsilon_{h,t}$$

What is meant to be captured with this is, I would like to interact the measure for immediacy benefits with $\beta_{h_j}^S$, in order to capture whether hedge funds that are "more similar" to others value the specialization of their prime broker more or less.

Table 9: Market Shares in Style in 2008 - Descriptive Statistics

Prime Broker	*Average Mkt Share in Style*	*Average of Mkt Share in Style* $\times \beta^{Style}$
Goldman Sachs	0.2166	0.1652
Morgan Stanley	0.2902	0.2354
JP Morgan	0.2396	0.2321
Credit Suisse	0.0627	0.0512
Deutsche Bank	0.0479	0.0261
UBS	0.1056	0.0983
Citi	0.1140	0.1537
Bank of America	0.0724	0.0657
Merrill Lynch	0.0368	0.0162
Soc Generale	0.3412	0.3026
Lehman Brothers	0.0500	0.0399
Barclays	0.0543	0.0283
HSBC	0.0075	0.0020
Average	0.1261	0.1090

Notes: Average Mkt Share in Style shows the average market share of the prime broker in the style of a hedge fund that it serves, where market share for each link is calculated by excluding the hedge fund itself. *Average of Mkt Share in Style* $\times \beta^{Style}$ is the average of the interaction term; market share in style of prime broker (exc. hedge fund itself) and co-movement of hedge fund with others in the same style.

5 An Empirical Matching Model Between Prime Brokers and Hedge Funds

Prime brokers and hedge funds form relationships with each other in a matching market. Unlike a discrete choice model, both prime brokers and hedge funds need to compete with other on their

[19] R_t^S is the "style return index" constructed similarly as the "prime broker return index"

Table 10: Market Shares in Style in 2015 - Descriptive Statistics

Prime Broker	*Average Mkt Share in Style*	*Average of Mkt Share in Style* $\times \beta^{Style}$
Goldman Sachs	0.1928	0.1975
Morgan Stanley	0.2290	0.2309
JP Morgan	0.1609	0.1463
Credit Suisse	0.1218	0.1314
Deutsche Bank	0.1159	0.1098
UBS	0.1227	0.1215
Citi	0.0725	0.0553
Soc Generale	0.3073	0.3121
Barclays	0.2203	0.3124
HSBC	0.0186	0.0157
BNP Paribas	0.0103	0.0075
BoA ML	0.0868	0.0800
Average	0.1382	0.1434

Notes: See Table 9 for details.

sides to match with their most preferred partner. The value that the prime broker and the hedge funds get depends on the resulting network of the prime broker. Furthermore, in this market, data on key variables such as profits, fees or maximum number of clients a prime broker could serve are not available. This limitation makes mainstream estimation techniques inapplicable in the context of prime brokers and hedge funds.

I use the information I have on the relationship between prime brokers and hedge fund. To main goal of this estimation is to learn something about these relationships without having access to a breadth of high quality data which is hard, if not impossible, to collect. Instead, I use the information that a hedge fund is a client of a prime broker and use returns and other information on characteristics to estimate the match-specific surplus generated from the set of observed matches.

I use the methodology introduced by Fox (2010) for matching estimation for many-to-many two-sided matching markets with transferable utility. In the model, the total surplus that a prime broker gets and the surplus that a hedge fund gets from this match are latent variables. However, I observe the outcome variable which is whether a match is formed between a prime broker and a hedge fund, which is informative when transfers exist.

To fix ideas, suppose we observe that Goldman Sachs is matched with Pure Epsilon and Morgan Stanley is matched with Pure Delta. Furthermore, we also observe that Goldman Sachs is not matched with Pure Delta and Morgan Stanley is not matched with Pure Epsilon. Since transfers are endogenous that clear the market, an implication of pairwise stability is the following. Goldman Sachs could have reduced its fee structure to attract Pure Delta, that would make Pure Delta want to take its business from Morgan Stanley to Goldman Sachs. However, at a pairwise stable equilibrium, the profits of Goldman Sachs would be lower if doing business with Pure Delta would cost it the business from Pure Epsilon. A similar argument applies for Morgan Stanley, resulting in two inequalities.

Following Fox (2010), I sum these two inequalities and equilibrium transfers drop out. This results in one single inequality that says these two matches are formed when the total match surplus with observed matches are greater than or equal to the total match surplus in a counterfactual world where the links are swapped. The actual composition of clients other than the ones in question in these pairwise comparisons are different for Goldman Sachs and Morgan Stanley. Hence, Pure Epsilon and Pure Delta contribute differently to the variables affecting the match surplus when they are clients of Goldman Sachs and Morgan Stanley, respectively, compared to when the links are swapped. Therefore, parameters affecting the match surplus could be identified without observing transfers or profits. I construct such inequalities for all possible and meaningful two pairs of prime broker-hedge funds.

5.1 Empirical Methodology and Identification

The empirical methodology employed in this paper relies on Fox (2010). I study a two-sided, many-to-many matching between prime brokers and hedge funds. I capture a prime broker with a vector of characteristics $\tilde{p} \in \tilde{P}$, where $\tilde{P} = P \times (\mathbb{Z}^{+} \cup \{\infty\})$ and $P \subseteq \mathbb{R}^{K_p}$. The first K_p elements of $\tilde{P}$ are all other characteristics except for the quota and the last characteristic is a quota, an upper bound on the number of matches a prime broker could form. A similar notation also captures what a hedge fund is. A hedge fund is a vector of characteristics $\tilde{h} \in \tilde{H}$, where $\tilde{H} = H \times (\mathbb{Z}^{+} \cup \{\infty\})$ and $H \subseteq \mathbb{R}^{K_h}$. Again, the first K_h elements of H are all other characteristics except for the quota and the last characteristic is the quota.

An outcome of the matching game with transferable utility is a measure μ on the space $\tilde{P} \times (\tilde{H} \times \mathbb{R})^{Q}$, where an element is a tuple $\langle \tilde{p}, (\tilde{h_1}, t_1), ..., ((\tilde{h_{N_p}}, t_{N_p})) \rangle$ for $N_P \leq Q_p$ where Q_p is the quota of a prime broker. For an outcome to feasible, the number of matches each firm is in must be less than or equal to their respective quotas. In the prime brokerage market analyzed in this paper, there are no data available on neither quotas nor transfers. For the estimation, observation of neither is necessary. Furthermore, quotas do not enter into payoffs, but they are just imposed as a constraint.

Next, I denote M to be a set of N physical matches in the data, $M = \{(p_1, h_1), ...(p_N, h_N)\}$. For example, in my data, this is $M = \{(GoldmanSachs, PureEpsilon), (MorganStanley, PureDelta), ...\}$. Let $\langle p, h_1, ..., h_{N_p} \rangle$ be a physical partner list. Finally, let μ^A be the assignment, the measure of physical partner lists implied by the outcome measure μ. For example, part of the assignment could be: $\langle GoldmanSachs, PureEpsilon, ABCFund, ... \rangle$ and $\langle MorganStanley, PureDelta, DEFFund, ... \rangle$ etc.

From these to go to the profits of prime brokers and hedge funds, suppose there are a total of P_I prime brokers and H_J hedge funds. Each prime broker p_i is matched with N_i hedge funds. I denote the physical matches of a prime broker, p_i, by $M_{p_i} = \{\langle p_i, h_i^1 \rangle, \langle p_i, h_i^2 \rangle, ...\langle p_i, h_i^{N_i} \rangle\}$. The subscript means that a hedge fund has a relationship prime broker p_i and the superscript is just a way of ordering the hedge funds in a prime broker's network. The profits of p_i can be written as:

$$\pi^p = \pi^p(M_{p_i}) + \sum_{m=1}^{N_i} t_{\langle p_i, h_i^m \rangle}$$

where $\pi^p(M_{p_i})$ are the profits obtained from match-specific characteristics that depend on the set of matches p_i is involved in. Everything else is subsumed in transfers.

Similarly, suppose a hedge fund h_j is matched with W_j prime brokers, resulting in a physical matches for h_j, which is: $M_{h_j} = \{\langle h_j, p_1\rangle, ..., \langle h_j, p_{W_j}\rangle\}$. I write the profits of a hedge fund h_j as:

$$\pi^h = \pi^h(M_{h_j}) - \sum_{k=1}^{W_j} t_{\langle p_k, h_j\rangle}$$

where $\pi^h(M_{h_j})$ are the profits obtained from match-specific characteristics that depend on the set of matches h_j is involved in. Notice that when a hedge fund is matched with a prime broker, it is indirectly matched with other hedge funds in a prime broker's network through the prime broker. Note that I assume transfers flow from hedge funds to prime brokers, hence prime brokers receive positive transfers and hedge funds give away transfers, which could be thought of commissions, fees etc.

5.1.1 Pairwise Stability, Sum of Profit Inequalities

The equilibrium concept used in the matching game between prime brokers and hedge funds is pairwise stability. This sub-section relies on Fox (2010).

Definition. An outcome will satisfy pairwise stability whenever:

1. The following inequality holds for all physical matches of p_i and p_q, such that both are prime brokers. p_i is matched with h_i, p_q is matched with h_q, but the opposite is not true. i.e. p_i is *not* matched with h_q, p_q is *not* matched with h_i :

$$\pi^p(M_{p_i}) + t_{\langle p_i, h_i\rangle} \geq \pi^p(M_{p_i} \setminus \{\langle p_i, h_i\rangle\}) \cup \{\langle p_i, h_q\rangle\} + \bar{t}_{\langle p_i, h_q\rangle} \tag{8}$$

   where

$$\bar{t}_{\langle p_i, h_q\rangle} \equiv \pi^h\Big((M_{h_q} \setminus \{\langle p_q, h_q\rangle\}) \cup \{\langle p_i, h_q\rangle\}\Big) - \Big(\pi^h(M_{h_q}) - t_{\langle p_q, h_q\rangle}\Big)$$

2. For all $\langle p, h, t\rangle$ for any partner list:

$$\pi^p(M_p) + t_{\langle p, h\rangle} \geq \pi^p(M_p \setminus \langle p, h\rangle)$$

3. For all $\langle p, h, t\rangle$ for any partner list:

$$\pi^h(M_h) - t_{\langle p, h\rangle} \geq \pi^h(M_h \setminus \langle p, h\rangle)$$

First inequality is just a mathematical representation of the following idea: Suppose we observe that Goldman Sachs is matched with Pure Epsilon and Morgan Stanley is matched with Pure Delta and we also observe that Goldman Sachs is not matched with Pure Delta and Morgan Stanley is not matched with Pure Epsilon. Transfers are endogenous that clear the market. Goldman Sachs could have reduced its fee structure to attract Pure Delta, that would make Pure Delta want to take its business from Morgan Stanley to Goldman Sachs. However, at a pairwise stable equilibrium, the profits of Goldman Sachs would be lower if doing business with Pure Delta would cost it the business from Pure Epsilon.

Part 2 and 3 of the definition say that matched firms cannot increase profits by unilaterally dropping links. An implication of the first part of the definition is used as the basis of estimation.

The inequalities used for the estimation are derived from part 1 of the definition, which is weaker than the usual pairwise stability, in the sense that when this is violated, usual pairwise stability would also be violated. The use of this definition is for tractability and the ability to estimate parameters when transfers are not observed. In the other conditions of pairwise stability, transfers would not drop out, hence they cannot be used to estimate parameters without data on transfers.

The inequalities that form the basis of the estimation are constructed as follows:

For all possible pairwise comparisons $\langle\{p_i, h_i\}, \{p_q, h_q\}\rangle$, where a prime broker p_i is matched with a hedge fund h_i, and a prime broker p_q is matched with h_q, but the opposite is not observed in the data, the following must be true according to pairwise stability:

$$\pi^p(M_{p_i}) + t_{\langle p_i,h_i\rangle} \geq \pi^p(M_{p_i} \setminus \{\langle p_i, h_i\rangle\}) \cup \{\langle p_i, h_q\rangle\} + \bar{t}_{\langle p_i,h_q\rangle} \tag{9}$$

$$\pi^p(M_{p_q}) + t_{\langle p_q,h_q\rangle} \geq \pi^p(M_{p_q} \setminus \{\langle p_q, h_q\rangle\}) \cup \{\langle p_q, h_i\rangle\} + \bar{t}_{\langle p_q,h_i\rangle} \tag{10}$$

where

$$\begin{aligned}
\bar{t}_{\langle p_i,h_q\rangle} &\equiv \pi^h\Big((M_{h_q} \setminus \{\langle p_q, h_q\rangle\}) \cup \{\langle p_i, h_q\rangle\}\Big) - \Big(\pi^h(M_{h_q}) - t_{\langle p_q,h_q\rangle}\Big) \\
\bar{t}_{\langle p_q,h_i\rangle} &\equiv \pi^h\Big((M_{h_i} \setminus \{\langle p_i, h_i\rangle\}) \cup \{\langle p_q, h_i\rangle\}\Big) - \Big(\pi^h(M_{h_i}) - t_{\langle p_i,h_i\rangle}\Big)
\end{aligned}$$

If p_i offered h_q the fee structure $\bar{t}_{\langle p_i,h_q\rangle}$, that would make h_q want to become a client of p_i. However, we observe that p_i is matched with h_i with the fee structure $t_{\langle p_i,h_i\rangle}$ instead of h_q at the fee structure $\bar{t}_{\langle p_i,h_q\rangle}$. Therefore, it must be lowering the profits of p_i, assuming that h_q would replace h_i. A similar argument applies for the mirroring case.

Inequalities (9) and (10) still have transfers in them, therefore parameters cannot be identified without observing transfers. However, plugging in for $\bar{t}_{\langle p_i,h_q\rangle}$ and $\bar{t}_{\langle p_q,h_i\rangle}$ and summing the inequalities, we obtain:

$$\begin{aligned}
\pi^p(M_{p_i}) + {}&\pi^h(M_{h_i}) + \pi^p(M_{p_q}) + \pi^h(M_{h_q}) \geq \\
&\pi^p((M_{p_i} \setminus \{\langle p_i, h_i\rangle\}) \cup \{\langle p_i, h_q\rangle\}) + \pi^h((M_{h_i} \setminus \{\langle p_i, h_i\rangle\}) \cup \{\langle p_q, h_i\rangle\}) + \\
&\pi^p((M_{p_q} \setminus \{\langle p_q, h_q\rangle\}) \cup \{\langle p_q, h_i\rangle\}) + \pi^h((M_{h_q} \setminus \{\langle p_q, h_q\rangle\}) \cup \{\langle p_i, h_q\rangle\})
\end{aligned}$$

Since each hedge fund interact differently with other clients of each bank, this will induce variation. Therefore, parameters could be identified. I construct an inequality the same way for all possible two-pair comparisons in my data, which forms the basis of the estimation.

5.1.2 Rank Order Property

So far, the matching game I have been analyzing is deterministic. To be able to do conduct statistical analysis, the rank order property is introduced, that makes it possible that each pair could be observed in equilibrium with positive probability (regardless of whether or not it is observed in equilibrium.). The estimation procedure will only be able to fit a certain number of sum of profit inequalities. In this section, I introduce a stochastic structure $\epsilon \in E$ that indexes the distributions of unobservables. As in Fox (2010), I assume that the assignment measure, admits a density measure $g^{\pi^p,\pi^h,\epsilon}$ over the list $\langle p_i, h_i^1, ..., h_i^{N_i}\rangle$, where the superscripts are the two profit functions and the distribution of unobservables. . The superscripts refer to the two structural profit functions, one for the prime brokers and one for hedge funds and the distribution of unobservables. This makes, each prime brokers list of partners a random draw from the conditional density of $(h_i^1, ..., h_i^{N_i})$ given p_i.

Property 1. *(Property 3.1 in Fox (2010)) Let π^p, π^h, ϵ be given. Let $L_1 = \langle p_i, h_i^1, ..., h_1^{N_i}\rangle, H_1 = \{h_i^1, ..., h_i^{N_1}\}$, $M_{p_i} = \{\langle p_i, h_i^1\rangle, ...\langle p_i, h_i^{N_1}\rangle\}$, $h_i \in H_i$, $L_2 = \langle p_q, h_q^1, ..., h_q^{N_q}\rangle, H_q = \{h_q^1, ..., h_q^{N_q}\}$, $M_{p_q} = \{\langle p_q, h_q^1\rangle, ...\langle p_q, h_q^{N_q}\rangle\}$, $h_q \in H_q$. Also let L_3 be the physical partner list formed from $(M_{p_i} \setminus \{\langle p_i, h_i\rangle\}) \cup \{\langle p_i, h_q\rangle\}$ and L_4 be the physical partner list formed from $(M_{p_q} \setminus \{\langle p_q, h_q\rangle\}) \cup \{\langle p_q, h_i\rangle\}$.*

The rank order property for one large market *states that the sum of surplus inequality holds if and only if:*

$$g^{\pi^p,\pi^h,\epsilon}(L_1).g^{\pi^p,\pi^h,\epsilon}(L_2) \geq g^{\pi^p,\pi^h,\epsilon}(L_3).g^{\pi^p,\pi^h,\epsilon}(L_4)$$

According to the rank order property, an inequality might be violated due to unobservables to the econometrician, but observable to market participants (for example, if a hedge fund manager and prime broker manager went to the same business school etc.). Rank order property, being an extension to the deterministic pairwise stability imposes that the observed two pairs for which the sum of profit inequality is greater are more likely to be observed than the counterfactual two pairs for which the sum of profit inequality is smaller. Fox (2010) shows that under the rank order property, parameters of the matching game are identified and can be consistently estimated.

5.1.3 Construction of the Objective Function

I model the surplus functions for both prime brokers and hedge funds, pre-transfers as linear functions.

$$S^{PB}(M) = (X_{PB})'\phi$$
$$S^{HF}(M) = (Z_{HF})'\gamma$$

where X_{PB} are the match-specific factors entering the surplus function for the prime broker and Z_{HF} are the match-specific factors entering the surplus function for the hedge fund and ϕ and γ are vectors of parameters. Then, this results in the following form for the sum of the surplus inequalities for each two pairs of observations of a link between a prime broker and hedge fund where the observed pairs are $\langle p_i, h_i\rangle$ and $\langle p_q, h_q\rangle$ and counterfactual pairs are $\langle p_i, h_q\rangle$ and $\langle p_q, h_i\rangle$:

$$(X_{PB}^{p_i,h_i})'\phi + (X_{PB}^{p_q,h_q})'\phi + (Z_{HF}^{p_i,h_i})'\gamma + (Z_{HF}^{p_q,h_q})'\gamma \geq$$
$$(X_{PB}^{p_i,h_q})'\phi + (X_{PB}^{p_q,h_i})'\phi + (Z_{HF}^{p_q,h_i})'\gamma + (Z_{HF}^{p_q,h_i})'\gamma$$

I define the following:

$$X_{PB}^{p_i,h_i,p_q,h_q} \equiv (X_{PB}^{p_i,h_i})' + (X_{PB}^{p_q,h_q})' - (X_{PB}^{p_i,h_q})' - (X_{PB}^{p_q,h_i})'$$
$$Z_{HF}^{p_i,h_i,p_q,h_q} \equiv (Z_{HF}^{p_i,h_i})' + (Z_{HF}^{p_q,h_q})' - (Z_{HF}^{p_i,h_q})' - (Z_{HF}^{p_q,h_i})'$$

Given $X_{PB}^{p_i,h_i,p_q,h_q}$ and $Z_{HF}^{p_i,h_i,p_q,h_q}$, I can rewrite each inequality as:

$$(X_{PB}^{p_i,h_i,p_q,h_q})'\phi + (Z_{HF}^{p_i,h_i,p_q,h_q})'\gamma \geq 0$$

The asymptotic argument in this framework relies on the assumption that the recorded observations on H_J hedge funds is a random sample from the "true" matching game with a continuum of hedge funds. Hence, the objective function is to maximize:

$$Q_{H_J}(\phi,\gamma) = \frac{2}{H_J(H_J-1)} \sum_{h_i=1}^{H_J-1} \sum_{h_q=h_i+1}^{H_J} \mathbb{1}\Big[(X_{PB}^{p_i,h_i,p_q,h_q})'\phi + (Z_{HF}^{p_i,h_i,p_q,h_q})'\gamma \geq 0\Big]$$

The estimator is the maximum rank correlation estimator by Han (1987). Under certain technical assumptions outlined in Fox (2010) and rank order property, the parameters that maximize the objective function are consistent estimators of the parameter vector in the data generating process. Sherman (1993) shows that the maximum rank correlation estimator is asymptotically normal. Subbotin (2007) shows that the bootstrap is consistent for the asymptotic distribution.

Implementation. Since the objective function is not differentiable, usual estimation procedures do not work with regular optimization methods. The way I estimate the model is by using a global maximization algorithm called differential evolution, which is an algorithm that can find the global maximum even without differentiability of the objective function (Storn and Price (1997)).

The coefficients of the function describing that profits are estimated by trying out a set of coefficients, scoring the number of pair reversals that generate failures of the theoretically constructed inequalities constructed by imposing pairwise stability, and systematically improving the fit by stochastically changing the coefficients to minimize the number of failures. Absent noise, at the conclusion, the coefficients would find no failures, but, because of noise, some will remain.

Since the algorithm does not guarantee that the maximizers are global maximizers, I run the algorithm multiple times with different starting values and boundary values to be confident. I implement the differential evolution procedure in MATLAB after I construct the inequalities in STATA. I construct the 95% confidence intervals by bootstrap, resampling hedge funds. I also use the Proclus server of Stanford University to parallelize the code across 600 cores at the maximum, where necessary.

This estimation is semi-parametric, in the sense that I do not make any assumptions about the distribution of the error terms. The point estimates that I get are valid up to scale. I normalize the coefficient on one of the variables to be +1 or −1. The maximization procedures finds whether it is +1 or −1 and find all other coefficients relative to that one such that the parameters maximize the number of matches that could be explained by the two-pair inequalities in the model.

5.2 Application to the Prime Brokerage Market

A General Formulation of Profits. The empirical methodology explained above assumes a static matching game played between players in the two-sides of the market. In this section, I present an application of the methodology to explain the matches between prime brokers and hedge funds.

I write the profits of a prime broker, p_i as:

$$\pi^{p_i}(M_{p_i}) = \sum_{m=1}^{N_i} t_{\langle p_i, h_i^m \rangle} - C(M_{p_i}, \phi)$$

The total profits of the prime brokers are the transfers that they receive from hedge funds, $\sum_{m=1}^{N_i} t_{\langle p_i, h_i^m \rangle}$, net of costs of serving hedge funds, which is a function of the equilibrium network of relationships of a prime broker. I parametrize this cost function. In the model, I interpret transfers any revenues that the prime brokers make from hedge funds, through cash payments, such as fees, commissions etc. The matches affect the profits through interactions between hedge funds in the prime brokerage network, that affect the cost function, such as higher HHI saving costs etc. In general, these could be interpreted as the match surplus. The benefit that the prime brokers get from its matches, aside from any direct cash payments. Note that any other variables that are not match-specific do not appear in the inequalities and do not pose any threat to identification. Hence, I abstract from them for simplicity.

I write the profits of a hedge fund, h_j as:

$$\pi^{h_j}(M_{h_j}) = \pi^{\bar{h}_j} + S(M_{h_j}, \gamma) - \sum_{k=1}^{W_j} t_{\langle p_k, h_j \rangle}$$

The total profits of a hedge fund are any idiosyncratic returns they get, $\pi^{\bar{h}_j}$, which will drop out of the inequalities in the estimation, they receive (positive or negative) profits from the matches with the prime brokers. This could be through the interaction of characteristics of the hedge funds and the prime brokers, or the interaction with the other clients of the prime brokers that they match with. Finally, they pay transfers to prime brokers they matched with, which is their costs. Again, note that anything else that is not match-specific will drop out of the inequalities and cannot be estimated, though not posing a threat to identification.

Parametrization of the Profit Functions. Following the discussion in Section 4.1, I write down the total match surplus accrued to prime brokers and the transfers as the following, by assuming a linear specification:[20]

$$\begin{aligned}\pi^{p_i}(M_{p_i}) =& \phi_1 \sigma_{below\_zero}(M_{p_i}) + \phi_2 HHI(M_{p_i}) + \\ & \phi_3 \bar{\beta}_p^{ownPB}(M_{p_i}) + \sum_{m=1}^{N_i} t_{\langle p_i, h_i^m \rangle}\end{aligned}$$

[20]Note that the variables I use are constructed variables which do not have precise economic meanings. For example, it is not easy to assess how one standard deviation in HHI affects the fraction of trades that are internalized, without making a lot of assumptions. Therefore, the model is not entirely structural, but a linear specification at least yields simple interpretations of coefficients.

where $\sum_{m=1}^{N_i} t_{\langle p_i,h_i m\rangle}$ are transfers prime broker receives from hedge funds. M_{p_i} denotes all the matches a prime broker p_i is in, that is $M_{p_i} = \{\langle p_i, h_i^1\rangle, \langle p_i, h_i^2\rangle, ...\langle p_i, h_i^{N_i}\rangle\}$. $\sigma_{below\_zero}(M_{p_i})$ is the lower semi-deviation at 0 of its portfolio and measures the downside risk [21]. $HHI(M_{p_i})$ is the Herfindahl index computed from the investment styles that a prime broker serves and $\bar{\beta}^{ownPB}(M_{p_i})$ is the average of the coefficients recovered from the regression 4.2 of its own returns on the prime broker return index.

Therefore, specialization measured by $HHI(M_{p_i})$ and $\bar{\beta}^{ownPB}(M_{p_i})$ affect costs. $\sigma_{below\_zero}(M_{p_i})$ is also a match-surplus, whose effect on profits, is the be estimated.

Following the discussion in Section 4.2, I write down the the match surplus for the hedge fund, net of transfers, in a linear specification:

$$\begin{aligned}\pi^{h_j}(M_{h_j}) = &\sum_{k=1}^{W_j} \gamma_1 Mkt\_Shr_{p_k}^{S_{h_j}} + \\ &\sum_{k=1}^{W_j} \gamma_2 Mkt\_Shr_{p_k}^{S_{h_j}} \times \beta_{h_j}^{S} - \\ &\sum_{k=1}^{W_j} t_{\langle p_k,h_j\rangle}\end{aligned}$$

where W_j is the total number of prime brokers it is matched with. M_{h_j} denotes all the matches hedge fund h_j is in. $Mkt\_Shr_{p_k}^{S_{h_j}}$ is the market share of the prime broker without the client itself. $Mkt\_Shr_{p_k}^{S_{h_j}} \times \beta_{h_j}^{S}$ is an interaction of how much they value the market share of the prime broker in their style, interacted with how much their returns co-move with others in the same style. Note that the individual impact of $\beta_{h_j}^{S}$ would drop out of the inequalities, hence it cannot be identified. The reason why this interaction term could be important is due to the fact that the more the hedge fund is similar to others, the faster any mis-pricing would be corrected by other hedge funds, increasing the value of immediacy.

5.3 Correlation Matrices of the Variables in Inequalities

In this subsection, I report the correlation matrices of the variables used in the estimation in 2008 and in 2015. The variables are the difference between the total surplus in the observed matches and the total surplus in the counterfactual matches.

6 Estimation Results and Discussion

Following the conceptual framework laid out in Section 4, I estimate the parameters of the matching game with the following profit equations for prime brokers and hedge funds, respectively.

Table 13 reports the point estimates and confidence intervals for the parameters of the reduced form linear profit functions for prime brokers and hedge funds for the 2014 and 2008 snapshots, respectively. Since data on transfers are not available, as explained in Section 5, parameters could

[21] Note that if this effect is so large that the match surplus gets negative, transfers would be positive whereby the hedge funds need to compensate the prime broker.

Table 11: Correlation Matrix in 2008

	X_1	X_2	X_3	Z_1	Z_2
X_1	1.00				
X_2	0.08	1.00			
X_3	0.08	0.07	1.00		
Z_1	-0.01	0.30	0.11	1.00	
Z_2	0.01	0.15	0.13	0.52	1.00

Table 12: Correlation Matrix in 2015

	X_1	X_2	X_3	Z_1	Z_2
X_1	1.00				
X_2	0.28	1.00			
X_3	0.28	0.26	1.00		
Z_1	0.31	0.46	0.33	1.00	
Z_2	0.27	0.35	0.35	0.73	1.00

Notes: (i) Tables show the correlation of the variables constructed from the pairwise comparisons of all possible and meaningful two pairs in the data.
(ii) $X_1 \equiv \sigma^{p_i,h_i,p_q,h_q}_{below\_zero}$,$X_2 \equiv HHI^{p_i,h_i,p_q,h_q}$, $X_3 \equiv \bar{\beta}^{ownPB;p_i,h_i,p_q,h_q}_{p}$ and $Z_1 \equiv Mkt\_Shr^{p_i,h_i,p_q,h_q}_{S}$, $Z_2 \equiv (Mkt\_Shr_S \times \beta^S_{h_j})^{p_i,h_i,p_q,h_q}$
(iii) For example, suppose we observe $\{p_i, h_i\}$ and $\{p_q, h_q\}$, but not $\{p_i, h_q\}$ and $\{p_q, h_i\}$. X_1 is the sum of the downside risk of the portfolio of clients for p_i and p_q with their observed matches included in the portfolio minus the downside risk of the portfolio of clients when instead of their observed clients, the counterfactual clients are in their portfolio. Other variables are the others included in the econometric model.

only be identified up to scale, after the normalization of one of the variables to be +1 or −1. I normalize the downside risk measure, which is the lower semideviation of the portfolio of the prime brokers for portfolio returns below zero.

6.1 Discussion of the 2015 Snapshot

In 2015, the model is able to explain 79.26% of the 1,623,628 constructed inequalities.

In the 2015 estimation, downside risk affects the profits of the prime broker negatively (the estimation procedure assigns a normalized value of −1 instead of +1), which is intuitive since if all hedge funds get negative returns at the same time, the prime broker could face stress, where it might have to liquidate collateral at low prices (in case a hedge fund with a long position defaults), or buy securities from the market at high prices (in case a hedge fund with a short position defaults) or issue margin calls. These could all be be costly and the prime broker hence gets lower profits from increased downside risk[22] .

The parameters on the Herfindahl index of investment styles in the portfolio (HHI) and the average portfolio co-movement ($\bar{\beta}_p^{ownPB}$) are 3.86 and 4.94, respectively. They are both significant at the 5% level. The point estimates of the coefficients in front of the variables $Mkt\_Shr_p^{S_h}$ and $Mkt\_Shr_p^{S_h} \times \beta_h^S$ are 0.23 and 0.09. They are also both statistically significant at the 5% level.

In column 2 of Table 13, I report the means and the standard deviations of the variables, across banks for the ones that enter into the prime broker surplus and across hedge funds for the ones that enter into the hedge fund surplus. Since, the parameters are estimated only up to scale, I can only assess their relative important in the match surplus. In order to interpret the coefficients I ask the following questions: Imagine a prime broker for which the values of the right-hand side variables are at the means. Suppose I reduce the downside risk by one standard deviation, while keeping everything else constant. In 2015, the standard deviation of σ_{below_zero} is 0.0077. A reduction of one standard deviation in σ_{below_zero} would increase the pre-transfer profits of the bank by 0.0077. How much should the other variables change in order to induce the same level of pre-transfer profits keeping everything else constant?

The answer is 0.0020 for HHI and 0.0016 for $\bar{\beta}_p^{ownPB}$. Given the standard deviations of these variables which are 0.09 and 0.15, respectively, these changes constitute a very small amount. In other words, a very small change in either HHI or $\bar{\beta}_p^{ownPB}$, could induce the same pre-transfer profits as a one standard deviation change in the measure of the downside risk. This result suggests that downside risk is not a very important factor determining the match surplus for a prime broker compared to HHI and $\bar{\beta}_p^{ownPB}$.

On the other side, for a single hedge fund, that has a $\beta_h^S = 0$, in order to get the same benefit a prime broker gets by a one standard deviation reduction in the downside risk, the market share of the prime broker in the style of the hedge fund needs to increase by 3.3 percentage points. The standard deviation of the $Mkt\_Shr_p^{S_h}$ variable is 8 percentage points. For larger β_h^S, the increase in $Mkt\_Shr_p^{S_h}$ needs to be smaller for a hedge fund to get the same benefit, everything else constant.

To put things in perspective, suppose the HHI of the prime broker increases by one standard deviation, holding everything else constant. For a hedge fund with $\beta_h^S = 0$, to get the same benefit as what the prime broker gets with the increase in HHI, $Mkt\_Shr_p^{S_h}$ needs to increase

[22] Notice that since this variable is normalized to get one of the two values, it is "super-consistent" and I cannot assign confidence intervals.

Table 13: Estimation Results

	2015		2008	
Prime Broker Surplus	(1)	(2)	(3)	(4)
	Estimates [95% C.I.]	Mean (St. Dev)	Estimates [95% C.I.]	Mean (St.Dev)
σ_{below_zero}	-1	0.02	+1	0.02
	-	(0.0077)	-	(0.01)
HHI	3.86	0.27	0.17	0.34
	[1.94,8.95]	(0.09)	[0.07,0.26]	(0.17)
$\bar{\beta}_p^{ownPB}$	4.94	0.85	0.36	0.73
	[2.69,15.74]	(0.15)	[0.26,0.42]	(0.18)
Hedge Fund Surplus				
$Mkt\_Shr_p^{S_h}$	0.23	0.13	0.03	0.12
	[0.10,0.68]	(0.08)	[0.01,0.04]	(0.10)
$Mkt\_Shr_p^{S_h} \times \beta_h^S$	0.09	0.14	0.002	0.10
	[0.04,0.30]	(0.10)	[0.0003,0.005]	(0.09)
# HFs	1,620		1,531	
# PBs	12		13	
# Links	2,224		1,532	
# Inequalities	1,623,628		994,922	
% Fit	79.26		82.48	

Notes: (i) Table shows the estimation results. Columns (1) and (2) are related to the estimation in 2015. Columns (3) and (4) are related to the estimation in 2008. The variables showed under "Prime Broker Surplus" and "Hedge Fund Surplus" are what determine the match surplus in the econometric model. The lower panel shows the number of hedge funds, the number of prime brokers, the number of links, the number of constructed inequalities and the percentage of inequalities that the model can explain in each year.
(ii) All inequalities are constructed in STATA. Estimates are generated by using the differential evolution algorithm using the package written by Markus Buehren for MATLAB (obtained from: http://www.mathworks.com/matlabcentral/fileexchange/18593-differential-evolution). For differential evolution, I use 100 population members, scaling parameter 0.5, run the estimation 30 times (different seeds) for 400 iterations each for 4 digits after the decimal point. The result is robust to other selections of the number of population members and the scaling parameter. I report the parameters for which the objective function achieves the maximum up to 2 digits after the decimal point. For confidence intervals, I randomly select 500 bootstrapped samples and report the 95% confidence intervals for the point estimates. Note that the variable σ_{below_zero} is normalized to be -1 or +1. Since it is normalized and it can get only two values no confidence intervals can be reported for that variable.
(iii) Columns (1) and (3) show the point estimates and 95% confidence intervals in 2015 and in 2008, respectively. Columns (2) and (4) show the mean and the standard deviations of the variables that enter the match surplus in the econometric model in 2015 and in 2008, respectively. In column (4), statistics are reported by taking out HSBC and Barclays, small prime brokers in 2008, with outlier values. Estimates are similar when HSBC and Barclays are excluded from the estimation in 2008.

by around 151 percentage points,[23] which means the marginal effect a prime broker gets from a standard deviation increase in HHI, is not reachable by a hedge fund through the marginal effect of immediacy. It is more reasonable for the prime broker to save more costs with *all* its clients, than a single hedge fund gets in immediacy benefits. Therefore, this provides a check for the credibility of the estimates.

These results suggest that downside risk does not play an important role in the preferences of the prime broker in creating match-surplus, compared to say HHI or $\bar{\beta}_p^{ownPB}$.

6.2 Discussion of the 2008 Snapshot

In 2008, the model is able to explain 82.48% of the 994,922 constructed inequalities.

Contrary to the matches in 2014, in the estimation of the 2008 snapshot, downside risk affects the profits of the prime broker positively (the estimation procedure assigns a normalized value of +1),[24] which is surprising since downside risk *increases* the profits of the prime broker.

This finding calls for an update of the theory. I update the theory in the following way. Prime brokers provide services to hedge funds. However, prime brokers are parts of large bank holding companies with trading desks. Therefore, a full theory of the prime brokerage market needs to include complementaries between prime brokers and trading desks. I rationalize this finding by prime brokers profiting from risky clients by taking the opposite positions of their clients through their trading desks. For example, consider a long position of a client that the trading desk disagrees with. Re-using client securities to take short positions on the security provides balance sheet efficiencies. One might ask if the trading desk wants to take a short position, why they would not just go ahead and do it. Doing so would increase the size of their balance sheets. On the other hand, re-using customer collateral keep balance sheets intact, while still inducing the benefit. This could be one way of rationalizing the result, but it relies on the assumption that trading desks actively contact prime brokers and re-use client collateral the prime brokerage unit obtains. This explanation is also consistent with the fact that, before the crisis the proprietary trading desks were active units of the broker-dealers, while after the crisis and with Volcker rule, their activities almost stopped, hence only the negative effects of risk have become important, which the result in 2015.

An alternative mechanism that would favor having risky clients could be that riskier collateral obtained by riskier clients could be put to a more profitable use than less risky ones. Therefore, it increases the match surplus for a prime broker, which is aside from the revenues the risky clients generate for the prime broker directly, through transfers. One possible explanation could be that the prime broker, suppose a third party asks for securities to borrow. If the prime broker charges higher fees to lend riskier securities than safer ones, and if the prime broker is confident about the protection it receives through margins/haircuts, it might be more profitable to have riskier clients. In this story, the change of the sign between 2008 and 2015, would be attributed to an increasing risk aversion after the crisis.

[23] Of course this is not possible. I assume a linear specification where the effects are meaningful only when they are local. In a true model of the surplus, possibly there would be a diminishing returns to scale economies for the value a hedge fund gets from immediacy. These estimates are obtained in a linear model, hence they are local.

[24] Notice again that since this variable is normalized to get one of the two values, it is super-consistent and I cannot assign confidence intervals.

These mechanisms explained above are some ways to rationalize the surprising finding that prime brokers preferred risky clients, even net of the payments they receive from them. However, they are not rigorous and there is no available data to test them. Therefore, even though I attempt to provide a rationalization, I leave the explanation of this finding as an open questions.

What is different in 2008 compared to 2015 is not only the change in the sign of the parameter of the downside risk in the surplus. In addition, in 2008, the parameters on the Herfindahl index of investment styles in the portfolio (HHI) and the average portfolio co-movement ($\bar{\beta}_p^{ownPB}$) are 0.17 and 0.36, respectively. These coefficients are much lower compared to what they are in the 2015 snapshot. Nevertheless, they are both significant at the 5% level. The point estimates of the coefficients in front of the variables $Mkt\_Shr_p^{S_h}$ and $Mkt\_Shr_p^{S_h} \times \beta_h^S$ are 0.03 and 0.002. $Mkt\_Shr_p^{S_h}$ and $Mkt\_Shr_p^{S_h} \times \beta_h^S$ are also significant at the 5% level. These results suggest that the market and the determinants of the match-surplus has changed since the financial crisis of 2008.

In column 4 of Table 13, I report the means and the standard deviations of the variables, across banks for the ones that enter into the prime broker surplus and across hedge funds for the ones that enter into the hedge fund surplus.[25]

In order to interpret the coefficients, again I ask the following questions: Imagine a prime broker for which the values of the right-hand side variables are the means. Suppose I increase the downside risk by one standard deviation (since downside risk affects the match-surplus positively), which is 0.01, while keeping everything else constant. That would increase the pre-transfer profits of the bank by 0.01 units. How much should the other variables change in order to induce the same level of pre-transfer profits keeping everything else constant?

The answer is 0.0588 for HHI and 0.0278 for $\bar{\beta}_p^{ownPB}$. These numbers, respectively are around 28 times and 15 times greater than the increase in these variables needed in 2015 to receive the same effect as a one standard deviation decrease in downside risk. Compared to 2015, where the importance of downside risk is negative and relatively small, in 2008, downside risk was more important in generating surplus.

On the other side, for a single hedge fund, to simplify the interpretation, I assume that the effect of the interaction variable is zero since it is indistinguishable from zero statistically. Therefore, in order to get the same benefit a prime broker gets by a one standard deviation increase in the downside risk, the market share of the prime broker in the style of the hedge fund needs to increase by 33 percentage points. The standard deviation of the $Mkt\_Shr_S^{h_j,p_k}$ variable is 12 percentage points. This also suggests that downside risk had a sizable effect in absolute value on the surplus in 2008 compared to 2015. This suggests larger immediacy benefits in 2008 than in 2015.

In the same exercise as above, I compare the iso-profit relations of HHI and $Mkt\_Shr_p^{S_h}$. To make the two estimation period comparable, I analyze the same change in HHI as in 2015, which is 0.09. The market share of the prime broker in hedge fund style needs to increase by 33 percentage points. Much smaller than the number in 2015, which is 151 percentage points.

Overall, the results suggest that, for a relationship formed in 2015, a prime broker asked a hedge fund whether it contributes to its portfolio concentration and co-movement with its portfolio, possibly for internalization purposes. How risky they are was not very important. In 2008,

[25] However, Barclays and HSBC form a very tiny fraction of the links in the market. Furthermore, Barclays is an outlier in terms of $\bar{\beta}_p^{ownPB}$. Therefore, to get a less noisy sense of variation, I report the summary statistics for the prime brokers without these two banks which provides a more accurate picture of the variation in the variables. I also run the estimation without the links of HSBC and Barclays and results stay very close to the original estimates.

contribution to concentration/internalization was also a factor. However, another question they asked was how risky their trades were going to be. The riskier it was the better.

7 How Much is the Value of Internalization?

In order to evaluate the quantitative importance of internalization, I write down a simple framework as set up in Section 4.1.1. Suppose the total order flow the prime broker receives is Q. Suppose a fraction, $i - i_L$ are long positions that were not internalized and a fraction $1 - i_S$ are short positions that were not internalized. The prime broker could internalize a fraction $i_L + i_S$ of the total order flow. For simplicity, suppose there are search and balance sheet costs, c per unit, for each non-internalized trade. Internalization reduces these costs to a fraction $f \in [0, 1]$. Therefore, internalization costs fc per unit. For brevity, denote $i \equiv i_L + i_S$. Profits, net of other costs, could be written as:

$$\pi^{Net} = R - (1-i) \times Q \times c - i \times Q \times (fc) \tag{11}$$

where R denotes total revenues. Per unit of internalized flow, the prime broker saves on costs net of the cost of internalization, that is $(1-f)c$. Therefore, the total realized value of internalization, V, is:[26]

$$V = (1-f) \times c \times i \times Q \tag{12}$$

Prime brokers do not report precise numbers regarding the revenues, profits, fraction of internalization done and total order flow. Furthermore, the variables affecting the total costs, c and f are hard to measure, even for the prime brokers themselves. In this section, in order to reduce the number of variables needed to be calibrated, I proceed by rearranging Equation (11), to get:

$$c = \frac{R - \pi^{Net}}{Q \times (1-i) + i \times Q \times f} \tag{13}$$

I denote net profit margins, for profits net of other operating costs as $m \equiv \frac{\pi^{Net}}{R}$. Plugging (13) back into Equation (12), I get:

$$V = \frac{(1-f) \times i \times (1-m)}{(1-i) + i \times f} R \tag{14}$$

Notice that doing so leads both c and Q to drop out of the equation. The comparative statics provide insights that explains for the estimation results of increased importance of concentration.

Now, in order to assess the value of internalization, there relevant pieces of information are revenues, net profit margins, the fraction of the total volume that is internalized and the relative

[26] This is just to illustrate the value of internalization and through which mechanism it arises. In Section 7, I will pick up from here to do an accounting analysis of internalization.

cost savings of internalization. I recover as much data as possible from several newspaper articles and blog posts that informs the calibration of these values.

Revenues from prime brokerage for Goldman Sachs for 2008 was \$3.4 billions[27] (Reuters (2012)) and \$373 millions in the second quarter of 2014 (WSJ (2014)). I annualize this to yearly revenues, \$1.4 billions.

The main interest in this section is to do comparative statics on how each affects the cost savings from internalization. The way I proceed is the following. First I get measures for the variables that affect the cost-savings from internalization. These measures are noisy measures of true meanings of the variables in the equation.

According to Tabb and Morgan (2012) and FTAlphaville (2012), of all the trades in US equities, 15% were internalized or traded at dark pools in 2008. This number has increased to 33% in 2012. These numbers are imprecise for overall levels of internalization, but I first assume that the number in 2012 remained the same in 2014 and these trades were divided equally between internalization and dark pools and were the same for everything else apart from US equities. With those assumptions, I calibrate the volume of trades internalized to 7.5% in 2008 and 16.5% in 2014. Note that this might not be a very precise measure since dark pools are quite different from the internalization that is discussed here. However, note that Cantor (2014) cites a study by Barclays and documents that "prime brokers obtain anywhere from 30-60% of their funding from internal efficiencies and 20-50% from short-term repo markets." Hence, my estimates are conservative estimates of internalization.

Finally, since c, the cost per unit includes search costs, balance sheet costs etc. It does not have a counterpart in the accounting data. Furthermore, these profits do not include operating costs such as real estate costs etc. In order to find an approximation, I use information on operating margins from a news article in LATimes (2006): "Prime brokers can be highly profitable, with operating margins at top firms of 45% or more, according to Deutsche Bank."[28] There is no good information on profit margins for 2014. According to the news article in Reuters (2012), which reports a conversations "with a head of prime brokerages at major firm: 'I talked to the head of PB and he said we're barely breaking even.'" I set the profit margins in 2014, by averaging quarterly profit margins of Goldman Sachs bank holding company, which is roughly 25%. This number over-estimates the profit margin, therefore downward biasing the value of internalization according to Equation 14.

The fraction of unit costs, f, of internalization is also an abstract object, with no counterpart in the data. In the context of search costs, Tabb and Morgan (2012) suggest that "[it is] almost costless since the prime broker could electronically solicit whether another hedge fund wants to take an opposite position in "microseconds"." Furthermore, Kirk, McAndrews, Sastry and Weed (2014) suggest that part of internalized securities go off-balance sheet. Furthermore, internalization that is done through derivatives also are off-balance sheets. Therefore, internalization also saves considerable amount of balance sheet costs. In order to calculate the value of internalization, I set $f = 10\%$ in both years..

[27] This number might not be directly comparable to the empirical model, since my data for 2008 ends at the end of August 2008 and this revenue, presumably, reflects revenues between January 2008 and December 2008, making these measures imprecise.

[28] Other operating costs are reflected in the profit margins in my model, therefore the margins in the model are presumably under-estimated compared to this number, putting an upper bound on the value of internalization for 2008.

I first calibrate the revenues, the fraction of internalization, the profit margins, the fraction of unit costs when trades are internalized to the values discussed above. I find that the value of internalization through implied cost savings for Goldman Sachs was \$135 million in 2008 and \$183 million in 2014.

In Figure 3, I show results for a range of f, calibrating all other variables to the values discussed above.

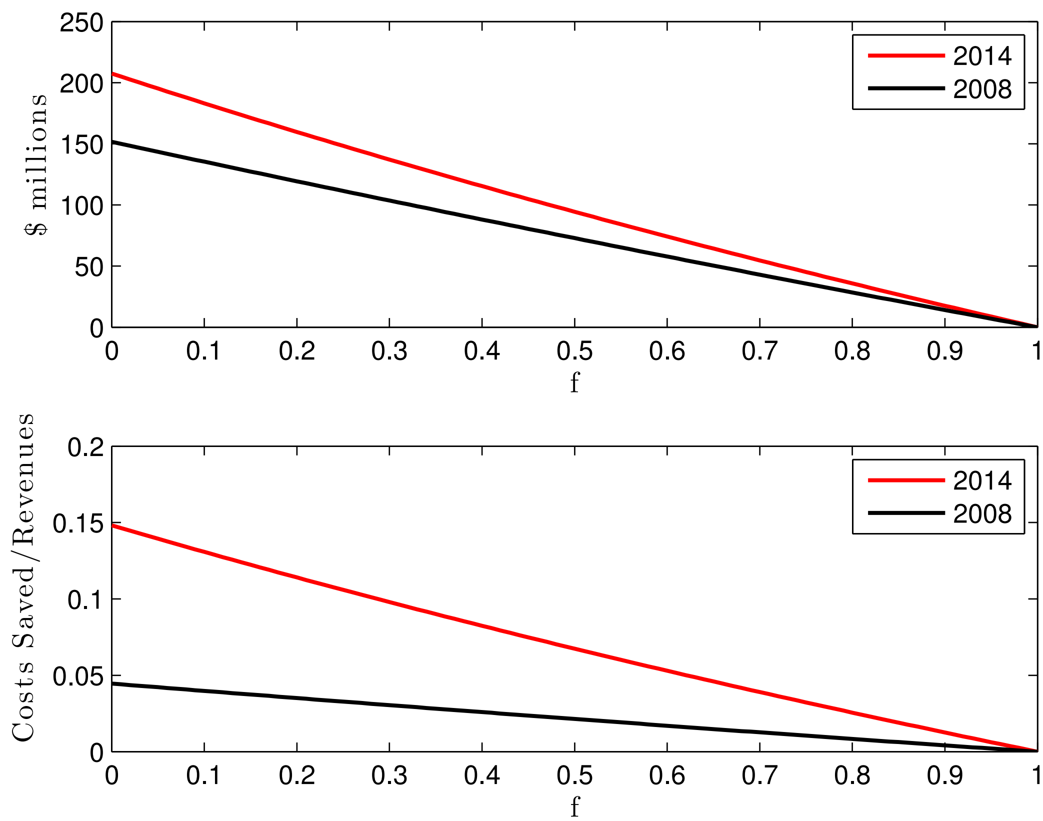

Figure 3: Value of Internalization for a range of relative costs, f.

Notes: R(2008)=\$3,4 billion, R(2014)=\$1,4 billion, $i(2008) = 0.075$,$i(2014) = 0.165$, $m(2008) = 0.45$, $m(2014) = 0.25$

Anecdotal Evidence. In 2014, JPMorgan (2014) published a report called "Leveraging the leverage ratio", which discusses the changes in prime brokerage and hedge fund relationships in the post-crisis world with the new regulations by Basel III, such as tougher capital, leverage, liquidity and funding requirements. This report is also relevant to improve understanding for recent developments that some hedge funds were fired by some prime brokers (See WSJ (2014) and Bloomberg (2015)). The JPMorgan (2014) report suggests that "[c]lients who may be particularly at risk are those whose strategies are significant consumers of balance sheet such as highly-levered, directional portfolios with little or no internalization value." FTAlphaville (2014) also has a story on the report and their conclusion is: " If you're a hedge fund client that is not bringing something to the table for your bank - be it hard returns or lots of juicy assets for it to internalise - then you could well find yourself facing significantly higher prime brokerage costs, or a lengthy search for a new prime broker."[29]

These pieces of anecdotal evidence are in line with the hypothesis in this paper that changing nature of the prime brokerage business, lower overall volumes of trading and regulatory pressures pushed prime brokers for more internalization in order to cut funding costs and generate higher profits from the business. Having similar hedge funds in the portfolio helped them increase the share of internalization done at their trading desks.

7.1 Cardinal Values of the Estimates

The results in Section 6 can only yield ordinal interpretations. In this section, I do a calibration exercise, in order to convert the estimates into cardinal amounts. Since the data is limited, this section will not give very precise estimates, however the reader should take it as an attempt to get a sense of the cardinality of the match-surplus.

In order to proceed, I first make the following assumption:

$$\alpha_p^{Year}\left(\hat{\phi}_2 HHI^p + \hat{\phi}_3 \bar{\beta}_p^{ownPB}\right) = VALUE\_OF\_INTERNALIZATION_p^{Year} + OTHER$$

where α_p^{Year} is the scale different for each year and $\hat{\phi}_2, \hat{\phi}_3$ are the estimates for each year. In Section 4, I argued that the value of concentration is that it reduces costs for the prime broker. In the case of internalization, it saves search costs and creates balance sheet efficiencies. However, it is possible to think of other sources of cost saving due to concentration that are unrelated to internalization, such as expertise.

Imposing the above relation is correct, I assume that value of concentration other than internalization is zero. Doing so would help me get a lower bound on the scale, α. In order to get a sense of what the scale might be, imposing the relation above, I need to get what the value of internalization in each year.

In Section 7, I did a simple accounting exercise and estimated the value of internalization to be \$135 million in 2008 and \$183 million in 2014 for Goldman Sachs. With the assumptions made about how internalization relates to HHI and $\bar{\beta}_p^{ownPB}$ above and setting HHI and $\bar{\beta}_p^{ownPB}$ to their respective values for Goldman Sachs in each year, this implies a lower bound on the scale to be \$367.4 million in 2008 and \$35.1 million in 2015 using estimates in Table 13.

This implies that in 2008, keeping everything else constant, one standard deviation increase (an increase of 0.01) in the downside risk of its portfolio would result in an increase of \$3.6 million in the match-surplus Goldman Sachs gets,[30] pre-transfers. A one standard deviation increase (which is an increase of 0.17) in HHI of its portfolio would imply cost savings of about \$10.6 million due to internalization. Similarly, a one standard deviation increase (which is an increase of 0.18) in $\bar{beta}_p^{ownPB}$ would imply cost savings of around \$23.8 million due to internalization. On the other side, a one percentage point increase in the market share of Goldman Sachs in a given style would provide immediacy benefits for a single hedge fund in that style which are around \$110,000, all in terms of annual surplus, pre-transfers. To put it in perspective, for a hedge fund with \$100 million assets under management, one percentage point increase in its prime broker market share in its investment style would bring in 11 basis points of return on assets, annually.

[29] "[T]he lengthy search for a new prime broker" reinforces the interpretation of the market as a matching market.
[30] Potentially through trading desks.

Table 14: Estimation Results with Scale

	2015		2008	
Prime Broker Surplus	(1)	(2)	(3)	(4)
	Estimates [95% C.I.] (in $ millions)	Mean (St. Dev)	Estimates [95% C.I.] (in $ millions)	Mean (St.Dev)
σ_{below_zero}	-35.1	0.02	367.4	0.02
	-	(0.0077)	-	(0.01)
HHI	135.7	0.27	62.4	0.34
	[68.2,314.8]	(0.09)	[25.7,95.5]	(0.17)
$\bar{\beta}^{ownPB}$	173.7	0.85	132.2	0.73
	[94.6,553.6]	(0.15)	[95.5,154.3]	(0.18)
Hedge Fund Surplus				
$Mkt\_Shr_p^{S_h}$	8.0	0.13	11.0	0.12
	[3.5,23.9]	(0.08)	[3.6,14.6]	(0.10)
$Mkt\_Shr_p^{S_h} \times \beta_h^S$	3.1	0.14	0.7	0.10
	[1.4,10.5]	(0.10)	[0.1,1.8]	(0.09)
# HFs	1,620		1,531	
# PBs	12		13	
# Links	2,224		1,532	
# Inequalities	1,623,628		994,922	
% Fit	79.26		82.48	

Notes: Since the estimation is based on inequalities, parameters are estimated only up to scale. This table is based on Table 13. The only difference is that following the assumption

$$\alpha_{GS}^{Year}\left(\hat{\phi}_2 HHI^{GS} + \hat{\phi}_3 \bar{\beta}_{GS}^{ownPB}\right) = VALUE\_OF\_INTERNALIZATION_p^{Year} + OTHER$$

and using the value obtained for internalization above, and assuming $OTHER = 0$, and using the estimates in both years, gives a lower bound for α in both years. Therefore, the scale is $35.1 million in 2015 and $367.4 million in 2008. All the point estimates and the confidence interval bounds in Table 13 are multiplied by the respective scales in each year. The rest of the table except for columns (1) and (3) are identical to Table 13.

In 2015, on the other hand, using the calibrated scale, the results could be interpreted as follows. In order to make 2008 and 2015 results comparable, I evaluate the impact of an identical change in the variables. Keeping everything else constant, an increase of 0.01 *increase* in the downside risk of its portfolio would result in a *decrease* of \$350,000 in the match-surplus Goldman Sachs gets, pre-transfers. An increase of 0.17 in the HHI of its portfolio would imply cost savings of about \$23 million due to internalization. Similarly, an increase of 0.18 in $\bar{\beta}_p^{ownPB}$ would imply cost savings of around \$31.2 million due to internalization. On the other side, a one percentage point increase in the market share of Goldman Sachs in a given style would provide immediacy benefits for a single hedge fund in that style which are around \$80,000, all in terms of annual surplus. Notice that again these are the values of the surplus generated pre-transfers. To put it in perspective, for a hedge fund with \$100 million assets under management, one percentage point increase in its prime broker market share in its investment style would bring in 8 basis points of return on assets, annually.

8 Value-Weighting Variables

Services that prime brokers provide to hedge funds appear on the balance sheets of their parent banks. Therefore, one might expect that size of the hedge funds that prime brokers serve is an important consideration driving their preference for the types of clients they want to form relationships with. However, as explained in Section 2.2, the data I use has limitations in assets under management, which might be a good proxy for the trades of hedge funds that appear on bank balance sheets.

In the benchmark results, I measure all variables by equally-weighting all hedge funds in the sample. In this section, I provide an alternative to equal-weighting by measuring all variables with value-weighting by using assets under management. In each year, I calculate the median of assets under management and replace the missing data on assets under management for hedge funds that do not report it with the median assets under management in each snapshot.

Note that there are multiple ways to correct for the missing data, none of which is obviously superior to others. This caveat makes the interpretations of results as only suggestive instead of definitive description of facts. Furthermore, also note that equal-weighting and value-weighting are measuring different things and are not perfect substitutes to one another. Value-weighting captures the size effects, while equal-weighting captures the number of clients with different bets.

In order to conduct this exercise, I proceed as follows: First, I replace the missing data on assets under management with the median assets under management each year. Second, for each hedge fund that has multiple prime brokers, I assume that the hedge fund divides its assets equally to all its prime brokers. As a result, when I take a value-weighted averages, the weight of a hedge fund for a prime broker is the assets the hedge fund has with the prime broker divided by the total assets of the clients that a prime broker serves.

I re-construct the measures used in the benchmark model as follows: I measure the value-weighted HHI, by denoting all styles as $S_1, S_2, ...S_{11}$:

$$HHI^{VW} = \sum_{i=1}^{11} \left(\frac{\text{Total AUM in } S_i^{PB}}{\text{Total Assets}^{PB}} \right)^2 \tag{15}$$

Table 15 reports the value-weighted HHI for each prime broker in a given year. Notice that, when value-weighted, the composition of hedge funds operating each year is less concentrated compared to the equally-weighted case, while the prime brokers have a higher portfolio concentration with value-weighting hedge funds than equally-weighting them.

Table 16 is a value-weighted reconstruction of Table 7. The way I construct this table is as follows: As in the benchmark case, I do the following regression for each possible hedge fund and prime broker pair.

$$R_{h,t} = \alpha_h + \beta_h^{MKT} R_t^{MKT} + \beta_h^{VW-PB} R_t^{VW-PB} + \epsilon_{h,t} \tag{16}$$

The only difference is that in this case, R_t^{VW-PB} is a value-weighted prime broker return index.

In Panel A of Table 16, I define:

$$\bar{\beta}^{VW-ownPB} \equiv \frac{1}{H} \sum_{h=1}^{H} \beta_h^{VW-ownPB} \tag{17}$$

$$\bar{\beta}^{MKT} \equiv \frac{1}{H} \sum_{h=1}^{H} \beta_h^{MKT} \tag{18}$$

where $\bar{\beta}^{ownPB}$ is the average of the coefficients on the return index on their own prime broker for all hedge funds in the sample. In order not to have mechanical correlations, I exclude the returns of the hedge fund itself from the prime broker return index, if the hedge fund is a client of the prime broker. $\bar{\beta}^{MKT}$ is the average of the coefficients on the market index when the prime broker return index is the one of their own prime broker. Note that the unit of observation here is a link instead of a hedge fund.

In Panel B of , I define:

$$\bar{\beta}_p^{VW-ownPB} \equiv \frac{1}{H_p} \sum_{h=1}^{H_p} \beta_h^{VW-ownPB} \tag{19}$$

$$\bar{\beta}_p^{VW-others} \equiv \frac{1}{H_p} \sum_{h=1}^{H_p} \Big(\frac{1}{P-1} \sum_{q \neq p} \beta_h^{VW-q} \Big) \tag{20}$$

where H_p is the number of hedge fund clients of a prime broker p, P is the number of prime brokers in the sample in a given year.

The overall level of co-movement is lower when the prime broker return index is value-weighted as opposed to equally-weighted. This result could be suggestive of smaller hedge funds not co-moving with the larger hedge funds in the observed network of a prime broker.

Table 17 shows the value-weighted version of the lower semideviation of below zero portfolio returns of a prime broker calculated from a value-weighted return index of the prime broker of value-weighted hedge fund returns each month. Note that this measures the downside risk of primarily the larger clients and how smaller hedge funds contribute to the overall downside risk when the larger clients get negative returns. The value-weighted downside risk measure is smaller than the equally-weighted measure in both years.

In this exercise, the variables entering the match surplus for the hedge funds are also value weighted. The market share of a prime broker in the investment style of the hedge fund is the total amount of assets under management of a prime broker in a given style excluding the hedge fund itself. The $\beta_h^V W - S$ is the coefficient on the regression of hedge fund returns on the market return index and a value-weighted style return index and a constant.

Table 18 shows the results of the estimation in 2015 and in 2008 with value-weighted variables, where missing data is replaced by the median AUM in each year. The first thing to note is that this specification can explain a larger number of matches in both years, with around 95% each year.

The second thing to note is that the coefficient on $\sigma^{VW}_{below\_zero}$ is negative in both years, suggesting an aversion to the riskiness of larger clients in both years. Furthermore, this aversion is larger compared to the benefits of specialization measured by value-weighting. In 2015, a one standard deviation increase in $\sigma^{VW}_{below\_zero}$, holding everything else constant, reduces profits for a prime broker in the same magnitude as around 3 standard deviation increase in HHI^{VW} increases profits, holding everything else constant. The reduction of profits resulting from a standard deviation increase in $\sigma^{VW}_{below\_zero}$ could be offset by an increase of 0.08 in $\bar{\beta}_p^{VW-ownPB}$, which has a standard deviation of 0.28. This suggests that $\bar{\beta}_p^{VW-ownPB}$ is still important, but valued less when traded-off against a value-weighted downside risk compared to an equally-weighted downside risk.

In 2008, a one standard deviation increase in $\sigma^{VW}_{below\_zero}$, holding everything else constant, reduces profits for a prime broker in the same magnitude as around half a standard deviation increase in HHI^{VW} increases profits, holding everything else constant. The reduction of profits resulting from a standard deviation increase in $\sigma^{VW}_{below\_zero}$ could be offset by an increase of 0.2 in $\bar{\beta}_p^{VW-ownPB}$, which has a standard deviation of 0.26. These results suggest that value-weighted downside risk was a more important consideration for prime brokers in 2008 compared to value-weighted measures of specialization. Specialization in terms of HHI^{VW} was more important than specialization in terms of $\bar{\beta}_p^{VW-ownPB}$.

The coefficient on the market share of the prime broker in the style of the hedge fund is positive and significant in both years. However, the interaction terms is insignificant in both years, suggesting that the size of competitors competing to correct mis-pricing is not important, while the number of competitors is important interpreted together with Table 13.

Given all the caveats arising from measurement, this exercise is not precise, yet could point at some other considerations of prime brokers and hedge funds. The preliminary results suggest that size of the hedge funds is an important consideration for prime brokers, as well as specialization and downside risk. For a hedge fund the market share of the prime broker in their style is important. The size of the network of the prime broker in their style is also important. The number of others competing for similar mis-pricings is important, while the size of them is not.

9 Policy and Financial Stability Issues

In this section, I discuss the risk and financial stability issues due to the changing market structure after the crisis. First, when prime brokers internalize more trades, an immediate implication is that those trades occur outside the public exchanges. This results in thinner public markets, with

Table 15: Concentration of Prime Broker Portfolio - Herfindahl Index - Value Weighted

Prime Broker	HHI^{VW} *in 2008*	HHI^{VW} *in 2015*
Morgan Stanley	0.3947	0.3395
Goldman Sachs	0.3401	0.2684
JP Morgan	0.3135	0.2208
UBS	0.3261	0.2416
Credit Suisse	0.2611	0.2549
Deutsche Bank	0.5501	0.2133
Citi	0.2182	0.1579
Societe Generale	0.4103	0.4591
HSBC	0.4517	0.4041
Barclays	0.5168	0.2413
Bank of America	0.9160	-
Merrill Lynch	0.2567	-
Lehman Brothers	0.2807	-
Boa Merrill	-	0.4571
BNP Paribas	-	0.3882
Average	**0.4028**	**0.3039**
All Hedge Funds	**0.2021**	**0.1726**

Notes: The Herfindahl Index for the prime brokers in 2008 and in 2015, when hedge funds are value-weighted. See Table 6 for further details.

more liquidity provision of hedge funds taken away from the markets.[31] Internalization relies on opposite market positioning of a number of clients. When the volume of internalization drops due to a shock that makes most of the clients take the same side of a trade, this could cause "flash" events in public markets. Indeed, SEC suggested internalization as an important in the flash crash of May 6, 2010 in stock markets (FTAlphaville (2012)).

FTAlphaville (2012) discusses the issue as follows:

"The point is that banks are internalising ever more flow because it makes them more efficient at beating the competition in terms of funding. They receive a cost of funding, or rather financing, advantage [...] Because more and more flow is executed away from the public market, the public market becomes detached from reality. It becomes thin and unable to handle large trades [...] As we've noted before, one popular theory for why the flash crash[32] happened is that flow became far too one-sided for internalisers to be able to handle the flow. Having breached internal limits, broker dealers that would usually internalise orders simply re-directed them to the public market - which being thin and illiquid, simply couldn't handle the sudden added pressure (all one sided).".

Second, a new provision of the Basel III regulations, liquidity coverage ratio (LCR), will fully come to effect in 2019. LCR aims to impose a tighter liquidity management for banks to survive a

[31]See Aragon and Strahan (2012) for evidence that hedge funds provide liquidity to markets.

[32]referring to the May 6, 2010 flash crash.

Table 16: Mean Co-movement of Hedge Fund Client and the Average Co-movement of those Hedge Funds with other Prime Brokers - Value Weighted PB Return Index

Panel A: Regression Results		
	1994-2008	1994-2015
$\beta^{VW-OwnPB}$	0.41	0.73
t-stat	[14.5]	[38.8]
β^{MKT}	1.03	0.89
t-stat	[39.6]	[34.3]

Panel B: Comparison across prime brokers				
Prime Broker	$\bar{\beta}_p^{VW-ownPB}$	$\bar{\beta}_p^{VW-others}$	$\bar{\beta}_p^{VW-ownPB}$	$\bar{\beta}_p^{VW-others}$
Morgan Stanley	0.30	0.09	0.76	0.48
Goldman Sachs	0.48	0.15	0.75	0.45
JP Morgan	0.80	0.10	0.96	0.50
UBS	0.28	0.23	0.57	0.46
Credit Suisse	0.09	0.24	0.33	0.42
Deutsche Bank	0.52	0.19	1.08	0.39
Citi	0.28	0.17	0.75	0.48
Societe Generale	0.72	-0.29	1.00	0.27
HSBC	0.53	-0.03	0.17	0.54
Barclays	0.33	0.15	0.73	0.59
Bank of America	0.44	0.07	-	-
Merrill Lynch	-0.12	0.11	-	-
Lehman Brothers	0.23	0.08	-	-
BoA ML	-	-	0.59	0.41
BNP Paribas	-	-	0.35	0.42

Notes: See Table 7 for further details.

Table 17: Downside Risk - Lower Semideviation at 0 - Value Weighted

	1994-2008	1994-2015
Prime Broker	$\sigma^{VW}_{below\_zero}$	$\sigma^{VW}_{below\_zero}$
Morgan Stanley	0.0170	0.0137
Goldman Sachs	0.0090	0.0123
JP Morgan	0.0102	0.0113
UBS	0.0090	0.0124
Credit Suisse	0.0134	0.0126
Deutsche Bank	0.0055	0.0085
Citi	0.0112	0.0114
Societe Generale	0.0217	0.0114
HSBC	0.0493	0.0148
Barclays	0.0087	0.0093
Bank of America	0.0173	-
Merrill Lynch	0.0170	-
Lehman Brothers	0.0085	-
BoA ML	-	0.0099
BNP Paribas	-	0.0350
Average	**0.0148**	**0.0135**

Notes: See Table 8 for further details.

Table 18: Estimation Results - Value Weighted Variables

	2015		2008	
Prime Broker Surplus	(1)	(2)	(3)	(4)
	Estimates [95% C.I.]	Mean (St. Dev)	Estimates [95% C.I.]	Mean (St.Dev)
$\sigma^{VW}_{below\_zero}$	-1	0.013	-1	0.012
	-	(0.006)	-	(0.004)
HHI^{VW}	0.02	0.30	0.04	0.38
	[0.01,0.05]	(0.10)	[0.01,0.05]	(0.19)
$\bar{\beta}^{VW-ownPB}_{p}$	0.07	0.67	0.02	0.36
	[0.04,0.10]	(0.28)	[0.01,0.05]	(0.26)
Hedge Fund Surplus				
$Mkt\_Shr^{S_h,VW}_{p}$	0.003	0.13	0.001	0.12
	[0.001,0.004]	(0.09)	[0.0011,0.0018]	(0.11)
$Mkt\_Shr^{S_h,VW}_{p} \times \beta^{VW-S}_{HF}$	0.0003	0.11	-0.0001	0.10
	[-0.0004,0.001]	(0.10)	[-0.0002,0.0002]	(0.13)
# HFs	1,620		1,531	
# PBs	12		13	
# Links	2,224		1,532	
# Inequalities	1,623,628		994,922	
% Fit	95.09		94.72	

Notes: See Table 13 for further details. HSBC and Barclays are excluded from the calculations in column (4), for the same reason as in Table 13.

30-day stress scenario. It measures hypothetical scenarios of increase in cash outflows and decrease in cash inflows and requires banks to hold high-quality liquid assets in excess of the calculated net cash outflows for a 30-day stress event to meet necessary cash requirements. In the calculation of cash outflows, LCR assumes that the ability to internalize trades of clients will reduce to 50% and create funding problems for the prime broker. JPMorgan (2014) explains how internalization will be affected by the LCR:

"One of the most notable rule changes is the significant reduction in internalization value that a Prime Broker can realize from customer activity. Internalization, or the ability to use the encumbered assets of one customer to cover the shorts of another customer, is reduced to 50% under new rules. This will have ramifications for hedge fund strategies that have benefited from pricing that reflects the value of internalization to the prime broker (It is more efficient and less costly for the prime broker to use client's securities to cover another client's shorts than to borrow the securities from an agent lender)..."

In the language of the accounting model, LCR makes internalization relatively more costly for prime brokers (increases f). According the results of the accounting model, that might put pressure to prime brokers to find other cost-efficient ways, given that they already operate with low profit margins. Internalization could be replicated synthetically through the use of derivatives, which is less costly and goes off-balance sheet, which makes it harder for regulators to monitor. Indeed, that transition may have already started. In the words of the head of equity finance at JPMorgan, "[i]f separate clients are long and short the same underlying on the synthetic side and we hedge the market exposures, we technically don't have a position anymore. We still have two derivatives, which creates an embedded capital efficiency." (dealbreaker.com (2013)). According to secfinmonitor.com (2015):

"It seems that the era of mergers between physical and synthetic finance businesses is finally upon us...[T]here is no question that regulation is the major driver of change. When faced with a request for a securities loan vs. a total return swap, the swap may be both easier and less capital intensive. Data has suggested for some years that synthetic finance and Delta One desks were building momentum. Analysis by Finadium shows synthetic financing revenues at an estimated US $7 billion for 2015 across nine leading prime brokers, a growth of 43% over 2012 figures...Physical financing revenues are estimated at $3.9 billion, just 61% of synthetic revenues. Physical revenues have also grown more slowly than synthetic, just 22% since 2012."

According to Kirk, McAndrews, Sastry and Weed (2014), "the degree to which dealer banks internalize trading activities or maintain available but untapped capacity to internalize positions is, at best, unclear." In this paper, with limited data, I showed that internalization is important and its importance might increase in the face of more competition and regulation. The main policy implication arising from this paper is that regulators should collect more data on the internalization capacity of prime brokers, in order to assess the new risks in financial markets more precisely.

10 Conclusion

In this paper, I documented that prime brokers specialize, serving hedge fund clients which trade within similar asset classes. I modeled their interactions as a matching market and discussed benefits of internalization, expertise, immediacy and positive and negative externalities arising from downside risk. I estimated the framework using a technique that does not require data on monetary transfers or profits.

This paper should be regarded as a first attempt to understand the complex and systemically important prime brokerage market. Data on the prime brokerage market is severely limited. This paper makes use of the available data to analyze the market and relationships formed. Variables used in this paper are, at best, noisy measures of economic measures I aim to capture and the results come with caveats that are discussed in the paper. Further data collection by regulators could vastly improve our understanding of this market. The findings in this paper could be used as a guide to identify the data needs and inform theoretical studies of securities markets and relationships between prime brokers and hedge funds.

Key findings to take away are the following. Specialization is an important driver of the match surplus and it is valued more in 2015 compared to 2008. Using a simple accounting framework, I argued that this is a response to increased competition and regulation after the crisis. I estimated that major prime brokers, such as Goldman Sachs, have saved \$100-200 million by internalization in annual terms in 2014. Furthermore, the preference for the riskiness of clients of prime brokers has changed for prime brokers between 2008 and in 2015. Three key concepts emerge from this paper in the analysis of this market which calls for future studies. They are specialization, downside risk and size of hedge funds that drive the relationships formed in this market.

Key mechanisms to take away from this paper are the following. First, prime brokers provide services to hedge fund clients and having hedge funds doing similar trades facilitates internalization. Internalization provides benefits to the prime broker due to savings on search and balance sheet costs. Second, viewed only as a service provider, downside risk of its clientele hurts the prime brokers through the price impact of the fire sales of similar collateral if hedge funds default. Third, there are complementarities between the operations of prime brokers as service providers and trading desks as traders to make profits for the bank holding company. Traders taking opposite positions of hedge fund trades facilitated by the prime brokers save on balance sheet costs through collateral re-use. It could also provide benefits of hedging the counterparty risk. Fourth, hedge funds get immediacy benefits from similar others belonging to the network of the same prime broker. Fifth, internalization, as a cost-saving mechanism becomes relatively more important, when operating with low profit margins, i.e. high costs relative to revenues or inability to charge high mark-ups due to increased competition.

The results of this paper opens new avenues for future research. A future research area that is of immediate relevance to this paper is the analysis of different forms of collateral re-use its effect on the financial system in more detail. Prime brokers and hedge funds are important institutions in financial networks. The insights and findings of this paper could inform the theoretical studies of financial networks. A particularly fruitful avenue is to model the broker-to-broker links and theoretically analyze endogenous formation of core-periphery networks. This paper provides a study of two snapshots of the prime brokerage market, one is pre-crisis, the other is a time period where Basel III regulations have only been partially implemented. The prime brokerage market is changing rapidly due to regulations that will fully come to effect in the coming years. Another interesting question might be how the new matches formed and the broken matches will be affected when regulation fully comes into effect. Another open question following the results of this paper is how the trade-offs within a bank due to downside risk with service provision and balance sheet efficiencies due to complementarities of the operations of prime brokers and trading desks weigh against each other. Another avenue for future research could be to analyze, within an industrial organization framework, the economies of scale and scope in the prime brokerage market in more detail and study the optimal size of prime brokers and bank holding companies.

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A Prime Brokers and Hedge Funds

Hedge funds are large investment funds that use private investment strategies and are loosely regulated. They often use both long and short positions to employ their trading strategies. Not widely available to public, they raise initial capital from institutional investors and high wealth individuals. Hedge funds often employ leveraged long and short positions to amplify returns from their investments.

The crux of the hedge fund and prime broker relationship is the leverage and financing that a prime broker provides to a hedge fund[33]. Except for a few large hedge funds, hedge funds do not have access to unsecured debt financing and their borrowing needs to be backed by collateral. The main sources of leverage for a hedge fund are collateralized borrowing through repurchase agreements (for long positions) or reverse repurchase agreements (for short positions), collateralized borrowing through margin loans and securities lending agreements[34] or through either exchange traded or Over-the-Counter (OTC) derivative agreements which is broadly called synthetic prime brokerage.

Collateralized Financing: Standard Prime Brokerage

A long position typically involves the hedge fund borrowing funds from the prime broker and posting securities bought as collateral. In a repo agreement or a margin loan, the prime broker and the hedge fund agree on the principal amount, interest rate, collateral type, haircut (or margin amount) and tenor of the agreement. Since this is similar to a secured loan, the prime broker chooses the haircut (or margin) to protect itself from the downside in the case that the hedge fund defaults. For example, if the hedge fund wants to take a position worth \$100 on a stock and the prime broker and the hedge fund agree on a 10% haircut, the prime broker buys the stock from the hedge fund for \$90 at the opening leg of the agreement and agrees to sell it back to the hedge fund for \$90 plus the interest rate at the settlement date. The prime broker is protected up to 10% downside, since it could sell the securities in the market and recover the amount it lent to the hedge fund in case the hedge fund is unable to return the security back to the prime broker.

A short position typically involves a hedge fund borrowing a security from the prime broker and then selling it. The hedge fund then posts collateral, typically in excess of the market value of the securities sold to protect the prime broker from an increase in the value of the security. A hedge fund creates a short position if it believes that a security is overvalued and will lose its value, which is when it buys the security back and delivers it back to the prime brokers and pays the shorting fees that they agreed upon at the opening leg of the shorting agreement. At that stage, the prime broker returns the collateral posted by the hedge fund back. The risk for a prime broker in this situation arises if the price of the security goes above the amount of excess collateral posted by the hedge fund in case the hedge fund is not able to redeliver the securities. If the prime broker wishes the re-buy the security, it would have to buy it at the higher market price.

Synthetic Prime Brokerage

[33] For other explorations of the hedge fund and prime broker relationships, see Aikman (2010), Brunnermeier and Pedersen (2009), Kirk, McAndrews, Sastry and Weed (2014) and Duffie (2010).

[34] Margin loans and repurchase agreements serve the same economic purpose that is secured lending. However, they have some distinctions as to how they are treated legally in terms of their balance sheet treatment. See King (2008) for the legal distinctions

A relatively new and emerging way to create the desired exposures for a hedge fund is through synthetic prime brokerage. It is called "synthetic" since it aims to create the same exposure for a hedge fund without having to own the underlying instruments directly. The most common use of synthetic prime brokerage is through "delta one" instruments which strives the replicate the return of an underlying one-to-one, such as total return swaps.

A total return swap works as follows. The parties agree on an exposure to a certain reference asset. The party who owns the reference asset receives a set rate and makes payments to the other party based on the total return received from the reference asset. This creates economically similar exposure for the hedge funds, without having to own the security and by just posting the margin required for the transaction[35].

Prime brokers could also provide exposures to hedge funds through other derivatives contracts such as futures, options, interest rate swaps, credit default swaps etc. and hedge those positions with either other clients or external parties.

Regulation T, Portfolio Margining and Delta-One

In the US, for equities, Regulation T requires non-broker-dealers to post at least 50% of the market value of the asset as initial margin, both in long and short positions. There are several ways to bypass that regulation. Prime brokers that finance multiple positions of a hedge fund could offer lower margin requirements for the hedged positions of a hedge fund since the multiple positions of a hedge fund could be partially offsetting risks compared to security-by-security margining[36].

All of the big prime brokerages have units in jurisdictions where these regulations do not apply. Another popular way to get around this is to do this transaction through a prime brokerage unit in a jurisdiction where regulation is loose or through the use of synthetic prime brokerage.

Additional Services Provided by a Prime Broker

In addition to providing leverage to clients through financing of long positions and securities lending, prime brokers offer other services to hedge funds such as custody, trade execution and clearing, trade settlement, trade reporting, trade settlement, capital introduction among others (Aikman (2010)).

Hedge Fund Free Credit Balances

Another important component of the prime brokerage business model is the free credit balances of hedge funds. Free credit balances refer to the cash held by a hedge fund in its margin account that in excess of margin requirements, short sale proceeds etc. that the hedge fund has the right to demand on short notice[37].

When a hedge fund has free credit balances and another hedge fund needs cash for a margin loan etc., the prime broker could channel funds from the margin account of the client with excess cash to the account of the client that needs cash.

The risk in this process is the possibility of withdrawal of free credit balances at a short notice. If the hedge fund with excess cash withdraws the excess cash on its margin account, the prime

[35] I discuss total return swaps in the context of the paper in more detail in Section 9.

[36] This could potentially explain why there might be a tension between diversifying between prime brokers and concentrating all activity into one.

[37] See Baily et al. (2010) for further information

broker needs to come up with funds to pay that hedge fund, since the cash is locked in the loan of another hedge fund.

The use of free credit balances is important both for the business model of the prime broker and for the systemic risk it creates. This is the most similar prime brokerage gets to the traditional banking system, where free credit balances are similar to deposits and the margin loans funded by free credit balances are similar to loans made to business. However there is one difference: there is no deposit insurance between prime brokers and hedge funds. This makes prime brokers vulnerable to bank runs. The liquidity coverage ratio of Basel III regulations introduces new regulations on the use of free credit balances[38].

Due to data limitations, the use of free credit balances is going to be beyond the scope of this paper.

[38] See Section 9 or JPMorgan (2014) for details.

B Robustness Checks

B.1 Taking Out the Family Effects

In the paper, I conduct the analysis at the "productreference" level for hedge funds in terms of the language of the Lipper database. However, multiple "productreference"s can belong to the same "company", which suggests that there might be family effects. Furthermore, sometimes, "productreference"s might report the same monthly returns. In order to do a robustness checks without multiple members of a family, I construct a variable called "duplicate." A "productreference" is called a duplicate if there is another productreference that belongs to the same family, has the same style, has a small identification number than the productreference in question and the productreference in question reports the same returns *at least once*.

Figures 4 and 5 show the composition of the sample in terms of duplicates. In both samples, in 2008 and in 2015, more than 85% of the hedge funds do not have any duplicates. Figures show the distribution of hedge funds that have duplicates. x-axis is the fraction of months the returns of a hedge fund is identical to another one in the same family, same style and one with a lower identification number. In this exercise, I drop all funds that are duplicates of another at least one month.

Table 19 shows the portfolio Herfindahl indices of the prime brokers. Except for Barclays in 2015, the results are similar to the benchmark case. Table 20 shows the co-movement of hedge funds with the ones served by their prime broker and others. The results are slightly weaker, but in the same direction as in the benchmark case. Table 21 shows the lower semi-deviation below zero of the prime brokers' portfolios. The results are similar to the benchmark case.

Table 22 shows the estimation results with the new samples in 2015 and in 2008. The point estimates are qualitatively similar. The only difference is that the coefficient on the HHI in 2015 is imprecisely estimated.

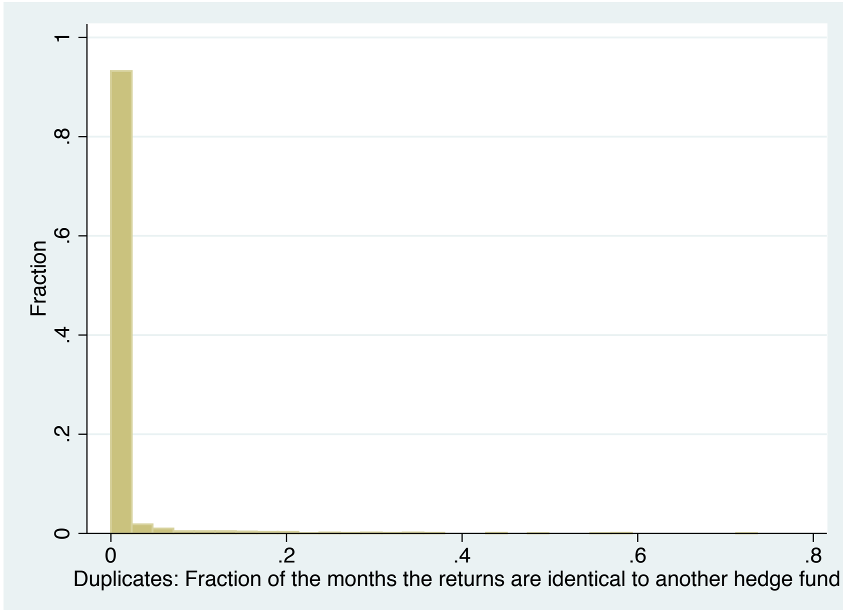

Figure 4: Fraction of hedge funds that report the same returns as another in 2008

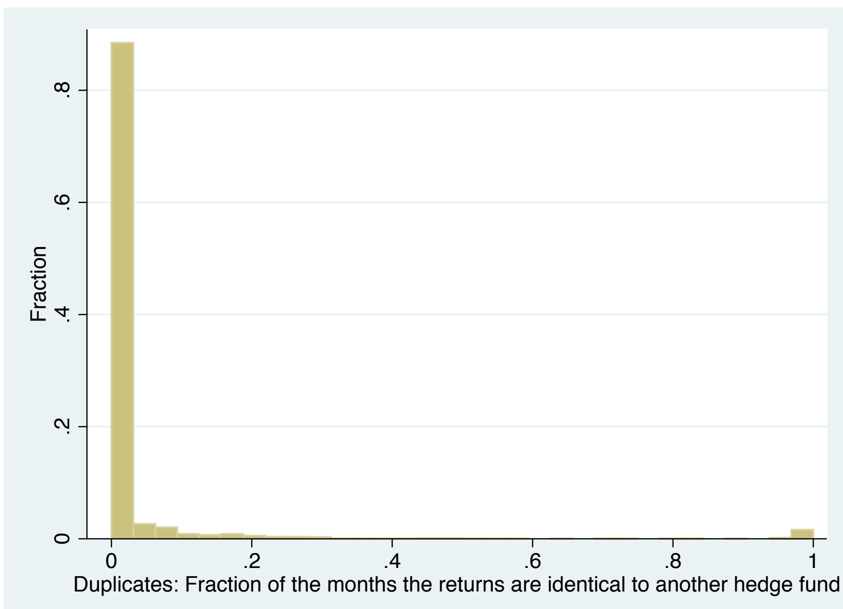

Figure 5: Fraction of hedge funds that report the same returns as another in 2015

Notes: Figures show the fraction of hedge funds in the original sample that report the returns as another hedge fund. In both samples, in 2008 and in 2015, more than 85% of the hedge funds do not have any duplicates. Figures show the distribution of hedge funds that have duplicates. x-axis is the fraction of months the returns of a hedge fund is identical to another one in the same family, same style and one with a lower identification number. In this exercise, I drop all funds that are duplicates of another at least one month.

Table 19: Concentration of Prime Broker Portfolio - Herfindahl Index - Duplicates are Excluded

Prime Broker	*HHI in 2008*	*HHI in 2015*
Morgan Stanley	0.4118	0.3389
Goldman Sachs	0.3441	0.2573
JP Morgan	0.1832	0.1636
UBS	0.3641	0.2095
Credit Suisse	0.2738	0.2523
Deutsche Bank	0.5076	0.2327
Citi	0.1378	0.1324
Societe Generale	0.4618	0.3895
HSBC	-	0.2653
Barclays	-	0.1100
Bank of America	0.7102	-
Merrill Lynch	0.2314	-
Lehman Brothers	0.1616	-
Boa Merrill	-	0.3546
BNP Paribas	-	0.3194
Average	**0.3443**	**0.2521**
All Hedge Funds	**0.2763**	**0.2080**

Notes: The Herfindahl Index for the prime brokers in 2008 and in 2015, when duplicates are excluded. See Table 6 for further details. Note that HSBC and Barclays are excluded in 2008, due to insufficient number of observations.

Table 20: Mean Comovement of Hedge Fund Client and the Average Comovement of those Hedge Funds with other Prime Brokers - Duplicates are excluded

Panel A: Regression Results				
	1994-2008		1994-2015	
β^{OwnPB}	0.78		0.85	
t-stat	[21.7]		[36.9]	
β^{MKT}	0.94		0.94	
t-stat	[28.0]		[34.0]	
Panel B: Comparison across prime brokers				
Prime Broker	$\bar{\beta}_p^{ownPB}$	$\bar{\beta}_p^{others}$	$\bar{\beta}_p^{ownPB}$	$\bar{\beta}_p^{others}$
Morgan Stanley	0.83	0.23	0.91	0.59
Goldman Sachs	0.83	0.32	0.81	0.53
JP Morgan	0.93	0.30	0.86	0.55
UBS	0.82	0.43	0.90	0.61
Credit Suisse	0.76	0.43	0.85	0.63
Deutsche Bank	0.49	0.26	0.90	0.59
Citi	0.80	0.32	0.85	0.53
Societe Generale	0.81	-0.70	0.76	-0.004
HSBC	-	-	0.57	0.53
Barclays	-	-	0.73	0.59
Bank of America	0.63	0.24	-	-
Merrill Lynch	0.43	0.25	-	-
Lehman Brothers	0.34	0.08	-	-
BoA ML	-	-	0.77	0.41
BNP Paribas	-	-	0.51	0.60

Notes: See Table 7 for further details.

Table 21: Downside Risk - Lower Semideviation at 0 - Duplicates are Excluded

	1994-2008	1994-2015
Prime Broker	σ_{below_zero}	σ_{below_zero}
Morgan Stanley	0.0193	0.0223
Goldman Sachs	0.0157	0.0220
JP Morgan	0.0163	0.0196
UBS	0.0240	0.0271
Credit Suisse	0.0281	0.0236
Deutsche Bank	0.0503	0.0204
Citi	0.0178	0.0176
Societe Generale	0.0336	0.0316
HSBC	-	0.0381
Barclays	-	0.0380
Bank of America	0.0239	-
Merrill Lynch	0.0140	-
Lehman Brothers	0.0185	-
BoA ML	-	0.0200
BNP Paribas	-	0.0370
Average	**0.0238**	**0.0264**

Notes: See Table 8 for further details.

Table 22: Estimation Results - Duplicates are Excluded

	2015		**2008**	
Prime Broker Surplus				
	Estimates [95% C.I.]	Mean (St. Dev)	Estimates [95% C.I.]	Mean (St.Dev)
σ_{below_zero}	-1	0.02	+1	0.02
	-	(0.0077)	-	(0.01)
HHI	0.18	0.25	0.10	0.34
	[-0.55,1.62]	(0.08)	[0.0008,0.16]	(0.17)
$\bar{\beta}_p^{ownPB}$	2.31	0.79	0.22	0.70
	[1.18,2.64]	(0.12)	[0.17,0.29]	(0.19)
Hedge Fund Surplus				
$Mkt\_Shr_p^{S_h}$	0.72	0.11	0.02	0.14
	[0.04,0.95]	(0.08)	[0.01,0.03]	(0.10)
$Mkt\_Shr_p^{S_h} \times \beta_{HF}^S$	0.03	0.11	0.001	0.12
	[0.01,0.06]	(0.10)	[-0.001,0.003]	(0.09)
# HFs	1,262		1,335	
# PBs	12		11	
# Links	1,735		1,336	
# Inequalities	965,255		758,099	
% Fit	75.65		83.08	

Notes: See Table 13 for further details. Note that HSBC and Barclays are excluded due to insufficient number of observations in 2008.