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Do prime brokers intermediate capital?☆

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ABSTRACT

Prime brokers play an important role in intermediating arbitrage capital to hedge funds. A fund's peer-group ranking, relative to funds that share the same prime broker, significantly affects how investors respond to its past performance. I decompose the standard performance-flow relationship into two components: (1) flows that respond to overall performance rank, and (2) flows that respond to relative (within prime broker) performance rank. Strong *relative* rank drives fund in-flows, while poor *overall* rank drives out-flows. These results suggest that prime brokers intermediate about 40% of the standard performance-flow relationship.

1. Introduction

Recent work has demonstrated that hedge funds, by producing information and engaging in arbitrage activities, help improve price discovery and market efficiency (see Kokkonen and Suominen, 2015; Cao et al., 2018a,b; Chen et al., 2019 and Chen et al., 2020). Capital is vital for this efficient arbitrage activity to take place, however, sourcing arbitrage capital is difficult because regulations prevent hedge funds from raising money from the general public and numerous informational frictions exist between investors and fund managers. Very little is known about the channels through which capital flows from investors to arbitrageurs.

Anecdotally, about two-thirds of institutional investors rely on prime broker "capital introduction" teams to introduce them to hedge fund managers.[2] Prime brokers ("primes") are typically units of large investment banks and are well-placed to help both investors and managers overcome information frictions. They work closely with their hedge fund clients on a daily basis, executing transactions, lending securities, and providing leverage. Furthermore, their parent bank acts as a trusted intermediary and advisor for large institutional investors and wealthy individuals. While investor capital no doubt flows through capital introduction, the question remains: do prime brokers intermediate a *meaningful* amount of arbitrage capital?[3]

Quantifying the effect of capital introduction is difficult because capital introduction is unobservable. To circumvent this, I take advantage of plausibly exogenous variation that affects the likelihood a fund

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[2] The Capital Introduction Group at J.P. Morgan publishes a yearly survey of institutional investors. In 2014 the group surveyed 368 institutional investors of J.P. Morgan, representing about 30% of the assets-under-management in the hedge fund industry. The group reports that over two-thirds of respondents indicate that they use prime broker capital introduction teams to source hedge fund managers (Tocco, 2015).

[3] Nota bene, I do not take a stand on whether prime brokers *actively* or *passively* intermediate funds. In the extreme, suppose prime brokers simply provide lists of hedge funds to their investors, and investors allocate capital to top performing funds on this list. I consider this to be a form of intermediation because it reduces search costs for investors. For example, if the prime broker were to shut down, its investors would need to find an alternative channel to source hedge funds.

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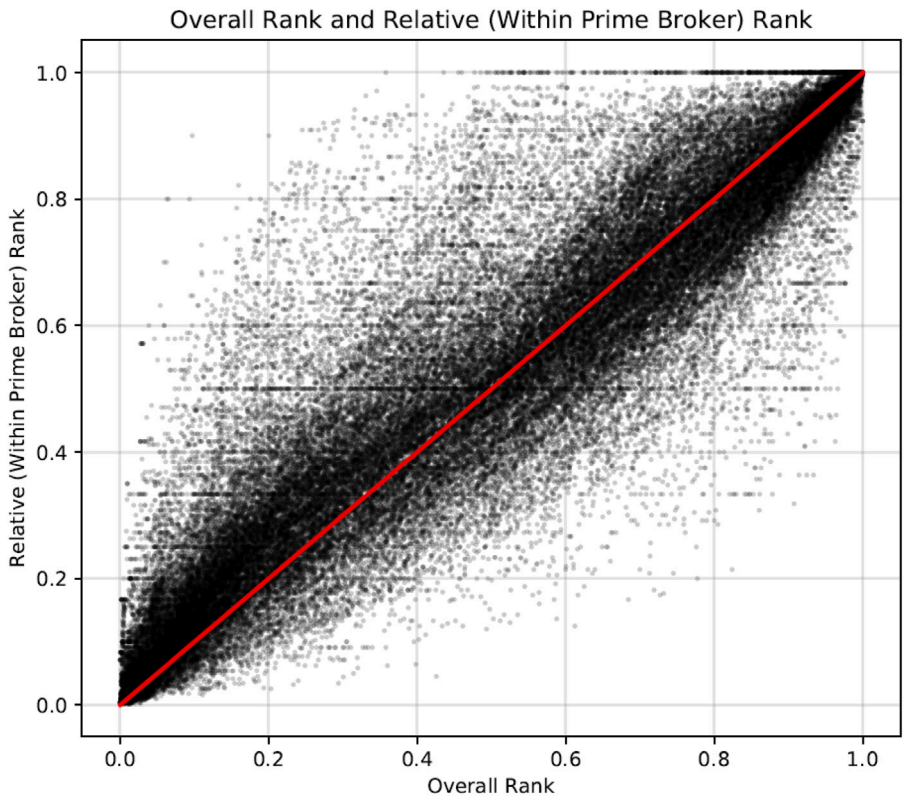

Fig. 1. Scatterplot of overall and relative rank.
This figure presents the scatterplot of overall rank and relative (within-prime broker) rank. Overall rank is a fund's percentile performance rank, measured using past 12-month returns, against all funds in the TASS database. Relative rank is a fund's percentile performance rank, measured using past 12-month returns, relative to peer funds that share the same prime broker. The red line is the 45 degree line.

participates in capital introduction. I build peer groups of hedge funds that all share the same prime broker, I then calculate: (1) a fund's overall percentile performance rank among observable funds ("*overall* rank"), and (2) a fund's within prime broker percentile performance rank ("*relative* rank"). There is a large degree of exogenous variation between a fund's relative peer-group rank and its overall rank, as can be seen in the dispersion in Fig. 1.

Controlling for overall rank, high relative rank proxies for funds that are more likely to benefit from capital introduction,[4] and consistent with this, I find that relative rank explains about 40% of the baseline relationship between past performance and future fund flows.[5] In particular, funds in the top tercile of relative rank receive higher future flows, while there is no effect for funds in the bottom or middle terciles. High *relative* rank predicts positive net flows, whereas low *overall* rank predicts negative net flows. This suggests that investors use the prime broker channel to source hedge funds, but do not use this channel when deciding to divest.

Relative rank, however, is highly correlated with overall rank (85.7%) which may create a multicollinearity problem that can bias both the coefficient estimates and the standard errors leading to potentially spurious inference. I build three tests to rule out the multicollinearity problem. In a placebo test, I randomly group funds into pseudo prime brokers and recalculate relative rank. This shuts down the prime broker channel while maintaining a high degree of correlation between relative and overall rank (93.1%). Placebo relative rank does not predict future fund flows. In the second test, I orthogonalize relative rank vis-à-vis overall rank to isolate its exogenous variation. Consistent with the prime broker channel, the orthogonal component has predictive power for future flows above and beyond overall rank. Finally, the high degree of correlation makes it difficult to interpret the regression coefficients.[6] To address this, I double-sort funds by overall and relative rank in order to hold overall rank constant, and then I study the predictive power of relative rank. At a given level of overall rank, future fund flows generally increase in relative performance rank.

Relative rank may also be correlated with other marketing channels, such as personal networks or third-party marketers. Personal networks are unobservable, but it is unlikely that, in any organized fashion, personal networks and prime broker networks span the same set of hedge funds. Third-party marketers, however, may be large and relative rank might be related to within-marketer rank. In my sample each marketer has 3.0 hedge fund clients on average, whereas each prime broker has an average of 166.2 clients, thus overlap is unlikely. I directly investigate the marketer channel by merging my data with Form

[4] For instance, on the extensive margin, only a prime's top performing funds are invited to capital introduction events. At these events, funds have the opportunity to meet potential investors, thus, search costs are reduced. On the intensive margin, at these events investors may rationally pursue higher ranked funds. The empirical literature has found evidence that hedge fund performance is persistent (see Jagannathan et al., 2010 and Fung et al., 2008.

[5] The performance-flow relationship is well-documented in the literature, and describes how fund flows vary positively with lagged measures of performance (see Goetzmann et al., 2003; Baquero and Verbeek, 2005; Fung et al., 2008; Aragon and Qian, 2009; Aragon et al., 2013; Baquero and Verbeek, 2021; Liang et al., 2015; Agarwal et al., 2018).

[6] For example, it is common to interpret coefficients by examining the predicted change from an interquartile increase in the variable of interest, holding all other independent variables constant. However, in this case, due to the high correlation between relative rank and overall rank, it may not be reasonable to consider a situation where there is an interquartile increase in relative rank while overall rank remains unchanged.

ADV to obtain information on third-party marketers. The prime broker channel remains robust when controlling for third-party marketers, and the presence of marketers does not appear to hinder the prime broker channel.

In a variety of ways, relative rank may also capture how investors search for funds and make investment decisions. For example, a fund's relative rank is correlated with its performance rank within a *style*, and if investors have heterogeneous preferences for certain investment styles, then the effects I document might simply be due to performance chasing within a style. I rule this out by noting that my results hold when controlling for style rank. Investment consultants and fund-of-funds provide another potentially confounding channel if they cover similar groups of funds as prime brokers, and unlike third-party marketers, they tend to be rather large. I use data from Form ADV and demonstrate that fund-of-funds are less likely to rely on the prime broker channel compared to other investors. That is, fund-of-funds do not drive the result in the baseline model.[7] Finally, since April 2012 hedge funds have been allowed to directly advertise to investors and this may weaken the reliance of both hedge funds and investors on prime brokers for capital intermediation. Consistent with expectations, I find weak evidence in the later period (July 2013 onward) that the JOBS Act has mitigated the importance of prime brokers in capital intermediation.

My results are also robust to potential measurement issues in the dependent and independent variables. I demonstrate that my results: (1) hold when using changes in market share instead of fund flows; (2) hold when limiting the analysis to large prime brokers; (3) are likely not due to flows from loyal clients instead of capital introduction; (4) are likely not subject to a survivorship bias; (5) are robust to including funds with multiple prime brokers; (6) are robust to subsequent data revisions; (7) hold when controlling for downside risk; and (8) hold when controlling for share restrictions and fund-level characteristics.

My results suggest that a large amount of arbitrage capital is intermediated through prime brokers. This has two implications: First, the prime broker channel directly affects the amount of capital available for arbitrage activity, which in turn has been shown to influence price discovery and market efficiency (see Kokkonen and Suominen, 2015; Cao et al., 2018a,b; Chen et al., 2019 and Chen et al., 2020). Second, if prime brokers (who are typically units of large financial intermediaries) are impaired or fail, then my results suggest that arbitrageurs will have difficulty raising capital and market efficiency will suffer. This provides another path through which intermediary balance sheets may affect market prices, as documented in Hu et al. (2013), Adrian et al. (2014), He et al. (2017), and Haddad and Sraer (2020).

My paper contributes to a long line of literature that studies the determinants of investor flows in the hedge fund market.[8] While the majority of studies examine how fund-level characteristics affect the performance-flow relationship, my study examines the channel through which this capital flows. Most closely related to my paper, Aragon et al. (2022) study the investment decisions of fund-of-funds, which comprise about 20% of hedge fund investors. They find evidence that prime brokers facilitate allocations from fund-of-funds to hedge funds, and that these facilitated allocations tend to outperform. My paper compliments theirs by demonstrating that the prime broker channel is even more important for non-fund-of-funds, however because I cannot disentangle passive from active intermediation, my setting does not allow for an analysis of whether this channel benefits investors.

[7] I am unable to control for investment consultants, but consultants and fund-of-funds are very similar, and if consultants use the prime broker channel in a similar way as fund-of-funds, then the bias introduced by this group will likely also work against the prime broker channel.

[8] See Goetzmann et al. (2003), Baquero and Verbeek (2005), Fung et al. (2008), Aragon and Qian (2009), Aragon et al. (2013), Baquero and Verbeek (2021), Liang et al. (2015), Agarwal et al. (2018), Aragon et al. (2022).

My paper also contributes to the recent literature that examines different channels through which prime brokers affect financial markets. These papers have examined the leverage channel (Mitchell and Pulvino, 2012), the facilitation channel (Aragon and Strahan, 2012), and the information channel (Chung and Kang, 2016; Kumar et al., 2020).[9] The capital channel documented here is fundamental because without capital a hedge fund cannot take on leverage, execute trades, or trade on information; that is, without capital the other three channels break down.

The remainder of this paper is organized as follows: Section 2 describes the hedge fund data, data cleaning, and variable construction. Section 3 discusses my empirical methodology. Section 4 studies the prime broker channel for capital flows and addresses multicollinearity. Section 5 investigates, and ultimately rejects, alternative channels that may explain the documented relationship between relative rank and future flows. Section 6 presents robustness tests related to measurement issues, and Section 7 concludes.

2. Data and variable construction

In this section I describe the data source, bias correction, data cleaning, variable construction, and summary statistics.

2.1. Hedge fund data

I obtain information on hedge fund performance, fund flows, and broker-links over time from the Lipper TASS database ("TASS"). TASS provides a time-series of returns and assets-under-management ("AUM"), as well as fund characteristics, including self-reported prime brokers.

A snapshot of the TASS data (i.e., a one-time download) includes a time-series of performance data, but does not include a time-series of company characteristics. As such, from a single snapshot, there is no way to know when a fund hired a prime broker, and whether the prime broker has changed over time.

To build a panel of characteristics over time, I use a collection of 12 snapshots from May 2000, September 2002, April 2005, December 2007, January 2008, February 2009, June 2011, September 2012, three from 2013 (March, May, and October), and April 2015.

TASS reports service provider relationships (e.g. administrator, auditor, bank, custodian, management firm, legal, and prime broker) in the "Companies.txt" file. Prime brokers are identified with the "Prime Broker" string in the "Company Type" field. I identify 1,210 unique strings, and of these, identify 426 unique prime broker families. Prime brokers are self reported, and as such, may be coded differently. I also roll subsidiaries up to their parent company, for example "Pershing" is a subsidiary of "BNY Mellon", and I consider these to be the same prime broker family.

The 426 unique prime broker families may include some instances of errors. For example, some funds report law firms as prime brokers. I restrict attention to prime brokers that have at least one month of data with at least 10 clients. This leaves me with 62 prime broker families, which represent 90.6% of the entire market share of prime brokers. At each date, I define a fund as being connected with a specific prime broker if the fund reports using that prime broker in the immediately preceding TASS snapshot.

Table 1 reports the number of prime brokers per hedge fund by snapshot date. In the first half of the sample, about 22% of funds report a prime broker. After the financial crisis, this increases to an average of about 34%. In general, the number of hedge funds in TASS declines after the financial crisis, but the prevalence of funds reporting prime brokers increases. About 86% of hedge funds reporting a prime broker report only one prime broker.

Table 1
Number of prime brokers per hedge fund.
This table summarizes the number of prime brokers per hedge fund in the TASS database. Each row i reports the number of hedge funds with i prime brokers. The data comes from twelve snapshots of the Lipper TASS dataset, between 2000 and 2015. Prime broker data is voluntary and self-reported, thus a report of no prime broker does not necessarily mean the fund does not use a prime broker. The row "Various" refers to funds that report multiple prime brokers, but do not identify them. The final row reports the fraction of funds reporting a "principal" prime broker, that is, conditional on reporting a prime the fraction of funds that report only one prime. Only alive funds are included.

# Prime Brokers	Count of hedge funds											
	2000–05	2002–09	2005–04	2007–12	2008–01	2009–02	2011–06	2012–09	2013–03	2013–05	2013–10	2015–04
0	2,348	4,227	5,997	8,441	8,382	7,603	6,079	5,097	4,567	4,465	4,203	3,284
1	772	533	1,962	2,107	2,053	2,081	2,701	2,683	2,477	2,419	2,195	1,779
2	39	27	6	101	114	93	215	202	183	164	162	134
3	5	5	0	23	21	29	46	57	68	86	76	78
4	2	1	0	13	13	8	36	56	59	59	38	26
5	0	0	1	0	0	1	38	40	39	39	38	33
6	0	0	0	1	1	0	10	8	4	4	4	4
Various	80	124	22	15	15	16	10	9	9	9	9	8
Total	3,246	4,917	7,988	10,701	10,599	9,831	9,135	8,152	7,406	7,245	6,725	5,346
Has PB	27.6%	14.0%	24.9%	21.1%	20.9%	22.7%	33.5%	37.5%	38.3%	38.4%	37.5%	38.6%
Has One PB	23.8%	10.8%	24.6%	19.7%	19.4%	21.2%	29.6%	32.9%	33.4%	33.4%	32.6%	33.3%
% One PB	86.2%	77.1%	98.8%	93.4%	92.8%	93.4%	88.4%	87.7%	87.2%	87.0%	86.9%	86.3%

Table 2
Summary statistics for main tests.
This table presents descriptive statistics for the sample of 2,632 funds used in the main tests. Variables are reported at the fund-month level. $Flows(t,j)$ are the fund flows from time t to time j. $Return(t,j)$ is the return of the fund from time t to time j. $Sharpe(t,j)$ is the Sharpe ratio of returns from time t to time j. $DeltaMS(t,j)$ is the change in market share in basis points for the fund, measured from time t to time j. $ln(AUM)$ is the natural logarithm of assets under management. $ln(Age)$ is the natural logarithm of fund age in months. $OverallRank$ is the fund's percentile performance rank, measured using past 12-month returns, relative to all funds in TASS. $RelativeRank$ is the fund's percentile performance rank, measured using past 12-month returns, relative to peer funds that share the same prime broker. $Placebo.RelativeRank$ is the fund's percentile performance rank, measured using past 12-month returns, relative to peer funds that share the same placebo prime broker. $Othog.RelativeRank$ is the orthogonal component of a fund's peer group rank $RelativeRank$ relative to its overall rank $OverallRank$. $StyleRank$ is the fund's percentile performance rank, measured using past 12-month returns, relative to funds that report the same style.

Variable	N	Mean	SD	Min	p25	p50	p75	Max
Flows(0,12)	86,004	0.08	1.08	−0.96	−0.28	−0.06	0.12	12.95
DeltaMS(0,12)	86,004	0.43	2.06	−4.72	−0.10	0.02	0.37	10.75
AUM (USD Million)	86,004	182.17	486.39	0.00	14.16	49.48	160.70	11,397.00
Age (Months)	86,004	85.73	51.06	4.00	48.00	75.00	112.00	421.00
Flows(−12,0)	86,004	0.25	1.46	−0.96	−0.23	−0.02	0.23	13.04
Sharpe(−12,0)	86,004	0.22	0.51	−0.78	−0.09	0.18	0.46	5.88
OverallRank	86,004	0.50	0.31	0.00	0.21	0.51	0.78	1.00
RelativeRank	86,004	0.52	0.29	0.00	0.27	0.53	0.78	1.00
Placebo.RelativeRank	86,004	0.54	0.29	0.00	0.30	0.56	0.79	1.00
Orthog.RelativeRank	86,004	0.00	0.11	−0.59	−0.06	−0.01	0.05	0.73
Relative-Overall Rank	86,004	0.02	0.12	−0.61	−0.03	0.01	0.07	0.80
StyleRank	86,004	0.49	0.29	0.00	0.24	0.49	0.75	1.00

Table A1 in the Internet Appendix reports hedge fund AUM broken down by prime broker for the 2,632 hedge funds in my main analysis. Prime brokers appear to have more or less equivalent breakdowns by size. Barclays and Pictet are outliers that tend to have larger and smaller clients, respectively. Table A2 in the Internet Appendix reports the style distribution of hedge fund clients, and generally, the distribution is disperse. Pictet is again an outlier, reporting only fund-of-fund clients. These tables demonstrate that there is not a significant difference in the hedge fund clients of prime brokers, particularly among the larger primes.

2.2. Bias corrections

I take a number of steps to address the documented biases that may arise when working with voluntary, self-reported data.

Fung and Hsieh (2000) find that funds join TASS after a period of outperformance, and estimate a backfill bias of 1.4% per year in TASS using a sample from 1994 to 1998. To control for backfill bias, I only use performance data after a fund joins TASS.[10]

Liang (2000) documents that survivorship bias arises when studies only consider surviving funds. Survivorship bias is significant and biases upward estimates of mean fund performance by over 2% per year. The TASS database contains both surviving and dead funds, and to control for survivorship bias I include both in this analysis.

Patton et al. (2015) analyze the reliability of hedge fund databases, and find that historical return series are routinely revised. This is problematic for studying how investor flows respond to recent performance. To mitigate this, I use performance data from the earliest snapshot record. For example, data from December 2001 will be reported in all snapshots from the September 2002 snapshot onward, however, I only use the amount reported in the September 2002 snapshot.[11]

Finally, "extinction bias" is important in my setting because I study the relationship between past performance and future flows. Managers

[9] See also Gerasimova (2014), Klaus and Rzepkowski (2009), and Goldie (2011) for a discussion on the relationship between prime brokers and hedge fund performance.

[10] A major drawback of the TASS database is that the $DateAddedtoTASS$ variable is largely missing for funds that join after March 2011. To mitigate this problem, I create a conservative estimate of the date added to TASS for funds with missing data. For these funds, I only use observations after the date of the first snapshot where the fund is reported as being alive.

[11] In Section 6.6 I demonstrate that the results are robust to using revised flow data from the latest snapshot.

typically delist for one of two reasons: one, the fund has performed well and managers decide to close the fund to new investment; or two, the fund has performed poorly and is shut down. If a group of funds persistently delists, then this group will have missing fund flow data, and this may bias the documented relationship between past performance and future fund flows. I will return to this issue in 6.4 in which I demonstrate that delisting has likely introduced no extinction bias.

2.3. Data cleaning

In addition to the bias corrections above, the TASS dataset requires careful cleaning before it can be used in analysis. I follow the cleaning guides recommended by Bhardwaj et al. (2014) and Getmansky et al. (2015).

Following Bhardwaj et al. (2014), I: (1) adjust foreign currency funds to USD, (2) remove backfill data, (3) remove funds that report returns gross of fees, and (4) remove funds with missing AUM. Following Getmansky et al. (2015), I: (1) recompute returns as changes in net-asset-value (NAV), (2) use reported return when NAV is missing, (3) only include funds that report monthly, (4) remove funds that start and stop reporting more than four times, and (5) reject four types of "suspicious looking" data.[12]

2.4. Variable calculation

I use monthly net-of-fee returns and AUM data from TASS to calculate fund flows at the hedge fund level.

Following Chevalier and Ellison (1997), Sirri and Tufano (1998), I calculate flows for fund i from time $t-12$ to time t as:

$$Flows_{i,t-12,t} = \frac{AUM_{i,t} - (1 + Return_{i,t-12,t})AUM_{i,t-12}}{AUM_{i,t-12}} \quad (1)$$

where $AUM_{i,t}$ are the assets under management, and $(1 + Return_{i,t-12,t})$ is the geometric product of monthly returns between time $t-12$ and time t.

I measure overall rank with the variable $OverallRank_{i,t}$, calculated as a hedge fund's percentile performance rank among all funds in the TASS dataset. To build relative rank, I group funds by prime broker and then calculate fund-level performance rank within peer groups. That is, suppose fund i is connected to prime broker p. I define fund i's peer group performance rank, $RelativeRank_{i,p,t}$, as fund i's percentile ranking at time t among all funds connected to prime broker p at time t. Both percentile rankings are defined on $[0, 1]$ (where 1 is the highest rank), and are calculated using past 12-month net returns.

A fund typically has one "principal" prime broker, which is paid the bulk of the transaction fees and, anecdotally, is more likely to invite its top-performing principal clients to capital introduction events. I can identify the principal prime for 86% of the sample, and I limit my analysis to principal primes (see Table 1). Thus, I will drop the p subscript and use $RelativeRank_{i,t}$ to denote relative rank.[13]

Table 2 reports summary statistics for variables used in the main analysis and robustness tests. The average fund experiences 8% net inflows per year, but the median fund experiences -6% net outflows. This skewness arises because fund flows have a limited downside but unlimited upside. The median fund size is $49.48 million, the average fund manages $182.17 million, and the largest fund in the sample has $11.397 billion in assets under management. The median fund is 75 months old and the oldest fund is over 35 years old (421 months). The average monthly Sharpe ratio (over a rolling 12-month period) is 0.22, in line with the broader market. The median overall, relative, placebo, and style ranks should in theory be 0.50, however, this is not observed in the final sample because ranking is done prior to the regression analysis and some observations are subsequently dropped due to incompleteness.

3. Empirical design

The objective of my empirical analysis is to investigate whether prime brokers intermediate capital from investors to hedge funds. It is difficult to study this question because the relationship between a hedge fund and its prime broker is endogenous and capital introduction is not observable. To study the prime broker channel for capital flows, I take advantage of a source of plausibly exogenous variation at the hedge fund level that only affects fund flows through the prime broker channel.

Relative rank, controlling for overall rank, provides this variation. For example, among the universe of funds, only one will be top ranked in any given month. However, *each* prime broker peer group will also have one top ranked fund each month. If there are an arbitrary number of prime brokers, then there will be an arbitrary number of top ranked funds on a relative basis.

From another point of view, consider the top decile of hedge funds based on overall performance. A given fund may be top decile overall, but it may fall either in or out of the top decile in its peer group. This is especially true for funds close to the cutoff. A fund at the 91st percentile of overall rank might not fall in the top decile of its prime broker, whereas a fund at the 89th percentile of overall rank might find itself in the top decile of its respective prime broker. The month-to-month variation in relative rank captures the random jostling of a group of hedge funds each vying to produce high returns. This can produce meaningful deviations between relative and overall rank. The orthogonal component of relative rank (compared to overall rank) has an interquartile range of 0.11, suggesting that deviations of up to a decile in rank are not uncommon.

When capital is intermediated through the prime broker channel, variation in relative rank affects whether a fund will benefit from capital introduction. Typically, a prime broker does not invite all of its hedge funds to capital introduction events. If say, only the top third of its funds get an invite, then a fund that is ranked in the 70th percentile overall but in the 60th percentile at the prime broker, will not be invited. Thus, on the extensive margin, relative rank influences whether a fund will be introduced to investors. Furthermore, at a capital introduction event, investors attention may be drawn to the relatively higher ranked funds. Investors have limited capacity to evaluate all funds because of due diligence costs, and investors may pay more attention to top ranked funds. Thus, on the intensive margin, relative rank influences whether investors will respond to a fund at a capital introduction event.

To test the prime broker channel hypothesis, I explore whether a fund's relative rank at its prime broker, controlling for overall rank, is related to future fund flows. As an example, consider two hedge funds, $H1$ and $H2$, that use prime brokers $P1$ and $P2$, respectively. Suppose that both funds have earned 10% returns over the past year. That is, they both rank the same overall. However, suppose that all the other funds at $P1$ had 9% returns, and all the other funds at $P2$ had 11% returns. Then, $H1$ will have a relative rank of 1, and $H2$ will have a relative rank of 0. If search costs are minimal, then $H1$ and $H2$ will receive similar levels of fund flows. However, if investors rely on the prime broker channel to source hedge fund managers, then $H1$ is likely to receive higher fund flows.

[12] These are: (1) monthly returns less than −100%, (2) monthly returns greater than 200%, (3) monthly returns equal to the past two monthly returns (stale observations), and (4) AUM figures that appear to be reported in inconsistent units. To test for inconsistent units, I remove funds that have an increase in AUM of over two orders of magnitude, followed by a decrease of over 100% within three months. There are a few such cases, most of which occur around the year end.

[13] In Section 6.5 I include funds with multiple prime brokers by using the fund's maximum relative rank across each of its prime brokers at each month. When including multiple prime brokers the results hold and become stronger.

To test this hypothesis, I estimate the following predictive fixed-effects regression specification:

$$Flows_{i,t,t+12} = \beta_1 OverallRank_{i,t} + \beta_2 RelativeRank_{i,t} + \boldsymbol{\beta_3'}\mathbf{X_{i,t}} + a_i + a_t + a_p + a_s \times a_t + u_{itps} \quad (2)$$

where $Flows_{i,t,t+12}$ are future fund flows for fund i from time t to $t+12$. $OverallRank_{i,t}$ and $RelativeRank_{i,t}$ are overall and relative rank, respectively, for fund i at time t. $\mathbf{X_{i,t}}$ are time-varying fund level controls, including the logarithm of assets under management, the logarithm of fund age in months, past fund flows, and past Sharpe ratio.[14] a_i are fund fixed-effects and allow me to control for both observable and unobservable time-invariant fund characteristics.[15] a_t are time fixed-effects and help control for the fact that flows may have an aggregate temporal component. a_p are prime broker fixed-effects and control for unobservable time-invariant characteristics at the peer-group level. a_s are style fixed-effects, which I interact with a_t, and together helps control for time-variant style level effect, such as if a particular style becomes popular among investors. I cluster standard errors at the fund, time, style, and prime broker levels.

By controlling for fund fixed-effects, my analysis studies variation at the same fund across time. The specification asks, for a specific fund, how do fund flows compare when its relative rank is high versus when its relative rank is low. Prime broker fixed-effects take into consideration the fact that the selection of funds at a given prime broker might be different. For example, suppose all the top decile funds bank with Morgan Stanley. Then relative rank will be lower than overall rank for over 90% of these funds. Controlling for prime broker fixed-effect helps adjust for this selection concern. I account for serial correlation in the dependent variable by clustering standard errors at the fund level. This is a particularly important adjustment because the dependent variable has an overlapping component across time. A similar methodology was employed by Chung and Kang (2016) in their study of prime broker level comovement and future hedge fund returns.

If the prime broker channel does not matter, then the additional variation induced by relative rank (controlling for overall rank) should not impact flows and the β_2 coefficient will not be statistically different from zero. However, if the prime broker channel intermediates fund flows, then relative rank should affect the likelihood a fund benefits from capital introduction, and β_2 will be positive and significant. A positive β_2 provides evidence capital is intermediated through the prime broker channel, but there may be other channels that are correlated with relative rank. I explore and rule out these alternative channels in Section 5.

4. Relative performance rank and future fund flows

I first study the linear relationship between relative rank and fund flows, and then study the shape of the performance-flow relationship. In the final part of this section I address the potential multicollinearity problem.

4.1. Future fund flows regressed on relative performance rank

I estimate Eq. (2) to test whether prime brokers intermediate capital. This specification asks whether a fund's relative rank at its prime broker influences future fund flows, controlling for overall rank. The results of this estimation are presented in Table 3. The first column reports the standard performance-flow relationship, and documents a sensitivity of flows to past performance rank of 0.35. The second column introduces relative rank. In the horse-race, the flow sensitivity to overall rank decreases to 0.22, and the flow sensitivity to relative rank enters at 0.14 and is significant at the 5% level. Thus, the prime broker channel explains approximately 40% (= 0.14/0.35) of the performance-flow relationship. For two funds with the same overall rank, if one fund ranks one decile higher at its prime broker it will expect to receive an additional 1.4 p.p. of fund flows over the next year.

Recall that the interquartile range for relative rank is 0.51 (see Table 2),[16] implying that for two funds with the same overall rank, a fund at the 75th percentile of peer group rank compared to a fund at the 25th percentile is expected to enjoy 7.1 p.p. higher funds flows over the next year. That is, the fund is expected to grow its total AUM by an additional 7.1% of AUM.

Overall and relative rank are highly correlated (85.7%), which may induce a multicollinearity problem. This is discussed in more detail in Section 4.3, but first, I first address this here briefly in column 3 of Table 3. In this specification, I replace $RelativeRank$ with $RelativeRank - OverallRank$. This regression does not suffer from the multicollinearity problem, and the results hold.[17]

4.2. The shape of the performance-flow relationship

I next analyze the shape of the performance-flow relationship. If prime brokers intermediate capital to hedge funds, then I expect that relative rank will drive inflows. If investors consult with prime brokers before divesting, or if investors benchmark funds relative to their prime broker peers, then relative rank will also predict fund outflows.

I build two sets of indicator variables: I first sort overall rank into nine quantiles, $OverallBin1_{i,t}$ to $OverallBin9_{i,t}$. I use nine quantiles for symmetry—one bin will be dropped from the estimation since it is collinear with the other bins. I then sort relative rank into nine quintiles, $RelativeBin1_{i,t}$ to $RelativeBin9_{i,t}$.

I next regress future fund flows on these bins. For each set of bins, I omit the median bin (5) so that all results are relative to the median bin. I estimate the following fixed-effects regression:

$$Flow_{i,t,t+12} = \boldsymbol{\beta_1'}\mathbf{OverallBin_{i,t}} + \boldsymbol{\beta_2'}\mathbf{RelativeBin_{i,t}} + \boldsymbol{\beta_3'}\mathbf{X_{i,t}} + a_i + a_t + a_p + a_s \times a_t + u_{itps} \quad (3)$$

where $OverallBin_{i,t}$ and $RelativeBin_{i,t}$ are vectors of nine indicator variables, each indicating whether fund i at time t is in the nth bin of overall and relative rank, respectively. The remainder of the variables and specification is identical to Eq. (2), and details are provided in the accompanying text.

The first column of Table 4 reports the standard performance-flow relationship; poor performance predicts outflows, and good performance predicts inflows. The second column of Table 4 introduces the vector of relative performance indicator variables. After the introduction of relative performance, overall performance continues to predict outflows, but no longer predicts inflows. However, relative rank appears to predict inflows: the top tercile (bins 7, 8, and 9) of relative performance rank report positive and significant coefficients.

[14] It is well known that hedge fund returns are not normally distributed (Lo, 2002; Goetzmann et al., 2002). In Section 6.7 I control for downside risk measures and the results hold.

[15] Liang et al. (2015) note that share restrictions are an important determinant of fund flows. Share restrictions are very persistent at the fund-level, and should be absorbed by fund fixed-effects. In Section 6.8 I include share restrictions and other fund-level characteristics and the results hold.

[16] I rank funds against all prime broker peers. This is done before I drop hedge funds with more than one prime broker. Thus the interquartile range is not exactly 0.50.

[17] The regression specification of the third column is

$$Flows_{i,t,t+12} = \beta_1 OverallRank_{i,t} + \beta_2 (RelativeRank_{i,t} - OverallRank_{i,t}) + \boldsymbol{\beta_3'}\mathbf{X_{i,t}} + a_i + a_t + a_p + a_s \times a_t + u_{itps}$$

This can be rearranged to show that the β_1 in column 2 (estimated from Eq. (2) should be equal to $\beta_1 - \beta_2$ in column 3, which it is (0.2248 = 0.3636-0.1388). All other coefficients should remain the same.

Table 3
Future fund flows regressed on overall and relative performance rank.
This table presents coefficients from the following fixed-effects regression: $Flows_{i,t,t+12} = \beta_1 OverallRank_{i,t} + \beta_2 RelativeRank_{i,t} + \boldsymbol{\beta_3' X_{i,t}} + a_i + a_t + a_p + a_s \times a_t + u_{itps}$. $Flows_{i,t,t+12}$ is the percentage fund flow of fund i from time t to $t+12$. $OverallRank_{i,t}$ is fund i's percentile performance rank at time t, measured using past 12-month returns, against all funds in the TASS database. $RelativeRank_{i,t}$ is fund i's percentile performance rank at time t, measured using past 12-month returns, relative to peer funds that share the same prime broker. Column 3 replaces $RelativeRank_{i,t}$ with $Relative - OverallRank_{i,t}$, which is the difference between relative and overall rank, or distance to the 45 degree line. $X_{i,t}$ are fund level controls, including the logarithm of assets under management, the logarithm of fund age in months, past fund flows, and past Sharpe ratio. a_i, a_t, a_p, and a_s are fund, time, prime broker, and style fixed effects respectively. I cluster standard errors at the fund, time, style, and prime broker levels.

	Flows(0,12)	Flows(0,12)	Flows(0,12)
ln(AUM)	−0.5540***	−0.5542***	−0.5542***
	(−12.23)	(−12.26)	(−12.26)
ln(Age)	−0.5343***	−0.5367***	−0.5367***
	(−5.57)	(−5.60)	(−5.60)
Flows(−12,0)	−0.0781***	−0.0781***	−0.0781***
	(−3.60)	(−3.60)	(−3.60)
Sharpe(−12,0)	0.1096*	0.1082*	0.1082*
	(2.08)	(2.06)	(2.06)
OverallRank	0.3496***	0.2248**	0.3636***
	(5.06)	(2.36)	(5.32)
RelativeRank		0.1388**	
		(2.50)	
Relative-OverallRank			0.1388**
			(2.50)
Observations	86,004	86,004	86,004
R^2	0.463	0.463	0.463
Adjusted R^2	0.431	0.431	0.431
FE	Yes	Yes	Yes
Cluster	Yes	Yes	Yes

t statistics in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

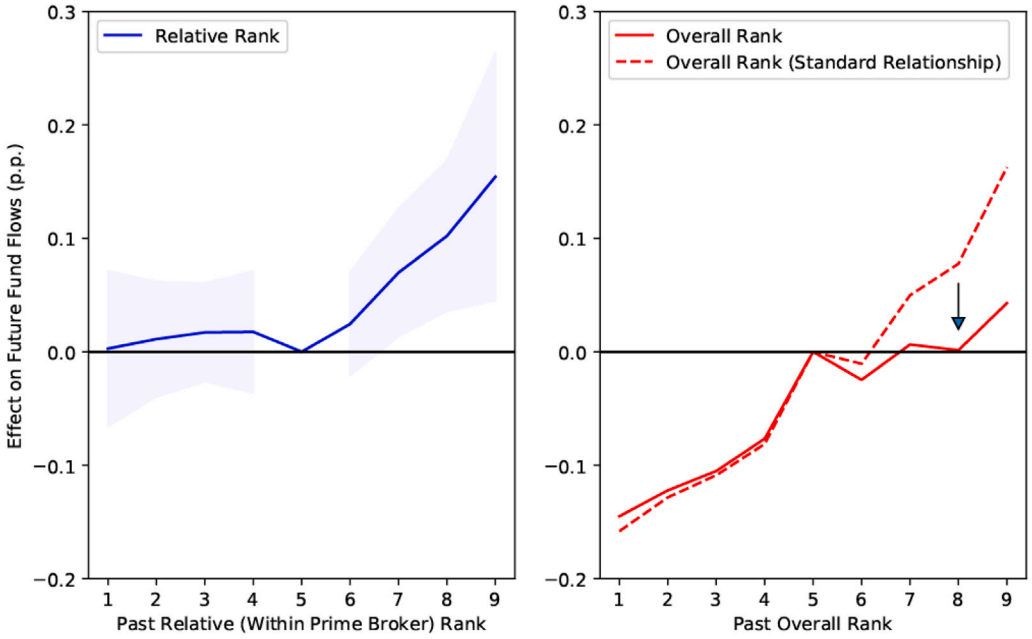

Fig. 2. The effect of relative performance rank effect on future fund flows
The plot on the left presents the effect of relative (within prime broker) rank on future fund flows. These are the coefficients from a regression of future fund flows on relative rank, controlling for overall rank (see column 2 in Table 4). The shaded area represents the 95% confidence intervals. In the plot on the right, the solid red line presents the effect of overall rank on future fund flows (controlling for relative rank). For comparison, the standard performance-flow relationship is plotted as the dashed red line (see column 1 of Table 4). The arrow highlights that the sensitivity of flows to overall good performance decreases after controlling for relative (within prime broker) performance. Both overall and relative rank are sorted into nine equally-sized groups, where group 1 contains the lowest performers and group 9 contains the highest performers. All coefficients are relative to the effect of the median group (5).

Additionally, relative rank does not appear related to fund outflows; the bottom and middle terciles have positive but insignificant coefficients. This implies the shape of the relative performance-flow relationship is flat at low and medium ranks, and increases in higher ranks. Since the median bin has been dropped, coefficients are interpreted relative to the median bin.

Fig. 2 illustrates the main finding of the paper: capital flows into top performers through the prime broker channel. The solid blue line in the left panel plots the relationship between within-broker relative rank and future fund flows. Funds in the top tercile of relative rank receive higher future flows, while there is no effect on flows for funds in the bottom or middle tercile. These results control for the effect of overall rank (the solid red line in the right panel). On the right panel, the dashed red line plots the coefficients on overall rank from the baseline regression in column 1 of Table 4. After including relative rank, the top tercile of overall rank is no longer related to future fund flows, suggesting that the prime broker channel is dominant for inflows. However, the bottom tercile of overall rank continues to predict future outflows, suggesting that prime brokers do not influence an investor's decision to exist a fund.

All else equal, if a fund were to move from the 25th percentile of relative rank ($RelativeBin3$) to the 75th percentile of relative rank ($RelativeBin7$), then it would expect to receive an additional 5.3 p.p. of fund flows over the next year. This is lower but roughly in line with the estimate of 7.1 p.p. from the previous regression on the linear variable $RelativeRank$. This is because the relationship between relative rank and future fund flows increases in rank. For instance, if a fund were to move from the 50th percentile of relative rank ($RelativeBin5$) to the 90th percentile of relative rank ($RelativeBin9$), then it would expect to receive an additional 15.4 p.p. of fund flows over the next year.

Taken together, the results suggest capital flows into top performers through the prime broker channel, and capital flows out of poor performers based on overall performance. That is, investors do not appear to benchmark poor performance against peer groups when making divestment decisions, nor do they consult with prime brokers when divesting.

4.3. Addressing multicollinearity

Multicollinearity is a key concern in this analysis because relative rank and overall rank are highly correlated (85.7%). This may induce a bias in the coefficient estimates and standard error calculations, leading to spurious inference. In this subsection I demonstrate that my results are not due to multicollinearity.

4.3.1. Placebo test with pseudo prime brokers

I first address multicollinearity by building a placebo relative rank variable. Placebo relative rank is highly correlated with overall rank (93.1%), but is unrelated to the prime broker channel for future flows. The placebo test maintains the potential multicollinearity problem but shuts down the prime broker channel. If my results are indeed spurious then placebo relative rank should also be related to future fund flows.

I use the same sample of funds as in the main analysis, and I assign hedge funds into 55 pseudo prime brokers. I use a squared uniform distribution to obtain a distribution of funds per prime broker that is roughly similar to the original sample. I then calculate a placebo relative rank using these randomly assigned pseudo prime brokers.

I conduct the placebo test for the performance-flow relationship by estimating the following fixed-effects regression:

$$Flows_{i,t,t+12} = \beta_1 OverallRank_{i,t} + \beta_2 Placebo.RelativeRank_{i,t} + \boldsymbol{\beta_3'}\mathbf{X_{i,t}} + a_i + a_t + a_p + a_s \times a_t + u_{itps} \quad (4)$$

where $Placebo.RelativeRank_{i,t}$ is the placebo relative rank for fund i at time t and the remaining variables are defined as in the paragraph following Eq. (2).

The results of this test are reported in Table 5. The coefficient on placebo relative rank is insignificant suggesting that multicollinearity does not drive my results.

4.3.2. Orthogonalized relative rank

I next explicitly remove the correlated component by orthogonalizing relative rank by overall rank. This is a simple projection of relative rank onto the space of overall rank. Orthogonalized relative rank is uncorrelated with overall rank by construction, yet will affect fund flows if capital is intermediated through prime brokers. This test is isomorphic to the main test in Section 4.1 and thus the coefficient on the uncorrelated orthogonalized relative rank should be the same as on the correlated relative rank in the main test. If the coefficients are not the same, then it indicates that the base results are driven by multicollinearity.

I construct the orthogonal component of relative rank, $Orthog.RelativeRank_{i,t}$, by estimating the following contemporaneous regression specification:

$$RelativeRank_{i,t} = \alpha + \beta OverallRank_{i,t} + Orthog.RelativeRank_{i,t} \quad (5)$$

where $RelativeRank_{i,t}$ and $OverallRank_{i,t}$ are the relative and overall performance ranks for fund i, respectively, α is a constant term, and $Orthog.RelativeRank_{i,t}$ is the error term (residual). Orthogonal relative rank is normally distributed with mean zero by construction.

I then study the relationship between orthogonal relative rank with future fund flows by estimating the following fixed-effects regression:

$$Flows_{i,t,t+12} = \beta_1 OverallRank_{i,t} + \beta_2 Orthog.RelativeRank_{i,t} + \boldsymbol{\beta_3'}\mathbf{X_{i,t}} + a_i + a_t + a_p + a_s \times a_t + u_{itps} \quad (6)$$

where $Orthog.RelativeRank_{i,t}$ is the orthogonal component of relative rank for fund i at time t, and the remaining variables are defined as in the paragraph following Eq. (2).

The results of this test are reported in column 1 of Table 6. The orthogonal component enters positively and significantly with a coefficient of 0.14. The coefficient is identical to the coefficient on relative rank in the baseline regression (Table 3), indicating that the results of the main test are not due to multicollinearity.

These results imply the exogenous variation created by the difference between within-broker relative rank and overall rank has an impact on future fund flows, consistent with the prime broker channel.

4.3.3. Holding overall rank constant

Multicollinearity may also affect the interpretation of the coefficients. For example, when examining the predicted change from an interquartile increase in relative rank, I hold overall rank constant. However, overall and relative rank are highly correlated. It might not be reasonable to assume that overall rank remains constant when investigating a large change in relative rank. I tackle this issue directly by studying the effect of relative rank while explicitly holding overall rank constant. To accomplish this I double-sort funds on overall and relative rank.

I sort funds into seven (7) bins based on overall rank, and sort funds into seven (7) bins based on relative rank. I then form 49 bins by taking the intersection of the two sets of bins.

I then estimate the following fixed-effects regression specification:

$$Flows_{i,t,t+12} = \boldsymbol{\beta'}\mathbf{DoubleSort_{i,t}} + \boldsymbol{\gamma'}\mathbf{X_{i,t}} + a_i + a_t + a_p + a_s \times a_t + u_{itps} \quad (7)$$

where $DoubleSort_{i,t}$ is a vector of 49 indicator variables capturing the overall bin and relative bin for fund i at time t. The remaining variables are defined as in the paragraph following Eq. (2).

Table 7 reports the results of this specification. Panel A reports estimates of the control variables, and Panel B reports estimates of the double-sort bins. $OverallBin1$ is the lowest overall rank bin, and $OverallBin7$ is the highest overall rank bin. Similarly, $RelativeBin1$ is the lowest relative rank bin, and $RelativeBin7$ is the highest relative rank bin. The results are normalized at the median bin ($OverallBin4$ and $RelativeBin4$), and coefficients are reported relative to this median bin. Panel B is also visually represented in a heatmap (Figure A1 in the

Table 4
The shape of the performance-flow relationship.
This table presents coefficients from the following fixed-effects regression: $Flows_{i,t,t+12} = \boldsymbol{\beta}_1'\mathbf{OverallBin_{i,t}} + \boldsymbol{\beta}_2'\mathbf{RelativeBin_{i,t}} + \boldsymbol{\beta}_3'\mathbf{X_{i,t}} + a_i + a_t + a_p + a_s \times a_t + u_{itps}$. $Flows_{i,t,t+12}$ is the percentage fund flow of fund i from time t to $t+12$. $OverallBin_{i,t}$ is the vector of indicator variables for fund i's binned performance rank, measured using past 12-month returns, measured against all funds in the TASS database. $RelativeBin_{i,t}$ is the vector of indicator variables for fund i's binned performance rank, measured using past 12-month returns, relative to peer funds that share the same prime broker. $X_{i,t}$ are fund level controls, including the logarithm of assets under management, the logarithm of fund age in months, past fund flows, and past Sharpe ratio. a_i, a_t, a_p, and a_s are fund, time, prime broker, and style fixed effects respectively. I cluster standard errors at the fund, time, style, and prime broker levels. Rank is divided into 9 bins, and normalized at bin 5. Column 3 limits the analysis to large prime brokers with more than 30 clients.

	Flows(0,12)		Flows(0,12)		Flows(0,12)	
ln(AUM)	−0.5537***	(−12.26)	−0.5540***	(−11.73)	−0.5488***	(−11.04)
ln(Age)	−0.5351***	(−5.62)	−0.5399***	(−5.67)	−0.5391***	(−5.23)
Flows(−12,0)	−0.0785***	(−3.56)	−0.0787***	(−3.48)	−0.0797***	(−3.65)
Sharpe(−12,0)	0.1152**	(2.26)	0.1097*	(2.16)	0.1441**	(2.65)
OverallBin1	−0.1581***	(−3.45)	−0.1450***	(−3.42)	−0.1524**	(−2.88)
OverallBin2	−0.1284**	(−2.72)	−0.1222**	(−2.66)	−0.1429**	(−2.27)
OverallBin3	−0.1088**	(−2.23)	−0.1051**	(−2.21)	−0.1138	(−1.74)
OverallBin4	−0.0813*	(−1.84)	−0.0766	(−1.76)	−0.0725	(−1.47)
OverallBin6	−0.0106	(−0.39)	−0.0248	(−0.92)	−0.0398	(−1.02)
OverallBin7	0.0498	(1.20)	0.0064	(0.15)	−0.0116	(−0.21)
OverallBin8	0.0776**	(2.39)	0.0014	(0.03)	−0.0376	(−0.80)
OverallBin9	0.1626***	(4.42)	0.0428	(0.63)	0.0092	(0.14)
RelativeBin1			0.0028	(0.09)	0.0219	(0.54)
RelativeBin2			0.0112	(0.48)	0.0275	(0.90)
RelativeBin3			0.0171	(0.86)	0.0318	(1.09)
RelativeBin4			0.0176	(0.72)	0.0282	(0.89)
RelativeBin6			0.0245	(1.17)	0.0342	(1.37)
RelativeBin7			0.0698**	(2.71)	0.0870**	(2.28)
RelativeBin8			0.1021***	(3.36)	0.1233***	(3.39)
RelativeBin9			0.1543***	(3.08)	0.1482**	(2.41)
Observations	86,004		86,004		71,571	
R^2	0.463		0.464		0.464	
Adjusted R^2	0.431		0.431		0.428	
FE	Yes		Yes		Yes	
Cluster	Yes		Yes		Yes	

t statistics in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5
Placebo test using randomly assigned prime broker peer groups.
This table presents coefficients from the following regression specification: $Flows_{i,t,t+12} = \beta_1 OverallRank_{i,t} + \beta_2 Placebo.RelativeRank_{i,t} + \boldsymbol{\beta}_3'\mathbf{X_{i,t}} + a_i + a_t + a_p + a_s \times a_t + u_{itps}$. $Flows_{i,t,t+12}$ is the percentage fund flow of fund i from time t to $t+12$. $OverallRank_{i,t}$ is fund i's percentile performance rank at time t, measured using past 12-month returns, against all funds in the TASS database. $Placebo.RelativeRank_{i,t}$ is fund i's percentile performance rank at time t, measured using past 12-month returns, relative to peer funds that share the same **pseudo** prime broker. $X_{i,t}$ are fund level controls, including the logarithm of assets under management, the logarithm of fund age in months, past fund flows, and past Sharpe ratio. a_i, a_t, a_p, and a_s are fund, time, pseudo prime broker, and style fixed effects respectively. I cluster standard errors at the fund, time, style, and pseudo prime broker levels.

	Flows(0,12)	Flows(0,12)
ln(AUM)	−0.5452***	−0.5452***
	(−12.03)	(−12.02)
ln(Age)	−0.5344***	−0.5342***
	(−5.09)	(−5.08)
Flows(−12,0)	−0.0753***	−0.0753***
	(−3.36)	(−3.36)
Sharpe(−12,0)	0.1208*	0.1227*
	(2.13)	(2.07)
OverallRank	0.3532***	0.3755***
	(4.60)	(3.94)
Placebo.RelativeRank		−0.0297
		(−0.27)
Observations	86,004	86,004
R^2	0.457	0.457
Adjusted R^2	0.424	0.424
FE	Yes	Yes
Cluster	Yes	Yes

t statistics in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6
Future flows regressed on orthogonalized relative rank.
This table presents coefficients from the following regression specification: $Flows_{i,t,t+12} = \beta_1 OverallRank_{i,t} + \beta_2' Orthog.RelativeRank_{i,t} + \boldsymbol{\beta_3'}\mathbf{X_{i,t}} + a_i + a_t + a_p + a_s \times a_t + u_{itps}$. $Flows_{i,t,t+12}$ is the percentage fund flow of fund i from time t to $t+12$. $OverallRank_{i,t}$ is fund i's percentile performance rank at time t, measured using past 12-month returns, against all funds in the TASS database. $Orthog.RelativeRank_{i,t}$ is the orthogonal component of $RelativeRank_{i,t}$ relative to $OverallRank_{i,t}$, and are the residuals from the regression presented in Column 1. $X_{i,t}$ are fund level controls, including the logarithm of assets under management, the logarithm of fund age in months, past fund flows, and past Sharpe ratio. a_i, a_t, a_p, and a_s are fund, time, prime broker, and style fixed effects respectively. I cluster standard errors at the fund, time, style, and prime broker levels.

	1st Stage	2nd Stage	
	RelativeRank	Flows(0,12)	Flows(0,12)
ln(AUM)		−0.5540***	−0.5542***
		(−12.23)	(−12.26)
ln(Age)		−0.5343***	−0.5367***
		(−5.57)	(−5.60)
Flows(−12,0)		−0.0781***	−0.0781***
		(−3.60)	(−3.60)
Sharpe(−12,0)		0.1096*	0.1082*
		(2.08)	(2.06)
OverallRank	0.8725***	0.3496***	0.3459***
	(883.92)	(5.06)	(4.95)
Orthog.RelativeRank			0.1388**
			(2.50)
Constant	0.0870***		
	(132.58)		
Observations	86,004	86,004	86,004
R^2	0.860	0.463	0.463
Adjusted R^2	0.860	0.431	0.431
FE	No	Yes	Yes
Cluster	No	Yes	Yes

t statistics in parentheses.
$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Internet Appendix). In the heatmap, red indicates positive values and blue indicates negative values; white corresponds to zero. In each cell, the coefficient and its significance level is noted on the top row, and the number of observations is noted in parentheses on the bottom row.

If the prime broker channel has no effect then, holding overall rank constant, relative rank should not impact flows. For the funds in bin $OverallBin6$, the subset of funds in bins $RelativeBin5$, $RelativeBin6$, and $RelativeBin7$ should all have similar coefficients. However, this is not the case. Instead, $RelativeBin5$ is not statistically different from zero, while the other two are positive and statistically significant. Generally, for a fixed overall rank, coefficients increase moving from low to high relative rank.

Additionally, if the prime broker channel does not matter, then only overall rank should determine flows. However, the results show that funds in the highest prime broker rank ($RelativeBin7$) tend to have higher flows than funds that rank higher overall. For example, funds that rank in the fifth highest overall bin ($OverallBin5$) but rank high in their prime broker set ($RelativeBin7$) have a statistically significant coefficient of 0.1759, whereas funds in the highest overall bin ($Overall7$) but are only in the fifth highest prime broker bin ($RelativeBin5$) have an insignificant coefficient of 0.0658. $RelativeBin7$ funds generally receive positive fund flows, regardless of overall rank.

Taken together, the three tests suggest that multicollinearity has not created spurious results in this analysis.

5. Alternative channels for capital flows

Does relative rank affect fund flows *other* than through the prime broker channel? In this section I address the most likely alternative channels, including other potential marketing channels and other ways investors source funds.

5.1. Other marketing channels

In the baseline regression I have controlled for the commercial database channel by including overall rank as a dependent variable, however, there are two other important channels for marketing hedge funds: (1) personal networks, and (2) third-party marketers. A potential concern is that high within-broker relative rank may also capture funds that are likely to receive capital through personal networks and third-party marketers. For this to be the case, there would need to be a high degree of overlap between the subset of funds at a particular prime broker and the subset of funds in the same marketer/personal network.

Personal networks are unobservable in my data, but it is unlikely that investors have personal networks that span the same set of hedge funds as prime broker networks. Thus, it is unlikely that within-broker relative rank will independently drive fund flows through personal networks.

The vast majority of hedge funds use one of the handful of bulge bracket prime brokers. In my analysis, prime brokers on average serve 166.2 clients. However, third-party marketers are much smaller operations; for the funds in my analysis, the average marketer has 3.0 clients. Thus, controlling for overall rank, within-broker relative rank is unlikely to be correlated with an increase in marketer effort.

To directly control for this, I use marketer data from Form ADV and investigate how this affects the prime broker channel. In Table 8 I add two variables called $HasMarketer$ and $LargeMarketer$ to the baseline regression specification. The first variable measures whether the fund's parent company reports using third-party marketers on Form ADV, and the second variable measures whether the company's largest marketer is in the top quartile of marketer size (by number of clients). In columns 2 and 4, the interaction of the marketer variables and relative rank is not statistically significant. However, the merge between TASS and ADV reduces the sample size to 18,254 fund-month observations, and thus I may lack sufficient statistical power. If I set the marketer

Table 7
Performance-flow relationship, double-sorted on overall and relative rank.
This table presents coefficients from the following fixed-effects regression: $Flows_{i,t,t+12} = \boldsymbol{\beta}'\mathbf{DoubleSort_{i,t}} + \boldsymbol{\gamma}'\mathbf{X_{i,t}} + a_i + a_t + a_p + a_s \times a_t + u_{i,t,p,s}$. $Flows_{i,t,t+12}$ are the percentage fund flows of fund i from time t to $t+12$. $DoubleSort_{i,t}$ is a vector of 49 indicator variables representing different levels of $OverallRank$ and $Relative$. Specifically, I group funds into 7 bins based on $OverallRank$, and group funds into 7 bins based on $RelativeRank$. I then form 49 bins by taking the intersection of these two sets of bins. Both rank variables are calculated using raw returns over the past twelve months. $X_{i,t}$ are fund level controls, including the logarithm of assets under management, the logarithm of fund age in months, past fund flows, and past Sharpe ratio. a_i, a_t, a_p, and a_s are fund, time, prime broker, and style fixed effects respectively. I cluster standard errors at the fund, time, style, and prime broker levels. Panel A reports the coefficients of the control variables, and Panel B reports the coefficients on the double-sorted bins.

Panel A: Control Variables

	Flows(0,12)
ln(AUM)	−0.5544***
	(−10.94)
ln(Age)	−0.5378***
	(−5.40)
Flows(−12,0)	−0.0784***
	(−3.11)
Sharpe(−12,0)	0.1143**
	(2.09)
Observations	86,004
R^2	0.464
Adjusted R^2	0.432
FE	Yes
Cluster	Yes

Panel B: Double Sort on Overall Rank and Relative Rank

	RelativeBin1	RelativeBin2	RelativeBin3	RelativeBin4	RelativeBin5	RelativeBin6	RelativeBin7
OverallBin1	−0.1225**	−0.1315**	−0.1474**	−0.0443	−0.0916	−0.0267	0.3438***
	(−2.54)	(−2.64)	(−2.29)	(−0.72)	(−1.20)	(−0.33)	(4.23)
OverallBin2	−0.0895	−0.1021*	−0.0774*	−0.0999	−0.0281	0.0281	0.1776*
	(−1.52)	(−1.98)	(−1.86)	(−1.64)	(−0.37)	(0.46)	(2.03)
OverallBin3	−0.1114	−0.0306	−0.0562*	−0.0684	−0.0334	−0.1660**	−0.2077*
	(−1.14)	(−0.56)	(−1.97)	(−1.05)	(−0.55)	(−2.39)	(−1.86)
OverallBin4	0.0604	−0.0624	0.0137	–	0.0243	0.1516**	0.5541***
	(0.56)	(−1.65)	(0.33)	–	(0.69)	(2.75)	(5.68)
OverallBin5	0.1826*	−0.0707	0.0150	.0256	0.0505	0.0588	0.1759***
	(2.10)	(−0.46)	(0.26)	(0.76)	(1.73)	(0.97)	(3.34)
OverallBin6	0.0000	−0.1192	−0.0973	0.0419	0.0278	0.1045**	0.1343***
	(0.00)	(−1.46)	(−1.11)	(0.78)	(0.72)	(2.62)	(3.70)
OverallBin7	0.0000	0.0000	−0.1211	−0.0984	0.0658	0.1405**	0.1867***
	(0.00)	(0.00)	(−0.82)	(−1.36)	(0.97)	(2.60)	(5.84)

t statistics in parentheses.
$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

variables equal to zero for all observations that I cannot match in ADV, then relative rank remains positive and statistically significant, and that the interaction terms of relative rank and the marketer variables are insignificant (see columns 6 and 8).

5.2. Alternative channels for investor search

It may also be possible that within-broker rank is correlated with other channels that investors use to search for funds.

5.2.1. Style rank

Style rank will be an important determinant of fund flows if investors have heterogeneous preferences among hedge fund styles. Furthermore, styles are broad categories each containing hundreds of hedge funds. If prime brokers tend to focus on certain styles, then within-broker relative rank may be correlated with within-style relative rank. That is, my relative rank measure might misattribute performance chasing within styles to intermediation through the prime broker channel.

However, this is not likely because the distribution of hedge fund styles does not significantly vary by prime broker (see Table A2 in the Internet Appendix). I also explicitly test the style channel by creating a variable called $StyleRank$, defined as a hedge fund's performance rank among all funds that share the same style. I then include style rank as an additional control in my baseline specification and report the results in columns 4 and 5 of Table 9. When controlling only for style rank (column 4), relative rank is positive and significant at the 1% level with a coefficient of 0.19, and when controlling for both style and overall rank (column 5), relative rank is positive and significant at the 1% level with a coefficient of 0.14.

5.2.2. Consultants and fund-of-funds

Many investors invest in hedge funds through investment consultants and/or fund-of-funds. Consultants are responsible for sourcing hedge funds for large clients, and my estimate of the prime broker channel may be biased. The consultant channel is unobservable, and I am unable to directly control for it. The fund-of-funds channel, however, works similarly to the consult channel and provides some evidence that the consultant bias might not work against me.

In contrast to consultants, aggregate fund-of-fund investments are observable in Form ADV. In Table 10 I add a variable called $PercentFoF$ to the baseline regression specification. This measures the percent of hedge fund clients at the parent company level that are fund-of-funds. In column 2, the interaction of fund-of-funds and relative rank is

Table 8
Third party marketers and prime broker intermediation.
This table presents coefficients from the following fixed-effects regression: $Flows_{i,t,t+12} = \beta_1 RelativeRank_{i,t} \times HasMarketer_{i,t} + \beta_2' \mathbf{X_{i,t}} + a_i + a_t + a_p + a_s \times a_t + u_{itps}$. $Flows_{i,t,t+12}$ is the percentage fund flow of fund i from time t to $t+12$. $RelativeRank_{i,t}$ is fund i's percentile performance rank at time t, measured using past 12-month returns, relative to peer funds that share the same prime broker. $HasMarketer_{i,t}$ is an indicator variable for whether fund i's management company employs third-party marketers at time t. $X_{i,t}$ are fund level controls, including the logarithm of assets under management, the logarithm of fund age in months, past fund flows, past Sharpe ratio, overall rank, and the marketer indicator variable. Columns 3 and 4 replaces the $HasMarketer$ variable with a large marketer variable, which indicates whether the fund's management company uses a marketer in the top quartile of marketer size (as measured by the number of clients). Columns 5 to 8 re-run the analysis assuming that if the marketer information is missing, the indicators are set to zero. a_i, a_t, a_p, and a_s are fund, time, prime broker, and style fixed effects respectively. I cluster standard errors at the fund, time, style, and prime broker levels.

	Flows(0,12)	Flows(0,12)	Flows(0,12)	Flows(0,12)	Flows(0,12)	Flows(0,12)	Flows(0,12)	Flows(0,12)
ln(AUM)	−0.5776***	−0.5779***	−0.5755***	−0.5759***	−0.5539***	−0.5538***	−0.5533***	−0.5532***
	(−5.07)	(−5.40)	(−5.33)	(−5.36)	(−12.26)	(−11.85)	(−11.83)	(−11.25)
ln(Age)	−0.6785**	−0.6798**	−0.6765**	−0.6805**	−0.5351***	−0.5363***	−0.5346***	−0.5341***
	(−2.93)	(−2.68)	(−2.88)	(−2.67)	(−5.51)	(−5.48)	(−5.43)	(−5.35)
Flows(−12,0)	−0.1185***	−0.1185***	−0.1185***	−0.1184***	−0.0781***	−0.0780***	−0.0779***	−0.0779**
	(−4.98)	(−3.52)	(−4.97)	(−3.76)	(−3.58)	(−3.37)	(−3.37)	(−2.72)
Sharpe(−12,0)	0.0581	0.0565	0.0619	0.0611	0.1083*	0.1069*	0.1104*	0.1085*
	(0.49)	(0.48)	(0.52)	(0.51)	(2.07)	(2.02)	(2.09)	(2.02)
OverallRank	0.2540	0.1356	0.2738*	0.2104	0.3393***	0.1921**	0.3409***	0.1970**
	(1.70)	(0.52)	(1.82)	(0.72)	(4.98)	(2.42)	(5.06)	(2.43)
HasMarketer	−0.0727	−0.0614			−0.1596	−0.0930		
	(−0.32)	(−0.26)			(−0.52)	(−0.34)		
OverallRank × HasMarketer	0.2798*	0.4801			0.4962	1.3124		
	(1.85)	(1.08)			(1.42)	(1.15)		
RelativeRank		0.1306		0.0695		0.1645***		0.1611***
		(0.67)		(0.33)		(3.93)		(3.27)
RelativeRank × HasMarketer		−0.2215				−0.9337		
		(−0.39)				(−0.96)		
LargeMarketer			0.1097	0.0941			−0.1245	−0.0140
			(0.25)	(0.22)			(−0.24)	(−0.03)
OverallRank × LargeMarketer			0.0466	−0.1532			0.5526	1.5622
			(0.13)	(−0.21)			(0.84)	(0.99)
RelativeRank × LargeMarketer				0.2265				−1.1987
				(0.37)				(−0.99)
Observations	18,254	18,254	18,254	18,254	86,004	86,004	86,004	86,004
R^2	0.507	0.508	0.507	0.507	0.463	0.464	0.463	0.464
Adjusted R^2	0.447	0.447	0.447	0.447	0.431	0.431	0.431	0.431
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 9
Performance flow relationship controlling for style rank.
This table presents coefficients from the following fixed-effects regression: $Flows_{i,t,t+12} = \beta_1 OverallRank_{i,t} + \beta_2 StyleRank_{i,t} + \beta_3 RelativeRank_{i,t} + \beta_4' \mathbf{X_{i,t}} + a_i + a_t + a_p + a_s \times a_t + u_{itps}$. $Flows_{i,t,t+12}$ is the percentage fund flow of fund i from time t to $t+12$. $OverallRank_{i,t}$ is fund i's percentile performance rank at time t, measured using past 12-month returns, against all funds in the TASS database. $StyleRank_{i,t}$ is fund i's percentile performance rank at time t, measured using past 12-month returns, relative to all funds in the same style. $RelativeRank_{i,t}$ is fund i's percentile performance rank at time t, measured using past 12-month returns, relative to peer funds that share the same prime broker. $X_{i,t}$ are fund level controls, including the logarithm of assets under management, the logarithm of fund age in months, past fund flows, and past Sharpe ratio. a_i, a_t, a_p, and a_s are fund, time, prime broker, and style fixed effects respectively. I cluster standard errors at the fund, time, style, and prime broker levels.

	Flows(0,12)	Flows(0,12)	Flows(0,12)	Flows(0,12)	Flows(0,12)
ln(AUM)	−0.5540***	−0.5542***	−0.5550***	−0.5548***	−0.5543***
	(−12.23)	(−12.34)	(−12.26)	(−12.26)	(−12.35)
ln(Age)	−0.5343***	−0.5348***	−0.5365***	−0.5387***	−0.5368***
	(−5.57)	(−5.54)	(−5.55)	(−5.63)	(−5.58)
Flows(−12,0)	−0.0781***	−0.0781***	−0.0780***	−0.0780***	−0.0781***
	(−3.60)	(−3.60)	(−3.62)	(−3.61)	(−3.60)
Sharpe(−12,0)	0.1096*	0.1073*	0.1171*	0.1133*	0.1074*
	(2.08)	(2.04)	(2.17)	(2.12)	(2.04)
OverallRank	0.3496***	0.2905			0.2059
	(5.06)	(1.26)			(0.87)
StyleRank		0.0633	0.3352***	0.1671**	0.0236
		(0.31)	(6.51)	(2.99)	(0.12)
RelativeRank				0.1913***	0.1353***
				(3.11)	(3.34)
Observations	86004	86004	86004	86004	86004
R^2	0.463	0.463	0.463	0.463	0.463
Adjusted R^2	0.431	0.431	0.430	0.431	0.431
FE	Yes	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 10
Fund-of-funds and prime broker intermediation.
This table presents coefficients from the following fixed-effects regression: $Flows_{i,t,t+12} = \beta_1 RelativeRank_{i,t} \times PercentFoF_{i,t} + \beta_2' \mathbf{X_{i,t}} + a_i + a_t + a_p + a_s \times a_t + u_{itps}$. $Flows_{i,t,t+12}$ is the percentage fund flow of fund i from time t to $t+12$. $RelativeRank_{i,t}$ is fund i's percentile performance rank at time t, measured using past 12-month returns, relative to peer funds that share the same prime broker. $PercentFoF_{i,t}$ measures the percent of fund-of-fund clients (among all hedge funds clients) of fund i's management company at time t. $X_{i,t}$ are fund level controls, including the logarithm of assets under management, the logarithm of fund age in months, past fund flows, past Sharpe ratio, overall rank, and the percent of fund-of-fund clients. Columns 3 and 4 re-runs the analysis assuming that $PercentFoF$ is set to zero if the fund-of-fund client information is missing. a_i, a_t, a_p, and a_s are fund, time, prime broker, and style fixed effects respectively. I cluster standard errors at the fund, time, style, and prime broker levels.

	Flows(0,12)	Flows(0,12)	Flows(0,12)	Flows(0,12)
ln(AUM)	−0.6566***	−0.6568***	−0.5542***	−0.5546***
	(−3.66)	(−3.67)	(−12.25)	(−12.25)
ln(Age)	−0.7466***	−0.7505***	−0.5355***	−0.5375***
	(−4.09)	(−4.05)	(−5.65)	(−5.68)
Flows(−12,0)	−0.1448***	−0.1448***	−0.0782***	−0.0782***
	(−6.30)	(−4.31)	(−3.58)	(−3.58)
Sharpe(−12,0)	0.1589	0.1562	0.1094*	0.1081*
	(1.66)	(1.54)	(2.09)	(2.07)
OverallRank	0.1556	0.0988	0.3479***	0.2082*
	(0.97)	(0.52)	(5.01)	(2.18)
PercentFoF	−0.0189**	−0.0191**	−0.0114**	−0.0107**
	(−3.09)	(−2.88)	(−3.04)	(−2.61)
OverallRank × PercentFoF	0.0024	−0.0006	0.0016	0.0141***
	(0.32)	(−0.05)	(0.68)	(3.55)
RelativeRank		0.0619		0.1559**
		(0.41)		(2.86)
RelativeRank × PercentFoF		0.0033		−0.0138*
		(0.22)		(−2.07)
Observations	11,565	11,565	86,004	86,004
R^2	0.527	0.527	0.463	0.463
Adjusted R^2	0.448	0.447	0.431	0.431
FE	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes

t statistics in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

not statistically significant, suggesting that fund-of-funds are not more or less likely to rely on the prime broker channel to source funds. However, the merge between TASS and ADV reduces the sample size to 11,565 fund-month observations, and thus this test may lack sufficient statistical power. If I assume that $PercentFoF = 0$ for all observations without client data, then relative rank remains positive and statistically significant and the interaction term of relative rank and $PercentFoF$ is negative and significant, suggesting that fund-of-funds are *less* likely to go through the prime broker channel compared with other investors.

In a recent survey of institutional investors conducted by the Capital Introduction Group at J.P. Morgan, about 10% of respondents were consultants (20% on an AUM basis) and 32% were fund-of-funds (35% on an AUM basis) (Tocco, 2016). Both consultants and fund-of-funds help pool capital from investors and direct this money to hedge funds. If consultants, like fund-of-funds, are less likely to rely on the prime broker channel, then both groups will bias downwards the effect of the prime broker channel documented in the baseline analysis in Table 3.

5.2.3. The JOBS act

The Jumpstart Our Business Startups Act of 2012 (the "JOBS Act") allows private funds, including hedge funds, to advertise directly to the public. This has the potential to greatly change the economics of fund raising. For example, the role of the prime broker may reduce significantly after the JOBS Act as hedge funds can now directly interact with potential investors.

In Table 11 I include an indicator variable called $JOBS$ which is equal to one in each month after April 2012 (when the JOBS Act was signed into law) and is equal to zero before hand. This variable is collinear with the time fixed effects, but here I am interested in the interaction of the JOBS Act with the prime broker channel. After controlling for the JOBS Act, relative rank continues to be positive and statistically significant. The change in the effect of the prime broker channel after the JOBS Act (as captured by the interaction term of relative rank and JOBS) is small, negative, and insignificant.

Columns three and four break up the post-JOBS Act period into an early period (April 2012 to June 2013) and a later period (July 2013 onward). Relative rank continues to be positive and statistically significant, but I find some evidence that the JOBS Act may have mitigated the importance of prime brokers. The coefficient on the interaction of relative rank with the late JOBS Act period is negative and large, and on the same order of magnitude as the coefficient on relative rank, however this estimate is noisy and is not statistically significant.

Taken together, this analysis suggests that the JOBS Act has had a limited effect on the role prime brokers play in intermediating capital to hedge funds, however, it will be fruitful in future research to further explore how this relationship has changed over time.

6. Measurement issues

These next set of robustness tests address measurement concerns regarding the independent and dependent variables.

6.1. Heteroegenous performance-flow sensitivity

Spiegel and Zhang (2013) note that when the sensitivity of flows to past performance is heterogeneous across funds, pooled analysis can yield false estimates of the performance-flow relationship. They note that changes in market share (instead of percentage fund flows) can serve as an alternative measure of flows that is more resilient to heterogeneity

Table 11
The JOBS act and prime broker intermediation.
This table presents coefficients from the following fixed-effects regression: $Flows_{i,t,t+12} = \beta_1 RelativeRank_{i,t} \times JOBS_t + \beta_2' \mathbf{X_{i,t}} + a_i + a_t + a_p + a_s \times a_t + u_{itps}$. $Flows_{i,t,t+12}$ is the percentage fund flow of fund i from time t to $t+12$. $RelativeRank_{i,t}$ is fund i's percentile performance rank at time t, measured using past 12-month returns, relative to peer funds that share the same prime broker. $JOBS_t$ is an indicator variable for whether the current time t is after April 2012, the month the JOBS Act was signed into law. In columns three and four I divide the JOBS Act indicator into an early period (between April 2012 and June 2013, $JOBSEarly$), and a late period (July 2013 onward, $JOBSLate$). $X_{i,t}$ are fund level controls, including the logarithm of assets under management, the logarithm of fund age in months, past fund flows, past Sharpe ratio, overall rank, and the interaction of overall rank and the JOBS Act indicator. a_i, a_t, a_p, and a_s are fund, time, prime broker, and style fixed effects respectively. I cluster standard errors at the fund, time, style, and prime broker levels.

	Flows(0,12)	Flows(0,12)	Flows(0,12)	Flows(0,12)
ln(AUM)	−0.5554***	−0.5556***	−0.5550***	−0.5554***
	(−11.92)	(−11.14)	(−11.06)	(−10.65)
ln(Age)	−0.5344***	−0.5367***	−0.5345***	−0.5370***
	(−5.56)	(−5.55)	(−5.30)	(−5.14)
Flows(−12,0)	−0.0778***	−0.0779***	−0.0777**	−0.0775**
	(−3.24)	(−3.23)	(−2.38)	(−2.58)
Sharpe(−12,0)	0.1058*	0.1044*	0.1055*	0.1041
	(1.97)	(1.88)	(1.97)	(1.73)
OverallRank	0.3175***	0.1903**	0.3184***	0.1886*
	(5.60)	(2.54)	(4.91)	(1.87)
JOBS × OverallRank	0.1766	0.1816		
	(1.68)	(1.06)		
RelativeRank		0.1413*		0.1442*
		(2.14)		(2.04)
JOBS × RelativeRank		−0.0050		
		(−0.05)		
JOBSEarly × OverallRank			0.2336*	0.0824
			(2.04)	(0.35)
JOBSLate × OverallRank			0.1077	0.2410
			(1.03)	(1.12)
JOBSEarly × RelativeRank				0.1679
				(0.87)
JOBSLate × RelativeRank				−0.1530
				(−0.88)
Observations	86,004	86,004	86,004	86,004
R^2	0.463	0.463	0.463	0.463
Adjusted R^2	0.431	0.431	0.431	0.431
FE	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes

t statistics in parentheses.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

As a robustness check, I rerun the main analysis using changes in market share as the dependent variable instead of percent fund flow (columns 1 and 2 of Table A3 in the Internet Appendix). The results generally hold: relative rank is positively related to future changes in market share.

6.2. Large prime brokers

A granularity problem may arise when comparing relative rankings between hedge funds at small prime brokers with those at large prime brokers. For example, if one prime broker has 10 clients, and another has 100 clients, then each prime broker's fifth best client is at the 50th percentile for the first prime broker, and at the 95th percentile for the second. To control for this, I restrict the analysis to prime brokers that have at least 30 clients and the results hold (see Column 3 of Table 4).

6.3. Returning investors

It is unclear whether the prime broker channel documented here reflects new introductions or new flows from old introductions. It is likely that investors rely on the prime broker channel for their initial investment, but not for subsequent investment decisions. This is supported by Fig. 2 which demonstrates that the prime broker channel matters for inflows, but not for outflows. When investors choose to leave an investment, the prime broker channel does not appear to play an important role.

To investigate whether the same is true for returning investors, I estimate flows due to the prime broker channel and study how these affect future flows and the future volatility of flows. The first set of tests capture the subsequent flows that occur after the initial capital introduction, and the second set of tests capture whether the investors are loyal. The results are presented in Table A4 in the Internet Appendix. The first three columns use flows predicted from Eq. (2) to estimate future fund flows at the 0 to 12 month, 12 to 24 month, and 24 to 36 month horizons. Here I do not find evidence that prime broker related flows are correlated with subsequent capital flows. The coefficients are insignificant, and the signs are also inconsistent. In columns 4–6 I repeat the analysis looking at the future volatility of fund flows. Here the coefficients are again insignificant and inconsistent. Taken together, I do not find evidence that prime broker related flows are linked to future fund flows, or to the volatility of future flows.

6.4. Delisted funds

Delisted funds will introduce extinction bias if the probability of delisting is related to a fund's relative rank (controlling for overall rank). This is because my analysis predicts fund flows, and if high/low relative rank funds are more likely to delist, then they are more likely

to have missing flow data. To test whether extinction bias has had a significant impact on my results I predict delisting using the baseline regression specification reported in Table 3. The results are presented in columns 3 and 4 of Table A3 in the Internet Appendix. Here relative rank has no relationship with the future probability of delisting. In contrast, overall rank has a strong negative relationship. My proxy for the prime broker channel is unrelated to future delisting, and thus I do not find evidence that delisting has introduced an extinction bias.

6.5. Multiple prime brokers

My analysis considers only hedge funds with one prime broker, which I do to ensure that the relative rank variable refers to a consistent prime broker across time. However funds with multiple prime brokers tend to be very different; they tend to be larger (about 70.3% larger) and more sophisticated (about 88 basis points higher alpha per year). These funds may not necessarily rely on the prime broker as much as smaller funds.

In this subsection I reintroduce funds with multiple prime brokers. To do this, I calculate a fund's relative rank at each of its prime brokers, and then take its maximum relative rank across all prime broker peer groups. This captures the idea that the prime broker channel effect is likely to be strongest when the fund is highest ranked. The results are presented in columns 5 and 6 of Table A3 in the Internet Appendix. The coefficient on relative rank, compared to the baseline specification in Table 3, has increased and become more statistically significant. That is, by adding these potentially larger and more sophisticated funds, the value of the prime broker channel increases.

6.6. Data revision

For each fund-month observation, I use its earliest reported record across my 12 snapshots. This was done to control for data reliability issues, and also to control for the information that actual investors have when making decisions. However, the revisions might better capture real fund flows over time, for example, if the initial return or AUM figures were incorrect.

To address this, I replace the dependent variable in the baseline regression specification (see Table 3) with $RevisedFlow$, which is calculated using data in the most recent snapshot. The independent variables are calculated using data that is observable to the investors at time t, while the dependent variable uses the potentially more accurate revised data. Columns 7 and 8 of Table A3 in the Internet Appendix reports the results of this test. The coefficient on relative rank increases compared to the baseline and becomes more statistically significant. The number of observations decreases from 86,004 to 79,715 because some funds are removed entirely from later snapshots.

6.7. Downside risk

Hedge fund returns are not normally distributed (Lo, 2002; Goetzmann et al., 2002), and investors may take this into account when making investment decisions. This may effect my results if the non-normality is related to a hedge fund's relative rank.

To address this, I include the Sortino ratio and semivariance of past 12-month hedge fund returns into the baseline regression specification, and I report the results in Table A5 in the Internet Appendix. The Sortino ratio is negative and insignificant, and the semivariance measure is negative and significant. This provides some evidence that, in addition to performance and Sharpe ratios, down-side risk also factors into investor decisions. Controlling for either measure of downside risk, relative rank remains positive and statistically significant.

6.8. Share restrictions and fund-level characteristics

Liang et al. (2015) note that share restrictions are an important determinant of fund flows. I have not controlled for share restrictions and fund-level characteristics directly because these are persistent variables that change exceedingly infrequently over the life of a fund, and thus, the effect will be largely absorbed by the fund fixed-effects.

In this section I extend the baseline regression to include share restrictions and other fund level persistent variables. These results are reported in Table A6 in the Internet Appendix. In the first two columns, I add the lockup period in days and the restriction period (the sum of the redemption frequency and notice period) in days. The effect of relative rank remains positive and significant. In columns 3 and 4, I introduce additional fund-level controls, including whether the fund accepts managed accounts, the management fee, the incentive fee, and whether it has a high-water mark. The coefficient on relative rank remains positive and significant.

7. Conclusion

This paper studies how capital flows to arbitrageurs. I provide evidence that prime brokers intermediate a meaningful amount of capital between investors and hedge funds. A fund's relative performance, relative to peer funds that share the same prime broker, explains about 40% of the standard performance-flow relationship. Furthermore, investigating the shape of this relationship reveals that the prime broker channel disproportionately drives fund in-flows but not fund out-flows.

My results matter because hedge funds play an important role in financial markets. They actively produce information, aid in the price discovery process, and help improve market efficiency (see Kokkonen and Suominen, 2015; Cao et al., 2018a,b; Chen et al., 2019 and Chen et al., 2020). Hedge funds require capital to engage in arbitrage activity, and my results demonstrate that the prime broker channel is fundamental for the flow of capital to arbitrageurs.

CRediT authorship contribution statement

Andrew J. Sinclair: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Roles/Writing – original draft, Writing – review & editing.

Data availability

The authors do not have permission to share data.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jfi.2022.101004.

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