

Intermediary Asset Pricing Through the Lens of a Demand System ^{*}

Dongryeol Lee[†]

Thu N.M. Nguyen[‡]

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Abstract

How does broker-dealers' leverage shift asset prices when their assets under management are relatively small? We explore the channel through which broker-dealers extend leverage to hedge funds using an asset demand system. During recessions, broker-dealers face binding leverage constraints and reduce their borrowing to hedge funds. Then, hedge funds are forced to sell assets and deleverage, creating demand pressures that shift asset prices. We find that hedge funds exert the largest price impact across all stocks among institutions, and their price impact increases substantially during crises as they need to deleverage. On average, a 1% increase in broker-dealers' leverage raises the price impact of the average hedge fund by 2% in the following year. These impacts are more pronounced among illiquid stocks. Our findings suggest that hedge funds significantly influence stock prices when broker-dealers' leverage constraints are binding.

Keywords: Intermediary Asset Pricing, Demand System, Broker-Dealers, Hedge Funds.

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[†]UCLA Anderson School of Management, Email: dongryeol.lee.phd@anderson.ucla.edu

[‡]Amsterdam Business School, University of Amsterdam, Email: n.m.t.nguyen@uva.nl

1 Introduction

Since the 2008 Global Financial Crisis (GFC), there has been a growing interest in the roles of financial intermediaries in financial markets. The Intermediary Asset Pricing literature shows that the financial health of intermediaries, typically proxied by broker-dealers' leverage, is crucial for understanding risk premia (e.g., [He and Krishnamurthy, 2013](#); [Adrian, Etula, and Muir, 2014](#); [He, Kelly, and Manela, 2017](#); [Haddad and Muir, 2021](#)).

However, broker-dealers represent a small portion of the stock market, with their holdings accounting for less than 2%. So, how can broker-dealers' leverage affect asset pricing when their assets under management are so small? We explore this question through the channel in which broker-dealers extend leverage to hedge funds. Hedge funds rely on broker-dealers to provide financing and facilitate trades through prime brokerage services. During recessions, broker-dealers face binding leverage constraints and reduce borrowing to hedge funds. Then, hedge funds are forced to sell assets, creating short-term demand pressures that shift asset prices. Thus, broker-dealers' (BD) leverage could impact financial markets through its effects on hedge funds.

We test this mechanism using stock-level 13F holding data from 2000:Q1 to 2023:Q3. We start by documenting that brokers-dealers reduce their lending to hedge funds when their leverage increases. A 1% increase in broker-dealer leverage is associated with a 4% decline in hedge fund leverage, measured as borrowing from prime brokers relative to net assets. As hedge funds' funding conditions tighten, they reduce their holdings, which implies they are forced to sell their assets and deleverage.

To examine how hedge funds' deleveraging impacts stock markets, we use the demand system of asset pricing ([Kojien and Yogo, 2019](#)). We find that hedge funds exert the largest price impact across all stocks among institutions, and their price impact increases substantially during crises. A 10% demand shock to hedge funds shifts stock prices by an average of 0.2% across all stocks, with the effect increasing to 0.3% during the 2008 financial crisis. In contrast, broker-dealers exhibit negligible price impact, suggesting their more inelastic demand and role as liquidity providers rather than price movers. Moreover, other institutional investors, aside from hedge funds and broker-dealers, also show smaller price impacts than hedge funds. Given that these institutions collectively hold more than 60% of the stock market, our results highlight the pivotal role hedge funds play in the stock market.

Finally, we find that higher broker-dealer leverage predicts greater price impacts. A 1% increase in BD leverage raises the price impact of hedge funds by 2% in the following year, a magnitude

comparable to that of all other institutions combined. Notably, when measuring price impact per million dollars of holdings, a 1% increase in BD leverage corresponds to a 23.8% price impact for hedge funds, compared to just 0.5% for other institutions. This finding further validates our claim that BD leverage influences the stock market through hedge funds.

This paper provides several insights into the role of broker-dealer leverage in shaping asset prices through hedge funds' holdings. While existing research has emphasized the importance of intermediaries in determining risk premia, this study highlights the channel through which broker-dealers can influence stock prices, even when their assets under management are relatively small. Specifically, we show that broker-dealers' leverage constraints during downturns amplify hedge funds' price impact, as hedge funds are forced to sell assets in response to tightened leverage conditions of broker-dealers. By quantifying the price impact of hedge fund demand shocks and linking these shocks to broker-dealer leverage, the paper provides empirical evidence that connects financial intermediary health to cross-sectional variations in stock returns.

Related literature. Our paper contributes to three strands of literature. First, the Intermediary Asset Pricing literature emphasizes the importance of intermediaries' financial health in understanding asset prices and risk premia. For example, [He and Krishnamurthy \(2013, 2018\)](#) show that when intermediaries face tighter leverage constraints, their ability to provide liquidity to the market decreases, leading to higher risk premia. [Brunnermeier and Pedersen \(2009\)](#) show that margin constraints on intermediaries lead to a feedback loop between asset prices and market liquidity, magnifying price fluctuations during periods of stress. However, little is known about what type of intermediaries influence asset prices, since institutional investors are heterogeneous. Our paper looks at broker-dealers, hedge funds, and other types of institutions.

Broker-dealers' leverage or capital constraint is typically proxied for the intermediaries' financial health. [Adrian, Etula, and Muir \(2014\)](#) find that the leverage of security broker-dealers reflects the tightness of their funding constraints. Shocks to the leverage construct an intermediary SDF as these shocks are priced in the cross-section of asset returns. [He, Kelly, and Manela \(2017\)](#) show that the capital constraints of primary dealers construct a priced risk factor. Besides, [Kargar \(2021\)](#) find that the wealth share of broker-dealers predicts stock market excess returns and shocks to the relative wealth share of broker-dealers explain the cross-section of stock returns. Alternatively, our paper highlights the link of leverage constraints and asset pricing through via the channel of hedge funds' demand for assets. Particularly, the leverage constraint influences hedge funds' price impact during economic downturns.

Besides, our findings are consistent with [Haddad and Muir \(2021\)](#) that intermediaries' financial

constraints have a more pronounced impact on asset classes where households are less active. Stocks are an important asset class, with institutions holding of at least 70% of total assets under management, while households own less than 30% by the end of 2020.

Second, the literature has documented the relationship between hedge funds and broker-dealers. Hedge funds, as large institutional investors, often rely on broker-dealers to provide financing and facilitate trades through prime brokerage services. Broker-dealers, in turn, use their balance sheets to extend leverage to hedge funds, making this relationship crucial for market liquidity.

[Adrian and Shin \(2010\)](#) show that during periods of financial stress, when broker-dealers reduce their leverage due to capital constraints, hedge funds are forced to deleverage, exacerbating market volatility. Our paper adds to the evidence of this relationship by looking at their demand for assets and price impacts. While existing research tends to focus on the systemic risks of leverage during crises, our study quantifies how broker-dealer leverage constraints affect hedge funds' price impact on stocks and cross-sectional asset pricing.

Also, studies focusing on hedge funds reinforce our findings. For example, [Boyson, Stahel, and Stulz \(2010\)](#) show that large adverse shocks to liquidity, such as poor dealer stock performance, increase the likelihood of contagion (clustering of extreme negative returns) across hedge funds. Similarly, [Ben-David, Franzoni, and Moussawi \(2012\)](#) demonstrates that hedge fund flows and leverage-driven trades can create price pressures. Using the demand system, we estimate the price impact of hedge funds on stocks. We find that higher leverage of broker-dealers predicts higher price impact of hedge funds on stocks.

Third, our paper contributes to understanding the role of institutional investors' demand on asset pricing. The demand-based approach to asset pricing introduced by [Kojen and Yogo \(2019\)](#) allow a more granular understanding of how different types of institutional investors nad household affect prices based on their portfolio choices. Our paper focuses on the interaction between broker-dealers and hedge funds. By showing that hedge funds, rather than broker-dealers, exert the largest price impact due to their higher demand elasticity, and that this impact is magnified during periods of financial stress when broker-dealer leverage is constrained, our findings provides insights into how institutional investors through their balance sheet constraints can affect asset pricing.

The remainder of the paper is organized as follows. [Section 2](#) explains how we construct the data and main variables. [Section 3](#) shows evidence on the channel that broker-dealers extend leverage to hedge funds. [Section 4](#) explores the impact of this channel on the stock market using the demand system of asset pricing. Finally, [Section 5](#) concludes.

2 Data Construction

2.1 Institutional Holdings and Stock Characteristics

We obtain the direct stock holdings of institutional investors from FactSet, sourced from regulatory 13F filings. Asset managers who own 13F securities of more than \$100 million in market value must report their long positions on the Securities and Exchange Commission Form 13F. In each quarter, the holding for each stock held by each institution equals shares multiplied by price. The assets under management (AUM) of each institution are then the sum of all holdings within each quarter. We follow [Koijen and Yogo \(2019\)](#) to assign zero holding when a stock from the previous 11 quarters is no longer in the portfolio since the investment universe of the median investor is persistent over 11 quarters.

We match the information on stocks from the Center for Research in Security Prices (CRSP) and Compustat. Our data set contains NYSE/AMEX/NASDAQ stocks with common share codes 10, 11, 12, or 18. Stock returns and shares outstanding come from CRSP Monthly Stock File. Accounting data are from CRSP/Compustat Merged Fundamentals Annual and Quarterly. We compute market equity as the price times shares outstanding. Since the holdings data are on a quarterly basis, we compound the returns over the quarter and keep other characteristics at quarter-end.

2.2 Investor Classification

We classify investors into three groups: Broker-dealers, hedge funds, and other types of institutions, using FactSet’s classification of investor types. The market clearing condition requires the shares outstanding of each stock to equal the total shares held by all investors in that stock. Hence, we assign the residual between shares outstanding and the total shares held by 13F investors to the holdings of households (i.e. individual investors). Any small investors who own less than \$10 million in AUM are also considered as households since small investors are not required to file Form 13F.¹ In case that the total holdings across investors for a stock exceed its market value, we scale the holdings of each investor proportionally, so that all holdings add up to the market value, following [Koijen and Yogo \(2019\)](#).

[Figure 1](#) shows the share of total AUM for broker-dealers and hedge funds. The main observation is that AUM share of broker-dealers has remained relatively small and stable throughout the period. Starting at around 1% in 2000, broker-dealers maintained a consistent share of AUM,

¹All small investors under this filter own a negligible fraction of the total market cap so they do not affect the findings if we include some of them as institutions.

with slight fluctuations, but overall their holdings do not exceed 2% of the total AUM. Even during periods of downturns, such as the 2008 GFC, broker-dealers' AUM share showed only a modest increase, implying their limited role as asset holders.

In contrast, the AUM share of hedge funds starts at a modest level of approximately 2% in 2000 but grows significantly over the next two decades. Hedge funds' share spikes around the 2008 financial crisis, reflecting their ability to accumulate assets during times of market volatility and stress. At their peak in the mid-2010s, hedge funds held over 6% of total AUM, a much larger share than broker-dealers. After reaching their peak, hedge funds' AUM share gradually declined, settling around 4-5% by 2023.

Table 1 reports the summary of holdings by each investor group over five periods from 2000 to 2023. In Panel A, which aggregates all institutions, the number of institutions and their percentage of market share steadily increases from 2,010 institutions holding 58.60% of the total AUM between 2000-2004, to a peak of 4,287 institutions holding 73.21% of the market between 2015-2019. However, the trend slightly reverses in the most recent period (2020-2023), with 5,444 institutions holding a reduced 66.24% market share. This shift indicates that while the number of institutions continues to grow, the average market share per institution has diminished slightly.

Specifically for hedge funds in Panel B, their influence on the market has also grown steadily. The percentage of market held by hedge funds increases from 1.30% in the early 2000s (2000-2004) to 4.25% by 2015-2019, before declining to 2.88% in the most recent period. This decline in market share in the latest period contrasts with their median and 90th percentile AUM figures, which show relatively high asset concentration. Hedge funds' 90th percentile AUM, for instance, rises to 2,932 million between 2015-2019 before slightly declining to 2,585 million by 2020-2023. These figures suggest the concentration of assets within a few major players.

In Panel C, broker-dealers maintain a relatively small but concentrated presence in the market. Despite only holding a small percentage of the market (from approximately 0.80% to 1.93% over the periods), the broker-dealers in the 90th percentile consistently manage large amounts of assets, with 46,858 million in AUM for the top 10% in the 2020-2023 period. This concentration highlights the role of large broker-dealers in managing significant amounts of capital despite their relatively small numbers in the market.

2.3 Broker-Dealers' Leverage

We follow [Adrian, Etula, and Muir \(2014\)](#) to use the leverage ratio measured by assets relative to the equity of all security broker-dealers, denoted as BD leverage:

$$lev_t^{BD} = \frac{\text{Total financial assets}_t^{BD}}{\text{Total financial assets}_t^{BD} - \text{Total liability}_t^{BD}} \quad (1)$$

where the total financial assets and the total liability of security broker-dealers are from the U.S. Flow of Funds. The leverage factor is then given by the seasonally adjusted log the leverage

$$levfac_t = [\Delta \ln(lev_t^{BD})]^{SA}. \quad (2)$$

We replicate the leverage factor to obtain the values up to 2023:Q3. The data for total assets and total liability are available on the FRED (respectively the series BOGZ1FL664090005Q and BOGZ1FL664190005Q).

3 Broker-Dealers Extending Leverage to Hedge Funds

In this section, we show evidence that broker-dealers extend leverage to hedge funds. [Figure 2](#) plots the time series of broker-dealers' leverage (BD Leverage) and hedge fund borrowing from prime brokers. The figure suggests hedge fund reduces their borrowing from prime brokers once BD leverage increases. This implies that broker-dealers do not extend leverage to hedge funds once their funding conditions tighten.

To further examine how hedge funds reduce their borrowing from broker-dealers, we regress their leverage on BD leverage. We first compute hedge funds' leverage as the ratio of their borrowing from prime brokers to net assets (*Net Leverage*) or net equity holdings (*Net Equity Leverage*). [Table 2](#) documents the results. The table suggests a 1% increase in BD leverage is associated with approximately 4% decline in hedge funds' leverage. This implies that broker-dealers reduce their borrowing substantially to hedge funds when they face leverage constraints.

Given that broker-dealers reduce their lending to hedge funds once their funding conditions tighten, we test whether hedge funds liquidate their positions in the stock market as they cannot borrow from broker-dealers. [Table 3](#) regresses hedge funds' holdings in the stock market on BD leverage. The table shows hedge funds reduce their stock holdings as BD leverage increases. Column (1) suggests a 1% increase in BD leverage is associated with \$34 billion decrease in hedge funds' stock holdings. We also examine their share of holdings to evaluate whether their reductions

exceed those of other investors. Column (2) confirms this result, showing that a 1% increase in BD leverage corresponds to a 5% decrease in hedge funds' stock holdings. This implies hedge funds actively reduce their positions in the stock market and deleverage once they face borrowing constraints.

4 Broker-Dealers' Leverage and Price Impacts

The previous section characterizes how an increase in broker-dealers' leverage leads hedge funds to reduce their borrowing from brokers and deleverage. This section explores its impact on the stock market using the demand system of asset pricing (Kojien and Yogo (2019)).

4.1 Characteristic-based Demand Estimation

During recessions, broker-dealers face binding leverage constraints and cannot extend leverage to hedge funds. Then, hedge funds are forced to sell assets, creating short-term demand pressures that shift asset prices. Thus, we outline the characteristic-based demand model used to investigate the demand elasticity of institutional investors, specifically hedge funds and broker-dealers.

Using the demand system asset pricing methodology from Kojien and Yogo (2019), we can model the demand of investor i for stock n as,

$$\frac{w_{it}(n)}{w_{it}(0)} = \exp \{ \beta_{0,it} \text{me}_t(n) + \beta'_{1,it} \mathbf{x}_t(n) + \alpha_{it} \} \varepsilon_{it}(n), \quad (3)$$

where $w_{it}(n)$ denotes investor i 's portfolio weight for stock n at quarter t , $w_{it}(0)$ denotes portfolio weight on the outside asset, me_t is the market cap, \mathbf{X}_t is a vector of characteristics, and ε_{it} is the latent demand. We include the same characteristics as in Kojien and Yogo (2019): an instrument for market equity, book equity, profitability, investment, dividends, and market beta. We estimate Equation (3) using the non-linear GMM method under the moment condition

$$\mathbb{E}_t[\varepsilon_{it}(n) | \widehat{\text{me}}_{it}(n), \mathbf{x}_t(n)] = 1 \quad (4)$$

where $\widehat{\text{me}}_{it}(n)$ denotes the instrument for market equity. For institutions with more than 1,000 holdings, we can estimate the model at the investor level. For those institutions with fewer than 1,000 holdings, we group them by type and then quantiles of AUM within each type to run a pooled estimation.

Figure 3 shows the cross-sectional mean of the estimated coefficients on characteristics by each investor type. Panel A reports the coefficients on log market-to-book equity for hedge funds,

broker-dealers, households, and other institutions. A higher coefficient (up to one) implies that the institution do not deviate away from their benchmark portfolio when the price changes. Thus, a higher coefficient implies a more inelastic demand.

We observe that the demand elasticity for hedge funds is lower than that of broker-dealers throughout the sample period, reflecting the more elastic demand of hedge funds relative to broker-dealers who face leverage constraints. Broker-dealers consistently show the highest demand elasticity, which remains relatively stable over time, while hedge funds experience a decline in elasticity until around 2009, after which their demand become more inelastic.

Panel B reports the coefficients on book equity, which measures the preference for size by institutional type. Broker-dealers have the highest coefficient on book equity, implying that they tilt their portfolio towards large-cap stocks. The result is consistent with banks in [Kojien and Yogo \(2019\)](#)'s sample, since banks are largely the parent holding institutions of broker-dealers. Hedge funds, in contrast, tilt their portfolio towards smaller stocks, although the trend in demand for larger stocks have increased over time.

4.2 Price Impacts

As an implication from the demand system, we can estimate the price impact on each stock for each type of institution. Then, we can examine how the price impact by each type of institution comove with BD leverage. Following [Kojien and Yogo \(2019\)](#), the market clearing condition suggests for each stock n ,

$$ME_t(n) = \sum_{i=1}^I A_{it} w_{it}(n, me, x, \varepsilon), \quad (5)$$

where A_i is investor i 's assets under management (AUM). Taking the log of the market clearing condition gives,

$$\mathbf{p}_t = \mathbf{f}(\mathbf{p}_t) = \log \left(\sum_i A_{it} \mathbf{w}_{it}(\mathbf{p}_t) \right) - \mathbf{s}_t, \quad (6)$$

where $s = \log(S)$ is the log of the number of shares outstanding. Thus, we can obtain an implicit function for the log price as follows,

$$\mathbf{p}_t = \mathbf{g}(\mathbf{s}_t, \mathbf{x}_t, \mathbf{A}_t, \boldsymbol{\beta}_t, \boldsymbol{\varepsilon}_t). \quad (7)$$

The equation implies that asset prices are fully determined by shares outstanding (s), characteristics (x), the wealth distribution (A), the coefficients on the characteristics (β), and the latent demand

(ε). The price impact of a change in investor i 's latent demand for stock n is given as the n -th diagonal element of the matrix has the form

$$PI_t^i := \frac{\partial \mathbf{p}_t}{\partial \log(\varepsilon_{i,t})'} = \left(\mathbf{I} - \sum_{j=1}^I A_{j,t} \beta_{0,j,t} \mathbf{H}_t^{-1} \mathbf{G}_{j,t} \right)^{-1} A_{i,t} \mathbf{H}_t^{-1} \mathbf{G}_{i,t}. \quad (8)$$

where $\beta_{0,j,t}$ is the coefficient of investor j on market-to-book, and matrices

$$\mathbf{H} := \text{diag} \left(\sum_i A_i \mathbf{w}_i \right) = \sum_i A_i \text{diag}(\mathbf{w}_i) \quad (9)$$

$$\mathbf{G}_i := \text{diag}(\mathbf{w}_i) - \mathbf{w}_i \mathbf{w}_i'. \quad (10)$$

Equation (8) represents the coliquidity matrix for investor i , which measures the *elasticity of asset price changes* (denoted by \mathbf{p}_t) with respect to idiosyncratic shocks to investor i 's latent demand (denoted by $\varepsilon_{i,t}$). The inverse of this matrix is the aggregate demand elasticity. The n -th diagonal element of the term outside the inverse in Equation (8) has the form

$$\frac{A_{i,t} w_{i,t}(n) [1 - w_{i,t}(n)]}{\sum_{j=1}^J A_{j,t} w_{j,t}(n)}. \quad (11)$$

which accounts for how sensitive investors' portfolio weights ($\mathbf{w}_{j,t}$) are to changes in asset prices. Thus, Equation (8) estimates the *price impact of demand shocks* for investor i . Following Kojen and Yogo (2019), we estimate the price impact for each stock and institution via the diagonal elements of $\frac{\partial \mathbf{p}_t}{\partial \log(\varepsilon_{i,t})'}$. For each stock, we estimate the price impact for each institution with a 10% demand shocks on that stock. We then aggregate the price impact on each stock by institutional types, weighted by their holding in the stock. Finally, we obtain the value-weighted price impact across all stocks for each institutional type, weighted by the stock market cap. This time-series captures the aggregate price impact of each type of institution on the overall stock market.

Figure 4 plots the price impact across all stocks over the sample period from 2004:Q1 to 2023:Q3. The price impact is represented as an elasticity, where an estimate of 0.1 implies that the price increases by 1% for a 10% demand shock. In Panel A, which depicts the price impact on all stocks, hedge funds consistently show a higher price impact than broker-dealers throughout the sample period. A 10% positive demand shock by the average hedge fund increases stock prices by 0.2% across all stocks.

Broker-dealers, in contrast, exhibit a relatively low price impact across the entire period. This

finding indicates that hedge funds, with a more elastic demand, exert greater influence on the prices of average stocks than broker-dealers, who have a more inelastic demand. The stable yet low impact from broker-dealers could reflect their more passive role in price setting across all stocks.

Figure 5 focuses on the price impact on the least liquid stocks. Least liquid stocks as those at the 90th percentile of the distribution of price impacts across all stocks². These stocks exhibit higher price sensitivity to demand shocks, meaning that changes in investor demand have a larger effect on their prices. During financial crises or periods of financial stress, liquidity often dries up, especially for the least liquid stocks.

Panel B shows that hedge funds have a larger impact on price movements in least liquid stocks. A 10% positive demand shock by the average hedge fund increases stock prices by 0.4% across these stocks. During recessions, particularly in the 2008 GFC, hedge funds' price impact spikes dramatically, with a 10% demand shock leading to an increase of up to 7% in stock prices. Importantly, the price impact from the hedge funds are economically large. Koijen and Yogo (2019) reports the price impact for the average investment advisor with a 10% demand shock on the least liquid stocks is approximately 0.22% in 2017:Q2. We find that the price impact for the average hedge fund with a 10% demand shock on the least liquid stocks is approximately 0.4% in 2017:Q2, doubled the average investment advisor.

This sharp increase reflects the vulnerability of illiquid stocks to shifts in hedge fund demand, especially during periods of market stress when liquidity is scarce. Broker-dealers, on the other hand, maintain a consistently low price impact on illiquid stocks, suggesting that they do not play as significant a role in driving price changes, even during periods of downturns.

Overall, among all institutions, we find that hedge funds exert the largest price impact across all stocks, and their price impact comoves with BD leverage. Although often broker-dealers are considered as marginal investors, broker-dealers themselves have a relatively muted price impact across all stocks, consistent with their more inelastic demand and their role as liquidity providers rather than price movers. This result implies that hedge funds' demand and price pressure on stocks comove with leverage. Providing leverage to hedge funds is an indirect way of how BD leverage matters for asset pricing.

Table 4 reports the main findings of this paper. This table reports the results from the single predictive regressions that examine how BD leverage predicts future price impacts for hedge funds

²Liquidity is associated with how quickly and easily a stock's price adjusts to changes in supply and demand, with less liquid stocks having a higher price impact for a given demand shock Koijen and Yogo (2019).

and broker-dealers, over time horizons ranging from one to eight quarters ahead. The regression has the following form:

$$PI_{t:t+q}^I = \alpha + \beta lev_t^{BD} + \varepsilon_{t:t+q}. \quad (12)$$

In Column (1)-(3), the dependent variable is the average price impact $PI_{t:t+q}^I$. In Column (4)-(6), the dependent variable is the average price impact scaled by total AUM of each type (in million USD). The regressions use BD leverage as the key predictor. We report t-statistics based on [Newey and West \(1987\)](#) corrections, respectively.

In Panel A, for hedge funds, we observe that a 1% increase in BD leverage leads to an increase in the aggregate price impact by 1.5% to 1.7% at in the followig quarter and the followig quarter year. When we measure the price impact per million dollars of holdings, the effect of BD leverage on hedge funds becomes much more pronounced: a 1% increase in BD leverage leads to a substantial price impact of 23.8% in the following quarter, decreasing to 18.0% over an two-year horizon (q=8). These findings highlight the significant sensitivity of hedge funds' price impacts to BD leverage, suggesting that hedge funds respond strongly to changes in BD leverage, especially in terms of their holdings' price impact per dollar invested.

Panels B and C reveal smaller price impacts for broker-dealers and other institutions. In Panel B, the aggregate price impact for broker-dealers is much lower, with coefficients around 0.8% across different quarters, and the price impact per million dollars of holdings is between 9.9% and 11.2%. In Panel C, other institutions exhibit similar aggregate price impact coefficients; yet, the price impact per million holdings is minimal (between 0.5% and 0.6%). These results suggest that the effect of BD leverage is particularly strong for hedge funds, significantly amplifying their price impacts compared to broker-dealers and other institutions. The relatively higher R^2 values in Panel B indicate that BD leverage explains a substantial portion of the variation in broker-dealers' price impacts, althoughthough the magnitude of the effect remains lower than for hedge funds.

Overall, the table indicates that hedge funds are the primary channel through which BD leverage affects stock market price impacts. The sensitivity of hedge funds' price impacts, especially when measured per million dollars, underscores their role in transmitting the effects of BD leverage to the broader market. This implies hat BD leverage influences the market primarily through hedge funds.

[Table 5](#) examines how BD leverage affects the price impacts of the least liquid stocks held by hedge funds, broker-dealers, and other institutions. In Panel A, for hedge funds, a 1% increase in BD leverage significantly raises the aggregate price impact on illiquid stocks by 4.3% to 5.0%,

with a large increase in price impact per million dollars of holdings, from 58.1% at a one-quarter horizon to 44.1% over eight quarters. This indicates that hedge funds' positions in less liquid stocks are highly sensitive to changes in BD leverage.

In contrast, Panels B and C show much smaller effects for broker-dealers and other institutions. Broker-dealers see an increase of about 1.2% in aggregate price impact and 15.9%-18.2% in price impact per million dollars. Other institutions experience minimal sensitivity, with only a 1.0%-1.1% increase in price impact per million holdings. These findings suggest that BD leverage primarily affects illiquid stock price impacts through hedge funds rather than through broker-dealers or other institutions.

In summary, BD leverage is a significant predictor of future price impacts for both hedge funds and broker-dealers. Interestingly, hedge funds exhibit a larger response to changes in BD leverage. These findings highlight the crucial role that intermediary leverage plays in shaping market dynamics, particularly by influencing the future price impacts of institutional investors.

5 Conclusion

This paper highlights the role of broker-dealers and hedge funds in asset pricing. Our findings imply that broker-dealers, despite their smaller share of total assets under management, shape the leverage for hedge funds. During periods of financial stress, when broker-dealers face tighter leverage constraints, hedge funds are forced to deleverage, leading to significant price impacts across stocks. This effect is particularly pronounced for less liquid stocks and those highly sensitive to leverage shocks, confirming the importance of intermediary health in driving cross-sectional variation in stock returns.

Using a characteristic-based demand system, we quantify the elasticity of demand for hedge funds and broker-dealers. Hedge funds, with their higher demand elasticity, show a stronger direct impact on prices, while broker-dealers influence asset prices indirectly through their role in providing leverage. This interplay between broker-dealers' leverage constraints and hedge funds' demand help us understand how financial health of intermediaries affect asset pricing, especially during times of economic downturns.

Future research could examine the impact of regulatory changes targeting broker-dealer leverage, such as capital requirements on asset pricing through shifts in hedge fund behavior. For example, we could assess how regulations like the Dodd-Frank Act or Basel III, which impose stricter capital standards on broker-dealers, alter hedge funds' ability to leverage and maintain positions,

particularly in high-volatility.

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Figure 1: Asset Under Management of Broker-Dealers and Hedge Funds

This figure plots the share of total asset under management (AUM) by each investor type. In each quarter, we aggregate the AUM share by each investor group. The AUM share is the percentage of AUM of each investor over the total share AUM in each quarter. AUM is the total holdings of each investor in each quarter. Holdings are reported in 13F institutional holdings from FactSet Ownership. The sample period runs from 2000:Q1 to 2023:Q3.

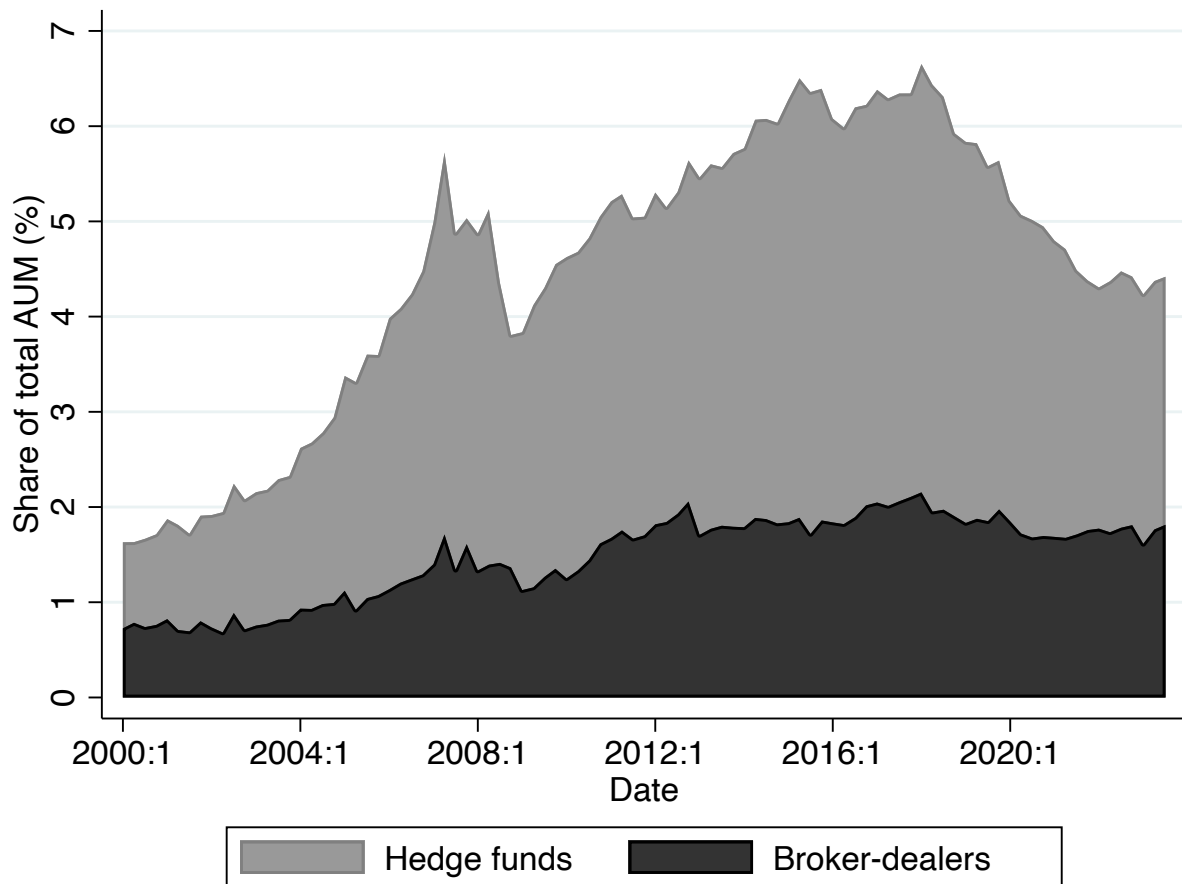


Figure 2: **Broker-Dealers' Leverage and Hedge Fund Borrowing**

This figure plots the time series of broker-dealers' leverage (*BD Leverage*) and hedge fund borrowing from prime brokers (*Hedge Fund Borrowing from BD*). Broker-dealers' leverage is from the Flow of Funds, and hedge fund borrowing from prime brokers is from the Office of Financial Research.

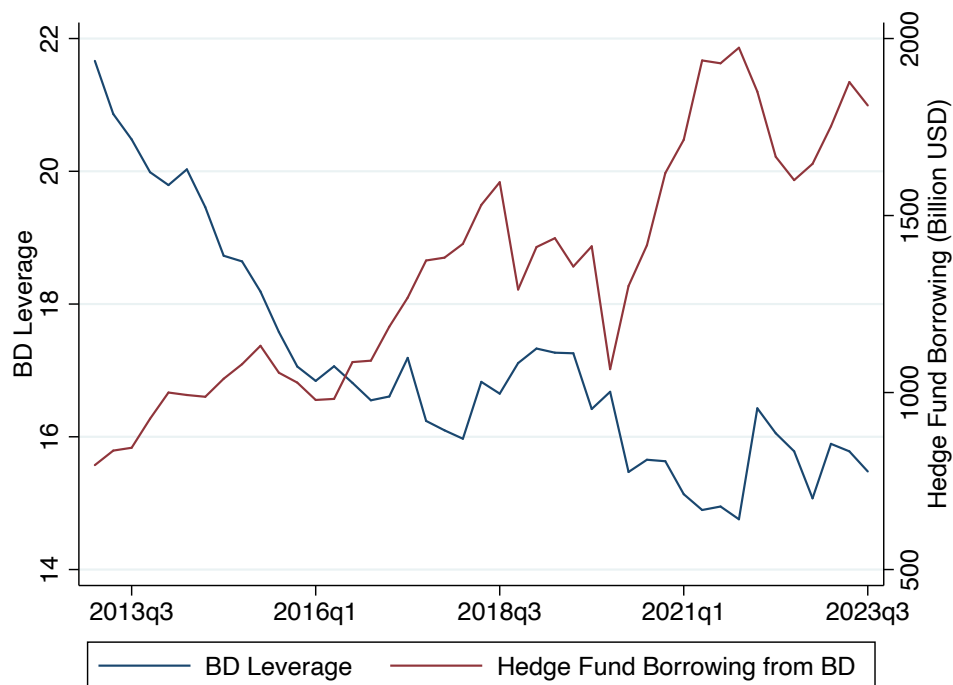


Figure 3: **Demand Elasticities**

This figure reports the cross-sectional mean of the estimated coefficients by institution type, weighted by assets under management. The sample period runs from 2000:Q1 to 2023:Q3. Panel A reports the coefficients on log market-to-book equity. A higher coefficient (close to 1) implies higher price elasticity of demand. Panel B reports the coefficients on book equity. A higher coefficient implies portfolio tilting towards large-cap stocks.

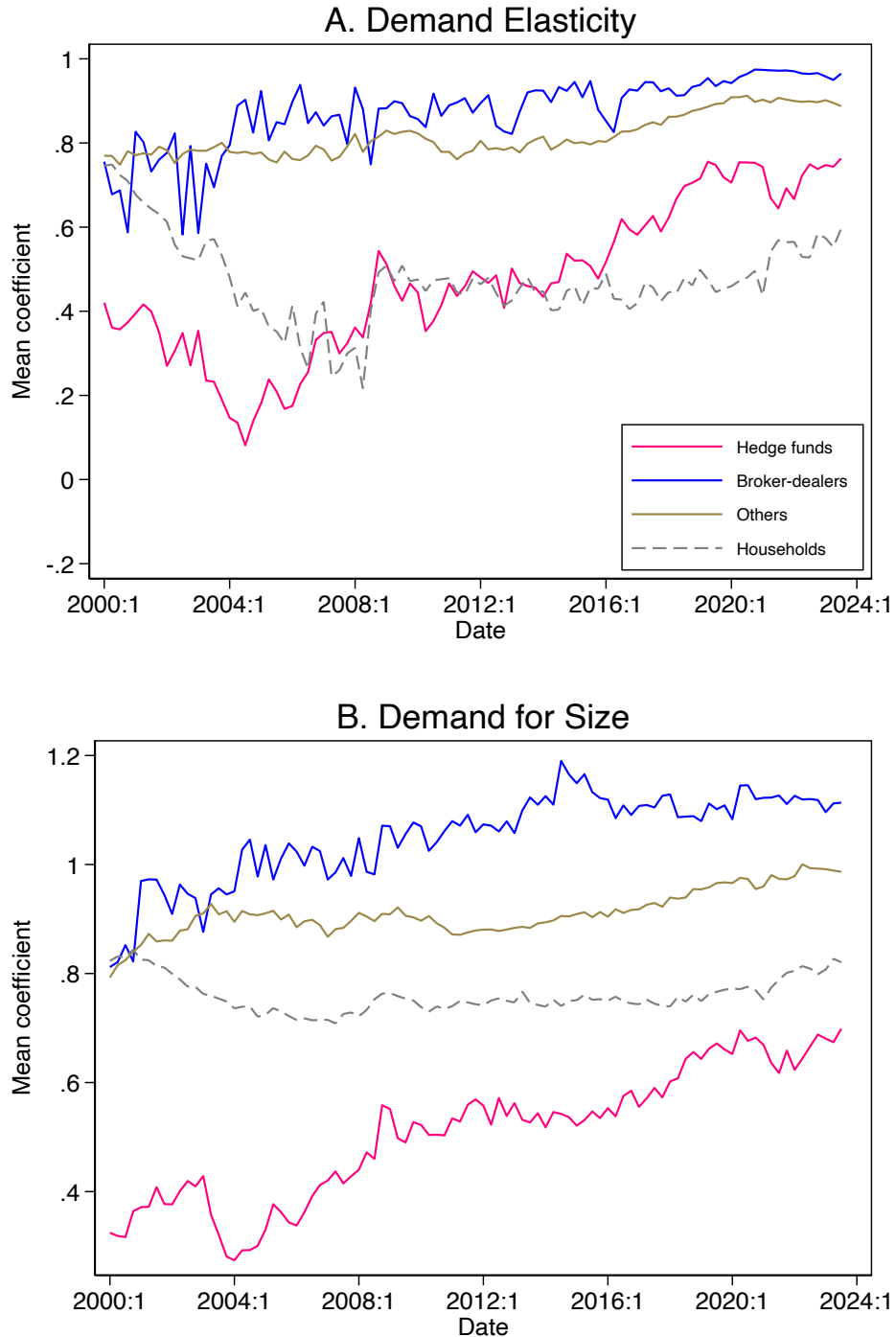


Figure 4: **Price Impact Across All Stocks**

This figure reports the cross-sectional distribution of price impact across all stocks for the average hedge funds, broker-dealers, and other investors. Price impact is defined as an elasticity, where an estimate of 0.1 implies that the price increases by 1% for a 10% demand shock. For each stock, we estimate the price impact for each institution with a 10% demand shocks on that stock, following [Kojen and Yogo \(2019\)](#). We then aggregate the price impact on each stock by institutional types, weighted by their holding in the stock. Finally, we take the value-weighted price impact across all stocks for each instituional type, weighted by the stock market cap. The sample period is from 2000:Q1 to 2023:Q3.

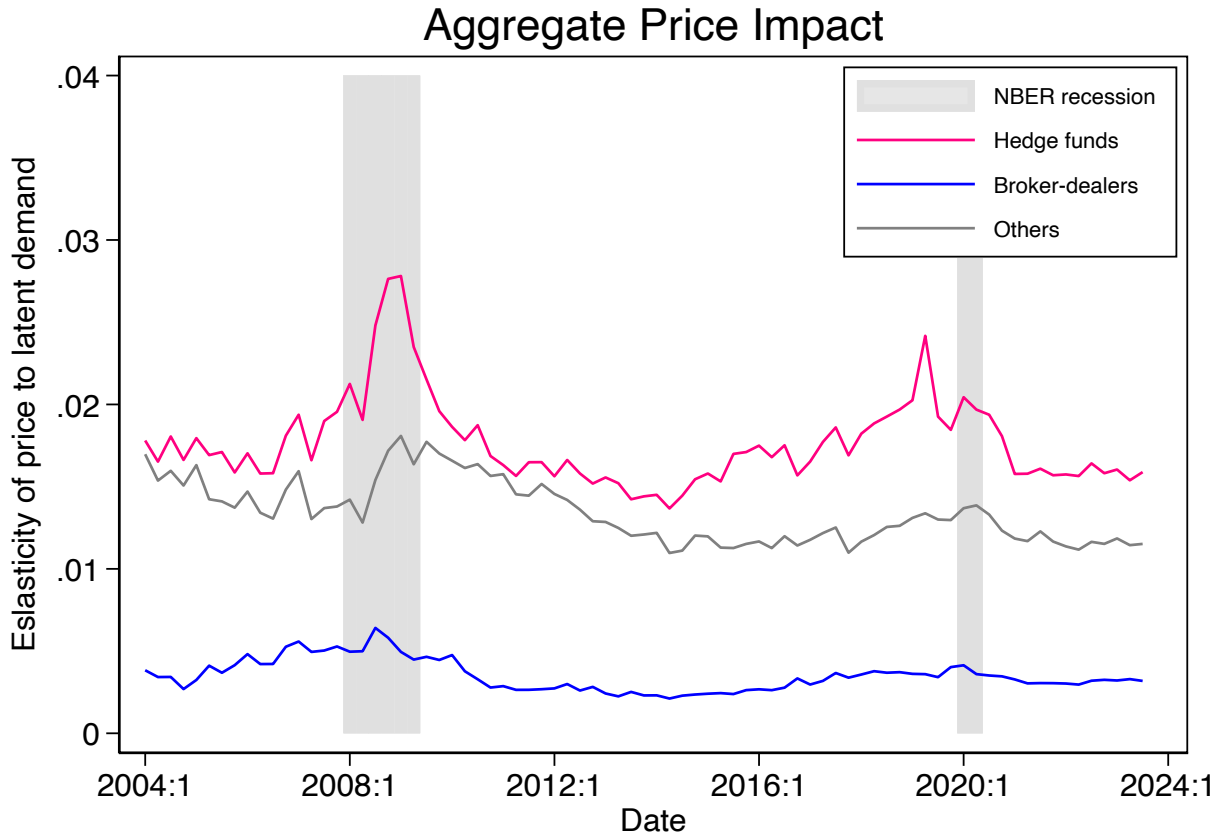


Figure 5: **Price Impact Across Least Liquid Stocks**

This figure reports the cross-sectional distribution of price impact across least liquid stocks for the average hedge funds, broker-dealers, and other investors. Price impact is defined as an elasticity, where an estimate of 0.1 implies that the price increases by 1% for a 10% demand shock. Least liquid stocks are defined based on their position in the cross-sectional distribution of price impact. Least liquid stocks are those at the 90th percentile of the distribution of price impacts across stocks. For each stock, we estimate the price impact for each institution with a 10% demand shocks on that stock, following [Kojien and Yogo \(2019\)](#). We then aggregate the price impact on each stock by institutional types, weighted by their holding in the stock. Finally, we take the value-weighted price impact across all stocks for each institutional type, weighted by the stock market cap. The sample period is from 2000:Q1 to 2023:Q3.

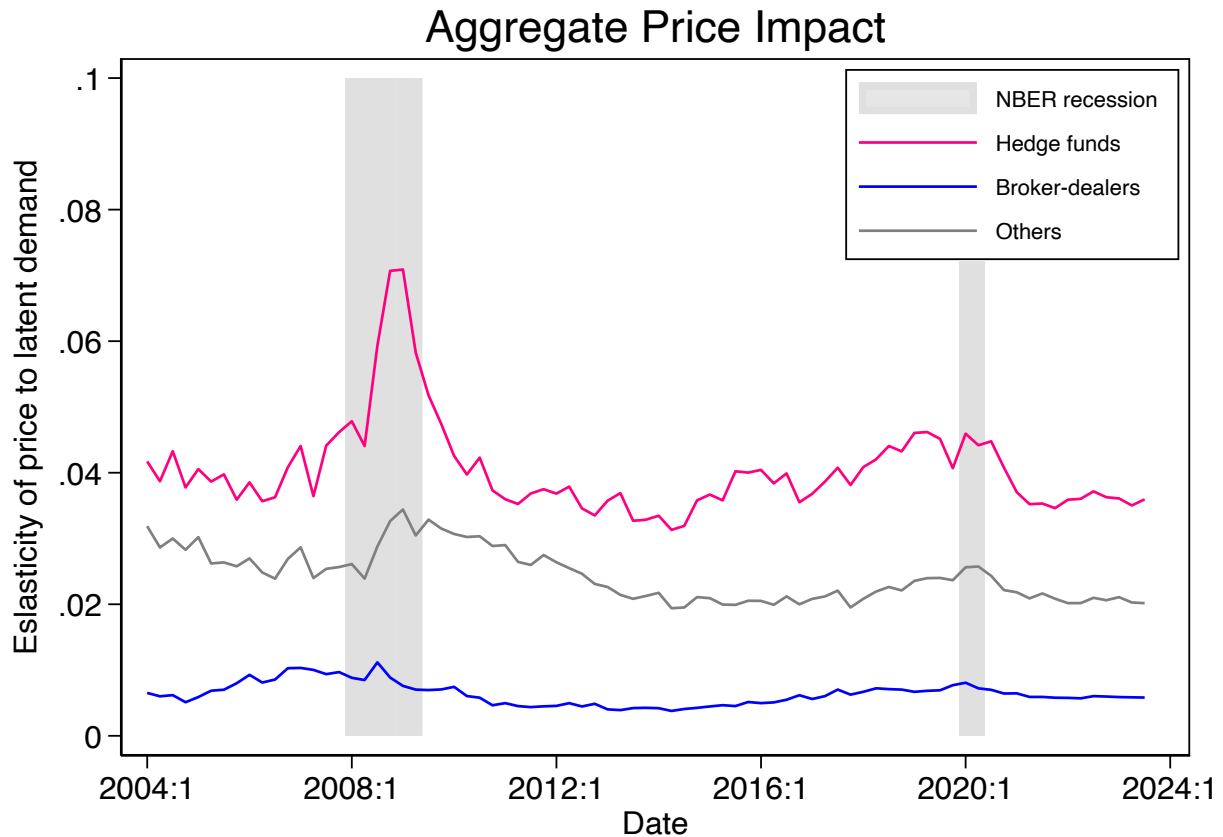


Table 1: **Summary of Holdings**

This table reports the average of each summary statistics within the given period. The table reports the number of institutions, the percentage of the market held, the median and 90th percentile AUM, and the median and 90th percentile number of stocks held. The sample period is from 2000:Q1 to 2023:Q3.

	(1) # Institutions	(2) % Mkt Held	(3) Median AUM	(4) 90th AUM	(5) Median # Stocks	(6) 90th # Stocks
<i>Panel A: All institutions</i>						
2000-2004	2,010	58.60	376	6,273	91	551
2005-2009	2,730	67.68	345	6,195	78	546
2010-2014	3,230	70.59	339	6,373	73	532
2015-2019	4,287	73.21	311	6,064	70	522
2020-2023	5,444	66.24	232	4,730	67	449
<i>Panel B: Hedge funds</i>						
2000-2004	288	1.30	254	1,318	45	169
2005-2009	580	3.04	259	1,973	32	181
2010-2014	652	3.65	292	2,454	26	179
2015-2019	834	4.25	341	2,932	20	214
2020-2023	869	2.88	271	2,585	18	196
<i>Panel C: Broker-dealers</i>						
2000-2004	18	0.80	1,533	22,266	586	2,263
2005-2009	30	1.28	1,685	26,672	556	2,254
2010-2014	44	1.73	917	26,994	453	2,331
2015-2019	53	1.93	787	28,951	321	2,144
2020-2023	61	1.74	1,003	46,858	310	1,899
<i>Panel D: Others</i>						
2000-2004	1,705	56.49	404	7,339	100	598
2005-2009	2,120	63.36	370	8,181	93	612
2010-2014	2,534	65.21	351	8,041	88	566
2015-2019	3,400	67.03	302	7,173	85	555
2020-2023	4,514	61.63	223	5,375	77	470

Table 2: **Broker-Dealers' and Hedge Funds' Leverage**

This table regresses hedge funds' leverage on broker-dealers' leverage (BD). *Net (Equity) Leverage* refers to the ratio of hedge funds' borrowing from prime brokers to their net assets (net equity holdings). *t*-statistics reported in the parentheses are based on Newey-West standard errors with 4 lags.

	Net Leverage	Net Equity Leverage
	(1)	(2)
BD Leverage	-0.038*** (-5.281)	-0.022*** (-6.216)
Observations	43	43
R^2	0.354	0.611
<i>t</i> statistics in parentheses		
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$		

Table 3: **Broker-Dealers' and Hedge Funds' Holdings**

This table regresses hedge funds' stock holdings on broker-dealers' leverage (BD). *Holding (Billion \$)* refers to the dollar amount of holdings in billion \$ and *Share* refers to its share of holdings in the stock market. *t*-statistics reported in the parentheses are based on Newey-West standard errors with 4 lags.

	Holdings (Billion \$)	Share
	(1)	(2)
BD Leverage	-33.849*** (-4.152)	-0.048** (-2.100)
Observations	95	95
R^2	0.496	0.169
<i>t</i> statistics in parentheses		
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$		

Table 4: **Predicting Price Impacts on All Stocks.** This table reports the coefficient of regressing future price impacts for each type of institutions on BD leverage: $PI_{t:t+q}^I = \alpha + \beta lev_t^{BD} + \varepsilon_{t:t+q}$. For each stock, we estimate the price impact for each institution with a 10% demand shocks on that stock, following [Koijen and Yogo \(2019\)](#). We then aggregate the price impact on each stock by institutional types, weighted by their holding in the stock. $PI_{t:t+q}^I$ is the value-weighted price impact across all stocks for each instituional type, weighted by the stock market cap. In Column (1)-(3), the dependent variable is the aggregate price impact $PI_{t:t+q}^I$. In Column (4)-(6), the dependent variable is the aggregate price impact scaled by total AUM of each type (in million USD). The sample period is from 2000:Q1 to 2023:Q3.

Dependent variable:	Aggregate price impact			Price impact per \$1M holdings		
	(1) q=1	(2) q=4	(3) q=8	(4) q=1	(5) q=4	(6) q=8
Panel A: Hedge funds						
BD leverage	0.015 [3.80]***	0.017 [2.75]***	0.014 [2.31]**	0.238 [4.30]***	0.225 [3.02]***	0.180 [3.12]***
R^2	0.094	0.175	0.171	0.135	0.162	0.170
RMSE	0.004	0.003	0.003	0.055	0.047	0.036
Panel B: Broker-dealers						
BD leverage	0.008 [9.25]***	0.008 [7.78]***	0.007 [4.16]***	0.112 [6.35]***	0.112 [4.70]***	0.099 [4.99]***
R^2	0.309	0.391	0.387	0.267	0.307	0.340
RMSE	0.001	0.001	0.001	0.017	0.016	0.013
Panel C: Others						
BD leverage	0.019 [4.33]***	0.018 [3.23]***	0.018 [4.49]***	0.005 [5.39]***	0.006 [3.92]***	0.005 [4.87]***
R^2	0.128	0.191	0.324	0.241	0.312	0.387
RMSE	0.004	0.003	0.002	0.001	0.001	0.001

t -ratio of Newey-West (1987) with k-1 lags in square brackets.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: **Predicting Price Impacts on Least Liquid Stocks.** This table reports the coefficient of regressing future price impacts for each type of institutions on BD leverage: $PI_{t:t+q}^I = \alpha + \beta lev_t^{BD} + \varepsilon_{t:t+q}$. For each stock, we estimate the price impact for each institution with a 10% demand shocks on that stock, following [Koijen and Yogo \(2019\)](#). We then aggregate the price impact on each stock by institutional types, weighted by their holding in the stock. $PI_{t:t+q}^I$ is the value-weighted price impact across least liquid stocks for each institutional type, weighted by the stock market cap. Least liquid stocks are defined at 90th percentile cross-sectional distribution of price impact. In Column (1)-(3), the dependent variable is the aggregate price impact $PI_{t:t+q}^I$. In Column (4)-(6), the dependent variable is the aggregate price impact scaled by total AUM of each type (in million USD). The sample period is from 2000:Q1 to 2023:Q3.

Dependent variable:	Aggregate price impact			Price impact per \$1M holdings		
	(1) q=1	(2) q=4	(3) q=8	(4) q=1	(5) q=4	(6) q=8
Panel A: Hedge funds						
BD leverage	0.043 [3.91]***	0.050 [2.92]***	0.042 [2.62]**	0.581 [4.22]***	0.554 [3.01]***	0.441 [3.13]***
R^2	0.106	0.206	0.210	0.129	0.158	0.168
RMSE	0.012	0.009	0.007	0.139	0.117	0.090
Panel B: Broker-dealers						
BD leverage	0.012 [8.68]***	0.011 [4.78]***	0.009 [2.32]**	0.182 [7.36]***	0.180 [5.63]***	0.159 [5.29]***
R^2	0.280	0.344	0.249	0.323	0.391	0.427
RMSE	0.002	0.001	0.001	0.024	0.021	0.017
Panel C: Others						
BD leverage	0.042 [4.36]***	0.039 [3.19]***	0.037 [4.32]***	0.011 [5.22]***	0.011 [3.77]***	0.010 [4.67]***
R^2	0.123	0.176	0.296	0.218	0.280	0.355
RMSE	0.010	0.008	0.005	0.002	0.002	0.001

t -ratio of Newey-West (1987) with $k-1$ lags in square brackets.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix: Additional results

Figure A1: **Coefficient on Characteristics.** This figure reports the cross-sectional mean of the estimated coefficients by institution type, weighted by assets under management. The sample period runs from 2000:Q1 to 2023:Q3. Panel A reports the coefficients on profitability. Panel B reports the coefficients on investment. Panel C reports the coefficients on dividend-to-book equity. Panel D reports the coefficients on market beta.

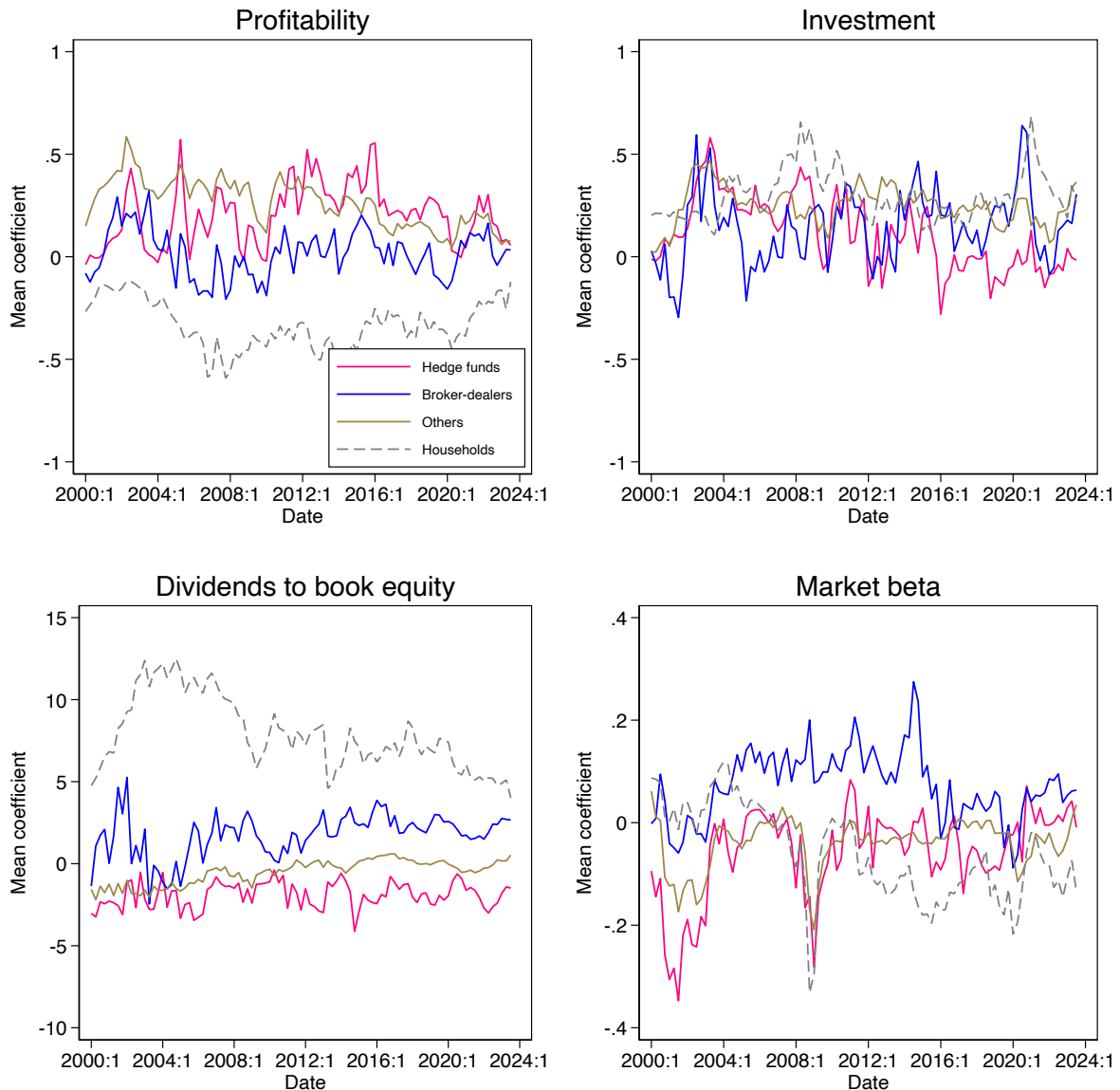


Figure A2: **Standard Deviation of Latent Demand.** This figure reports the cross-sectional standard deviation of log latent demand by institution type, weighted by assets under management. The sample period is from 2000:Q1 to 2023:Q3. A higher standard deviation implies more extreme portfolio weights tilted away from observed characteristics.

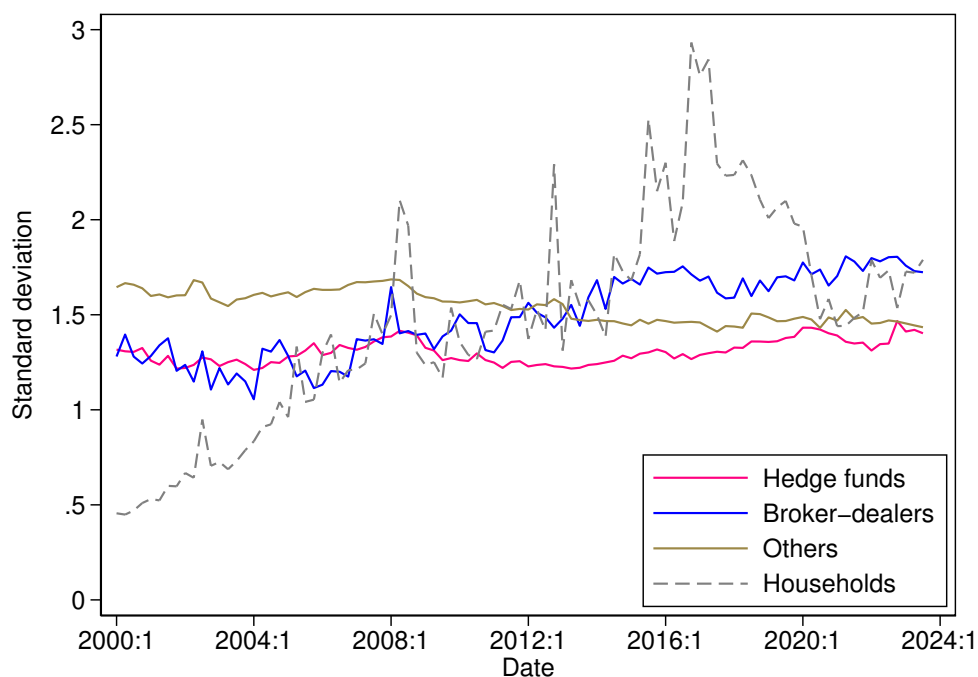


Table A1: **Predicting Price Impacts across All Stocks using Primary-Dealer Capital Ratio.** This table reports the coefficient of regressing future price impacts for each type of institutions on capital ratio: $PI_{t:t+q}^I = \alpha + \beta \eta_t + \varepsilon_{t:t+q}$. For each stock, we estimate the price impact for each institution with a 10% demand shocks on that stock, following [Kojien and Yogo \(2019\)](#). We then aggregate the price impact on each stock by institutional types, weighted by their holding in the stock. $PI_{t:t+q}^I$ is the value-weighted price impact across all stocks for each institutional type, weighted by the stock market cap. In Column (1)-(3), the dependent variable is the aggregate price impact $PI_{t:t+q}^I$. In Column (4)-(6), the dependent variable is the aggregate price impact scaled by total AUM of each type (in million USD). The sample period is from 2000:Q1 to 2023:Q3.

Dependent variable:	Aggregate price impact			Price impact per \$1M holdings		
	(1) q=1	(2) q=4	(3) q=8	(4) q=1	(5) q=4	(6) q=8
Panel A: Hedge funds						
PD capital ratio	0.111 (3.39)*** [3.35]***	0.098 (3.11)*** [2.77]***	0.094 (4.50)*** [4.40]***	1.904 (5.48)*** [5.42]***	1.642 (3.52)*** [3.11]***	1.375 (2.84)*** [2.73]***
R^2	0.233	0.282	0.374	0.389	0.400	0.478
RMSE	0.004	0.003	0.002	0.047	0.040	0.029
Panel B: Broker-dealers						
PD capital ratio	0.038 (4.73)*** [4.68]***	0.035 (3.78)*** [3.44]***	0.036 (6.19)*** [5.99]***	0.582 (5.18)*** [5.12]***	0.587 (3.58)*** [3.19]***	0.566 (3.81)*** [3.66]***
R^2	0.309	0.361	0.513	0.328	0.388	0.535
RMSE	0.001	0.001	0.001	0.016	0.015	0.011
Panel C: Others						
PD capital ratio	0.147 (4.69)*** [4.64]***	0.106 (2.84)*** [2.51]**	0.083 (2.47)** [2.36]**	0.026 (4.46)*** [4.42]***	0.024 (2.83)*** [2.49]**	0.023 (2.44)** [2.34]**
R^2	0.358	0.315	0.348	0.256	0.259	0.333
RMSE	0.004	0.003	0.002	0.001	0.001	0.001

t -ratio of Hodrick (1992) with $k-1$ lags in parentheses.

t -ratio of Newey-West (1987) with $k-1$ lags in square brackets.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Predicting Price Impacts across Least Liquid Stocks using Primary-Dealer Capital Ratio. This table reports the coefficient of regressing future price impacts for each type of institutions on capital ratio: $PI_{t:t+q}^I = \alpha + \beta \eta_t + \varepsilon_{t:t+q}$. For each stock, we estimate the price impact for each institution with a 10% demand shocks on that stock, following [Koijen and Yogo \(2019\)](#). We then aggregate the price impact by institutional types, weighted by their holding in the stock. $PI_{t:t+q}^I$ is the value-weighted price impact on each stock across least liquid stocks for each institutional type, weighted by the stock market cap. Least liquid stocks are defined at 90th percentile cross-sectional distribution of price impact. In Column (1)-(3), the dependent variable is the aggregate price impact $PI_{t:t+q}^I$. In Column (4)-(6), the dependent variable is the aggregate price impact scaled by total AUM of each type (in million USD). The sample period is from 2000:Q1 to 2023:Q3.

Dependent variable:	Aggregate price impact			Price impact per \$1M holdings		
	(1) q=1	(2) q=4	(3) q=8	(4) q=1	(5) q=4	(6) q=8
Panel A: Hedge funds						
PD capital ratio	0.295 (3.19)*** [3.15]***	0.263 (2.87)*** [2.56]**	0.252 (4.54)*** [4.44]***	4.716 (5.32)*** [5.26]***	4.063 (3.45)*** [3.06]***	3.362 (2.84)*** [2.74]***
R^2	0.220	0.267	0.369	0.382	0.394	0.472
RMSE	0.011	0.009	0.007	0.117	0.100	0.071
Panel B: Broker-dealers						
PD capital ratio	0.060 (4.65)*** [4.60]***	0.049 (4.04)*** [3.73]***	0.051 (3.20)*** [3.05]***	0.914 (5.44)*** [5.38]***	0.849 (3.95)*** [3.56]***	0.829 (4.72)*** [4.55]***
R^2	0.303	0.307	0.392	0.366	0.401	0.564
RMSE	0.002	0.001	0.001	0.023	0.021	0.015
Panel C: Others						
PD capital ratio	0.347 (4.89)*** [4.83]***	0.256 (3.00)*** [2.66]***	0.194 (2.60)*** [2.49]**	0.057 (4.69)*** [4.64]***	0.052 (2.94)*** [2.60]**	0.048 (2.47)** [2.38]**
R^2	0.380	0.351	0.389	0.287	0.288	0.357
RMSE	0.009	0.007	0.005	0.002	0.002	0.001

t -ratio of Hodrick (1992) with $k-1$ lags in parentheses.

t -ratio of Newey-West (1987) with $k-1$ lags in square brackets.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$