Comovement in Arbitrage Limits

by*

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Abstract

Estimates of mispricing, such as deviations from no-arbitrage relations, strongly comove across five financial markets. One common component—the arbitrage gap—explains the majority of variability in mispricing estimates for futures, Treasury securities, foreign exchange, and options. Prominent equity anomalies also comove significantly with the arbitrage gap. Variables affecting arbitrage capital availability, such as the TED spread and hedge-fund flows and returns, explain two-thirds of the arbitrage gap's variation. During periods of tighter capital constraints, the comovement in mispricings becomes stronger. The findings support theoretical predictions that common sources of funding shocks can cause comovement in mispricings across markets.

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1 Introduction

In a frictionless world, arbitrage requires no capital, and asset mispricing relative to fundamental value should be instantaneously eliminated. Real-life arbitrageurs require capital, often raised from external sources. When that capital becomes less available, deviations of prices from no-arbitrage relations—arbitrage spreads—can arise and persist. A shock to capital availability can cut across arbitrageurs in different markets, resulting in a simultaneous widening of arbitrage spreads. For example, during the severe funding freeze of 2008, spreads widened in multiple markets (Mitchell and Pulvino, 2012).

Do arbitrage spreads, or mispricings more generally, comove across different financial markets? If so, is the comovement associated with fluctuations in the availability of arbitrage capital? These are the central questions of this study.

I provide empirical evidence that mispricings comove across five major financial markets: stock-index futures, stock options, foreign exchange, Treasury securities, and equities. I also find that this comovement is closely related to variables that proxy for aggregate capital constraints. When capital limits are looser, arbitrage spreads in all markets are smaller, are less sensitive to variations in funding variables, and exhibit weaker comovement. When funding constraints are tighter, arbitrage spreads are wider in all markets, are correlated more with funding variables, and exhibit strong comovement.

These findings support a growing theoretical literature relating capital constraints and the limits of arbitrage. The basic arguments advanced by this literature are as follows. Real-life arbitrageurs have limited wealth shares and are subject to borrowing constraints. Following a reduction in their wealth or a tightening of borrowing constraints, arbitrageurs are less able to correct prices, resulting in nontrivial and persistent mispricings.[1] Moreover, when arbitrageurs rely on external equity capital, their arbitrage capacities can be further constrained by a worsening of mispricings. Arbitrageurs betting on price convergence suffer short-run losses if mispricings widen. The resulting losses induce outside financiers to withdraw money because of information asymmetry. Therefore, arbitrageurs become less willing to hold positions betting on price convergence as prices diverge further from their fundamental values (Shleifer and Vishny, 1997).

The above literature provides two empirical predictions about mispricings across different

[1] A non-exhaustive list of related studies includes Detemple and Murthy (1997), Shleifer and Vishny (1997), Basak and Croitoru (2000), Gromb and Vayanos (2002, 2009, and 2018), Liu and Longstaff (2004), Brunnermeier and Pedersen (2009), and Gârleanu and Pedersen (2011).

markets. First, mispricings in different markets "connected" by the same pool of capital should comove together. In other words, when arbitrage capital is mobile and exploits arbitrage opportunities across different markets, or when arbitrageurs in different markets are subject to a common source of funding shocks, one should expect mispricings to rise and fall in different markets simultaneously (Gromb and Vayanos 2009, 2018, and Gârleanu and Pedersen, 2011). Second, the comovement is governed by capital constraints. When funding constraints tighten more, mispricings worsen in all markets, become more sensitive to variations in funding constraints, and exhibit stronger comovement.

Consistent with those predictions, my empirical findings reveal that mispricings across major asset classes have a strong common factor, and the comovement is closely related to aggregate funding constraints. First, I construct arbitrage spreads as deviations from familiar no-arbitrage relations in stock-index futures, stock options, foreign exchanges and Treasury securities. These arbitrage spreads, rather than necessarily reflecting true arbitrage opportunities, are better viewed as low-variance estimates of mispricing.[2] A single common component, which I call the arbitrage gap, explains 60% of the total variation in arbitrage spreads over a sample spanning over three decades. Such commonality is not purely driven by the recent financial crisis; in the pre-2007 sample, the arbitrage gap explains 51% of the overall variation.

The variation in the arbitrage gap is closely associated with the tightness of arbitrage capital constraints. In the literature, four variables are commonly used to capture arbitrageurs' funding tightness; the TED spread, the hedge-fund flows and returns, and primary dealers' repo financings growth which captures intermediaries balance sheets' expansion and contraction. These funding variables all exhibit significant explanatory power for the arbitrage gap. In a multiple regression including all four funding measures, they jointly explain 66% of the variation in the arbitrage gap and all coefficients are statistically significant and economically large. In a univariate regression, the TED spread accounts for 25% of the variation in the arbitrage gap in a sample of more than thirty years. Hedge-fund sector flows and returns explain 22% of the variation when included in the regression. The sign of the coefficients indicate that the arbitrage gap becomes wider when the TED spread rises, the hedge fund sector suffers outflows or losses, or the growth in repo financings slows.

As predicted by theoretical studies, the degree of comovement between arbitrage spreads should be negatively associated with the tightness of funding constraints. I indeed find that

[2] The four arbitrage spreads in stock-index futures, stock options, foreign exchange, and Treasury securities are based on the futures-cash parity, put-call parity, the covered interest-rate parity, and the Nelson-Siegel pricing model. See Section 2 for details.

when the TED spread is wide or the hedge-fund sector suffers losses, the comovement is strong. Particularly, I find both the TED spread and the hedge-fund sector returns exhibit significant explanatory power for the average pairwise correlation. The economic magnitude of the effect is quite substantial. A one-standard-deviation spike in the TED spread is associated with an increase of five percentage points in the average pairwise correlation. A one-standard-deviation decline in the hedge-fund-sector return is associated with a four-percent-point increase in the average correlation.

I also include a fifth market, equities, in my investigation. I show that mispricings in the equity market positively comove with the arbitrage gap. In the equity market, stocks' fundamental values are unknown and explicit no-arbitrage relations are rare. Mispricings are simply manifested in relative price differences or return spreads, labeled as anomalies, that cannot be justified by expected payoffs or risk exposures. Unlike deviations from no-arbitrage relations in derivatives or foreign exchange, estimates of equity mispricings, subject to the joint hypothesis problem, have much higher variances. In other words, the payoffs of trades exploiting them can be much more uncertain. So, fundamental risks can also deter arbitrageurs from correcting mispricings, whereas such risks are less likely to affect low-variance opportunities (Gromb and Vayanos, 2010). Nevertheless, I find that when arbitrageurs are more financially constrained, equity mispricings become significantly worse. The arbitrage gap comoves significantly with the magnitudes of three well-documented equity anomalies: the closed-end fund discount, the merger and acquisition (M&A) spread, and long-short alpha spreads based on sorts by certain characteristics.[3] Trading strategies exploiting these anomalies represent major strategies used by real-life arbitrageurs (Pedersen, 2015).

In particular, I find that a one-standard-deviation increase in the arbitrage gap accompanies a 0.66-standard-deviation increase in the average closed-end fund discount, defined as the difference between closed-end funds' net asset values and their share prices. The same increase in the arbitrage gap results in a widening difference between offer and traded prices of M&A target stocks (M&A spread) by 0.53 standard deviations. I also investigate the relation between the arbitrage gap and the long-short alpha spreads of popular anomalies, such as value, profitability, investment, and momentum. I find that during periods when the arbitrage gap is high, the magnitudes of anomalies' long-short alpha spreads become much smaller; on average, a one-standard-deviation increase in the arbitrage gap is associated

[3]The third anomaly concerns the predictability of stocks' returns based on past prices or earnings that can be hardly reconciled by risk-return trade-offs (e.g., momentum and profitability anomalies). Behavioral explanations attribute such predictability to non-instantaneous price correction (Stambaugh, Yu, and Yuan, 2012). Stock prices fail to incorporate news instantaneously, and predictability is realized during the process of price correction.

with around 0.3% decrease in anomalies' alphas. This is consistent with less price correction during those periods.

In the final part of my study, I investigate dynamic lead-lag relations between the arbitrage gap and the funding measures using vector autoregression (VAR) analysis. The feedback mechanisms between mispricings and capital constraints, which have been proposed in arbitrage-limit theories, such as those by Shleifer and Vishny (1997) and Brunnermeier and Pedersen (2009), predict a bidirectional linkage. In one direction, insufficient capital impairs arbitrageurs' trading capacity and leads to larger arbitrage spreads. In the reverse direction, widened mispricings produce immediate losses to arbitrageurs who bet on price correction. Because arbitrageurs primarily invest with external equity and debt capital, information asymmetry between arbitrageurs and financiers can induce uninformed financiers to withdraw equity capital and tighten borrowing constraints, further exacerbating mispricings.

Consistent with these predictions, the VAR results show strong bidirectional links between the arbitrage gap and the funding variables. In one direction, capital-tightening (loosening) shocks to the funding variables lead to a wider (narrower) arbitrage gap. A one-standard-deviation positive shock to the TED spread leads to a 0.4-standard-deviation jump in the arbitrage gap at the onset of the shock, and the response slowly decays to zero over six months. Similarly, a one-standard-deviation negative shock to the hedge-fund returns leads to a significant 0.2-standard-deviation increase in AG, which reverts back to zero after four months. In the reverse direction, a positive one-standard-deviation shock to the arbitrage gap leads to significant tightening responses in all four funding variables. In particular, in the month following the shock, the hedge fund return drops by an annualized three percentage points, the hedge-fund sector flow declines by 0.3 percent of the total assets under management, the TED spread increases by 0.05 percentage points, and repo financing growth slows by one percentage point.

To the best of my knowledge, my study is the first to document (i) strong comovement across mispricings in five major asset classes over a sample of three decades and (ii) the role of aggregate arbitrage capital constraints in this comovement. My findings relate to a number of areas in the literature, in addition to theoretical studies mentioned above.

First, my study relates to a vast empirical literature documenting price anomalies in various markets. A partial list includes MacKinlay and Ramaswamy (1988) and Brennan and Schwartz (1990) for index futures; Ofek and Richardson (2003) and Battalio and Schultz (2006) for stock options; Frenkel and Levich (1977) and Du, Tepper, and Verdelhan (2018) for exchange rates; and Krishnamurthy (2002) and Musto, Nini, and Schwarz (2018) for fixed income. Barberis and Thaler (2003) and Gromb and Vayanos (2010) provide extended surveys of prominent price anomalies documented in the equity market.

My study is also related to the limits of arbitrage literature. Early studies in this literature focus on the "asset side of the balance sheet" (Mitchell and Pulvino, 2012), showing that transaction costs and holding costs can deter efficient arbitrage activities (e.g., Pontiff, 1996 and Mitchell, Pulvino, and Stafford, 2002). Barberis and Thaler (2003) and Gromb and Vayanos (2010) also provide comprehensive overviews discussing these frictions.

Recent empirical studies examine the impact of capital constraints on mispricings, but the majority of these studies document the association between capital constraints and separate mispricings for convertible bonds (Mitchell, Pedersen, and Pulvino, 2007), covered interest rate parity (Mancini-Griffoli and Ranaldo, 2010, Gârleanu and Pedersen, 2011, Du et al., 2018), credit default swaps (Gârleanu and Pedersen, 2011), Treasury securities (Hu, Pan, and Wang, 2013), and equity anomalies (Asness, Moskowitz, and Pedersen, 2013). Several notable exceptions examine mispricings across different markets. Mitchell and Pulvino (2012) provide evidence that various mispricings all worsened in the wake of the 2008 financial crisis. Fleckenstein, Longstaff, and Lustig (2014) show that TIPS mispricing comoves with other fixed-income mispricings in a five-year sample surrounding the global financial crisis. Pasquariello (2014) combines mispricings in the currency market as an indicator for financial market dislocations and focuses on its pricing ability in global stock and currency markets. Boyarchenko, Eisenbach, Gupta, Shachar, and van Tassel (2018) show that in the aftermath of the 2008 financial crisis, stringent bank regulations contribute to increasing mean levels of mispricings in different markets. My work is also related to Rösch, Subrahmanyam, and van Dijk (2017), who document comovement across different aggregate efficiency measures in the equity market and find such comovement is associated with funding measures.

The remainder of the paper proceeds as follows. Section 2 constructs the arbitrage spreads. Section 3 explores comovement in the spreads and constructs the arbitrage gap. Section 4 investigates the association between the arbitrage gap and external funding constraints. Section 5 investigates the relation between the arbitrage gap and equity mispricing. Section 6 explores the dynamic relations between the arbitrage gap and funding constraints. Section 7 concludes.

2 Arbitrage spreads

In this section, I construct four arbitrage spreads, specifically the futures-cash basis for the S&P 500 index futures, the box spread for individual stock options, the covered interest rate parity spread for currency pairs, and the Treasury mispricing measure for Treasury notes/bonds. The reasons for choosing these markets are as follows.

First, for these asset classes, mispricings can be identified with low variances, because either absolute or relative fundamental values are ascertained, and no-arbitrage parities are known in the literature. Moreover, they are major financial markets where long historical data are publicly available. In the remainder of the section, I describe how I construct the spreads in subsections 2.1 to 2.4 in more details, and analyze their time-series features in subsection 2.5.

2.1 The futures-cash basis

The first arbitrage spread is based on the futures-cash parity for index futures, defined as the difference between an index's price and its synthetic analog based on its futures contract's price. In a frictionless world, the value of an index price should equal to the value of a replicating portfolio based on its futures contracts with interest rates and expected dividend yields adjustments. Any difference between the two captures mispricing.

I focus on the S&P 500 index because its futures contracts are among the most liquid assets and have a fairly long history starting from April 1982. The futures-cash parity is defined as follows:

$$F_t \times e^{-(r_t - \delta_t)(T-t)} = S_t, \tag{1}$$

where F_t denotes the settlement price of contract i on day t. r_t and δ_t denote the interest rate and index's dividend yield rate from t up to maturity, $T - t$. S_t is the S& P 500 index's closing price on day t.

Then, the futures-cash basis is defined as:

$$Futbasis_t = \left| \log \frac{F_t \times e^{-(r_t - \delta_t)(T-t)}}{S_t} \right| \tag{2}$$

I use the front-month contract to compute the futures-cash basis because it is the most actively traded contract. One issue of using a single contract is that the time series of its futures price exhibits seasonality. In particular, in expiry months (March, June, September, and December), the basis is substantially lower than in other months. I adjust the seasonality issue by subtracting the means of corresponding months. In all what follows, I use only the seasonal-adjusted basis series.

Three concerns are related to the futures-cash basis calculation. First, errors in the dividend yields' estimations can contribute to the basis. I find that both realized dividend yields and expected dividend yields (based on past two years) deliver very similar futures-cash bases. Also, the correlation between the basis and the dividend yield is very low (0.04). So, the dividend yield is unlikely to be the driver of the futures-cash basis. Second, specifying unattainable benchmark riskfree rates can also drive a wedge. In my benchamark analysis, I use the LIBOR yield curves. The results are almost unchanged if I use the Truasury yield curve on the GC repo curve instead.

The third potential problem is asynchronous quotes between stocks and futures market. The publicly available end-of-the-day futures prices are recorded at 4:15 p.m. EST, whereas stock market close prices are taped at 4:00 p.m. EST at the end of regular trading sessions. A fifteen-minute time-stamp mismatch can give rise to fictitious wedge between futures prices and index prices. However, I find that all the results are robust to using calendar speads as the mispricing measure. Calendar spread is defined as the difference between the left-hand-side values of the equation (1) for futures with different maturities but same underlying. Construction of calendar spreads avoids using stock index price completely and thus circumvent the timestamp mismatch issue.[4] The average calendar spread has a correlation of 63% with the futures-cash basis.

Futures contracts' end-of-day prices come from Bloomberg. The zero-coupon yields used in the calculation are interpolated from the LIBOR zero curves provided by OptionMetrics. The OptionMetrics database starts in 1996; before 1996, I use zero-coupon yield curves inferred from Treasury bills. Index dividend yields are calculated as value-weighted averages of individual stocks' realized dividend yields.

2.2 The box spread

The second arbitrage spread is derived from the put-call parity. The put-call parity, one of the classic laws of financial economics, states that for a non-dividend-paying stock, the

[4] An earlier version of this paper uses the calendar spread to do main analysis.

prices of European call and put options with the same maturities and strikes (i.e., a put-call pair) should satisfy the following relation:

$$C_t - P_t + PV_{t,T}(K) = S_t, \tag{3}$$

where C_t and P_t are the time t prices of the call and put options maturing at time T; $PV_{t,T}(K)$ is the present value of the strike K at t; and S_t is the stock price at time t.

However, two issues can arise if Equation (3) is directly used to construct put-call parity violations. First, identifying the gap between the two sides of Equation (3) requires synchronized quotes on options and stocks. Battalio and Schultz (2006) find that asynchronous quotes in the U.S. stock and option markets are responsible for a majority of detected put-call violations. Second, all stock options traded on the U.S. exchanges are American options. So gaps between synthetic and real stock prices may be due to early exercise premia.

To deal with early exercise value, I only consider options whose underlying stocks do not pay out any dividends during these options' life cycles. For nondividend payers, American and European call options have the same prices. As for American put options, I estimate early exercise premia following Ofek, Richardson, and Whitelaw (2004) and Battalio and Schultz (2006). In particular, I obtain implied volatilities for American puts and then use them to back out the prices of European puts. Early exercise premia (EEP) are calculated as the price differences of derived European puts and observed American puts. Similar to the literature, I find that EEP are negligible relative to put prices.

To address asynchronous quotes across the two markets, I use the box spread to capture put-call parity violations (Ronn and Ronn, 1989). Consider a stock i that has two put-call pairs (m, n) with both pairs sharing the same maturity but having different strikes. The log difference between the corresponding synthetic stock prices is

$$\left|\log \frac{S^*_{i,m,t}}{S^*_{i,n,t}}\right| = \left|\log \frac{C_{i,m,t} - P^E_{i,m,t} + PV_{t,T}(K_{i,m})}{C_{i,n,t} - P^E_{i,n,t} + PV_{t,T}(K_{i,n})}\right|. \tag{4}$$

Here, $P^E_{i,m,t}$ is the implied European put price defined as the difference between the American put price and the corresponding EEP. Then stock i's average box spread is calculated as

$$Box_{i,t} = \frac{1}{N_I} \sum_{(m,n)\in I} \left|\log \frac{S^*_{i,m,t}}{S^*_{i,n,t}}\right|, \tag{5}$$

where I denotes a set containing all possible box pairs, and $N_{I,i}$ denotes the number of pairs.

The aggregate box spread is a simple average across all N_t stocks:

$$Box_t = \frac{1}{N_t}\sum_{i=1}^{N_t} Box_{i,t}. \tag{6}$$

Monthly box spread is defined as an average of daily values of Box_t. Option data come from OptionMetrics, starting from 1996. Interest rates are interpolated from the zero-coupon curves based on LIBOR from OptionMetrics.

2.3 The covered interest rate parity spread

The third arbitrage spread is based on covered interest rate parity (CIP) in the foreign exchange. Consider the following scenario. An investor borrows one unit of currency A at an interest rate $r_{t,A}$ for time T, exchanges it to currency B at an exchange rate $S_t^{A\to B}$, and then lends it in currency B at interest rate $r_{t,B}$ for the same time period. Define a synthetic forward exchange rate from A to B as

$$\hat{F}_{t,T}^{A\to B} = \frac{S_t^{A\to B}(1+r_{t,B})}{(1+r_{t,A})}. \tag{7}$$

In the absence of arbitrage, the observed forward rate $F_{t,T}^{A\to B}$ should be equal to $\hat{F}_{t,T}^{A\to B}$. Any deviation manifests a potential mispricing.

I examine CIPs for the eleven most liquid major currency pairs, with the U.S. dollar, Euro, and British pound as bases. The list Ω of pairs includes EUR/USD, GBP/USD, JPY/USD, CHF/USD, AUD/USD, CAD/USD, GBP/EUR, CHF/EUR, JPY/EUR, CHF/GBP, and JPY/GBP. One-, three-, and six-month synthetic forward rates are derived for each exchange rate pair using the LIBORs with corresponding maturities.

I calculate log deviations between synthetic and observed forward exchange rates for 33 pair-maturity combinations. The aggregate CIP spread is computed as an average of all individual deviations:

$$CIP_t = \frac{1}{33}\sum_{T\in\{1,3,6\}}\sum_{A/B\in\Omega}\left|\log\frac{\hat{F}_{t,T}^{A\to B}}{F_{t,T}^{A\to B}}\right|. \tag{8}$$

Monthly CIP spread is computed as an average of daily values of CIP_t. All the data, which include exchange spot and forward rates and LIBORs, come from Bloomberg. I include months in which at least three currency pairs' data are available. The sample then starts in January 1987. One caveat with the Bloomberg's exchange spot and forward rates is that they are not executable. The results remain unchanged if I instead rely on the Thompson Reuters' (TR) data. The TR's rates are based on tradable quotes taken from several trading platforms at 4:00 p.m. GMT, so they are not subject to this issue. However, the sample covered by the TR's data is almost 10-year shorter.

2.4 The Treasury mispricing measure

To identify low-variance mispricings for the Treasury securities, I construct the aggregate Treasury mispricing measure following a popular approach in the literature (e.g., Hu et al., 2013). Particularly, for a given individual note/bond, its mispricing measure is defined as the difference between the observed price and the one implied by a term structure model.

As in the classic model of Nelson and Siegel (1987), I assume the following functional form for the continuous discount factor $Z(t, T_i, b_t)$ on day t for a zero-coupon bond with maturity T_i:[5]

$$-\frac{1}{T_i}\log Z(t, T_i, b_t) = \theta_{0,t} + (\theta_{1,t} + \theta_{2,t})\frac{1 - e^{-\frac{T_i - t}{\lambda_t}}}{\frac{T_i - t}{\lambda_t}} - \theta_{2,t}e^{-\frac{T_i - t}{\lambda_t}}. \tag{9}$$

On day t, the parameter vector $b_t = \{\theta_{0,t}, \theta_{1,t}, \theta_{2,t}, \lambda_t\}$ is estimated to minimize

$$\sum_{j=1}^{N_t}\left[P(t, T_{n_j}, c_j) - P^{NS}(t, T_{n_j}, c_j, b_t)\right]^2, \tag{10}$$

where $P(t, T_{n_j}, c_j)$ is the observed day t price of bond j that pays \$100 at its maturity T_{n_j} and has a coupon rate of c_j. The sum is taken with respect to day t Treasury notes/bonds with maturities from 1 month to 10 years. $P^{NS}(t, T_{n_j}, c_j, b_t)$ is the fair value computed based on discount rates of zero-coupon bonds,

$$P^{NS}(t, T_{n_j}, c_j, b_t) = 100 \times c_j \sum_{i=1}^{n_j} Z(t, T_i, b_t) + 100 \times Z(t, T_{n_j}, b_t). \tag{11}$$

Here, n_j is the number of periods before expiration.

The Treasury mispricing measure for note/bond j is then defined as

$$TrMispr_{j,t} = \left|\log\frac{P(t, T_{n_j}, c_j)}{P^{NS}(t, T_{n_j}, c_j, \hat{b}_t)}\right|, \tag{12}$$

[5] Hu et al. (2013) use the continuous discoutn factor implied by an extended model proposed by Svensson (1994). The mispricing measure based on the extended Nelson-Siegel model yields very similar results. However, the parameter estimates from the extended Nelson-Siegel model are less stable than those from the Nelson-Siegel model.

where $\hat{b}_t$ denotes the day t estimated value of the underlying parameters vector. The market-wide Treasury mispricing measure is a simple average of individual measures across all notes/bonds available:

$$TrMispr_t = \frac{1}{N_t} \sum_{j=1}^{N_t} TrMispr_{j,t}. \tag{13}$$

Monthly Treasury mispricing measure is computed as an average of daily values of $TrMispr_t$. The Treasury securities data come from the CRSP Treasury Database.

2.5 Time variation in arbitrage spreads

Figure 1 displays time-series plots for the four arbitrage spreads. The time-series for the futures-cash basis and the Treasury mispricing spans from 1985 to 2017, while the CIP spread and box spread become available only starting from 1987 and 1996, respectively. As seen from the four time series plots, all of them show significant time variation. Through casual eyeballing, one can see that all four series trace anecdotal stressful events in financial markets well. For example, the three spreads that are available before 1990 ($Futbasis$, CIP, and $TrMispr$) spike up around the 1987. All series rise sharply around Asian and Russian crises in 1997 and 1998, the burst of the dot-com bubble around 2000, and, especially, the global financial crisis from 2008 to 2009.

At the same time, the four spreads display distinct asset-specific features. As seen in Table 1, the means and standard deviations differ across the four asset classes. For example, CIP has much lower mean (3 basis points) than Box (25 basis points). Market-specific features, such as different margin requirements for long-short trades, can generate the heterogeneity in the mean levels of spreads. As shown in Gârleanu and Pedersen (2011), when arbitrageurs are financially constrained, mean levels of arbitrage spreads in the cross-section are positively correlated with the margin requirements for trading each asset class. Though the heterogeneity in the mean levels is interesting by itself, this paper abstracts from it and focuses only on the time-series variations. I therefore standardize the spreads by subtracting corresponding means and dividing by standard deviations estimated based on five-year rolling windows. In what follows, I use these standardized series for my analyses. Meanwhile, standardized futures-cash basis, box spread, CIP spread and Treasury mispricings are denoted as: $Futbasis_t^s$, Box_t^s, CIP_t^s, and $TrMispr_t^s$.

3 Comovement in arbitrage spreads

In this section, I investigate the comovement structure between the four standardized spreads. In the main analysis of the comovement structure, individual arbitrage spreads have different sample sizes. I require all series to have at least three-year history (36 months) for the standardization purpose. As a result, the samples of $Futbasis^s_t$ and $TrMispr^s_t$ are from April 1985 to December 2017. The sample of CIP^s_t spans from January 1990 to December 2017, and the sample of Box^s_t is from January 1999 to December 2017. Subsection 3.1 analyzes the comovement structure of the four. In subsection 3.2, I describe the time-series features of their common component.

3.1 Comovement structure

Panels A and B of Table 2 report pairwise correlation matrices for the spreads in the whole sample and in the pre-global-financial-crisis sample, respectively. As shown in Panel A, over a sample of more than 30 years, the average pairwise correlation is 46%. The lowest one is 22% which is between $TrMispr^s_t$ and Box^s_t while the highest is 59% which is between CIP^s_t and Box^s_t. All of them are positive and significant at the 5% level. Importantly, as seen in Panel B, the comovement is not purely driven by the most recent financial crisis. In the precrisis sample from April 1985 to December 2007, all the pairwise correlations remain significantly positive and have an average of 34%.

As a robustness check, I also use a regression approach to examine the comovement structure. In particular, I regress each arbitrage spread on a simple average (AG^c_t) of the other three spreads. Table 3 reports the coefficients, t-statistics and adjusted R-squareds from the regressions. Because the arbitrage spreads are standardized using rolling windows, a positive serial correlation in error terms can be introduced and inflates the t-statistics. So, I use Newey-West adjusted standard errors with 12 lags for t-statistics construction.

The regression results deliver a similar message. AG^c_t exhibits significant explanatory power for each individual arbitrage spread, with t-statistics ranging from 4.11 to 11.01. However, the magnitudes of the coefficients differ for different arbitrage spreads, with 0.59 the lowest for Treasury mispricing and 1.17 the highest for CIP violations. Economically, the sensitivity of arbitrage spreads (mispricings) in different assets to the variation in funding constraints can be different. Exploring what asset-specific features give rise to such heterogeneity is out of the scope of this paper but can be another interesting direction for future research.

Principal component analysis also suggests strong comovement between arbitrage spreads. From 1985 to 2017, the first principal component of the four spreads accounts for 60% of the total variation (this number should be 25% for four independent series). In the precrisis sample from 1985 to 2007, the first principal component explains 51% of the total variation.

Furthermore, monthly innovations to the arbitrage spreads also display positive correlations, albeit being smaller in magnitude. I obtain monthly innovations to individual arbitrage spreads as the residuals from AR(1) regressions. The average pairwise correlation between the four innovation series is 29%. I find that all the correlation coefficients are significant at the 5% level. The full pairwise correlation matrix is reported in Table A1 in the Appendix.

3.2 The common component

Mispricings in the four markets comove strongly together. The first principal component explains the majority of the total variability, reflecting systematic component in price (in)efficiencies across distinct markets. In this subsection, I describe the time-series features of this common component in more details. To avoid forward-looking bias, I use a simple average of the spreads to compute the common component. It has a correlation of 99.9% with the first principal component. In what follows, this common component is referred to as the arbitrage gap and denoted by AG.

Panel A of Figure 2 plots the monthly arbitrage gap. Not surprisingly, the series traces anecdotal stress periods pretty well. It spikes up in 1987, 1998, and 2009 and remains high in the late 1980s, in the late 1990s, and in the aftermath of the global financial crisis. In the early 2009, it rises as high as eight standard deviations above its mean, reaching its in-sample maximum, and drops as low as two standard deviations below the mean right after the dot-com bubble burst.

Panel B of Figure 2 plots the series of innovations to the arbitrage gap, computed as AR(1) residuals. The stressful periods around 1987, 1998, and 2009 are consistently marked by large shocks to AG. However, during tranquil periods, such as the early 1990s and mid-2000s (2004 to 2006), the series is much less volatile.

4 The arbitrage gap and funding constraints

The arbitrage spreads in different markets capture the marginal profits of raising one additional unit of arbitrage capital. In equilibrium, the marginal profit should equal to the marginal cost of raising additional capital. Thus, the common variations in the shadow cost of funding can give rise to a common component in the arbitrage spreads. In practice, arbitrageurs are exposed to common funding shocks. Different hedge funds borrow from the same prime brokers at similar financing rates and also face correlated in/outflows. In this section, I empirically examine the association between the arbitrage gap and the variables that are used to measure the cost of raising capital.

First, I find that the arbitrage gap covaries strongly with traditional funding-constraint measures, such as TED, hedge fund sector flows and returns, and prime brokers' repo growth. Consistent with the intuition, the variation in the arbitrage gap reflects the overall funding constraints faced by arbitrageurs. Second, I find that when funding constraints are tighter, arbitrage spreads in different markets become more correlated. That is, the degree of the comovement among arbitrage spreads is time-varying. In the periods when arbitrageurs face loose funding constraints (the shadow cost of capital drops to zero), the arbitrage spreads in different markets are small, and their variations are dominated by the idiosyncratic components (e.g. measurement errors) and thus exhibit significantly lower degree of comovement.

Subsection 4.1 describes the traditional funding variables used to proxy for overall funding tightness. In subsection 4.2, I investigate the abilities of the funding variables to explain the arbitrage gap. Subsection 4.3 shows that comovement between arbitrage spreads is time-varying and becomes stronger during the periods when funding constraints are tight.

4.1 Funding measures

Four variables are commonly used in the literature to capture the funding constraints faced by arbitrageurs. They are, the TED spread, aggregate hedge-fund flows and returns, and primary dealers' repo financings growth. In this subsection, I describe the intuition behind choosing these variables and describe the construction of these measures in details.

The TED spread, defined as the difference between the 3-month LIBOR and Treasury-bill rates, is the most widely used measure to capture the overall funding condition (e.g. Frazzini and Pedersen, 2014, and Rösch et al., 2017). In a theoretical frame work by Gârleanu and Pedersen (2011), the TED spread directly measures the shadow cost of raising external capital faced by constrained arbitrageurs. The TED spread series is downloaded from FRED website.

Hedge funds are among the most sophisticated investors who are actively involved in correcting mispricings in the capital market (e.g., Akbas, Armstrong, Sorescu, and Subrahmanyam, 2015 and Cao, Liang, Lo, and Petrasek, 2017). The aggregate hedge-fund flows and returns result in direct changes in the equity capital available to hedge-fund sector and in turn affects their funding-constraint tightness (e.g. He and Krishnamurthy, 2013). Moreover, returns of the hedge funds can lead to future changes in the funding tightness due to agency issues (Shleifer and Vishny, 1997). For example, hedge funds' investors can interpret their short-term losses as signals of lack of skills and thus pull capital further out of the fund.

The aggregate flow to the hedge-fund sector is defined as

$$HFFL_t = \frac{\sum_{i=1}^{N_t}[AUM_{i,t} - AUM_{i,t-1} \times (1 + R_{i,t})]}{\sum_{i=1}^{N_t} AUM_{i,t-1}}, \tag{14}$$

where $AUM_{i,t}$ denotes assets under management (AUM) for fund i at the end of month t; $R_{i,t}$ is its return from the end of month $t-1$ to the end of month t; and N_t is the total number of funds in month t.

The monthly aggregate return to the hedge-fund sector is calculated as the weighted average of individual funds' monthly returns with lagged month-end AUMs as weights.

$$HFR_t = \frac{\sum_{i=1}^{N_t}[AUM_{i,t-1} \times (1 + R_{i,t})]}{\sum_{i=1}^{N_t} AUM_{i,t-1}} - 1, \tag{15}$$

The funds' data come from TASS.[6] I include all available hedge funds, except funds of funds. Because the TASS database provides data on dissolved funds starting from 1994, I only consider observations after January 2004 to mitigate the survival bias concern. The sample spans from January 1994 to December 2017.

The forth funding variable is the growth of aggregate primary dealers' repo financings. Fluctuations in this variable capture contractions and expansions of financial intermediaries' balance sheets. A growing literature argues that healthiness of intermediaries' balance sheets is closely associated with arbitraguers' cost of funding (e.g. Adrian, Etula, and Muir, 2014,

[6] TASS and HFR are the two largest databases for hedge funds information. Liang (2000) shows that TASS offers a more complete coverage of dissolved funds.

Du et al., 2018, Boyarchenko et al., 2018). For example, hedge funds rely heavily on financing from intermediaries, and shocks to intermediaries balance sheets can therefore affect the supply of arbitrage capital.

Balance-sheet quantities, such as the leverage ratios and asset growths, have been used in the literature to capture the healthiness of intermediaries' balance sheets (e.g. Adrian et al., 2014, He, Kelly, and Manela, 2017). However, such measures are available only at quarterly frequency. In this paper, I instead use weekly data on primary dealers' repo financing growth from NY Fed as my main measure of intermediaries' balance sheet activities. Repo is an important instrument through which intermediaries adjust their balance sheets. Adrian and Shin (2010) provide evidence that intermediaries' repo financing growth is significantly and positively related to total asset growth or leverage growth. In this sense, the weekly data on repo financings can capture primary dealers' balance-sheet changes at higher frequency. The repo growth is constructed as the sum of all repo contracts oustanding across all maturities and security types. Monthly changes in aggregate primary dealers' repo financings are calculated as the first differences of the log month-end aggregate repo financings.

4.2 Funding measures and the arbitrage gap

In this subsection, I investigate the abilities of the four funding measures to explain the variation in the arbitrage gap. Specifically, I conduct a battery of regressions of AG onto different groups of the funding measures. I find that all funding variables exhibit economically and statistically significant explanatory powers for AG when included separately or jointly.

I conduct regressions over three different samples due to data availability.[7] Table 4 reports coefficients and adjusted R-squareds from monthly regressions of AG_t onto different sets of funding variables. As shown in column (5), in a twenty-year sample from 1998 to 2017, four funding variables jointly can explain 66% of the variation in AG_t and all of them exhibit significant explanatory power with the absolute values of t-statistics ranging from 2.77 to 6.30. The economic magnitudes are also big. A one-standard-deviation increase in TED_t is accompanied by a 0.75-standard-deviation increase in AG_t. A one-standard-deviation hedge-fund sector's outflow or loss in returns are associated with a 0.20-to 0.25-standard-deviation increase in AG_t. A one-standard-deviation slowdown in primary dealers' repo financing growth is associated with a 0.one-standard-deviation increase of AG_t.

[7] In particular, the three sets of regressions start from January 1986, January 1994 and February 1998 respectively, and include funding variables that are available at the beginning of the sample.

In the longer samples, the three funding variables for which data is available, TED_t, $HFFL_t$ and HFR_t, continue to exhibit strong explanatory power for AG_t. As reported in column (1), TED_t explains 25% of variations in AG_t over a sample from 1986 to 2017 with a t-statistic of 2.34. The economic magnitude is big; a one-standard-deviation increase in TED is accompanied by a 0.5-standard-deviation increase in AG_t. Column (3) reports the results when aggregate hedge-fund flows and returns are added into the regression in addition to TED_t in the sample from 1994 to 2017. The three jointly can explain 60% of the variation in AG_t and the coefficients of these three have very similar magnitudes and statistical significance to those discussed in column (5).

Consistent with the hypothesis, the common mispricing component indeed comoves significantly with traditional funding variables with two thirds of its variation been explained by them. Moreover, the signs of the coefficients indicate that when the funding constraints become tighter, captured by widening TED spread, outflows and losses to the hedge-fund sector, or slower primary dealers' repo financing growth, the arbitrage gap increases significantly.

As robustness checks, I also control for bond and equity risk factors.[8] Bond and equity risks may factor in for the following reasons. First, arbitrage spreads may load on interest rate risks, because arbitrageurs may unwind the corresponding positions before their maturities. I use the term spread ($TERM$), defined as the difference between the yields of 10-year Treasury bonds and 3-month Treasury bills, as the interest rate factor. Moreover, arbitrage spreads may also load on default risk factors, since the implied profits from the spreads are no longer ascertained if arbitrageurs face counterparty risks. I use the difference between the yields of BAA- and AAA-graded corporate bonds as the default risk factor (DEF). Both factors are standard in the literature (Fama and French, 1993).

I also control for equity market factors, such as market volatility and returns. Market volatility may affect the margin requirements that arbitrageurs are subject to, given that value-at-risk, an indicator often used to set margins, increases with volatility. I include the implied volatility of the S&P 100 index (VXO).[9] Finally, I include aggregate stock market's excess returns (MKT) to control for general market conditions.

Columns (2), (4), and (6) report the regression results when these controls are included in

[8] In the Appendix, I also control for variables capturing liquidity demand, such as the FED-fund rate and Tbill-over-GDP ratio (Nagel, 2016). The results are barely changed.

[9] Alternative measures for market volatility, such as monthly standard deviation of daily market returns, monthly average idiosyncratic-volatility series proposed by Herskovic, Kelly, Lustig, and Van Nieuwerburgh (2016) deliver similar results.

addition to the funding measures. The presence of the controls barely change the coefficients and t-statistics of the funding variables and the controls exhibit little explanatory powers for AG_t.

A popular alternative measure used to capture intermediaries' intermediation capacity is the leverage ratio, for example, the leverage ratio factor of Adrian et al. (2014). In column (7), I include the leverage ratio by Adrian et al. (2014) in the quarterly regression along with other funding variables. It has no significant explanatory power for AG_t in the multiple regression. A potential reason can be the low testing power due to lower frequency. In a univariate regression over the entire sample from 1985 to 2017, the coefficient of Lev_t has a t-statistic of -2.17, which suggests an association in the correct direction. When intermediaries' balance sheets shrink, their intermediation capacity shrinks and results in a wider arbitrage gap.

Because AG is quite persistent, with a first-order autocorrelation of 78%, I also test the abilities of shocks to the funding measures to explain variation in shocks to AG_t. Shocks are obtained as the residuals from the AR(1) regressions. I then conduct regressions with shocks using the similar specifications as those with levels.

Table 5 reports the results in the same manner as Table 4 does. The overall patterns are quite similar. Shocks to $HFFL_t$, HFR_t, TED_t, and $Repo_t$, denoted as ΔHFR_t, $\Delta HFFL_t$, ΔTED_t and $\Delta Repo_t$, display significant abilities to explain variation in the shocks of AG_t (ΔAG_t). As shown in column (5), the four jointly explain 40% of the variation in ΔAG_t, and coefficients on ΔHFR_t and ΔTED_t are statistically significant with t-statistics of -2.68 and 5.09. In the univariate regression, ΔTED_t can explain 29% of the variation in ΔAG_t over a sample from 1986 to 2017. However, $\Delta HFFL_t$ no long exhibits significant explanatory power. One interesting observation is that shocks to VXO_t (ΔVXO_t) exhibit significant explanatory power for ΔAG_t contrary to the relations between level series. The effect of uncertainty as limits of arbitrage might be temporary; a sudden increase in uncertainty level results in an increase in the arbitrage gap which is then corrected quickly.

4.3 Time varying comovement

In this subsection, I test the hypothesis that the degree of comovement between the arbitrage spreads is time-varying and negatively associated with the aggregate funding tightness. The basic intuition behind this hypothesis is as follows. The common variation in the arbitrage spreads in different markets comes from the variation in the shadow cost of raising capital.

When the funding constraints are loose, the shadow cost is close to zero, and idiosyncratic components dominate the individual spreads' variation (e.g. due to measurement errors). Thus, they exhibit weak comovement. This basic intuition has been formalized in the theoretical frameworks by Gârleanu and Pedersen (2011) and Gromb and Vayanos (2018).

Using weekly arbitrage spreads data, I calculate the average pairwise correlation between the four spreads in each quarter t, denoted as $\overline{Corr}_t$. Then, I regress $\overline{Corr}_t$ onto the four funding variables,[10] which are converted into quarterly frequency. Table 6 reports the regression results. Overall, when the funding variables change in the tightening directions, $\overline{Corr}_t$ becomes larger. In particular, TED_t and HFR_t exhibit significant association with $\overline{Corr}_t$. The coefficients and t-statistics of these two are significant in both economic and statistic sense. In a univariate regression, the coefficient on TED_t is 0.13 with a t-statistic of 1.89 as reported in column (1). The economic magnitude is big: a one-standard-deviation increase in TED_t, amounting to a 0.42-percentage-point increase, is associated with an increase of five percentage points in the average pairwise correlation.

The other variable significantly associated with $\overline{Corr}_t$ is HFR_t. When the hedge-fund flows and returns are included in the regressions, as shown in column (2), the coefficient on HFR_t is -1.21×10^{-2} with a t-statistic of -1.96. A one-standard-deviation decrease in HFR_t, amounting to a decrease of 3.6 percentage points, is associated with an increase in the average correlation of more than four percentage points. At the same time, $HFFL_t$ and $Repo_t$ do not have significant explanatory power for $\overline{Corr}_t$.

5 Mispricings in the equity market

Arbitrageurs, such as hedge funds, are active players in the equity market, using strategies that aim to exploit mispricings. Capital constraints that limit their ability to take on aggressive arbitrage position should affect the magnitudes of the equity market's anomalies, provided that mispricings contribute at least partially to the anomalous return spreads. In this section, I examine the association between the arbitrage gap and three prominent equity anomalies. They are closed-end fund discount, M&A spread and long-short risk-adjusted alpha spreads based on sorts by certain characteristics.

These anomalies concern either the anomalous price differences of assets or the pre-

[10] In robustness checks, I also include the same set of controls as in the previous subsection, and all results remain unchanged.

dictability of stocks' returns based on past prices and earning information. They can hardly be justified by expected cash flows or risk exposures, and studies have shown that they are at least partially related to mispricings.[11] In practice, strategies that exploit these three anomalies represent three major strategy categories in the equity market (Pedersen, 2015).

However, these strategies are far from riskless, privided that mispricings may only partially account for the return/price differences. The payoffs from these strategies are uncertain and risky, and the trading horizons are also uncertain. Therefore, because of the risky nature of these strategies, arbitrage impediments can also arise from other sources in addition to capital constraints. Nevertheless, I show that all three anomalies exhibit significant association with the arbitrage gap, indicating that aggregate funding availability still has significant impact on the magnitudes of equity mispricings.

In subsections 5.1 and 5.2, I investigate the relation between AG and closed-end fund discounts and M&A spreads. Subsection 5.3 studies the relation between AG and long-short spreads included in the Fama-French five-factor model (Fama and French, 2015).

5.1 Closed-end fund discount

Closed-end fund discount is a classic example of the law of one price violation in the equity market. It arises when closed-end funds' shares and securities constituting their portfolios (funds' net asset values, or NAVs) are traded at different prices. Such discrepancies are referred to as discounts since most funds are traded below their NAVs.

One of the prominent explanations of the closed-end fund discount relies on excessive noise traders' demand for closed-end funds' shares (Lee et al., 1991). Arbitrage trades that exploit corresponding mispricings are capital-intensive and risky. A straightforward passive arbitrage strategy is to buy shares of funds.[12] However, such arbitrage trades are costly and risky for arbitrageurs (Pontiff, 1996). Without a direct channel to redeem funds' shares at NAVs, the discounts may take a long time to converge. Arbitrage capital can be locked in those positions for a long time, and the payoffs are uncertain.[13] Nevertheless, a strategy

[11] Lee, Shleifer, and Thaler (1991) show that closed-end fund discount can reflect retail investors' sentiment. Mitchell and Pulvino (2001) and Baker and Wurgler (2006) find that M&A spread can hardly be reconciled by traditional risk-factor models, and is positively related to limits-of-arbitrage measures. Stambaugh et al. (2012) provide empirical evidence that long-short alpha spreads based on characteristics-sorts are all affected by investors' sentiment.

[12] Ideally, the passive investment strategy also involves hedging with underlying portfolios. However, the underlying assets held by the funds at each point of time are not publicly available.

[13] An alternative active strategy is to open-end funds through capital-intensive activism campaign.

that buys and holds a portfolio of closed-end funds that are traded below their NAVs earns significant risk-adjusted alphas. In my sample, a monthly-rebalanced strategy can earn an alpha of 0.35% per month with respect to Fama-French three factors.

Intuitively, during the periods when AG is high and arbitrageurs are financially constrained, closed-end fund discount is expected to become wider. To formally test this intuition, I regress the level of aggregate closed-end discount onto AG at monthly frequency. In particular, in each month, discounts for all individual funds are calculated as log difference between their NAVs and funds' share prices. I then take a simple average of individual discounts across all funds traded below their NAVs as the aggregate closed-end discount measure ($CEFD$). Similar to individual arbitrage spreads, I standardize $CEFD$ using means and standard deviations estimated based on 5-year rolling windows.

Table 7 reports the results of the regressions. Consistent with the hypothesis, a one-standard-deviation increase in AG is associated with a significant 0.66-standard-deviation increase in the average closed-end discount, as shown in column (1). Moreover, this strong association is not purely driven by the most recent financial crisis. In the subsample excluding 2008 and 2009, the coefficient of AG is barely changed, as reported in column (4). To control for equity market risks, I also include implied volatility (VXO_t) and market excess returns (MKT_t) as controls.

Interestingly, when other four funding variables, TED, $HFFL$, HFR, and *Repo* are included in the regression as shown in columns (2) and (3), the coefficient on AG is almost unaffected and exhibits dominating explanatory power for the closed-end funds discount. None of the four funding variables, except hedge-fund flows, exhibits significant explanatory ability. Although the four funding variables explain almost two thirds of the variation in AG, they are imperfect measures of the shadow cost of funding faced by arbitrageurs and thus underperform AG in capturing the common variation in mispricings across different markets. Finally, controlling for implied volatility (VXO), term ($TERM$) and default spreads (DEF), and market returns (MKT) in the regressions does not affect the results in any important way.

Bradley, Brav, Goldstein, and Jiang (2010) show that arbitrageurs actively use this approach, and discounts are significantly reduced upon such campaigns.

5.2 M&A spread

In this subsection, I examine the association between M&A spread and the arbitrage gap. M&A arbitrage is a popular strategy pursued by hedge funds and other Wall Street proprietary trading desks (e.g., Mitchell and Pulvino, 2001 and Pedersen, 2015). After an M&A deal announcement, target firms' stocks are typically traded at a small discount to acquirers' offers. A strategy to buy shares of target firms (and hedge by shorting acquiring firms' shares in case of stock deals) and wait until deals completion can earn significantly positive risk-adjusted alphas (Baker and Wurgler, 2006 and Mitchell and Pulvino, 2001). Consistent with their findings, I find that an equal-weighted portfolio of all target stocks traded at the discounts by the end of previous month indeed earns significant abnormal alphas of 1.08% per month relative to Fama-French three factors.

However, M&A arbitrage is risky. The timing of price convergence and the mere completion of deals are uncertain. Arbitrage capital can be easily locked up for a long period of time. Therefore, when arbitrageurs are financially constrained, they are not able or willing to put on such capital-intensive trades, resulting in larger uncorrected M&A spreads.

This intuition predicts that M&A spreads should become wider when AG is higher. I formally examine whether the level of M&A spreads exhibit strong and positive association with AG. Consistent with this intuition, the level of M&A spread comoves significantly and positively with AG across all regression specifications as shown in Table 8.

In particular, in month t, I take a simple average of individual deal spreads across all ongoing cash deals in that month and denote it as $MAspread_t$. An individual deal spread is simply the log difference between the offer price and the price at which the target is traded at, adjusted for share splits. Similar to the previous exercise with the closed-end fund discount, I standardize $MAspread_t$ using means and standard deviations estimated based on 5-year rolling windows. Then, I regress the standardized $MAspread_t$ onto AG_t along with other funding variables and controls.

As shown in column (1) of Table 8, AG_t exhibits significant association with $MAspread_t$ with a t-statistics of 6.24. The economic magnitude is also significant; a one-standard-deviation increase in AG_t is associated with a 0.53-standard-deviation increase in the level of $MAspread_t$. When the other four funding variables are include as shown in column (3), only TED_t exhibits significant explanatory power for $MAspread_t$ with a t-statistic of 2.52. However, TED_t's explanatory power is mainly driven by the most recent financial crisis. In the subsample excluding 2008 and 2009, TED_t as well as the other three funding variables no longer have significant explanatory power for $MAspread_t$ as shown in column (6). The coefficient on TED_t drops to 0.49 with a t-statistic of 1.26. Meanwhile, AG's ability to explain $MAspread_t$ remains almost unchanged in the subsample. Adding other controls, such as VXO_t, $TERM_t$, DEF_t, and MKT_t have little impact on the coefficients and t-statistics of AG_t for $MAspread_t$.

5.3 Characteristics-sorted portfolios

In this subsection, I investigate the association between AG and long-short return spreads based on characteristics-sorts. Anomalous expected return predictability based on book-to-market, earnings, investment and past prices is well known to the literature and challenges standard asset-pricing models (Gromb and Vayanos, 2010). The long-short spreads based on these four characteristics are not only widely studied in academia but also actively traded by practitioners. Although the literature have included them in the factor models,[14] many studies also provide evidence that mispricing at least partially contribute to the risk-adjusted alphas of these anomalies.[15] At the same time, mispricings are unlikely to contribute to the size premium.[16] In what follows, I investigate the association between AG and value, profitability, investment and momentum return spreads, while the size and market factors are used to control for risk.

Accroding to the mispricing explanation of equity anomalies, stocks in the long-leg portfolios (e.g., past winners when sorted by momentum or profitable firms when sorted by profitability) are likely to be underpriced. During gradual price correction by arbitrageurs, positive risk-adjusted returns are observed. Similarly, stocks in the short-leg portfolios are likely to be overpriced (e.g., past losers or unprofitable firms), and thus generate significantly negative risk-adjusted alphas during the process of non-instantaneous price correction. When capital constraints tighten, arbitrageurs' capacity to correct mispricings is jeopardized. With less price correction, we should expect smaller magnitudes of risk-adjusted returns of long-short spreads. Overall, the findings described in this subsection support this hypothesis. I

[14] Fama and French (2015) include value, investment, and profitability factors in a five-factor model and Carhart (1997) includes momentum in the Carhart-four-factor model.

[15] For example, Skinner and Sloan, 2002, Ali, Hwang, and Trombley, 2003 and Ball, Gerakos, Linnainmaa, and Nikolaev (2017) find evidence consistent with that BM captures mispricings. Stambaugh et al. (2012) show that profitability, investment, and momentum can be predicted by the investor sentiment measure in a manner consistent with mispricing story.

[16] Stambaugh and Yuan (2016) and Asness, Frazzini, Israel, Moskowitz, and Pedersen (2018) find evidence that small stocks are more likely to be overpriced and thus should underperform large stocks, which goes in the wrong direction relative to size premium.

find that for all four anomalies the magnitudes of long-short risk-adjusted return spreads are much smaller when the expected AG level is high.

Table 9 reports the results of regressions of long-short return spreads of value (HML_t), profitability (RMW_t), investment (CMA_t), momentum (MOM_t) as well as their average (Avg_t) onto AG_t. All factors are downloaded from Ken French's website. To investigate whether association between AG and anomalies' returns is contemporaneous or exhibit some lead-lag patterns, I decompose AG into expected and unexpected parts ($\widehat{AG}_t$ and ΔAG_t) by fitting an $AR(1)$ model and include both parts in the regressions.

All four factors load negatively on $\widehat{AG}_t$. The economic magnitudes are big. As shown in Table 9, a one-standard-deviation increase in $\widehat{AG}_t$ for period t is associated with a 0.59-percentage-point decrease in HML_t, a 0.47-percentage-point decrease in CMA_t, a 0.28-percentage-point decrease in MOM_t, although the last one is not statistically significant. On average, a one-standard-deviation increase in $\widehat{AG}_t$ is associated with a 0.35-standard-deviation decrease in alpha across the four factors with a t-statistic of -3.00. Note that the literature commonly uses the TED spread as the funding liquidity proxy to test the funding constraints' impact on equity anomalies (e.g. Frazzini and Pedersen, 2014 and Asness et al., 2013). However, I find that both expected and unexpected parts of the TED spread have virtually no explanatory power for the long-short return spreads in the presence of AG.

These results echo the findings in Asness et al. (2013) but with several differences. They examine the loadings of value and momentum strategies on the traditional funding variables such as TED and find value and momentum load oppositely on it. They therefore suggest that different exposure to funding liquidity risks can provide an explanation for the negative correlation between value and momentum. Using AG, a funding constraint measure based on equilibrium prices, I find that both value and momentum load negatively on expected level of AG. Thus, value and momentum's exposures to the aggregate funding condition are unlikely explanations for their negative correlation structure. On the other hand, their negative exposures to AG is consistent with that the price-correction process is weakened when arbitrageurs face tighter funding constraints.

6 Arbitrage-limit dynamics

In this section, I explore the dynamic relations between AG and the funding measures using VAR analysis. Feedback mechanisms between mispricings and capital constraints arise as an important feature of many theoretical studies about arbitrage under capital constraints. In one direction, tightened capital constraints limit arbitrageurs' trading capacity, resulting in widening mispricings (e.g., Shleifer and Vishny, 1997, Brunnermeier and Pedersen, 2009, and Kondor, 2009).

In the reverse direction, worsening mispricings can further exacerbate funding conditions in following ways. First, arbitrageurs who hold positions betting on price correction would experience losses when mispricings continue widening. Because arbitrageurs, such as hedge funds, invest with delegated money, losses can induce uninformed outside investors to withdraw their money, depleting funds' equity capital (Shleifer and Vishny, 1997). Moreover, uninformed lenders (e.g., prime brokers), being uncertain about arbitrageurs' expected payoffs, are likely to increase margin requirements and to reduce overall lending activity (Brunnermeier and Pedersen, 2009). Meanwhile, because prime dealers can repledge arbitrageurs' assets, losses to arbitrageurs and worsening mispricings reduce the amount and quality of collateral available to prime dealers. In turn, this leads to a higher interbank rate and deleveraging by intermediaries.

In subsection 6.1, I investigate the dynamic relations between AG and the four funding variables that exhibit a substantial contemporaneous association with AG (Section 3). VAR analysis reveals strong bidirectional relations between the arbitrage gap and the level of capital availability. Such relations provide empirical evidence for the feedback mechanisms.

6.1 Bidirectional links between AG and funding measures

I use the VAR(2) specification to investigate the dynamic links between AG and the funding measures. The number of lags is chosen according to the Bayesian information criterion (Schwarz, 1978).

$$\tilde{Y}_t = \boldsymbol{B_0} + \boldsymbol{B_1}\tilde{Y}_{t-1} + \boldsymbol{B_2}\tilde{Y}_{t-2} + \tilde{V}_t, \tag{16}$$

$$\tilde{Y}_t = \begin{bmatrix} TED_t \\ HFR_t \\ HFFL_t \\ Repo_t \\ AG_t \end{bmatrix}.$$

Here, vector $\tilde{Y}_t$ includes the four funding measures, namely, the TED spread (TED_t), hedge-fund returns (HFR_t), hedge-fund flow ($HFFL_t$), and changes in the primary dealers' repo financings ($Repo_t$), as well as the aggregate aribtrage gap AG_t. The VAR system is estimated over the sample from 1998 to 2017 on a monthly frequency.

I consider orthogonalized impulse responses to shocks hitting the elements of the $\tilde{Y}_t$ vector. I use the inverse of the Cholesky decomposition of the residual covariance matrix to orthogonalize the shocks. Variables are ordered as in $\tilde{Y}_t$ vector, shown in equation (16). The impulse responses remain similar to different variable orderings, or if generalized impulse responses (Pesaran and Shin, 1998) are considered.

First, I examine how widening arbitrage spreads affect funding measures. Figure 4 plots orthogonalized impulse responses of AG and four funding measures to a one-standard-deviation positive AG shock traced forward over 12 months.[17] Bootstrap 1.96-standard-error bands are provided. As shown in Panel A, the shock increases AG by a half-standard-deviation. The jump of AG slowly decays and becomes insignificant after 5 months.

As shown in Panel B of Figure 4, the shock to AG increases the TED by 0.05 percentage points in the following month, which reverts back to insignificant level in the second month. Panels C and D show that the shock to AG has a lasting and significantly negative effect on both aggregate hedge-fund sector flows and returns. The hedge-fund sector suffers a drop in monthly returns of 0.23 percentage points in the following month, and reverts back to insignificant level in month 2. In addition, the hedge-fund sector experiences a decrease in flows of 0.3% of the total AUM in month 1, which stays significantly negative up to 7 months.

Panel E of Figure 4 plots the responses of primary dealers' repo growth to the AG shock. In the month following the shock, the repo growth slows down significantly by 1.2 percentage points. The effect reverts back to insignificant level in the month 2.

A shock widening AG increases the marginal profit of arbitrage capital immediately. However, instead of being eliminated instantaneously, the shock in AG leads to future increase in the cost of raising arbitrage capital. This pattern is consistent with the model predictions from theoretical literature including Shleifer and Vishny (1997) and Brunnermeier and Pedersen (2009).

Next, I explore the effects in the reverse direction, namely the responses of AG to positive shocks to funding variables. Figure 5 plots the orthogonalized IRFs of AG to a one-standard-deviation positive shock to a funding variable $X \in \{TED, HFR, HFFL, Repo\}$. Note that a positive shock to TED is a tightening shock whereas positive shocks to hedge funds' flows

[17]The one-standard-deviation shock is with respect to AG's residuals from VAR system.

and returns ($HFFL$ and HFR) and primary dealers' repo growth *Repo* are shocks easing the funding constraints.

As seen from Panels A and B of Figures 5, A one-standard-deviation positive shock to TED triggers AG to jump up by 0.4 standard-deviation, and the positive response of AG remains significant for around 7 months. On the other side, a positive one-standard-deviation shock to the hedge fund returns leads to a 0.22-standard-deviation drop in AG in the following month and the negative effect remains significant for almost four months. Positive shocks to hedge-fund flows and primary dealers' repo growth have no significant impact on AG. Consistent with the theoretical prediction, shocks that increase (decrease) the shadow cost of raising arbitrage capital are accompanied by an increase (decrease) in the required rate of returns for arbitrage—wider (narrower) arbitrage spreads.

7 Conclusion

In this paper, I document that mispricings comove strongly across five major financial markets. Arbitrage spreads—deviations from familiar no-arbitrage relations—in stock-index futures, stock options, foreign exchange, and Treasury securities comove strongly in a sample spanning over three decades. Prominent equity anomalies, such as closed-end fund discount, M&A spread, and positive long-short alpha spreads of portfolios sorted by certain characteristics, share this commonality.

The common component in arbitrage spreads across distinct markets—the arbitrage gap—is closely associated with the tightness of arbitrage capital constraints. A few funding-related variables, such as the hedge-fund returns and flows, the TED spread and the primary dealers' repo financing growth, can explain the lion's share of variation in the arbitrage gap. Moreover, when capital become scarcer, the comovement in mispricings strengthens.

Furthermore, I also provide empirical evidence supporting feedback mechanisms between the arbitrage gap and the funding variables. VAR analysis reveals significant bidirectional lead-lag relations between the two. In one direction, shocks to the arbitrage gap lead to worsening funding conditions. In the reverse direction, capital-tightening shocks to the funding variables lead to widening arbitrage gap. Such bidirectional links are consistent with a feedback loop between mispricing and capital constraints (e.g., Shleifer and Vishny, 1997 and Brunnermeier and Pedersen, 2009).

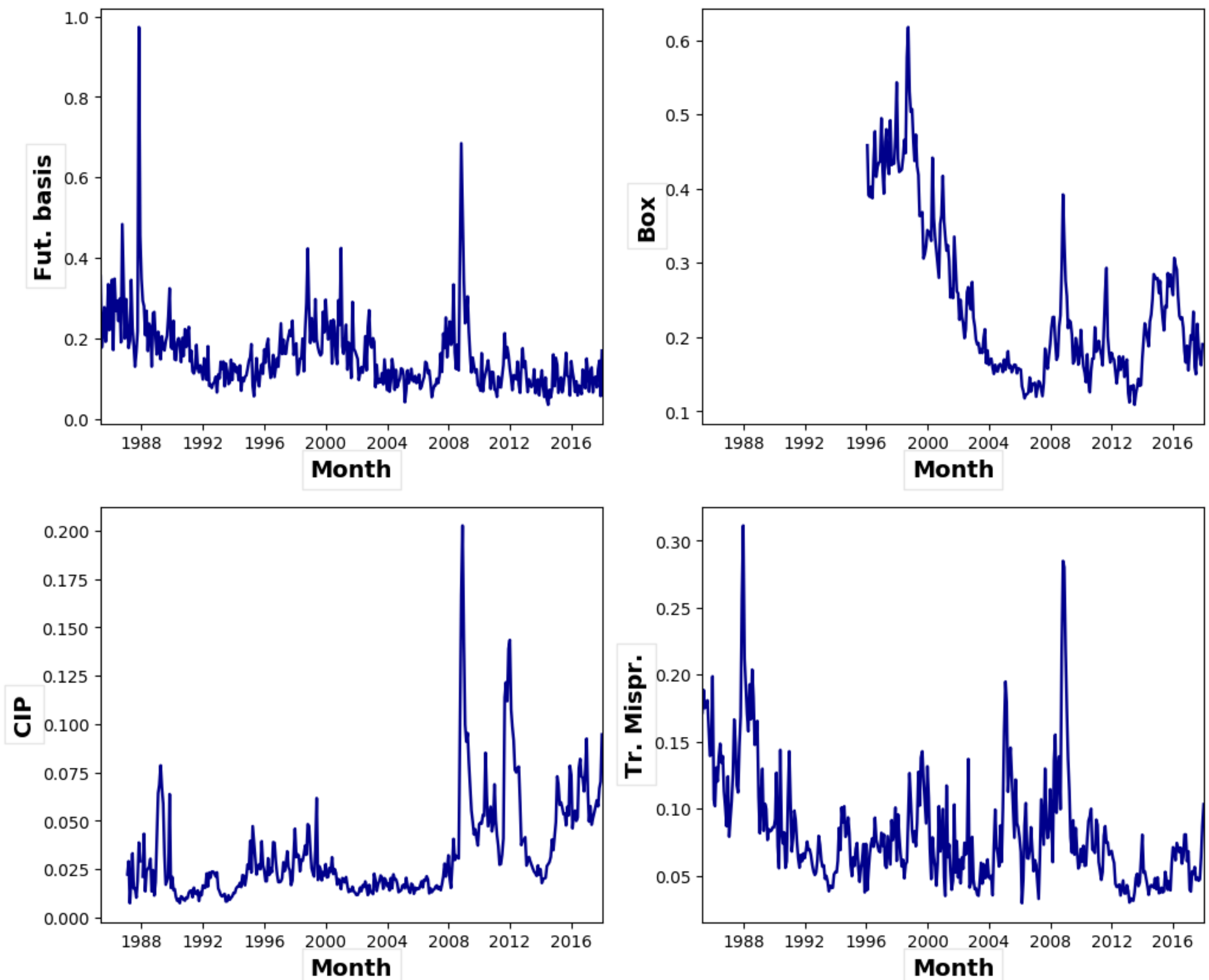
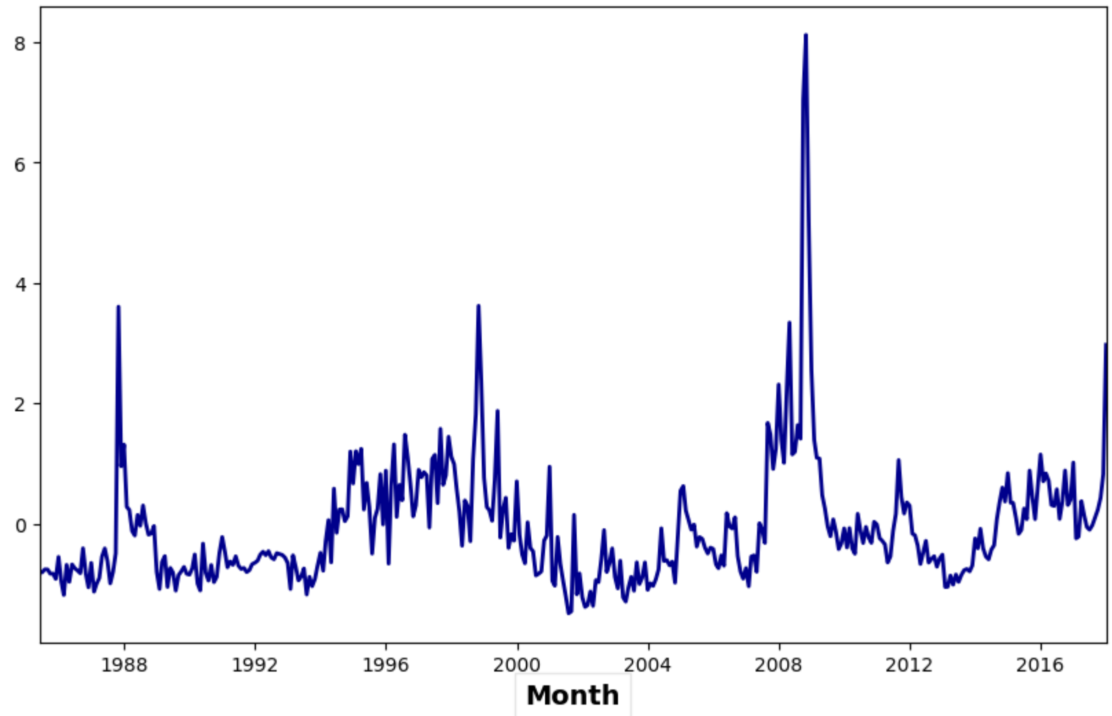


Figure 1 Time series of four arbitrage spreads. Spreads and their sample spans are: the futures-cash basis (Futbasis) for the S&P 500 index is from April 1985 to December 2017; the box spread (Box) for stock options is from January 1996 to December 2017; the covered interest rate parity spread (CIP) for currency pairs is from January 1987 to December 2017; the Treasury mispricing measure (Tr Mispr.) for Treasury notes/bonds is from January 1985 to December 2017.

Panel A: The aggregate arbitrage gap



Panel B: Shocks to the arbitrage gap

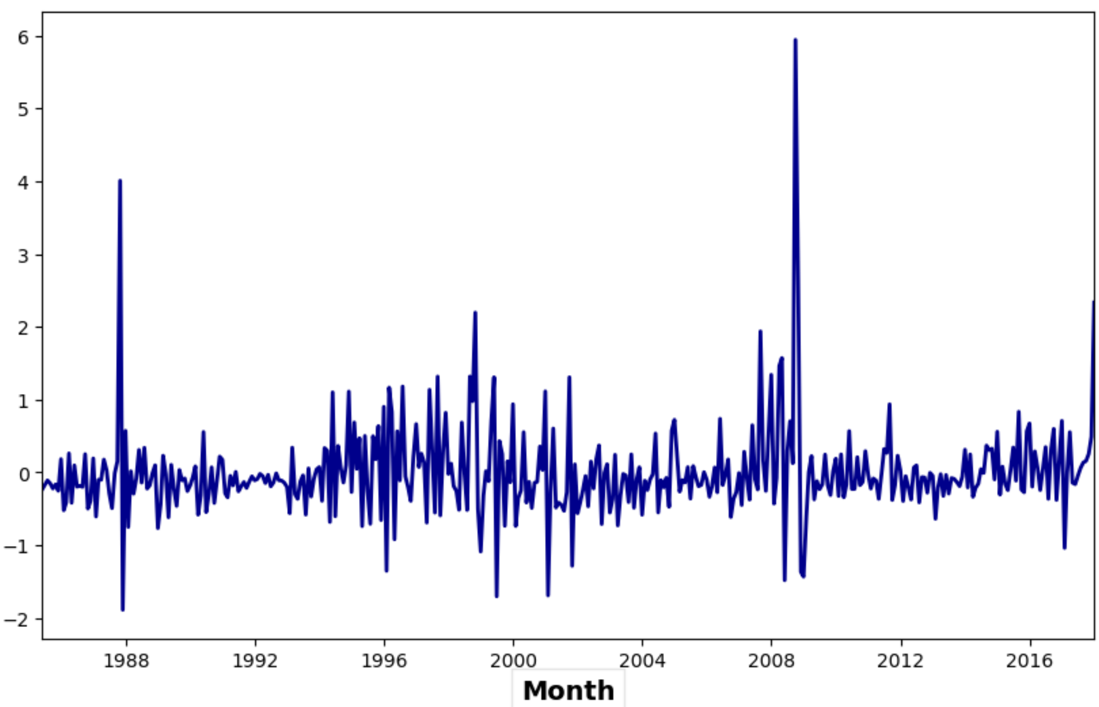


Figure 2 Panel A: The arbitrage gap. The arbitrage gap is calculated as an average of four standardized arbitrage spreads. The four arbitrage spreads are: the futures-cash basis for the S&P 500 index, the box spread for stock options, the CIP spread for currency pairs, and the Treasury mispricing measure for Treasury notes/bonds. Each series is standardized using means and standard deviations estimated based on 5-year rolling windows. Panel B: Shocks to the arbitrage gap. Shocks are defined as AR(1) residuals. The sample period is from January 1985 to December 2017.

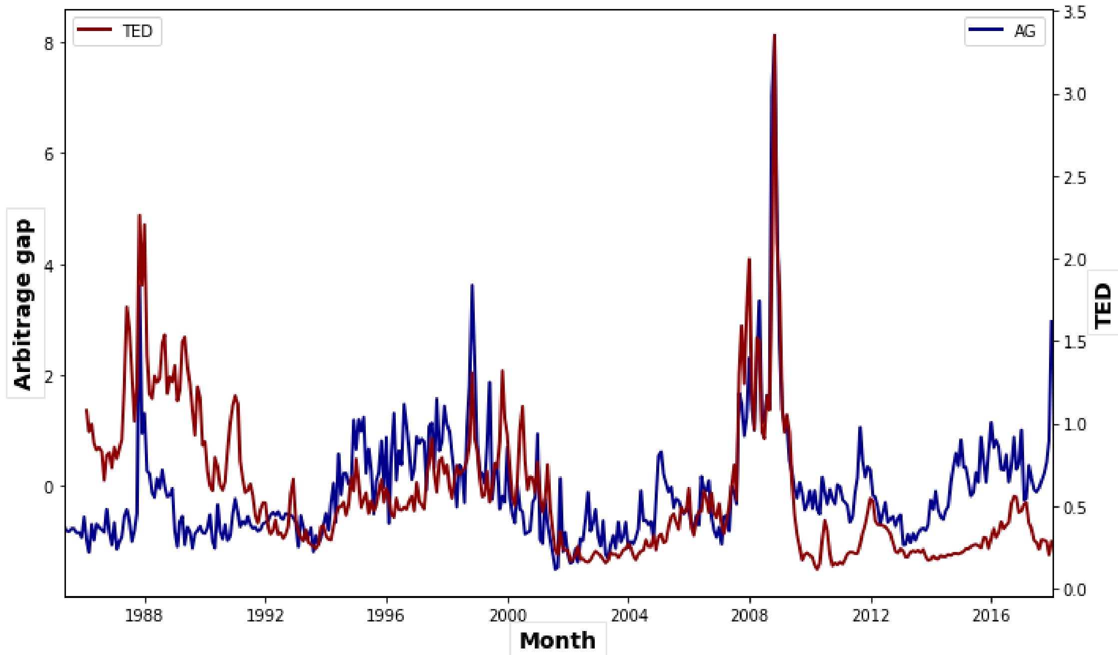


Figure 3 The aggregate arbitrage gap (AG) and the TED spread. The TED spread is the difference between the 3-month LIBOR and the 3-month Treasury-bill yield. The sample period is from January 1985 to December 2017.

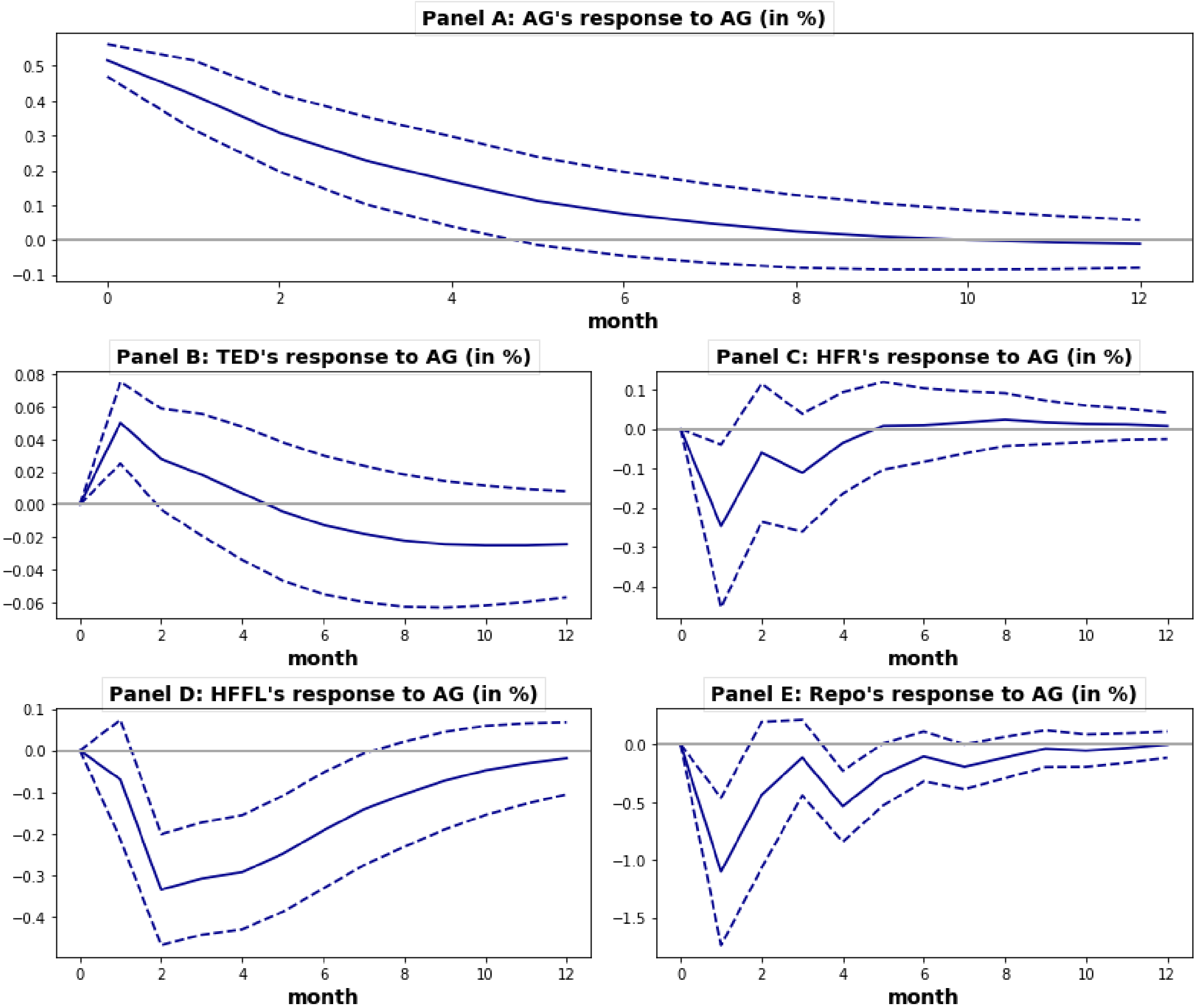


Figure 4 Impulse response functions to a one-standard-deviation positive shock to the arbitrage gap (AG_t). Solid lines represent orthogonalized impulse response functions of AG_t, the TED spread (TED_t), the hedge-fund sector returns (HFR_t) and flows ($HFFL_t$), and the primary dealers' repo financing growth ($Repo_t$) to a positive one-standard-deviation shock to AG_t. Dashed lines represent 95% bootstrap confidence intervals. Impulse response functions are based on the VAR(2) model with five variables: TED_t, HFR_t, $HFFL_t$, $Repo_t$, and AG_t. The same variables ordering is used to orthogonalize the impulses. The sample period is from January 1998 to December 2017.

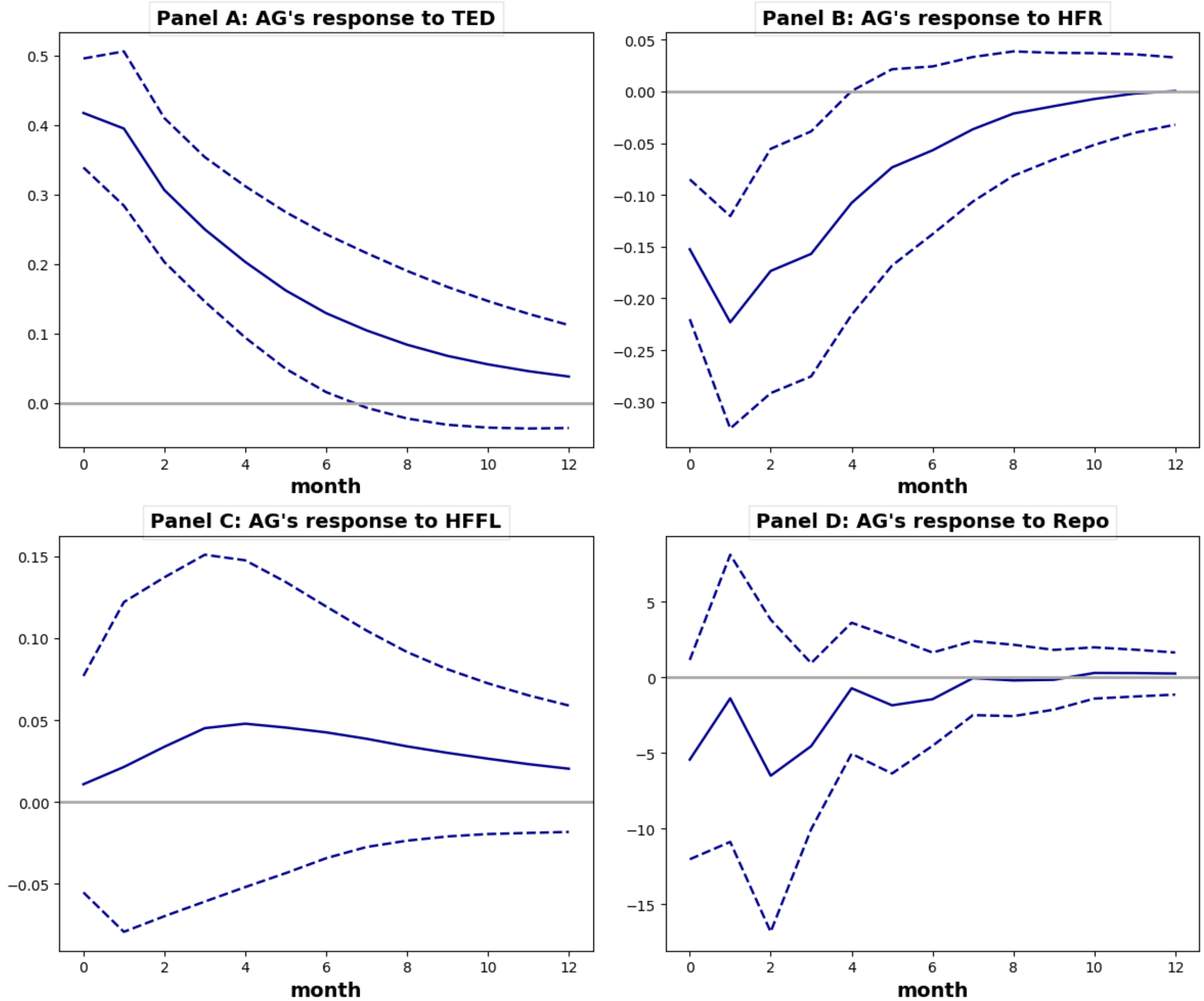


Figure 5 Impulse response functions of AG to shocks to four funding variables. Solid lines from panels A to D represent orthogonalized impulse responses of AG_t to a positive one-standard-deviation shock to TED_t, HFR_t, $HFFL_t$ and $Repo_t$, respectively. Dashed lines represent 95% bootstrap confidence intervals. Impulse responses are based on the VAR(2) model with five variables: TED_t, HFR_t, $HFFL_t$, $Repo_t$, and AG_t. The same variables ordering is utilized to orthogonalize the impulses. The sample period is from January 1998 to December 2017.

Table 1
Summary statistics for four arbitrage spreads

The table reports the numbers of observations, means, standard deviations, minimum, median, and maximum values for four arbitrage spreads: the futures-cash basis ($Futbasis_t$) for the S&P 500 index; the box spread (Box_t) for stock options; the covered interest rate parity spread (CIP_t) for currency pairs; the Treasury mispricing measures ($TrMispr_t$) for Treasury notes/bonds. Panel A reports summary statistics from January 1985 to December 2017. Panel B reports summary statistics over the pre-financial crisis sample from January 1985 to December 2007. The sample for $Futbasis_t$ and $TrMispr_t$ start from April 1985. The sample for Box_t starts from January 1996 and CIP_t starts from January 1987.

	$Futbasis_t$	Box_t	CIP_t	$TrMispr_t$
Panel A: April 1985 – December 2017				
No.mo.	393	264	372	393
Mean	0.16	0.25	0.03	0.08
SD	0.12	0.11	0.03	0.04
Min	0.04	0.11	0.01	0.03
Median	0.13	0.21	0.02	0.07
Max	0.96	0.62	0.20	0.31
Panel B: April 1985 – December 2007				
No.mo.	273	144	252	273
Mean	0.17	0.28	0.02	0.09
SD	0.13	0.13	0.01	0.04
Min	0.04	0.12	0.01	0.03
Median	0.15	0.26	0.02	0.08
Max	0.96	0.62	0.08	0.31

Table 2
Pairwise correlations for four arbitrage spreads

The table reports pairwise correlations for four standardized arbitrage spreads. The four arbitrage spreads are: the futures-cash basis for the S&P 500 index; the box spread for stock options; the covered interest rate parity spread for currency pairs; the Treasury mispricing measure for Treasury notes/bonds. Each series is standardized using means and standard deviations estimated based on 5-year rolling windows. The standardized series are denoted as $\{Futbasis_t^s,\ Box_t^s,\ CIP_t^s,\ TrMispr_t^s\}$. Panel A reports the pairwise correlation matrix and p-values for the four standardized arbitrage spreads from April 1985 to December 2017. Panel B reports the same statistics over the pre-financial crisis sample from April 1985 to December 2007.

	Pearson Correlations:				p-values:			
	$Futbasis_t^s$	Box_t^s	CIP_t^s	$TrMispr_t^s$	$Futbasis_t^s$	Box_t^s	CIP_t^s	$TrMispr_t^s$
				Panel A: April 1985 - December 2017				
$Futbasis_t^s$	—	0.51	0.57	0.44	—	< 0.0001	< 0.0001	< 0.0001
Box_t^s		—	0.59	0.22		—	< 0.0001	0.0007
CIP_t^s				0.44			—	< 0.0001
$TrMispr_t^s$				—				—
				Panel B: April 1985 - December 2007				
$Futbasis_t^s$	—	0.49	0.30	0.31	—	< 0.0001	< 0.0001	< 0.0001
Box_t^s		—	0.52	0.18		—	< 0.0001	0.0380
CIP_t^s			—	0.23			—	0.0006
$TrMispr_t^s$				—				—

Table 3
Ability of the arbitrage gap to explain the individual spreads

The table reports coefficient estimates, t-statistics, and adjusted R-squareds from the regressions of four standardized arbitrage spreads on AG_t^c, where AG_t^c is constructed as a simple average of three arbitrage spreads other than the left-hand-side one. The four arbitrage spreads are: the futures-cash basis for the S&P 500 index; the box spread for stock options; the covered interest rate parity spread for currency pairs; the Treasury mispricing measure for Treasury notes/bonds. Each series is standardized using means and standard deviations estimated based on 5-year rolling windows. The standardized series are denoted as: $\{Futbasis_t^s$, Box_t^s, CIP_t^s, $TrMispr_t^s\}$. Heteroscedasticity- and autocorrelation-adjusted t-statistics (Newey and West, 1987) with 12-month lags are reported in parentheses. The sample period for $Futbasis_t^s$ and $TrMispr_t^s$ are from April 1985 to December 2017. The sample periods for Box_t^s is from January 1999 to December 2017, and the sample for CIP_t^s is from January 1990 to December 2017.

	$Futbasis_t^s$	Box_t^s	CIP_t^s	$TrMispr_t^s$
AG_t^c	0.69	0.75	1.17	0.59
	(6.26)	(10.20)	(4.11)	(11.01)
Adj. R^2	0.36	0.38	0.53	0.31

Table 4
Abilities of funding variables to explain the arbitrage gap

The table reports coefficient estimates, t-statistics, and adjusted R-squareds from regressions of the arbitrage gap (AG_t) onto funding variables and control variables. Funding variables include: the TED spread (TED_t), the hedge-fund sector returns (HFR_t) and flows ($HFFL_t$), the primary dealers' repo financing growth ($Repo_t$), and the broker-dealer leverage factor (Adrian et al., 2014). Control variables are: the implied volatility of the S&P 100 index (VXO_t); bond term spread ($TERM_t$), defined as the difference between the 10-year Treasury yield and the 2-year Treasury yield; the bond default factor (DEF_t), defined as the spread between the BAA-graded bond yield and the AAA-graded bond yield; the stock market excess return (MKT_t). Heteroscedasticity- and autocorrelation-adjusted t-statistics (Newey and West, 1987) with 12-month lags are reported in parentheses. Columns (1) and (2) are monthly regressions from January 1986 to December 2017, Columns (3) and (4) are monthly regressions from January 1994 to December 2017, and Columns (5) and (6) are monthly regressions from February 1998 to December 2017. Column (7) is a quarterly regression from 1998-Q1 to 2017-Q4.

	Dependent variable: AG_t						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
TED_t	1.22	1.13	1.94	2.21	1.78	2.12	1.90
	(2.34)	(2.10)	(6.44)	(6.28)	(6.30)	(6.84)	(9.65)
$HFFL_t$			−0.11	−0.14	−0.14	−0.16	−0.07
			(−2.12)	(−3.42)	(−2.77)	(−3.56)	(−3.82)
HFR_t			−0.10	−0.11	−0.14	−0.17	−0.09
			(−2.78)	(−3.25)	(−3.51)	(−4.23)	(−3.91)
$Repo_t$					−1.63	−1.32	−1.28
					(−3.01)	(−2.12)	(−2.57)
Lev_t							0.00
							(0.46)
VXO_t		0.02		−0.00		−0.01	−0.00
		(1.31)		(−0.14)		(−1.03)	(−0.57)
$TERM_t$		0.12		0.17		0.22	0.16
		(0.82)		(1.56)		(2.16)	(2.17)
DEF_t		−0.14		−0.38		−0.21	−0.25
		(−0.46)		(−1.84)		(−1.01)	(−1.19)
MKT_t		−2.04		0.96		1.35	1.80
		(−1.05)		(0.86)		(1.14)	(2.12)
Adj. R^2	0.25	0.29	0.60	0.62	0.66	0.68	0.78

Table 5
Abilities of shocks to funding variables to explain shocks to the arbitrage gap

The table reports coefficient estimates, t-statistics, and adjusted R-squareds from regressions of shocks to the arbitrage gap (ΔAG_t) onto shocks to funding variables and shocks to control variables. Shocks to funding variables include: shocks to the TED spread (ΔTED_t), shocks to the hedge-fund sector returns (ΔHFR_t) and flows ($\Delta HFFL_t$), and shocks to the primary dealers' repo financing growth ($\Delta Repo_t$). Control variables are: shocks to bond term spread ($\Delta TERM_t$), where $TERM_t$ is defined as the difference between the 10-year Treasury yield and the 2-year Treasury yield; shocks to the bond default factor (ΔDEF_t), where DEF_t is defined as the spread between the BAA-graded bond yield and the AAA-graded bond yield; shocks to the implied volatility of S&P 100 index (ΔVXO_t); the stock market return (MKT_t). Shocks to all variables are defined as $AR(1)$ residuals. Heteroscedasticity-adjusted t-statistics (White, 1980) are reported in parentheses. Columns (1) and (2) are monthly regressions from February 1986 to December 2017, Columns (3) and (4) are monthly regressions from February 1994 to December 2017, and Columns (5) and (6) are monthly regressions from March 1998 to December 2017.

	Dependent variable: ΔAG_t					
	(1)	(2)	(3)	(4)	(5)	(6)
ΔTED_t	1.89	1.68	1.76	1.75	1.89	1.90
	(5.10)	(6.45)	(4.87)	(5.75)	(5.09)	(6.01)
$\Delta HFFL_t$			0.02	0.01	0.02	0.01
			(0.66)	(0.42)	(0.57)	(0.40)
ΔHFR_t			−0.10	−0.12	−0.10	−0.13
			(−3.56)	(−3.51)	(−2.68)	(−2.85)
$\Delta Repo_t$					−0.68	−1.20
					(−0.89)	(−1.87)
ΔVXO_t		0.05		0.05		0.05
		(3.10)		(2.29)		(2.00)
$\Delta TERM_t$		0.00		−0.07		−0.04
		(0.01)		(−0.26)		(−0.14)
ΔDEF_t		−0.29		−0.55		−0.76
		(−1.45)		(−2.12)		(−2.35)
MKT_t		1.14		4.34		4.45
		(1.10)		(2.22)		(1.96)
Adj. R^2	0.29	0.36	0.34	0.38	0.40	0.44

Table 6
Time-varying comovement between arbitrage spreads

The table reports coefficient estimates, t-statistics, and adjusted R-squareds from regressions of quarterly average pairwise correlation ($\overline{Corr}_t$) of four standardized arbitrage spreads onto four funding variables. $\overline{Corr}_t$ is computed as the average of pairwise correlations between four weekly arbitrage spreads in each quarter t. Four arbitrage spreads are: the futures-cash basis for the S&P 500 index; the box spread for stock options; the covered interest rate parity spread for currency pairs; the Treasury mispricing measure for Treasury notes/bonds. Each series is standardized using means and standard deviations estimated based on 5-year rolling windows. Funding variables are: the TED spread (TED_t), the hedge-fund sector returns (HFR_t) and flows ($HFFL_t$), and the primary dealers' repo financing growth ($Repo_t$). Heteroscedasticity- and autocorrelation-adjusted t-statistics (Newey and West, 1987) with 4-quarter lags are reported in parentheses. The sample for column (1), (2), and (3) start in 1986-Q1, 1994-Q1, and 1998-Q1 respectively, and end in December, 2017.

		$\overline{Corr}_t$	
	(1)	(2)	(3)
TED_t	0.13	0.26	0.28
	(1.89)	(5.93)	(6.22)
$HFFL_t$		0.57×10^{-2}	0.80×10^{-2}
		(1.10)	(1.41)
HFR_t		-1.21×10^{-2}	-1.10×10^{-2}
		(−1.96)	(−1.40)
$Repo_t$			−0.11
			(−0.66)
Adj. R^2	0.05	0.22	0.28

Table 7
Closed-end funds discount and the arbitrage gap

The table reports coefficient estimates, t-statistics, and adjusted R-squareds of regressions of the aggregate closed-end funds discount onto AG and other variables. Panel A reports the results from the regressions in the sample from January 1995 to December 2017, while Panel B reports the results in the sample excluding 2008 and 2009. The dependent variable is standardized average closed-end funds discount ($CEFD_t$) and independent variables include AG, four funding variables $\{TED_t, HFR_t, HFFL$, and $Repo_t\}$, and control variables. Individual closed-end fund discount is calculated as $\log(NAV_t/Price_t)$, where NAV_t is fund's net asset value and $Price_t$ is fund's share price. The average closed-end funds discount is average of all individual closed-end fund discounts for those funds whose discounts are below zero. The average closed-end funds discount is standardized using means and standard deviations estimated based on 5-year rolling windows. Control variables are: the implied volatility of the S&P 100 index (VXO_t); the bond term spread ($TERM_t$), defined as the difference between the 10-year Treasury yield and the 2-year Treasury yield; the bond default factor (DEF_t), defined as the spread between the BAA-graded bond yield and the AAA-graded bond yield; the stock market excess return (MKT_t). Heteroscedasticity- and autocorrelation-adjusted t-statistics (Newey and West, 1987) with 12-month lags are reported in parentheses. Note that the sample for columns (3) and (6) starts from February 1998.

	Dependent variable: $CEFD_t$					
	Panel A: Whole sample			Panel B: Subsample excluding 2008−2009		
	(1)	(2)	(3)	(4)	(5)	(6)
AG_t	0.66	0.58	0.50	0.68	0.49	0.40
	(6.18)	(3.12)	(2.64)	(5.46)	(2.58)	(2.11)
TED_t		0.22	0.31		0.71	0.77
		(0.39)	(0.56)		(1.46)	(1.59)
$HFFL_t$			−0.14			− 0.20
			(−1.92)			(−2.75)
HFR_t			−0.01			0.03
			(−0.14)			(0.31)
$Repo_t$			−0.56			−0.72
			(−0.48)			(−0.63)
VXO_t	0.01	0.01	0.01	−0.00	− 0.00	0.00
	(0.81)	(0.52)	(0.60)	(−0.05)	(−0.12)	(0.07)
$TERM_t$		−0.16	−0.13		− 0.05	− 0.03
		(−1.16)	(−0.89)		(−0.33)	(−0.19)
DEF_t		0.21	−0.12		−0.46	−0.79
		(0.69)	(−0.29)		(−0.82)	(−1.35)
MKT_t	−2.74	−2.88	−2.81	− 4.82	− 5.03	− 6.18
	(−1.15)	(−1.24)	(−0.75)	(−2.00)	(−2.26)	(−1.79)
Adj. R^2	0.39	0.40	0.41	0.24	0.28	0.30

Table 8
M&A anomaly and the arbitrage gap

The table reports coefficient estimates, t-statistics, and adjusted R-squareds of regressions of the standardized average M&A spread ($MAspread_t$) onto AG, funding variables and control variables. Panel A reports the results from the regressions in the sample from January 1985 to December 2017, while Panel B reports the results in the sample excluding 2008 and 2009. The dependent variable is standardized average M&A spread and independent variables include AG, four funding variables $\{TED_t$, HFR_t, $HFFL$, and $Repo_t\}$, and control variables. For each ongoing M&A cash deal, M&A spread is calculated as $\log(Offer_t/Price_t)$, where $Offer_t$ is target's offer price and $Price_t$ is target's trading price. The average M&A spread is an average of all individual M&A spreads. The average M&A spread is standardized using means and standard deviations estimated based on 5-year rolling windows. Control variables are: Control variables are: the implied volatility of the S&P 100 index (VXO_t); the bond term spread ($TERM_t$), defined as the difference between the 10-year Treasury yield and the 2-year Treasury yield; the bond default factor (DEF_t), defined as the spread between the BAA-graded bond yield and the AAA-graded bond yield; the stock market excess return (MKT_t). Heteroscedasticity- and autocorrelation-adjusted t-statistics (Newey and West, 1987) with 12-month lags are reported in parentheses. Note that the sample for columns (3) and (6) starts from February 1998.

	Dependent variable: $MAspread_t$					
	Panel A: Whole sample			Panel B: Subsample excluding 2008−2009		
	(1)	(2)	(3)	(4)	(5)	(6)
AG_t	0.53	0.31	0.29	0.45	0.36	0.38
	(6.24)	(2.18)	(2.26)	(2.68)	(2.13)	(3.41)
TED_t		1.00	0.91		0.65	0.49
		(2.41)	(2.52)		(1.52)	(1.26)
$HFFL_t$			−0.12			−0.07
			(−1.57)			(−0.95)
HFR_t			−0.12			−0.18
			(−1.11)			(−1.51)
$Repo_t$			−1.39			−1.02
			(−1.55)			(−1.35)
VXO_t	0.01	−0.00	0.00	0.01	0.01	0.01
	(0.87)	(−0.01)	(0.18)	(0.41)	(0.24)	(0.58)
$TERM_t$		0.17	0.11		0.15	0.07
		(1.53)	(1.04)		(1.39)	(0.66)
DEF_t		0.06	−0.33		−0.30	−0.94
		(0.15)	(−0.89)		(−0.79)	(−2.05)
MKT_t	0.87	0.16	3.09	1.93	1.42	6.34
	(0.49)	(0.07)	(0.83)	(1.12)	(0.78)	(1.77)
Adj. R^2	0.29	0.32	0.38	0.12	0.13	0.24

Table 9
Long-short equity factors and the aggregate arbitragae gap

The table reports coefficient estimates, t-statistics, and adjusted R-squareds of regressions of long-short equity factors onto AG, TED as well as market (MKT_t) and size (SMB_t) factors. The long-short equity factors include value (HML_t), profitability (RMW_t), investment (CMA_t), momentum factor (MOM_t) as well as a simple average of the four factors. AG_t and TED_t are decomposed into expected part and unexpected part based on an AR(1) process. Expected parts of AG and TED are denoted as: $\widehat{AG}_t$ and $\widehat{TED}_t$, and unexpected parts are denoted as ΔAG_t and ΔTED_t. MKT_t and SMB_t are included in the regressions as benchmarks. Heteroscedasticity-adjusted t-statistics (White, 1980) are reported in parentheses. The sample period is from January 1985 to December 2017.

	HML_t (%) (1)	RMW_t(%) (2)	CMA_t(%) (3)	MOM_t (%) (4)	$Avg.$(%) (5)
$Const.$	0.50	0.51	0.23	0.44	0.42
	(1.80)	(2.66)	(1.28)	(1.09)	(2.99)
$\widehat{AG}_t$	−0.59	−0.05	−0.47	−0.28	−0.35
	(−3.01)	(−0.38)	(−3.51)	(−0.81)	(−3.00)
ΔAG_t	0.53	−0.02	0.26	−0.67	0.03
	(1.91)	(−0.09)	(1.45)	(−1.30)	(0.14)
$\widehat{TED}_t$	−0.40	0.01	0.21	0.33	0.04
	(−0.89)	(0.02)	(0.83)	(0.48)	(0.18)
ΔTED_t	−1.36	−0.59	−1.20	1.95	−0.30
	(−1.24)	(−1.02)	(−2.07)	(1.15)	(−0.53)
MKT_t	−13.30	−17.42	−17.97	−21.06	−17.44
	(−2.80)	(−4.45)	(−5.90)	(−2.66)	(−5.70)
SMB_t	−0.09	−0.33	0.00	0.07	−0.08
	(−1.06)	(−3.80)	(0.11)	(0.49)	(−2.47)
Adj.R^2	0.08	0.27	0.16	0.03	0.22

APPENDIX

This Appendix includes three tables reporting results of robustness checks. Table A1 reports the pairwise correlation matrix for shocks to the four arbitrage spreads. Table A2 reports the regression results of AG onto the four funding variables and liquidity-related controls. Both market liquidity and the demand for liquid assets may play a role in giving rise bases. In Tables A2 and A3, I examine whether variations in the common component in market liquidity across different markets or convenience yields of liquid assets have significant explanatory power for AG_t. For market liquidity controls, I extract a common component from the average bid-ask spread for stock options, average bid-ask spread for Treasury securities, average bid-ask spread for stocks, and Pastor-Stambaugh liquidity factor and Amihud liquidity factor. I also include the on/off-the run premium as market liquidity control following Asness et al. (2013). To control for convenience yield of liquidity assets, I include, the spread between three-month GC repo rate and three-month Treasury rate—a proxy for Treasury securities convenience yield, the effective federal fund rate—a proxy for the opportunity cost of money; log T-bill-to-GDP ratio—a proxy for near-money asset supply; and implied volatility VXO to capture the flight-to-liquidity effect. Greenwood, Hanson, and Stein (2015) find that the liquidity premium of T-bills is negatively related to the ratio of T-bills to GDP. Nagel (2016) shows that the effective federal fund rate as a proxy for the opportunity cost of money is closely related to liquidity premium. Table A3 reports the regression results of shocks to AG onto shocks to variables that are considered in Table A2. All shocks are obtained as residuals from AR(1) regressions.

Table A1
Pairwise correlations for shocks to four arbitrage spreads

The table reports pairwise correlations and p-values for shocks to four standardized arbitrage spreads: shocks to the standardized futures-cash basis ($\Delta Futbasis_t^s$); shocks to the standardized box spread (ΔBox_t^c); shocks to the standardized CIP (ΔCIP_t^s); shocks to the Treasury mispricing measure ($\Delta TrMispr_t^s$). Shocks to the four standardized series are obtained as residuals from AR(1) regressions. $\Delta Futbasis_t^s$ and $\Delta TrMispr_t^s$ start from May 1985, ΔCIP_t^s start from February 1990 and ΔBox_t^s start from February 1999. All four series end in December 2017.

	Pearson Correlations:				p-values:			
	$\Delta Futbasis_t^s$	ΔBox_t^s	ΔCIP_t^s	$\Delta TrMispr_t^s$	$\Delta Futbasis_t^s$	ΔBox_t^s	ΔCIP_t^s	$\Delta TrMispr_t^s$
$\Delta Futbasis_t^s$	—	0.36	0.32	0.30	—	0.0001	0.0001	0.0001
ΔBox_t^s		—	0.29	0.20		—	0.0001	0.0025
ΔCIP_t^s			—	0.29			—	0.0001
$\Delta TrMispr_t^s$				—				—

Table A2
Abilities of the funding variables
to explain the arbitrage gap (with liquidity controls)

The table reports coefficient estimates, t-statistics, and adjusted R-squareds from regressions of the arbitrage gap (AG_t) onto four funding variables and control variables. Funding variables are: the hedge-fund sector returns (HFR_t) and flows ($HFFL_t$), the TED spread (TED_t), and the primary dealers' repo financing growth ($Repo_t$). Control variables are: on- and off-the run premium for Treasury securities ($On/Off\ Prem_t$); first principal component of liquidity factors of Pástor and Stambaugh (2003) and Amihud (2002), and average bid-ask spreads for stock options, Treasury securities, stocks, denoted as $MktLiq_t$; the difference between three month general collateral repo rate and three month Treasury rate ($Repo_t - Tbill_t$); log T-bill outsanding to GDP ratio ($log(TBill_t/GDP_t)$); effective federal funds rate from ($FedFunds_t$); the implied volatility of the S&P 100 index (VXO_t). Heteroscedasticity- and autocorrelation-adjusted t-statistics (Newey and West, 1987) with 12-month lags are reported in parentheses.

	(1)	(2)
HFR_t	−0.1315	−0.1421
	(−3.52)	(−3.51)
$HFFL_t$	−0.0274	−0.1026
	(−0.61)	(−1.89)
TED_t	2.2181	1.8341
	(9.34)	(6.66)
$Repo_t$	−0.8248	−1.5461
	(−1.37)	(−2.91)
$On/Off\ Prem_t$		−0.1434
		(−1.36)
$Repo_t - Rf_t$	0.2459	
	(0.48)	
$MktLiq_t$		0.0997
		(0.62)
$log(TBill_t/GDP_t)$	0.1741	
	(0.39)	
$FedFunds_t$	−0.1653	
	(−3.01)	
VXO_t	−0.0040	
	(−0.46)	
Adj. R^2	0.76	0.69

Table A3
Abilities of shocks to funding variables
to explain shocks to the arbitrage gap (with liquidity controls)

The table reports coefficient estimates, t-statistics, and adjusted R-squareds from regressions of shocks to the arbitrage gap (ΔAG_t) onto shocks to four funding variables and shocks to control variables. Shocks to funding variables are: shocks to the hedge-fund sector returns (ΔHFR_t) and flows ($\Delta HFFL_t$), shocks to the TED spread (ΔTED_t), and shocks to the primary dealers' repo financing growth ($\Delta Repo_t$). Control variables are: shocks to the on- and off-the-run premium for Treasury securities ($\Delta On/Off\ Prem_t$); shocks to the first principal component of liquidity factors of Pástor and Stambaugh (2003) and Amihud (2002), and average bid-ask spreads for stock options, Treasury securities, stocks, denoted as $\Delta MktLiq_t$; shocks to the difference between the three month general collateral repo rate and the three month Treasury rate ($\Delta(Repo_t - Tbill_t)$); shocks to the three month Treasury rate (($\Delta log(TBill_t/GDP_t)$)); shocks to the effective federal funds rate from ($\Delta FedFunds_t$); shocks to the implied volatility of the S&P 100 index (ΔVXO_t). Shocks to all variables are defined as AR(1) residuals. Heteroscedasticity-adjusted t-statistics (White, 1980) are reported in parentheses.

	(1)	(2)
ΔTED_t	1.3249	1.9519
	(5.01)	(7.02)
$\Delta Repo_t$	−0.4528	−0.5664
	(−0.84)	(−0.68)
$\Delta HFFL_t$	0.0152	0.0229
	(0.71)	(1.08)
ΔHFR_t	−0.0199	−0.0964
	(−0.65)	(−2.53)
$\Delta On/Off\ Prem_t$ (in %)		−157.12
		(−1.41)
$\Delta(Repo_t - TBill_t)$	1.1034	
	(1.33)	
$\Delta FedFunds_t$	−0.0866	
	(−0.24)	
$\Delta MktLiq_t$		0.0580
		(0.76)
$\Delta log(TBill_t/GDP_t)$	2.3698	
	(2.04)	
ΔVXO_t	0.0285	
	(2.37)	
Adj. R^2	0.49	0.44

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