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Essays In Market Efficiency And Empirical Asset Pricing

Jianan Liu
University of Pennsylvania, jiananl@upenn.edu

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Essays In Market Efficiency And Empirical Asset Pricing

Abstract

This dissertation consists of two chapters that address question about market efficiency in asset pricing.

In the first chapter, ``Comovement in Arbitrage Limits", I document that estimates of mispricing, such as deviations from no-arbitrage relations, strongly comove across five financial markets. In particular, I find that 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. Existing theories propose that funding constraints faced by arbitrageurs can impair market efficiency. Consistent with these theories, I find that 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.

In the second chapter, ``Size and Value in China," joint with Robert F. Stambaugh and Yu Yuan, we construct size and value factors in China. The size factor excludes the smallest 30\% of firms, which are companies valued significantly as potential shells in reverse mergers that circumvent tight IPO constraints. The value factor is based on the earnings-price ratio, which subsumes the book-to-market ratio in capturing all Chinese value effects. Our three-factor model strongly dominates a model formed by just replicating the Fama and French (1993) procedure in China. Unlike that model, which leaves a 17\% annual alpha on the earnings-price factor, our model explains most reported Chinese anomalies, including profitability and volatility anomalies.

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Jianan Liu

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For the Graduate Group in Managerial Science and Applied Economics

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Supervisor of Dissertation

_____

Robert F. Stambaugh, Miller Anderson & Sherred Professor of Finance

Graduate Group Chairperson

_____

Catherine Schrand, Celia Z. Moh Professor, Professor of Accounting

Dissertation Committee

David Musto, Ronald O. Perelman Professor in Finance

Nikolai Roussanov, Moise Y. Safra Associate Professor of Finance

ESSAYS IN MARKET EFFICIENCY AND EMPIRICAL ASSET PRICING

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ABSTRACT

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Jianan Liu

Robert F. Stambaugh

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In the first chapter, "Comovement in Arbitrage Limits", I document that estimates of mispricing, such as deviations from no-arbitrage relations, strongly comove across five financial markets. In particular, I find that 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. Existing theories propose that funding constraints faced by arbitrageurs can impair market efficiency. Consistent with these theories, I find that variables affecting arbitrage capital availability, such as the TED spread and hedge-fund flows and returns, explain two-thirds of the arbitrage gaps variation. During periods of tighter capital constraints, the comovement in mispricings becomes stronger.

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CHAPTER 1: Comovement in Arbitrage Limits

1.1. Introduction

In a frictionless world, arbitrage requires no capital, and asset mispricing relative to funda-
mental 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 simulta-
neous 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 mar-
kets? 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. Follo-
wing 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,

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[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).

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 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.

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[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 1.2 for details.

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 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 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 feed-

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[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.

back 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 aggre-

gate efficiency measures in the equity market and find such comovement is associated with funding measures.

The remainder of the paper proceeds as follows. Section 1.2 constructs the arbitrage spreads. Section 1.3 explores comovement in the spreads and constructs the arbitrage gap. Section 1.4 investigates the association between the arbitrage gap and external funding constraints. Section 1.5 investigates the relation between the arbitrage gap and equity mispricing. Section 1.6 explores the dynamic relations between the arbitrage gap and funding constraints. Section 1.7 concludes.

1.2. 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 1.2.1 to 1.2.4 in more details, and analyze their time-series features in subsection 1.2.5.

1.2.1. 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.

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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:

$$F_t \times e^{-(r_t - \delta_t)(T-t)} = S_t, \tag{1.1}$$

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:

$$Futbasis_t = \left| \log \frac{F_t \times e^{-(r_t - \delta_t)(T-t)}}{S_t} \right| \tag{1.2}$$

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 (1.1) 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.

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

$$C_t - P_t + PV_{t,T}(K) = S_t, \tag{1.3}$$

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 (1.3) is directly used to construct put-call parity violations. First, identifying the gap between the two sides of Equation (1.3) requires

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

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

$$\left| \log \frac{S^*_{i,m,t}}{S^*_{i,n,t}} \right| = \left| \log \frac{C_{i,m,t} - P^E_{i,m,t} + PV_{t,T}(K_{i,m})}{C_{i,n,t} - P^E_{i,n,t} + PV_{t,T}(K_{i,n})} \right|. \tag{1.4}$$

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

$$Box_{i,t} = \frac{1}{N_I} \sum_{(m,n) \in I} \left| \log \frac{S^*_{i,m,t}}{S^*_{i,n,t}} \right|, \tag{1.5}$$

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:

$$Box_t = \frac{1}{N_t} \sum_{i=1}^{N_t} Box_{i,t}. \qquad (1.6)$$

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.

1.2.3. 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

$$\hat{F}_{t,T}^{A \to B} = \frac{S_t^{A \to B}(1 + r_{t,B})}{(1 + r_{t,A})}. \qquad (1.7)$$

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:

$$CIP_t = \frac{1}{33} \sum_{T \in \{1,3,6\}} \sum_{A/B \in \Omega} \left| \log \frac{\hat{F}_{t,T}^{A \to B}}{F_{t,T}^{A \to B}} \right|. \tag{1.8}$$

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 TRs 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.

1.2.4. 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]

$$-\frac{1}{T_i} \log Z(t, T_i, b_t) = \theta_{0,t} + (\theta_{1,t} + \theta_{2,t}) \frac{1 - e^{-\frac{T_i - t}{\lambda_t}}}{\frac{T_i - t}{\lambda_t}} - \theta_{2,t} e^{-\frac{T_i - t}{\lambda_t}}. \tag{1.9}$$

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[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.

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

$$\sum_{j=1}^{N_t} \left[P(t, T_{n_j}, c_j) - P^{NS}(t, T_{n_j}, c_j, b_t)\right]^2, \tag{1.10}$$

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,

$$P^{NS}(t, T_{n_j}, c_j, b_t) = 100 \times c_j \sum_{i=1}^{n_j} Z(t, T_i, b_t) + 100 \times Z(t, T_{n_j}, b_t). \tag{1.11}$$

Here, n_j is the number of periods before expiration.

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

$$TrMispr_{j,t} = \left| \log \frac{P(t, T_{n_j}, c_j)}{P^{NS}(t, T_{n_j}, c_j, \hat{b}_t)} \right|, \tag{1.12}$$

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:

$$TrMispr_t = \frac{1}{N_t} \sum_{j=1}^{N_t} TrMispr_{j,t}. \tag{1.13}$$

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.

1.2.5. 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 $TrMispr_t^s$.

1.3. 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 $Futbasis_t^s$ and $TrMispr_t^s$ are from April 1985 to December 2017. The sample of CIP_t^s spans from January 1990 to December 2017, and the sample of Box_t^s is from January 1999 to December 2017. Subsection 1.3.1 analyzes the comovement structure of the four. In subsection 1.3.2, I describe the

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time-series features of their common component.

1.3.1. Comovement structure

Panels A and B of Table 1 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 $TrMispr_t^s$ and Box_t^s while the highest is 59% which is between CIP_t^s and Box_t^s. 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_t^c) 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_t^c 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.

1.3.2. 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.

1.4. 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 1.4.1 describes the traditional funding variables used to proxy for overall funding tightness. In subsection 1.4.2, I investigate the abilities of the funding variables to explain the arbitrage gap. Subsection 1.4.3 shows that comovement between arbitrage spreads is time-varying and becomes stronger during the periods when funding constraints are tight.

1.4.1. 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

$$HFFL_t = \frac{\sum_{i=1}^{N_t}[AUM_{i,t} - AUM_{i,t-1} \times (1 + R_{i,t})]}{\sum_{i=1}^{N_t} AUM_{i,t-1}}, \tag{1.14}$$

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.

$$HFR_t = \frac{\sum_{i=1}^{N_t}[AUM_{i,t-1} \times (1 + R_{i,t})]}{\sum_{i=1}^{N_t} AUM_{i,t-1}} - 1, \qquad (1.15)$$

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, 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 ounstanding across all maturities and security types. Monthly changes in aggregate primary dealers' repo financings are

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[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.

calculated as the first differences of the log month-end aggregate repo financings.

1.4.2. 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.

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

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[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.

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 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

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[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.

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.

1.4.3. 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 $\overline{Corr}_t$.

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

1.5. 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 predictability 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 1.5.1 and 1.5.2, I investigate the relation between AG and closed-end fund discounts and M&A spreads. Subsection 1.5.3 studies the relation between AG and long-short spreads included in the Fama-French five-factor model (Fama and French, 2015).

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[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.

1.5.1. 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 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.

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

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.

1.5.2. 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 $MAspread_t$.

1.5.3. 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-

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[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.

short spreads. Overall, the findings described in this subsection support this hypothesis. I 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.

1.6. 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 1.6.1, I investigate the dynamic relations between AG and the four funding variables that exhibit a substantial contemporaneous association with AG (Section 1.3). 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.

1.6.1. 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).

$$\tilde{Y}_t = \boldsymbol{B_0} + \boldsymbol{B_1}\tilde{Y}_{t-1} + \boldsymbol{B_2}\tilde{Y}_{t-2} + \tilde{V}_t, \tag{1.16}$$

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

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 (1.16). 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 3 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.

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

As shown in Panel B of Figure 3, 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 3 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 4 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 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 4, 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.

1.7. 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).
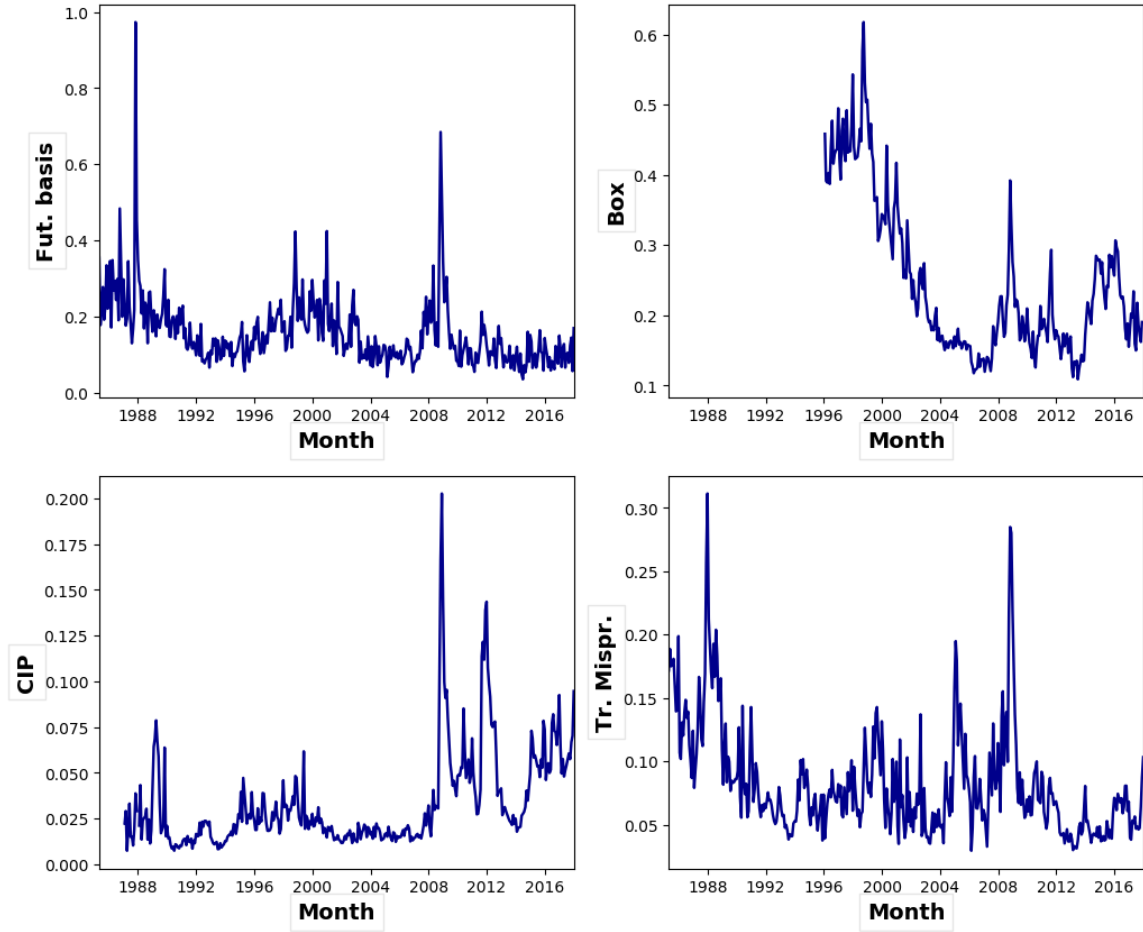
Figure 1 Time series of four arbitrage spreads.

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
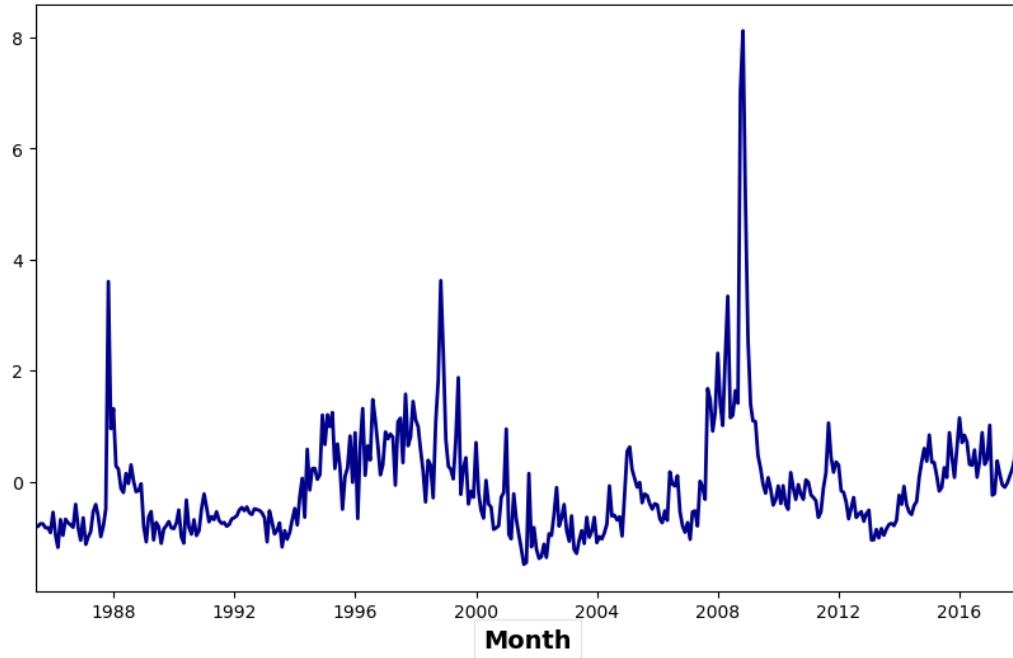
Panel B: Shocks to the arbitrage gap
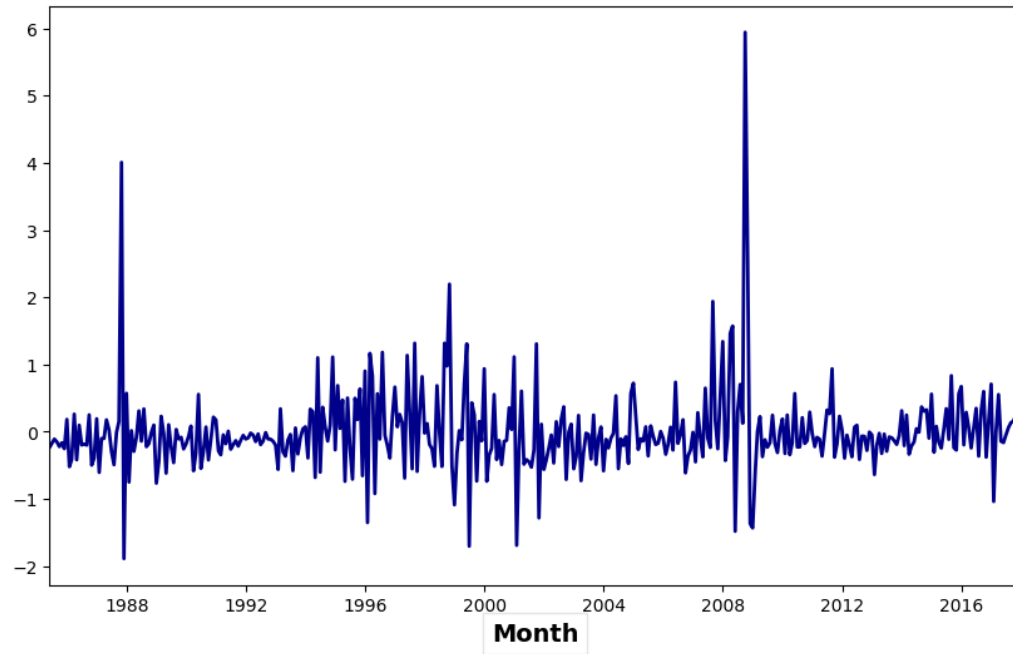
Figure 2 Time-series of the arbitrage gap: levels and shocks

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.
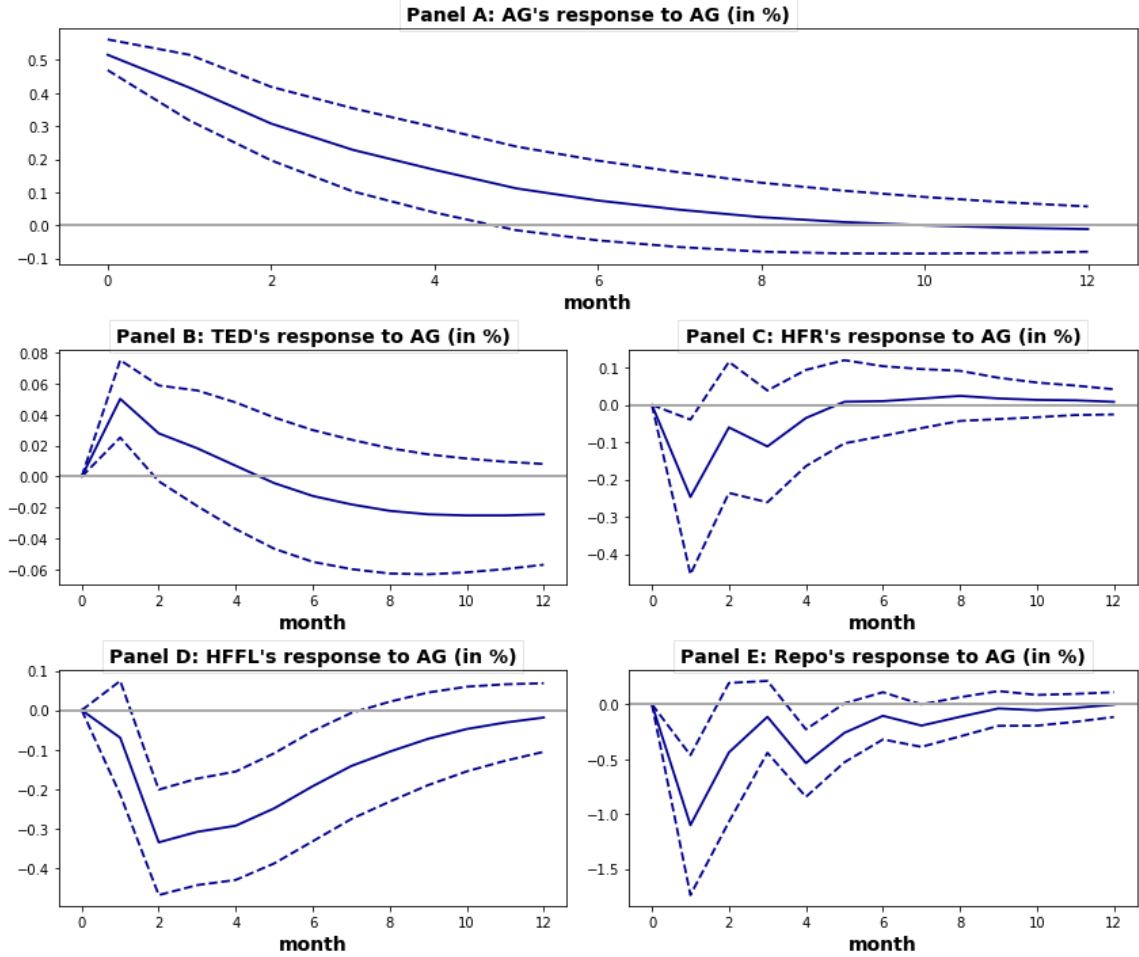
Figure 3 Impulse response functions to a one-standard-deviation positive shock to the arbitrage gap (AG_t).

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.
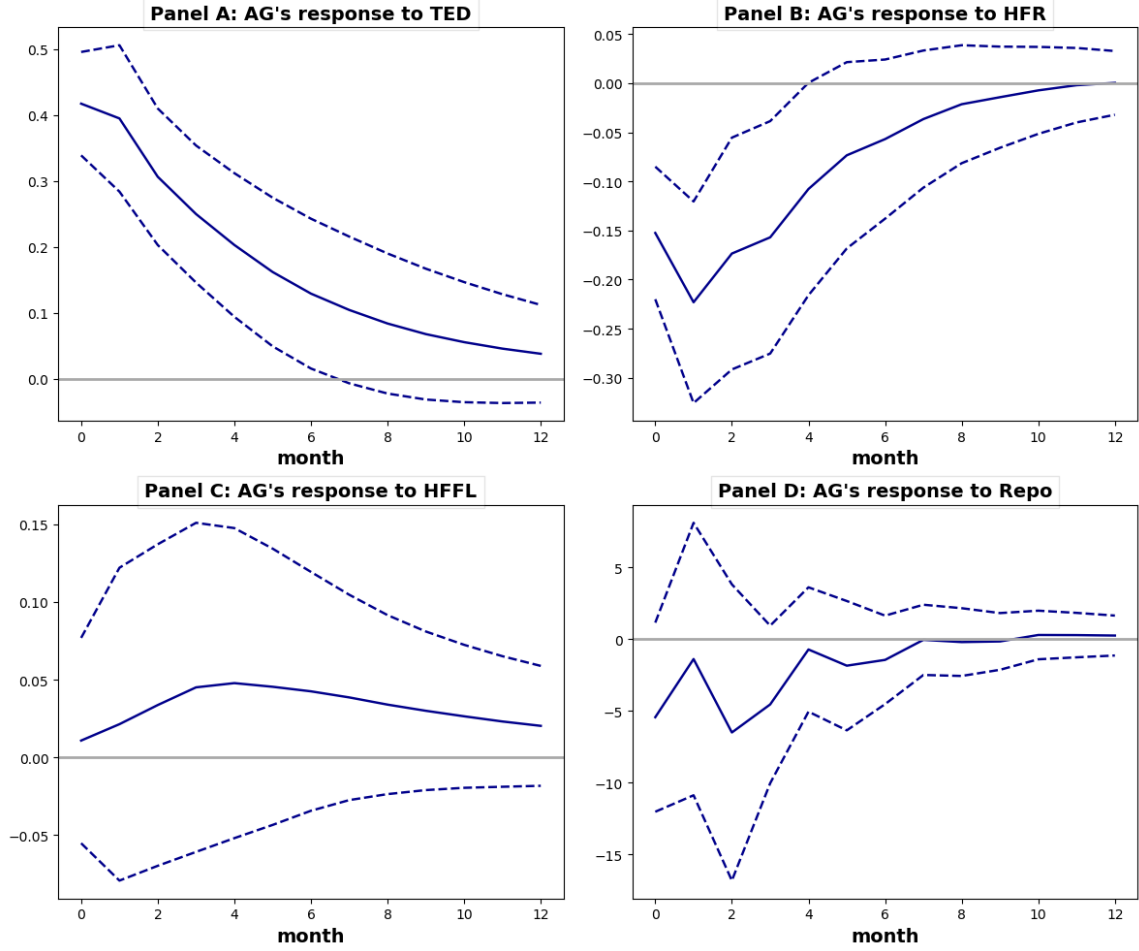
Figure 4 Impulse response functions of AG to shocks to four funding variables.

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.

	$Futbasis_t$	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 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.

	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 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.

	$Futbasis_t^s$	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 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Dependent variable: AG_t				
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 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.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable:ΔAG_t					
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 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.

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

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.

	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 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 $\{TED_t, HFR_t, HFFL, \text{and } Repo_t\}$, 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: $MAspread_t$					
	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 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 $\{TED_t, HFR_t, HFFL, \text{ and } Repo_t\}$, 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.

	HML_t (%)	RMW_t(%)	CMA_t(%)	MOM_t (%)	$Avg.$(%)
	(1)	(2)	(3)	(4)	(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

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.

CHAPTER 2: Size and Value in China

2.1. Introduction

China has the world's second-largest stock market, helping to finance an economy that some predict will be the world's largest within a decade.[1] China also has political and economic environments quite different from those in the US and other developed economies. Moreover, China's market and investors are separated from the rest of the world. China largely prohibits participation by foreign investors in its domestic stock market as well as participation by its domestic investors in foreign markets.[2]

Factor models provide a cornerstone for investigating financial asset pricing and for developing investment strategies. Many studies of China's stock market use a three-factor model constructed by following the Fama and French (1993) procedure for US factors.[3] The advisability of simply replicating a US model in China is questionable, however, given China's separation and the many differences in economic and financial systems. We explore and develop factor models in China, allowing its unique environment to dictate alternative approaches.

We start by examining size and value effects in the Chinese market. These two effects have long been recognized elsewhere as important characteristics associated with expected return: Banz (1981) reports a firm-size effect, and Basu (1983) finds an effect for the earnings-price ratio, a popular value metric. Size and value are the most prominent characteristics used by many institutions to classify investment styles. The most widely used nonmarket factors in academic research are also size and value, following the influential study by Fama and

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[1] According to the World Bank, the 2016 equity values of listed domestic companies, in trillions of US dollars, are 27.4 in the US and 7.3 in China, followed by 5.0 in Japan. For a forecast that China's gross domestic product will reach that of the US by 2028, see Bloomberg (https://www.bloomberg.com/graphics/2016-us-vs-china-economy/).

[2] At the end of 2016, 197 foreign institutions were authorized to invest in A-shares, China's domestically traded stocks, but with a quota of just 0.6% of total market value (and even less in earlier years). Chinese domestic investors can invest in international financial markets only through a limited authorized channel.

[3] Examples of such studies include include Yang and Chen (2003), Fan and Shan (2004), Wang and Chin (2004), Chen et al. (2010), Cheung, Hoguet, and Ng (2015), and Hu et al. (2019).

French (1993). Our study reveals that size and value effects are important in China but with properties different from the US. We construct size and value factors for China.

The size factor is intended to capture size-related differences in stock risk and return that arise from size-related differences in the underlying businesses. In China, however, the stock of a small listed firm is typically priced to reflect a substantial component of value related not to the firm's underlying business but instead to the Chinese initial public offering (IPO) process. In China, the IPO market is strictly regulated, and a growing demand for public listing confronts the low processing capacity of the regulatory bureau to approve IPOs. As a consequence, private firms seek an alternative approach, a reverse merger, to become public in a timely manner. In a reverse merger, a private firm targets a publicly traded company, a so-called shell, and gains control rights by acquiring its shares. The shell then buys the private firm's assets in exchange for newly issued shares. While reverse mergers occur elsewhere, IPO constraints are sufficiently tight in China such that the smallest firms on the major exchanges become attractive shell targets, unlike in the US, for example.

The smallest listed firms are the most likely shells. In fact, 83% of the reverse mergers in China involve shells coming from the smallest 30% of stocks. For a typical stock in the bottom 30%, we estimate that roughly 30% of its market value reflects its potential shell value in a reverse merger. Our estimate combines the empirical probability of being targeted in a reverse merger with the average return accompanying that event. Consistent with the contamination of small-firm stock prices by shell value, we also find that when compared to other firms, the smallest 30% have returns less related to operating fundamentals, proxied by earnings surprises, but more related to IPO activity. Therefore, to avoid shell-value contamination when constructing any of our factors, we delete the bottom 30% of stocks, which account for 7% of the stock market's total capitalization.

The value effect in China is best captured by the earnings-price (EP) ratio, versus other valuation ratios. Following Fama and French (1992), we treat the choice among alternative valuation ratios as an empirical question, asking which variable best captures the cross-

sectional variation in average stock returns. As in that study, we run a horse race among all candidate valuation ratios, including EP, book-to-market (BM), asset-to-market, and cash-flow-to-price ratios. In a Fama-MacBeth regression including those four ratios, EP dominates all others, just as Fama and French (1992) find BM dominates in the US market. Relying on the latter US result, Fama and French (1993) use BM to construct their value factor. Relying on our result for China, we use EP to construct our value factor.

Size and value are important factors in China, as revealed by their average premiums as well as their contributions to return variance. Our size and value factors both have average premiums exceeding 1% per month over our 2000–2016 sample period. For the typical stock in China, size and value jointly explain an additional 15% of monthly return variance beyond what the market factor explains. In comparison, size and value explain less than 10% of additional return variance for the typical US stock during the same period.

Our three-factor model, CH-3, includes the market factor as well as size and value factors incorporating the above China-specific elements. For comparison, we construct an alternative three-factor model, FF-3, by simply replicating the Fama and French (1993) procedure. We find that CH-3 strongly dominates FF-3. Specifically, FF-3 cannot price the CH-3 size and value factors, which have (significant) FF-3 annualized alphas of 5.6% and 16.7%. In contrast, CH-3 prices the FF-3 size and value factors, which have (insignificant) CH-3 annualized alphas of just −0.5% and 4.1%. A Gibbons, Ross, and Shanken (1989) test of one model's ability to price the other's factors gives a p-value of 0.41 for CH-3's pricing ability but less than 10^{-12} for FF-3's ability.

We also investigate the ability of CH-3 to explain previously reported return anomalies in China. A survey of the literature reveals anomalies in nine categories: size, value, profitability, volatility, return reversal, turnover, investment, accruals, and illiquidity. We find each of the first six categories contains one or more anomalies that produce significant long-short alphas with respect to the single-factor capital asset pricing model (CAPM). CH-3 accommodates all anomalies in the first four of those six categories, including profitability

and volatility, whose anomalies fail FF-3 explanations in the US. CH-3 fails only with some of the reversal and turnover anomalies. In contrast, FF-3 leaves significant anomalies in five of the six categories. A total of ten anomalies are unexplained by the CAPM; CH-3 explains eight of them, while FF-3 explains three. The average absolute CH-3 alpha for the ten anomalies is 5.4% annualized, compared to 10.8% for FF-3 (average absolute t-statistics: 1.12 versus 2.70).

Hou, Xue, and Zhang (2015) and Fama and French (2015) add two factors based on investment and profitability measures in their recently proposed factor models, Q-4 and FF-5. Investment does not produce a significant CAPM alpha in China, and profitability is fully explained by CH-3. In an analysis reported in the Appendix, we find that a replication of FF-5 in China is dominated by CH-3.

Overall, CH-3 performs well as a factor model in China, and it captures most documented anomalies. In US studies, researchers often supplement the usual three factors (market, size, and value) with a fourth factor, such as the momentum factor of Carhart (1997) or the liquidity factor of Pástor and Stambaugh (2003). We also add a fourth factor, motivated by a phenomenon rather unique to China: a stock market dominated by individuals rather than institutions. Over 101 million individuals have stock trading accounts in China, and individuals own 88% of the market's free-floating shares. This heavy presence of individuals makes Chinese stocks especially susceptible to investor sentiment. To capture sentiment effects, we base our fourth factor on turnover, which previous research identifies as a gauge of both market-wide and stock-specific investor sentiment (e.g., Baker and Stein, 2004; Baker and Wurgler, 2006; Lee, 2013). The resulting four-factor model, CH-4, explains the turnover and reversal anomalies in addition to the anomalies explained by CH-3, thereby handling all of China's reported anomalies.

The remainder of the paper proceeds as follows. Section 2 discusses data sources and sample construction. Section 3 addresses the interplay between firm size and China's IPO constraints and explores the importance of shell-value distortions in small-stock returns.

Section 4 investigates value effects in China. In Section 5, we construct CH-3 and FF-3 and compare their abilities to price each other's factors. In Section 6, we compare the abilities of those three-factor models to price anomalies. In Section 7, we construct CH-4 by including a turnover factor and then analyze the model's additional pricing abilities. Section 8 summarizes our conclusions.

2.2. Data source and samples

The data we use, which include data on returns, trading, financial statements, and mergers and acquisitions, are from Wind Information Inc. (WIND), the largest and most prominent financial data provider in China. WIND serves 90% of China's financial institutions and 70% of the Qualified Foreign Institutional Investors (QFII) operating in China.

The period for our main analysis is from January 1, 2000, through December 31, 2016. China's domestic stock market, the A-share market, began in 1990 with the establishment of the Shanghai and Shenzhen exchanges. We focus on the post-2000 period for two reasons. The first is to assure uniformity in accounting data. The implementation of rules and regulations governing various aspects of financial reporting in China did not largely take shape until about 1999. Although 1993 saw the origination of principles for fair trade and financial disclosure, firms received little guidance in meeting them. Companies took liberties and imposed their own standards, limiting the comparability of accounting data across firms. Not until 1998 and 1999 were laws and regulations governing trading and financial reporting more thoroughly designed and implemented. For example, detailed guidelines for corporate operating revenue disclosure were issued in December 1998 and implemented in January 1999. Securities laws were passed in December 1998 and implemented in July 1999. Only by 1999 did uniformity in accounting standards become widely accomplished. Because portfolios formed in 2000 use accounting data for 1999, our post-2000 sample for portfolio returns relies on accounting data more comparable across firms than in earlier years.

The second reason for beginning our sample in 2000 is to ensure sufficient numbers of

observations. Portfolios are used in our study to construct factors and conduct many of the tests. To enable reasonable precision and power, we require at least 50 stocks in all portfolios after imposing our filters, which include eliminating stocks (i) in the bottom 30% of firm size, (ii) listed less than six months, and (iii) having less than 120 trading records in the past year or less than 15 trading records in the past month. This last pair of conditions is intended to prevent our results from being influenced by returns that follow long trading suspensions. Only by 1999 do the numbers of stocks in the market allow these criteria to be met.

WIND's data on reverse mergers begin in 2007, when the China Securities Regulatory Commission identified the criteria of a merger and acquisition (M&A) proposal that classify it as a reverse merger, making such deals easier to trace. In Section 3.2, we use reverse merger data to estimate shell values. Additional details about the data and the construction of empirical measures are provided in the Appendix.

2.3. Small stocks and IPO constraints

Numerous studies in finance address China's unique characteristics. For example, Allen, Qian, and Qian (2003, 2005) compare China to other developed countries along various political, economic, and financial dimensions. Brunnermeier, Sockin, and Xiong (2017) study China's government interventions in its trading environment. Bian et al. (2018) show the special nature of leveraged investors in China's stock market. Song and Xiong (2018) emphasize the necessity of accounting for the economy's uniqueness when analyzing risks in China's financial system. Allen et al. (2009) and Carpenter and Whitelaw (2017) provide broader overviews of China's financial environment.

One aspect of the Chinese market especially relevant for our study is the challenge faced by firms wishing to become publicly traded. As discussed earlier, market values of the smallest firms in China include a significant component reflecting the firms' potential to be shells in reverse mergers. Private firms often employ reverse mergers to become publicly traded

rather than pursue the constrained IPO process. Section 3.1 describes that IPO process, while Section 3.2 describes reverse mergers and presents a notable example of one in China. In Section 3.3, we compute a simple estimate of the fraction of firm value associated with being a shell for a potential reverse merger, and we find the fraction to be substantial for the smallest stocks. Consistent with that result, we show in Section 3.4 that the returns on those stocks exhibit significantly less association with their underlying firms' fundamentals.

Our evidence demonstrating the importance of the shell component of small-firm values is buttressed by contemporaneous research on this topic, conducted independently from ours. In a study whose principal focus is the importance of shell values in China, Lee, Qu, and Shen (2017) also show that the shell component is a substantial fraction of small-firm values and that, as a result, the returns on small-firm stocks exhibit less sensitivity to fundamentals but greater sensitivity to IPO activity. Lee, Qu, and Shen (2017) explore models for pricing the shell-value firms, whereas we focus on models for pricing the "regular" stocks constituting the other 93% of the stock market's value.

2.3.1. The IPO process

In China, the IPO market is controlled by the China Securities Regulatory Commission (CSRC). As a central planner, the CSRC constrains the IPO process to macro-manage the total number of listed firms (e.g., Allen et al., 2014). Unlike the US, where an IPO can clear regulatory scrutiny in a matter of weeks, undertaking an IPO in China is long and tedious, easily taking three years and presenting an uncertain outcome. As detailed in the Appendix, the process involves seven administrative steps, three bureau departments, and a select 25-member committee that votes on each application. The committee meets for both an initial review and a final vote, with those meetings separated by years. As of November 2017, the CSRC reported 538 firms being processed, with just 31 having cleared the initial review. The IPOs approved in early 2017 all entered the process in 2015.

The long waiting time can impose significant costs. During the review process, firms are

discouraged from any sort of expansion and must produce consistent quarterly earnings. Any change in operations can induce additional scrutiny and further delay. A firm undertaking an IPO may thus forgo substantial investment opportunities during the multi-year approval process. Moreover, policy changes can prolong the process even more. In 2013, the CSRC halted all reviews for nearly a year to cool down the secondary market.

2.3.2. Reverse mergers

Facing the lengthy IPO process, private firms wishing to become public often opt for an alternative: reverse merger. A reverse merger, which is regulated as an M&A, involves fewer administrative steps and is much faster. We illustrate the process via a real-life case involving the largest delivery company in China, SF Express (SF).

In 2016, SF decided to become public through a reverse merger. To be its shell firm, SF targeted the small public company, DT Material (DT), with market value of about $380 million. SF and DT agreed on merger terms, and in May 2016, DT officially announced the deal to its shareholders. At the same time, DT submitted a detailed M&A proposal to the CSRC. The plan had DT issuing more than three billion shares to SF in exchange for all of SF's assets. The intent was clear: three billion shares would account for 97% of DT's stock upon the shares' issuance. With those shares, SF would effectively be the sole owner of DT, which would in turn be holding all of SF's assets. DT would become essentially the same old SF company but with publicly traded status. The M&A authorization went smoothly. By October 2016, five months after the application, the CSRC gave its conditional approval, and final authorization came two months later. The merged company was trading as SF on the Shenzhen Stock Exchange by February 2017. That same month, IPO applicants in the 2015 cohort had just begun their initial reviews.

The entire SF-DT process took less than a year, fairly typical for a reverse merger. The greater speed of a reverse merger comes with a price tag, however. In addition to regular investment banking and auditing fees, the private firm bears the cost of acquiring control of

the public shell firm. In the SF-DT case, DT kept 3% of the new public SF's shares, worth about $938 million. In the course of the deal, DT's original shareholders made about 150%.

Reverse mergers also occur in the US. As in China, they have long been recognized as an IPO alternative. From 2000 through 2008, the US averaged 148 reverse mergers annually (Floros and Sapp, 2011). There is, however, a fundamental difference between reverse mergers in the US versus China: because IPOs are less constrained in the US, the value of being a potential shell is much lower. In the US, the median shell's equity market value is only $2 million (Floros and Sapp, 2011), versus an average of $200 million in China. Nearly all shell companies in the US have minimal operations and few noncash assets. Their Chinese counterparts are typically much more expensive operating businesses. As a result, while small stocks on China's major exchanges are attractive shell targets, small stocks on the major US exchanges are not. Consistent with this difference, Floros and Sapp (2011) observe that their US reverse-merger sample includes almost no shell targets listed on the three major exchanges.

2.3.3. Small stocks with large shell values

A private firm's price tag for acquiring a reverse-merger shell depends essentially on the shell's market value. Not surprisingly, shells are most often small firms. Fig. 1 displays the size distribution of public shells in our sample of reverse mergers covering the 2007–2016 period. Of the 133 reverse mergers, 83% come from the bottom 30%, and more than half come from the bottom 10%. Given this evidence, we eliminate the bottom 30% when constructing factors to avoid much of the contamination of stock prices reflecting the potential to be targeted as shells. Although the 30% cutoff is somewhat arbitrary, our results are robust to using 25% and 35% as cutoffs.

What fraction of a firm's market value owes to the firm potentially becoming a reverse-merger shell? A back-of-the-envelope calculation suggests the fraction equals roughly 30% for the stocks we eliminate (the bottom 30%). Let p denote the probability of such a stock

becoming a reverse-merger shell in any given period, and let G denote the stock's gain in value if it does become a shell. We can then compute the current value of this potential lottery-like payoff on the stock as

$$S = \frac{pG + (1-p)S}{1+r} = \frac{pG}{r+p},$$ (2.1)

where r is the discount rate. We take p to be the annual rate at which stocks in the bottom 30% become reverse-merger shells, and we take G to be the average accompanying increase in stock value. Both quantities are estimated over a two-year rolling window. The annual discount rate, r, is set to 3%, the average one-year deposit rate from 2007 to 2016.

Panel A of Fig. 2 plots the estimated daily ratio of shell value to market value, S/V, with V equal to the median market value of stocks in the bottom 30%. Over the 2009–2016 sample period, the average value of S/V is 29.5%, while the series fluctuates between 10% and 60%. Eq. (2.1) implicitly assumes the stock remains a potential shell in perpetuity, until becoming a shell. In other words, the role of small stocks in reverse mergers is assumed to be rather permanent in China, as the IPO regulatory environment shows no overall trend toward loosening. Even if we reduce the horizon to 20 years, the average S/V remains about half as large as the series plotted.

Panel B of Fig. 2 plots the estimated shell value, S, expressed in renminbi (RMB). This value exhibits a fivefold increase over the eight-year sample period, in comparison to barely a twofold increase for the Shanghai-Shenzhen 300 index over the same period. The rise in S is consistent with the significant premium earned over the period by stocks in the bottom 30% of the size distribution. Recall, however, that these stocks account for just 7% of the stock market's total capitalization. As we demonstrate later, constructing factors that include these stocks, whose returns are distorted by the shell component, impairs the ability of those factors to price the regular stocks that constitute the other 93% of stock market value.

2.3.4. Return variation of small stocks

Given that the shell component contributes heavily to the market values and average returns of the smallest stocks, we ask whether this component also contributes to variation in their returns. If it does, then when compared to other stocks, returns on the smallest stocks should be explained less by shocks to underlying fundamentals but more by shocks to shell values. We explore both implications.

To compare responses to fundamentals, we analyze returns accompanying earnings announcements. We divide the entire stock universe into three groups, using the 30th and 70th size percentiles. Within each group, we estimate a panel regression of earnings-window abnormal return on standardized unexpected earnings (SUE),

$$R_{i,t-k,t+k} = a + b\, SUE_{i,t} + e_{i,t}, \tag{2.2}$$

in which earnings are announced on day t, and $R_{i,t-k,t+k}$ is the cumulative return on stock i, in excess of the market return, over the surrounding trading days from $t - k$ through $t + k$. We compute $SUE_{i,t}$ using a seasonal random walk, in which $SUE_{i,t} = \Delta_{i,t}/\sigma(\Delta_i)$, $\Delta_{i,t}$ equals the year-over-year change in stock i's quarterly earnings, and $\sigma(\Delta_i)$ is the standard deviation of $\Delta_{i,t}$ for the last eight quarters.

Under the hypothesis that the shell component is a significant source of return variation for the smallest stocks, we expect those stocks to have a lower b in Eq. (2.2) and a lower regression R^2 than the other groups. The first three columns of Table 10 report the regression results, which confirm our hypothesis. Panel A contains results for $k = 0$ in Eq. (2.2), and Panel B has results for $k = 3$. In both panels, the smallest stocks have the lowest values of b and R^2. For comparison, we conduct the same analysis in the US and report the results in the last three columns of Table 10. The US sample period is 1/1/1980–12/31/2016, before which the quality of quarterly data is lower. In contrast to the results for China, the smallest stocks in the US have the highest values of b and R^2.

We also compare stocks' return responses to shell-value shocks, using two proxies for such shocks. One is the average return that public stocks experience upon becoming shells in reverse mergers. Our rationale is that the higher the return, the greater is the potential value of becoming a shell. The other proxy is the log of the total number of IPOs, with the rationale that a greater frequency of IPOs could be interpreted by the market as a relaxing of IPO constraints. Consistent with the importance of the shell component for the smallest stocks, only that group's returns covary both positively with the reverse-merger premium and negatively with the log of the IPO number. The results are presented in the Appendix.

2.4. Value effects in China

 A value effect is a relation between expected return and a valuation metric that scales the firm's equity price by an accounting-based fundamental. The long-standing intuition for value effects (e.g., Basu, 1983; Ball, 1992) is that a scaled price is essentially a catchall proxy for expected return: a higher (lower) expected return implies a lower (higher) current price, other things equal.

Our approach to creating a value factor in China follows the same path established by the two-study sequence of Fama and French (1992, 1993). Following Fama and French (1992), the first step is to select the valuation ratio exhibiting the strongest value effect among a set of candidate ratios. The valuation ratios Fama and French (1992) consider include EP, BM, and assets-to-market (AM). The authors find BM exhibits the strongest value effect, subsuming the other candidates. Based on that result, the subsequent study by Fama and French (1993) uses BM to construct the value factor (HML).

In this section, we conduct the same horse race among valuation ratios. Our entrants are the same as in Fama and French (1992), plus cash-flow-to-price (CP). As in that study, we estimate cross-sectional Fama and MacBeth (1973) regressions of individual monthly stock returns on the valuation ratios, with a stock's market capitalization and estimated CAPM beta (β) included in the regression. For the latter variable we use the beta estimated

from the past year's daily returns, applying a five-lag Dimson (1979) correction. Following Fama and French (1992), we use EP to construct both EP^+ and a dummy variable, with EP^+ equal to EP when EP is positive, and zero otherwise, and with the dummy variable, $D(EP < 0)$, equal to one when EP is negative, and zero otherwise. In the same manner, we construct CP^+ and $D(CP < 0)$ from CP. Due to the shell-value contamination of returns discussed earlier, we exclude the smallest 30% of stocks.

Table 11 reports average slopes from the month-by-month Fama-MacBeth regressions. Similar to results in the US market, we see from column (1) that β does not enter significantly. Also as in the US, the size variable, $logME$, enters with a significantly negative coefficient that is insensitive to including β: in columns (2) and (3), without and with β beta included, the size slopes are -0.0049 and -0.0046 with t-statistics of -2.91 and -2.69. These results confirm a significant size effect in China.

Columns (4) through (7) of Table 11 report results when each valuation ratio is included individually in its own regression. All four valuation ratios exhibit significant explanatory power for returns. When the four valuation ratios are included in the regression simultaneously, as reported in column (8), EP dominates the others. The t-statistic for the coefficient on EP^+ is 4.38, while the t-statistics for $logBM$, $logAM$, and CP^+ are just 1.31, 0.99, and 1.35. In fact, the coefficient and t-statistic for EP^+ in column (8) are very similar to those in column (6), in which EP is the only valuation ratio in the regression. The estimated EP effect in column (8) is also economically significant. A one standard-deviation difference in EP^+ implies a difference in expected monthly return of 0.52%.

Because BM likely enters the horse race as a favorite, we also report in column (9) the results when BM and EP are the only valuation ratios included. The results are very similar, with the coefficient and t-statistic for EP^+ quite close to those in column (8) and with the coefficient on $\log BM$ only marginally significant.

Fama and French (1992) exclude financial firms, whereas we include them in Table 11. We

do so because we also include financial firms when constructing our factors, as do Fama and French (1993) when constructing their factors. If we instead omit financial firms (including real estate firms) when constructing Table 2, the results (reported in the Appendix) are virtually unchanged.

In sum, we see that EP emerges as the most effective valuation ratio, subsuming the other candidates in a head-to-head contest. Therefore, in the next section, we construct our value factor for China using EP. The dominance of EP over BM is further demonstrated in the next section, where we show that our CH-3 model with the EP-based value factor prices a BM-based value factor, whereas the BM-based model, FF-3, cannot price the EP-based value factor.

2.5. A three-factor model in China

In this section, we present our three-factor model, CH-3, with factors for size, value, and the market. Our approach incorporates the features of size and value in China discussed in the previous sections. Section 5.1 provides details of the factor construction. We then compare our approach to one that ignores the China-specific insights. Section 5.2 illustrates the problems with including the smallest 30% of stocks, while Section 5.3 shows that using EP to construct the value factor dominates using BM.

2.5.1. Size and value factors

Our model has two distinct features tailored to China. First, we eliminate the smallest 30% of stocks, to avoid their shell-value contamination, and we use the remaining stocks to form factors. Second, we construct our value factor based on EP. Otherwise, we follow the procedure used by Fama and French (1993). Specifically, each month we separate the remaining 70% of stocks into two size groups, small (S) and big (B), split at the median market value of that universe. We also break that universe into three EP groups: top 30% (value, V), middle 40% (middle, M), and bottom 30% (growth, G). We then use the intersections of those groups to form value-weighted portfolios for the six resulting size-

EP combinations: S/V, S/M, S/G, B/V, B/M, and B/G. When forming value-weighted portfolios, here and throughout the study, we weight each stock by the market capitalization of all its outstanding A shares, including nontradable shares. Our size and value factors, denoted as SMB (small-minus-big) and VMG (value-minus-growth), combine the returns on these six portfolios as follows:

$$SMB = \frac{1}{3}(S/V + S/M + S/G) - \frac{1}{3}(B/V + B/M + B/G),$$

$$VMG = \frac{1}{2}(S/V + B/V) - \frac{1}{2}(S/G + B/G).$$

The market factor, MKT, is the return on the value-weighted portfolio of our universe, the top 70% of stocks, in excess of the one-year deposit interest rate.

Table 12 reports summary statistics for the three factors in our 204-month sample period. The monthly standard deviations of SMB and VMG are 4.52% and 3.75%, each roughly half of the market's standard deviation of 8.09%. The averages of SMB and VMG are 1.03% and 1.14% per month, with t-statistics of 3.25 and 4.34. In contrast, the market factor has a 0.66% mean with a t-statistic of just 1.16. Clearly, size and value command substantial premiums in China over our sample period. All three factors are important for pricing, however, in that each factor has a significantly positive alpha with respect to the other two factors. Specifically, those two-factor monthly alphas for MKT, SMB, and VMG are 1.57%, 1.91%, and 1.71%, with t-statistics of 2.30, 6.92, and 7.94. Each factor's two-factor alpha exceeds its corresponding simple average essentially due to the negative correlations of VMG with both MKT and SMB (-0.27 and -0.62). In China, smaller stocks tend to be growth stocks, making the negative correlation between size and value stronger than it is in the US. Fama-Macbeth regressions also reveal a substantial negative correlation between China's size and value premiums. For example, the correlation between the coefficients on $logME$ and EP^+ underlying the results reported in column (6) of Table 11 equals 0.42. Note that a positive correlation there is consistent with a negative correlation between the premiums on (small) size and value.

As Ross (2017) argues, explaining average return is one of two desiderata for a parsimonious factor model. Explaining return variance is the other. Table 13 reports the average R-squared values in regressions of individual stock returns on one or more of the CH-3 factors. Panel A includes all listed stocks in China, while Panel B omits the smallest 30%. For comparison with the US, over the same period from January 2000 through December 2016, Panel C reports results when regressing NYSE/Amex/Nasdaq stocks on one or more of the three factors of Fama and French (1993). All regressions are run over rolling three-year windows, and the R-squared values are then averaged over time and across stocks.

We see from Table 13 that our size and value factors explain substantial fractions of return variance beyond what the market factor explains. Across all Chinese stocks, for example, the three CH-3 factors jointly explain 53.6% of the typical stock's return variance, versus 38.5% explained by just the market factor. The difference between these values, 15.1%, is actually higher than the corresponding 9.6% difference for the US (27.3% minus 17.7%). Size and value individually explain substantial additional variance, again with each adding more R-squared in China than in the US. We also see that the explanatory power of the CH-3 factors, which are constructed using the largest 70% of stocks, improves when averaging just over that universe (Panel B versus Panel A). The improvement is rather modest, however, indicating that our factors explain substantial variance even for the shell stocks.

A striking China-US difference is that the market factor in China explains more than twice as large a fraction of the typical stock's variance than the market factor explains in the US: 38.5% versus 17.7%. The high average R-squared in China is more typical of earlier decades in US history. For example, Campbell et al. (2001) report average R-squared values exceeding 30% in the US during the 1960s. Exploring potential sources of the higher explanatory power of the market factor in China seems an interesting direction for future research.

Naturally, diversification allows the CH-3 factors to explain larger fractions of return variance for portfolios than for individual stocks. For example, we form value-weighted portfo-

lios within each of 37 industries, using classifications provided by Shenyin-Wanguo Security Co., the leading source of industry classifications in China. On average across industries, the CH-3 factors explain 82% of the variance of an industry's return, versus 72% explained by the market factor. For the anomalies we analyze later, the CH-3 factors typically explain 90% of the return variance for a portfolio formed within a decile of an anomaly ranking variable, versus 85% explained by the market.

We keep negative-EP stocks in our sample and categorize them as growth stocks, observing that negative-EP stocks comove with growth stocks. Returns on the negative-EP stocks load negatively on a value factor constructed using just the positive-EP sample, with a slope coefficient of -0.28 and a t-statistic of -3.31. As a robustness check, we exclude negative-EP stocks and find all our results hold. On average across months, negative-EP stocks account for 15% of the stocks in our universe.

In sum, size and value, as captured by our model's SMB and VMG, are important factors in China. This conclusion is supported by the factors' average premiums as well as their ability to explain return variances.

2.5.2. Including shell stocks

If we construct our three factors without eliminating the smallest 30% of stocks, the monthly size premium increases to 1.36%, while the value premium shrinks to 0.87%. As observed earlier, the value of being a potential reverse-merger shell has grown significantly over time, creating a shell premium that accounts for a substantial portion of the smallest stocks' average returns. Consequently, a size premium that includes shell stocks is distorted upward by the shell premium. At the same time, the shell premium distorts the value premium downward. Market values of small firms with persistently poor or negative earnings nevertheless include significant shell value, so those firms' resulting low EP ratios classify them as growth firms. Misidentifying shell firms as growth firms then understates the value premium due to the shell premium in returns on those "growth" firms.

High realized returns on shell stocks during our sample period should not necessarily be interpreted as evidence of high expected returns. The high returns could reflect unanticipated increases in rationally priced shells, or they could reflect overpricing of shells in the later years (implying low expected subsequent returns). With rational pricing, an increase in shell value could either raise or lower expected return on the shell firms' stocks, depending on the extent to which shell values contain systematic risks. We do not attempt to explain expected returns on shell stocks. Lee, Qu, and Shen (2017) link expected returns on these stocks to systematic risk related to regulatory shocks.

Including shell stocks also impairs the resulting factor model's explanatory power. When the three factors include the bottom 30% of stocks, they fail to price SMB and VMG from CH-3, which excludes shells: shell-free SMB produces an alpha of -23 basis points (bps) per month (t-statistic: -3.30), and VMG produces an alpha of 27 bps (t-statistic: 3.32). These results further confirm that the smallest 30% of stocks are rather different animals. Although they account for just 7% of the market's total capitalization, including them significantly distorts the size and value premiums and impairs the resulting model's explanatory ability. Therefore, excluding shells is important if the goal is to build a model that prices regular stocks.

2.5.3. Comparing size and value factors

The obvious contender to CH-3 is FF-3, which follows Fama and French (1993) in using BM instead of EP as the value metric. In this section, we compare CH-3 to FF-3, asking whether one model's factors can explain the other's. Using the same stock universe as CH-3, we construct the FF-3 model's size and value factors, combining the six size-BM value-weighted portfolios (S/H, S/M, S/L, B/H, B/M, B/L). The size groups are again split at the median market value, and the three BM groups are the top 30% (H), middle 40% (M), and bottom 30% (L). The returns on the resulting six portfolios are combined to

form the FF-3 size and value factors as follows:

$$FFSMB = \frac{1}{3}(S/H + S/M + S/L) - \frac{1}{3}(B/H + B/M + B/L),$$

$$FFHML = \frac{1}{2}(S/H + B/H) - \frac{1}{2}(S/L + B/L).$$

The market factor is the same as in the CH-3 model.

Our CH-3 model outperforms FF-3 in China by a large margin. Panel A of Table 14 reports the alphas and corresponding t-statistics of each model's size and value factors with respect to the other model. CH-3 prices the FF-3 size and value factors quite well. The CH-3 alpha of $FFSMB$ is just -4 bps per month, with a t-statistic of -0.66, while the alpha of $FFHML$ is 34 bps, with a t-statistic of 0.97. In contrast, FF-3 prices neither the size nor the value factor of CH-3. FF-3 removes less than half of our model's 103 bps size premium, leaving an SMB alpha of 47 bps with a t-statistic of 7.03. Most strikingly, the alpha of our value factor, VMG, is 139 bps per month (16.68% annually), with a t-statistic of 7.93.

Panel B of Table 14 reports Gibbons-Ross-Shanken (GRS) tests of whether both of a model's size and value factors jointly have zero alphas with respect to the other model. The results tell a similar story as above. The test of zero CH-3 alphas for both $FFSMB$ and $FFHML$ fails to reject that null, with a p-value of 0.41. In contrast, the test strongly rejects jointly zero FF-3 alphas for SMB and VMG, with a p-value less than 10^{-12}. The Appendix reports additional details of the regressions underlying the results in Table 14.

The above analysis takes a frequentist approach in comparing the abilities of models to explain each other's factors. Another approach to making this model comparison is Bayesian, proposed by Barillas and Shanken (2018) and also applied by Stambaugh and Yuan (2017). This approach compares factor models in terms of posterior model probabilities across a range of prior distributions. Consistent with the above results, this Bayesian comparison of FF-3 to CH-3 also heavily favors the latter. Details of the analysis are presented in the Appendix.

In the US, two additional factors, profitability and investment, appear in recently proposed models by Hou, Xue, and Zhang (2015) and Fama and French (2015). Guo et al. (2017) construct the Fama-French five-factor model in China (FF-5) and find that, when benchmarked against the CAPM, the investment factor is very weak, while the profitability factor is significant. We also find that the investment effect is weak in China, yielding no significant excess return spread or CAPM alpha. A profitability spread has a significant CAPM alpha but does not survive CH-3. Accordingly, in the same tests as above, CH-3 again dominates. The CH-3 alphas for the nonmarket factors in FF-5 produce a GRS p-value of 0.88, whereas the FF-5 alphas for the SMB and VMG factors of CH-3 produce a GRS p-value of 0.0003. Details are presented in the Appendix.

2.6. Anomalies and factors

A factor model is often judged by its ability not only to price another model's factors but also to explain return anomalies. In this section, we explore the latter ability for CH-3 versus FF-3. We start by compiling a set of anomalies in China that are reported in the literature. For each of those anomalies, we compute a long-short return spread in our sample, and we find ten anomalies that produce significant alphas with respect to a CAPM benchmark. Our CH-3 model explains eight of the ten, while FF-3 explains three.

2.6.1. Anomalies in China

Our survey of the literature reveals 14 anomalies reported for China. The anomalies fall into nine categories: size, value, profitability, volatility, reversal, turnover, investment, accruals, and illiquidity. The literature documenting Chinese anomalies is rather heterogeneous with respect to sample periods, data sources, and choice of benchmarking model (e.g., one factor, three factors, or no factors). Our first step is to reexamine all of the anomalies using our data and sample period. As discussed earlier, our reliance on post-2000 data and our choice of WIND as the data provider offer the most reliable inferences. We also use one model, the CAPM, to classify all the anomalies as being significant or not. Unlike the previous

literature, we also evaluate the anomalies within our stock universe that eliminates the smallest 30% so that shell values do not contaminate anomaly effects. For the 14 anomalies we find in the literature, the Appendix reports their CAPM alphas as well as the conclusions of each previous study examining one or more of the anomalies.

For our later analysis of the pricing abilities of the three-factor models, we retain only the anomalies that generate significant CAPM alphas for long-short spreads between portfolios of stocks in the extreme deciles. This nonparametric approach of comparing the extreme deciles, as is common in the anomalies literature, is robust to any monotonic relation but relies on having a sufficiently large sample to achieve power. After imposing our filters, the number of stocks grows from 610 in 2000 to 1872 in 2016, so each portfolio contains at least 60 stocks even early in the sample period. Nevertheless, our 17-year period is somewhat shorter than is typical of US studies, so any of our statements about statistical insignificance of an anomaly must be tempered by this power consideration.

We compute alphas for both unconditional and size-neutral sorts. We conduct the latter sort because correlation between an anomaly variable and size could obscure an anomaly's effect in an unconditional sort, given China's large size premium of 12.36% annually. For each of the 14 anomalies, the two sorting methods are implemented as follows. The unconditional sort forms deciles by sorting on the anomaly variable. (For EP and CP, we sort only the positive values.) We then construct a long-short strategy using deciles one and ten, forming value-weighted portfolios within each decile. The long leg is the higher-performing one, as reported by previous studies and confirmed in our sample. For the size-neutral version, we first form size deciles by sorting on the previous month's market value. Within each size decile, we then create ten deciles formed by sorting on the anomaly variable. Finally, we form the anomaly decile portfolios used in our tests. We pool all stocks that fall within a given anomaly decile for any size decile. The returns on those stocks are then value-weighted, using the individual stocks' market capitalizations, to form the portfolio return for that anomaly decile. As with the unconditional sort, the long-short strategy again uses

deciles one and ten.

Our procedure reveals significant anomalies in six categories: size, value, profitability, volatility, reversal, and turnover. Almost all of the anomalies in these categories produce significant CAPM-adjusted return spreads from both unconditional and size-neutral sorts. Although the investment, accrual, and illiquidity anomalies produce significant CAPM alphas in the US, they do not in China, for either unconditional or size-neutral sorts. The estimated monthly alphas for investment are small, at 0.22% or less per month, and the accrual alphas are fairly modest as well, at 0.42% or less. The estimated illiquidity alphas, while not quite significant at conventional levels, are nevertheless economically substantial, as high as 0.83% per month. This latter result raises the power issue mentioned earlier. Also unlike the US, there is no momentum effect in China. There is, however, a reversal effect, as past losers significantly outperform past winners.

Reversal effects in China are especially strong. Past performance over any length window tends to reverse in the future. In contrast, past returns in the US correlate in different directions with future returns, depending on the length of the past-return window. That is, past one-month returns correlate negatively with future returns, past two-to-twelve-month returns correlate positively (the well-documented momentum effect), and past three-to-five-year returns correlate negatively. In China, past returns over various windows all predict future reversals. In untabulated results, we find that past returns over windows of one, three, six, and twelve months, as well as five years, all negatively predict future returns, in monotonically weakening magnitudes. For a one-month window of past return, the decile of biggest losers outperforms the biggest winners with a CAPM alpha of 18% annually (t-statistic: 2.96). The alpha drops to 6% and becomes insignificant (t-statistic: 0.90) when sorting by past one-year return.

We choose one-month reversal for the anomaly in the reversal category. One potential source of short-run reversals that does not appear to be related to this anomaly is bid-ask bounce, e.g., Niederhoffer and Osborne (1966). The WIND data beginning in 2012 allow

us to average each stock's best bid and ask prices at the day's close of trading. Using the resulting mid-price returns to compute the one-month reversal anomaly gives a result virtually identical to (even slightly higher than) that obtained using closing price returns: 2.21% versus 2.15% for the average long-short monthly return over the 2012–2016 subperiod.

Altogether we find ten significant anomalies. Table 15 reports their average excess returns along with their CAPM alphas and betas. The results for the unconditional sorts appear in Panel A. The monthly CAPM alphas range from 0.53%, for 12-month turnover, to 1.49%, for one-month reversal, and most display significant t-statistics. The average alpha for the ten anomalies is 1.02%, and the average t-statistic is 2.21.

Panel B of Table 15 reports the corresponding results for the size-neutral sorts. Two differences from Panel A emerge. First, size-neutralization substantially increases the alphas of several anomalies. For example, the ROE monthly alpha increases by 0.57%, the EP alpha increases by 0.52%, and the alpha for 12 month turnover increases by 0.21% bps. Second, for almost all of the long-short spreads, standard deviations decrease and thus t-statistics increase. The decrease in standard deviations confirms that size is an important risk factor. The size-neutral sorting essentially gives the long-short spreads a zero SMB loading and thus smaller residual variance in the single-factor CAPM regression. Panel B conveys a similar message as Panel A, just more strongly: all ten anomalies generate significant CAPM-adjusted return spreads. The average monthly CAPM alpha for the size-neutral sorts is 1.17%, and the average t-statistic is 2.91.

2.6.2. Factor model explanations of anomalies

Table 16 reports CH-3 alphas and factor loadings for the ten anomalies that survive the CAPM, the same anomalies as in Table 16. For the most part, our CH-3 model explains the anomalies well. Panel A of Table 16 reports results for the unconditional sorts. Not surprisingly, CH-3 explains the size anomaly. More noteworthy is that the model explains all the value anomalies (EP, BM, and CP), each of which loads positively on our value

factor. The monthly CH-3 alphas of the three value anomalies are 0.64% or less, and the highest t-statistic is just 1.02. These findings echo the earlier Fama-MacBeth regression results, in which EP subsumes both BM and CP in terms of cross-sectional abilities to explain average returns.

Perhaps unexpectedly, given the US evidence, CH-3 fully explains the profitability anomaly, return on equity (ROE). In the US, profitability's strong positive relation to average return earns it a position as a factor in the models recently advanced by Hou, Xue, and Zhang (2015) and Fama and French (2015). In China, however, profitability is captured by our three-factor model. The ROE spread loads heavily on the value factor (t-statistic: 9.43), and the CH-3 monthly alpha is -0.36%, with a t-statistic of just -0.88.

CH-3 also performs well on the volatility anomalies. It produces insignificant alphas for return spreads based on the past month's daily volatility and the past month's maximum daily return (MAX). The CH-3 monthly alphas for both anomalies are 0.27% or less, with t-statistics no higher than 0.65. We also see that both of the anomalies load significantly on the value factor. That is, low (high) volatility stocks behave similarly to value (growth) stocks.

Recall from the previous section that the estimated CAPM alpha for the illiquidity anomaly, while not quite clearing the statistical-significance hurdle, is as high as 0.83% per month. In contrast, we find that the corresponding CH-3 alpha is just 0.23%, with at t-statistic of 1.14. That is, if we were to add the illiquidity anomaly to our set of ten, given its substantial estimated CAPM alpha, we see that illiquidity would also be included in the list of anomalies that CH-3 explains.

To say for short that our CH-3 model "explains" an anomaly, as in several instances above, must prompt a nod to the power issue mentioned earlier. Of course, more accurate would be to say that the test presented by the anomaly merely fails to reject the model. In general, however, the anomalies for which we can make this statement produce not only insignificant

t-statistics but also fairly small estimated CH-3 alphas. Across the eight anomalies that the CH-3 model explains, the average absolute estimated monthly alpha is 0.30% in the unconditional sorts and 0.26% in size-neutral sorts. In contrast, the same anomalies produce average absolute FF-3 alphas of 0.84% and 0.90% in the unconditional and size-neutral sorts.

CH-3 encounters its limitations with anomalies in the reversal and turnover categories. While the reversal spread loads significantly on SMB, its monthly alpha is nevertheless 0.93% (t-statistic:1.70). In the turnover category, CH-3 accommodates 12 month turnover well but has no success with abnormal 1 month turnover. The latter anomaly's return spread has small and insignificant loadings on SMB and VMG, and its CH-3 monthly alpha is 1.28%, nearly identical to its CAPM alpha (t-statistic: 2.86).

The size-neutral sorts, reported in Panel B of Table 16, deliver the same conclusions as the unconditional sorts in Panel A. CH-3 again explains all anomalies in the value, profitability, and volatility categories. The monthly alphas for those anomalies have absolute values of 0.61% or less, with t-statistics less than 0.98 in magnitude. For the reversal and turnover categories, CH-3 displays the same limitations as in Panel A. The CH-3 monthly alpha for reversal is 1.13%, with a t-statistic of 2.12. Abnormal turnover has an alpha of 1.24%, with a t-statistic of 3.04.

In the same format as Table 16, Table 17 reports the corresponding results for the FF-3 model. These results clearly demonstrate that FF-3 performs substantially worse than CH-3, leaving significant anomalies in five of the six categories—all categories except size. Consider the results in Panel A, for example. Similar to FF-3's inability to price our EP-based value factor, FF-3 fails miserably with the EP anomaly, leaving a monthly alpha of 1.54% (t-statistic: 5.57). Moreover, as in the US, FF-3 cannot accommodate profitability. The ROE anomaly leaves a monthly alpha of 1.75% (t-statistic: 5.67). Finally, for all anomalies in the volatility, reversal, and turnover categories, FF-3 leaves both economically and statistically significant alphas.

Table 18 compares the abilities of models to explain anomalies by reporting the average absolute alphas for the anomaly long-short spreads, the corresponding average absolute t-statistics, and GRS tests of whether a given model produces jointly zero alphas across anomalies. The competing models include unconditional means (i.e., zero factors), the single-factor CAPM, and both of the three-factor models, CH-3 and FF-3. As in Tables 16 and 17, Panel A reports results for the unconditional sorts, and Panel B reports the size-neutral sorts. First, in both panels, observe that CH-3 produces much smaller absolute alphas than do the other models: 0.45% for CH-3 versus at least 0.9% for the other models. In Panel A, for the unconditional sorts, the GRS p-value of 0.15 for CH-3 fails to reject the joint hypothesis that all ten anomalies produce zero CH-3 alphas. In contrast, the corresponding p-values for the other models are all less than 10^{-4}. For the size-neutral sorts (Panel B), a similar disparity occurs for a test of jointly zero alphas on nine anomalies (size is omitted). The CH-3 p-value is 0.05 versus p-values less than 10^{-4} for the other models. Because size, EP, and BM are used to construct factors, we also eliminate those three anomalies and conduct the GRS test using the remaining seven. As shown in the last two rows of each panel, the results barely change—CH-3 again dominates.

2.7. A four-factor model in China

Notwithstanding the impressive performance of CH-3, the model does leave significant alphas for reversal and turnover anomalies, as noted earlier. Of course, we see above that these anomalies are not troublesome enough to cause the larger set that includes them to reject CH-3 when accounting for the multiple comparisons inherent in the GRS test. At the same time, however, the latter test confronts the same power issue discussed earlier. Moreover, the reversal and turnover anomalies both produce alpha estimates that are not only statistically significant but also economically large, over 1% per month in the size-neutral sorts reported in Panel B of Table 16. We therefore explore the addition of a fourth factor based on turnover. In Section 7.1, we discuss this turnover factor's sentiment-based motivation, describe the factor's construction, and explain how we also modify the

size factor when building the four-factor model, CH-4. Section 7.2 then documents CH-4's ability to explain all of China's reported anomalies.

2.7.1. A turnover factor

A potential source of high trading intensity in a stock is heightened optimism toward the stock by sentiment-driven investors. This argument is advanced by Baker and Stein (2004), for example, and Lee (2013) uses turnover empirically as a sentiment measure at the individual stock level. High sentiment toward a stock can affect its price, driving it higher than justified by fundamentals and thereby lowering its expected future return. Two assumptions underly such a scenario. One is a substantial presence in the market of irrational, sentiment-driven traders. The other is the presence of short-sale impediments.

China's stock market is especially suited to both assumptions. First, individual retail investors are the most likely sentiment traders, and individual investors are the major participants in China's stock market. As of year-end 2015, over 101 million individuals had trading accounts, and individuals held 88% of all free-floating shares (Jiang, Qian, and Gong, 2016). Second, shorting is extremely costly in China.[4]

Shorting constraints not only impede the correction of overpricing. They also sign the likely relation between sentiment and turnover. As Baker and Stein (2004) argue, when pessimism about a stock prevails among sentiment-driven investors, those who do not already own the stock simply do not participate in the market, as short-sale constraints prevent them from acting on their pessimistic views. In contrast, when optimism prevails, sentiment-driven investors can participate broadly in buying the stock. Thus, shorting constraints make high turnover (greater liquidity) more likely to accompany strong optimism as opposed to strong pessimism.

Given this sentiment-based motivation, to construct our fourth factor we use abnormal turnover, which is the past month's share turnover divided by the past year's turnover. We

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[4]Costs of short selling in China are discussed, for example, in the CSRC publication, Chinese Capital Market Development Report (translated from Mandarin).

construct this turnover factor in precisely the same manner as our value factor, again neutralizing with respect to size. That is, abnormal turnover simply replaces EP, except the factor goes long the low-turnover stocks, about which investors are relatively pessimistic, and goes short the high-turnover stocks, for which greater optimism prevails. We denote the resulting factor PMO (pessimistic minus optimistic). We also construct a new SMB, taking a simple average of the EP-neutralized version of SMB from CH-3 and the corresponding turnover-neutralized version. The latter procedure for modifying SMB when adding additional factors essentially follows Fama and French (2015). The new size and turnover factors have annualized averages of 11% and 12%. The market and value factors in CH-4 are the same as in CH-3.

2.7.2. Explaining all anomalies with four factors

For model CH-4, Table 19 reports results of the same analyses conducted for models CH-3 and FF-3 and reported in Tables 16 and 17. Adding the fourth factor produces insignificant alphas not just for the abnormal turnover anomaly but also for reversal. In Panel A, for the unconditional sorts, the CH-4 monthly alphas for those anomalies are 0.00% and 0.49%, with t-statistics of -0.01 and 0.87. The size-neutral sorts in Panel B produce similar results. Adding the turnover factor essentially halves the reversal anomaly's unconditional alpha relative to its CH-3 value in Table 16, even though the rank correlation across stocks between the sorting variables for the turnover and reversal anomalies is just 0.3, on average.

CH-4 accommodates the above two anomalies, thus now explaining all ten, while also lowering the average magnitude of all the alphas. For the unconditional sorts, the average absolute alpha drops to 0.30%, versus 0.45% for CH-3, and the average absolute t-statistic drops to 0.69, versus 1.12 for CH-3. The GRS test of jointly zero alphas for all ten anomalies produces a p-value of 0.41, versus 0.15 for CH-3, thereby moving even farther from rejecting the null. Similar improvements occur for the size-neutral sorts.

2.8. Conclusion

Size and value are important factors in the Chinese stock market, with both having average premiums exceeding 12% per year. Capturing these factors well, however, requires that one not simply replicate the Fama and French (1993) procedure developed for the US.

Unlike small listed stocks in the US, China's tight IPO constraints cause returns on the smallest stocks in China to be significantly contaminated by fluctuations in the value of becoming corporate shells in reverse mergers. To avoid this contamination, before constructing factors we eliminate the smallest 30% of stocks, which account for just 7% of the market's total capitalization. Eliminating these stocks yields factors that perform substantially better than using all listed stocks to construct factors, whereas the Fama and French (1993) procedure essentially does the latter in the US.

Value effects in China are captured much better by EP than by BM, used in the US by Fama and French (1993). The superiority of EP in China is demonstrated at least two ways. First, in an investigation paralleling Fama and French (1992), cross-sectional regressions reveal that EP subsumes other valuation ratios, including BM, in explaining average stock returns. Second, our three-factor model, CH-3, with its EP-based value factor, dominates the alternative FF-3 model, with its BM-based value factor. In a head-to-head model comparison, CH-3 prices both the size and value factors in FF-3, whereas FF-3 prices neither of the size and value factors in CH-3. In particular, FF-3 leaves a 17% annual alpha for our value factor.

We also survey the literature that documents return anomalies in China, and we find ten anomalies with significant CAPM alphas in our sample. Our CH-3 model explains eight of the anomalies, including not just all value anomalies but also profitability and volatility anomalies not explained in the US by the three-factor Fama-French model. In contrast, the only two anomalies in China that FF-3 explains are size and BM. The two anomalies for which CH-3 fails, return reversal and abnormal turnover, are both explained by a four-factor

model that adds a sentiment-motivated turnover factor.
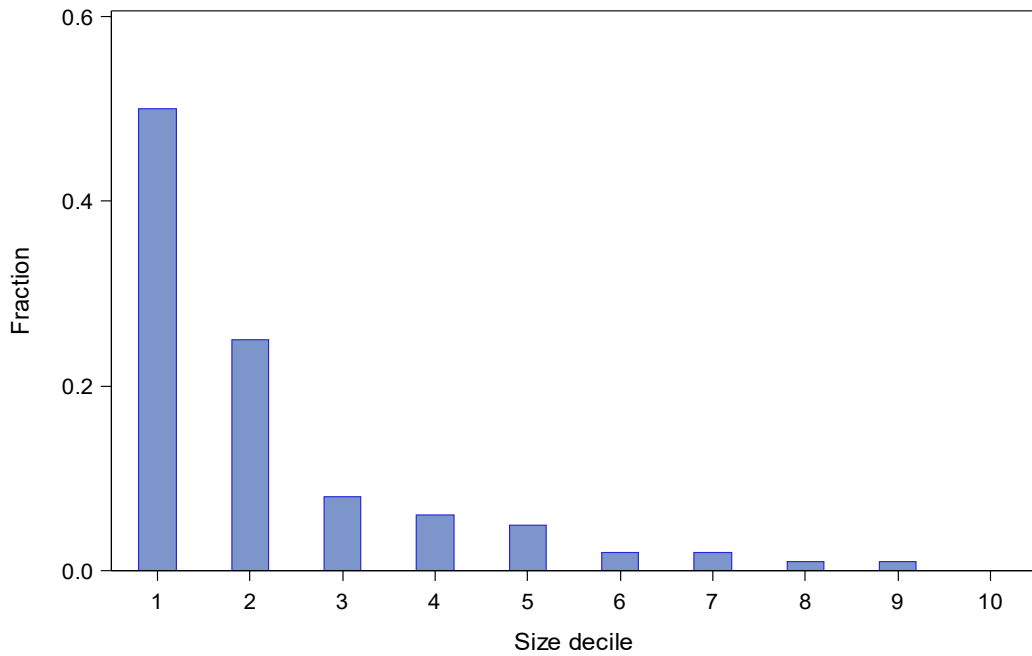
Figure 5 Size distribution of firms acquired in reverse-merger deals

The figure displays the size distribution of firms acquired in reverse-merger deals from January 2007 through December 2016. A total of 133 reverse-merger deals occurred, and the fraction of those deals falling into a given firm size decile is displayed in the bar chart. Size deciles reflect month-end market values three months before the deal month.

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Panel A. Ratio of estimated shell value to market cap
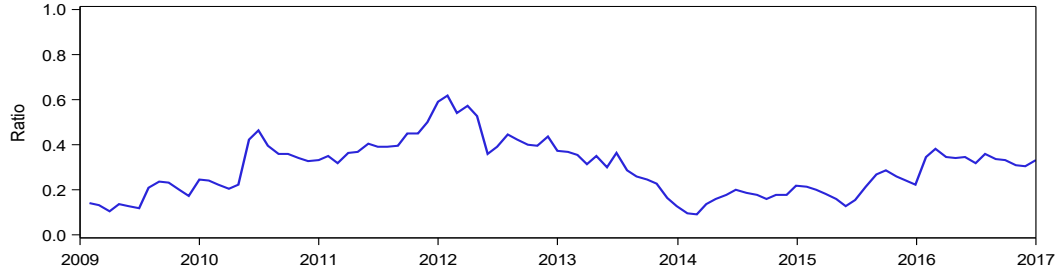
Panel B. Estimated shell value (RMB)
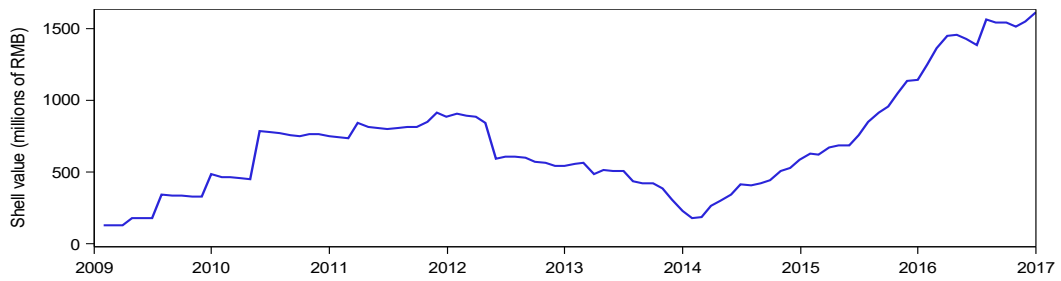
Figure 6 Shell values over time.

Panel A displays the time series of the ratio of estimated shell value to firm market capitalization. Panel B displays the time series of the estimated shell value (in RMB). The sample period is January 2009 through December 2016.

Quantity	China			US		
	Smallest	Middle	Largest	Smallest	Middle	Largest
Panel A: k = 0						
b	0.14	0.17	0.24	0.19	0.07	0.05
	(6.34)	(12.42)	(17.28)	(7.51)	(6.99)	(9.90)
R^2	0.003	0.010	0.017	0.005	0.003	0.002
Panel B: k = 3						
b	0.43	0.58	0.59	0.52	0.20	0.13
	(9.74)	(17.91)	(17.60)	(7.84)	(6.03)	(10.68)
R^2	0.006	0.016	0.021	0.012	0.005	0.003

Table 10 Return reactions to earnings surprises across different size groups in China and the US

The table reports slope estimates and R-squares in a panel regression of earnings-window returns on earnings surprises,

$$R_{i,t-k,t+k} = a + b\,SUE_{i,t} + e_{i,t},$$

in which earnings are announced on day t; $R_{i,t-k,t+k}$ is the cumulative return on stock i, in excess of the market return, over the surrounding trading days from $t - k$ through $t + k$; $SUE_{i,t} = \Delta_{i,t}/\sigma(\Delta_i)$; $\Delta_{i,t}$ equals the year-over-year change in stock i's quarterly earnings; and $\sigma(\Delta_i)$ is the standard deviation of $\Delta_{i,t}$ for the last eight quarters. Panel A contains results for $k = 0$; Panel B contains results for $k = 3$. The regression is estimated within each of three size groups in both the China and US markets. The groups are formed based on the top 30%, middle 40%, and bottom 30% of the previous month's market capitalizations. The sample periods are January 2000 through December 2016 for China and January 1980 through December 2016 for the US. The US returns data are from the Center for Research in Security Prices (CRSP) and the earnings data are from Compustat. White (1980) heteroskedasticity-consistent t-statistics are reported in parentheses. The estimates of b are multiplied by 100.

Quantity	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.0149	0.0581	0.0571	0.0659	0.0629	0.0690	0.0564	0.0716	0.0728
	(1.94)	(3.32)	(3.19)	(3.90)	(3.74)	(4.03)	(3.19)	(4.40)	(4.39)
β	−0.0002		−0.0010	−0.0018	−0.0017	0.0002	−0.0010	−0.0002	−0.0004
	(−0.09)		(−0.37)	(−0.71)	(−0.67)	(0.07)	(−0.37)	(−0.06)	(−0.15)
$logME$		−0.0049	−0.0046	−0.0046	−0.0048	−0.0068	−0.0047	−0.0066	−0.0064
		(−2.91)	(−2.69)	(−2.73)	(−3.00)	(−4.34)	(−2.80)	(−4.49)	(−4.40)
$logBM$				0.0057				0.0022	0.0035
				(3.21)				(1.31)	(1.76)
$logAM$					0.0045			0.0014	
					(3.03)			(0.99)	
EP^+						0.9503		0.7825	0.7960
						(4.88)		(4.38)	(5.06)
$D(EP<0)$						0.0006		−0.0005	−0.0001
						(0.31)		(−0.29)	(−0.04)
CP^+							0.0546	0.0181	
							(3.41)	(1.35)	
$D(CP<0)$							0.0019	0.0016	
							(3.11)	(2.37)	
R^2	0.0196	0.0277	0.0441	0.0652	0.0677	0.0615	0.0454	0.0832	0.0776

Table 11 Fama-MacBeth regressions of stock returns on beta, size, and valuation ratios

The table reports average slope coefficients from month-by-month Fama-MacBeth regressions. Individual stock returns are regressed cross-sectionally on stock characteristics as of the previous month. The columns correspond to different regression specifications, with nonempty rows indicating the included regressors. The regressors include preranking CAPM β_t estimated using the past 12 months of daily returns with a five-lag Dimson (1979) correction; the log of month-end market cap ($logM$); the log of book-to-market ($logBM$); the log of assets-to-market ($logAM$); EP^+, which equals the positive values of earnings-to-price, and zero otherwise; $D(EP < 0)$, which equals one if earnings are negative, and zero otherwise; CP^+; and $D(CP < 0)$ (with the last two similarly defined). The last row reports the average adjusted R-squared for each specification. The sample period is January 2000 through December 2016. The t-statistics based on Newey and West (1987) standard errors with four lags are reported in parentheses.

Factor	Mean	Std. dev.	t-stat.	Correlations		
				MKT	SMB	VMG
MKT	0.66	8.09	1.16	1.00	0.12	-0.27
SMB	1.03	4.52	3.25	0.12	1.00	-0.62
VMG	1.14	3.75	4.34	-0.27	-0.62	1.00

Table 12 Summary statistics for the CH-3 factors

This table reports the means, standard deviations, t-statistics, and pairwise correlations for the three factors in the CH-3 model. The means and standard deviations are expressed in percent per month. The sample period is January 2000 through December 2016 (204 months).

Factors	Avg. R-square
Panel A: All individual stocks in China	
MKT	0.385
MKT, SMB	0.507
MKT, VMG	0.471
MKT, SMB, VMG	0.536
Panel B: All but the smallest 30% of stocks in China	
MKT	0.417
MKT, SMB	0.528
MKT, VMG	0.501
MKT, SMB, VMG	0.562
Panel C: All individual stocks in the US	
MKT	0.177
MKT, SMB	0.231
MKT, HML	0.226
MKT, SMB, HML	0.273

Table 13 Average R-squares for individual stocks in China and the US

The table compares the average R-squares in regressions of monthly individual stocks' returns on factors in China's and the US stock markets. Regressions are estimated for four models: one with just the excess market return (MKT); one with MKT plus the size factor; one with MKT plus value factor; and the three-factor model with market plus size and value factors. In China's stock market, we use our CH-3 model's market (MKT), size (SMB), and value (VMG) factors, while in the US market, we use FF-3's three factors: market, SMB and BM-based HML. For each stock, we run rolling-window regressions of each stock's monthly returns on factors over the past three years (36 months). We average the R-square across time for each stock and then compute the mean of these averages across all stocks. Panel A reports average R-squares across all individual stocks on China's main boards and the Growth Enterprise Market (GEM), including the bottom 30% of stocks. Panel B reports average R-squares of all but the smallest 30% of stocks. Panel C reports average R-squares of all common stocks from the NYSE, Amex, and Nasdaq for the US. The sample periods for both China and the US are from January 2000 through December 2016 (204 months).

	Alphas with respect to:	
Factors	CH-3	FF-3
Panel A: Alpha (t-statistic)		
FFSMB	-0.04	-
	(-0.66)	-
FFHML	0.34	-
	(0.97)	-
SMB	-	0.47
	-	(7.03)
VMG	-	1.39
	-	(7.93)
Panel B: GRS F-statistics (p-value)		
FFSMB, FFHML	0.88	-
	(0.41)	-
SMB, VMG	-	33.90
	-	(2.14×10^{-13})

Table 14 Abilities of models CH-3 and FF-3 to explain each other's size and value factors

Panel A reports a factor's estimated monthly alpha (in percent) with respect to the other model (with White, 1980, heteroskedasticity-consistent t-statistics in parentheses). Panel B computes the Gibbons-Ross-Shanken (1989) F-test of whether a given model produces zero alphas for the factors of the other model (p-value in parentheses). The sample period is January 2000 through December 2016.

Category	Anomaly	$\bar{R}$	α	β	$t(\bar{R})$	$t(\alpha)$	$t(\beta)$
Panel A: Unconditional sorts							
Size	Market cap	1.09	0.97	0.18	1.92	1.81	1.90
Value	EP	1.27	1.37	−0.16	2.58	2.93	−2.15
Value	BM	1.14	1.14	0.01	2.08	2.13	0.06
Value	CP	0.73	0.70	0.04	1.67	1.69	0.55
Profitability	ROE	0.83	0.93	−0.15	1.77	2.11	−2.09
Volatility	1-Month vol.	0.81	1.03	−0.34	1.64	2.31	−5.55
Volatility	MAX	0.57	0.81	−0.36	1.26	2.02	−6.39
Reversal	1-Month return	1.47	1.49	−0.02	2.96	3.06	−0.22
Reversal	12-Month turn.	0.33	0.53	−0.29	0.63	1.09	−3.46
Turnover	1-Mo. abn. turn.	1.14	1.27	−0.19	2.44	2.92	−2.66
Panel B: Size-neutral sorts							
Value	EP	1.80	1.89	−0.14	4.32	4.72	−2.25
Value	BM	1.14	1.10	0.05	2.23	2.22	0.64
Value	CP	0.78	0.76	0.04	2.27	2.25	0.71
Profitability	ROE	1.45	1.50	−0.07	3.90	4.11	−1.30
Volatility	1-Month Vol.	0.66	0.90	−0.37	1.41	2.19	−6.20
Volatility	MAX	0.39	0.60	−0.32	0.93	1.61	−6.14
Reversal	1-Month return	1.67	1.65	0.02	3.65	3.68	0.32
Reversal	12-Month turn.	0.51	0.74	−0.34	1.06	1.74	−4.94
Turnover	1-Mo. abn. turn.	1.29	1.39	−0.15	3.19	3.68	−2.56

Table 15 CAPM alphas and betas for anomalies

For each of ten anomalies, the table reports the monthly long-short return spreads, average ($\bar{R}$), CAPM alpha (α), and CAPM beta (β). In Panel A, for the unconditional sorts, the long leg of an anomaly is the value-weighted portfolio of stocks in the lowest decile of the anomaly measure, and the short leg contains the stocks in the highest decile, with a high value of the measure being associated with lower return. In Panel B, long/short legs are neutralized with respect to size. That is, we first form size deciles by sorting on the previous month's market value. Within each size decile, we then create ten deciles formed by sorting on the anomaly variable. Finally, we form the anomaly's decile portfolios, with each portfolio pooling the stocks in a given anomaly decile across the size groups, again with value weighting. Panel B omits the size anomaly, whose alpha equals zero by construction with size-neutral sorts. Our sample period is January 2000 through December 2016 (204 months). All *t*-statistics are based on the heteroskedasticity-consistent standard errors of White (1980).

Category	Anomaly	α	β_{MKT}	β_{SMB}	β_{VMG}	$t(\alpha)$	$t(\beta_{MKT})$	$t(\beta_{SMB})$	$t(\beta_{VMG})$
Panel A: Unconditional sorts									
Size	Market cap	0.21	0.01	1.45	−0.54	1.71	0.77	40.88	−11.70
Value	EP	0.04	0.04	−0.38	1.40	0.16	1.31	−4.73	14.75
Value	BM	0.64	0.06	−0.03	0.43	1.02	0.65	−0.14	1.64
Value	CP	0.20	0.14	−0.28	0.64	0.45	2.10	−1.95	4.00
Profitability	ROE	−0.36	0.03	−0.29	1.28	−0.88	0.70	−2.35	9.43
Volatility	1-Month vol.	0.23	−0.23	−0.12	0.75	0.44	−3.81	−0.67	3.86
Volatility	MAX	0.27	−0.30	−0.05	0.48	0.65	−4.57	−0.30	2.55
Reversal	1-Month return	0.93	−0.06	0.56	0.01	1.70	−0.69	3.15	0.03
Turnover	12-Month turn.	0.42	−0.14	−0.85	0.77	1.30	−3.69	−9.33	7.90
Turnover	1-Mo. abn. turn.	1.28	−0.22	0.18	−0.16	2.86	−2.78	0.93	−0.76
Panel B: Size-neutral sorts									
Value	EP	0.23	0.02	0.05	1.32	0.82	0.47	0.57	11.97
Value	BM	0.61	0.13	−0.15	0.53	0.98	1.60	−0.80	2.19
Value	CP	0.18	0.11	−0.06	0.52	0.54	1.98	−0.50	3.84
Profitability	ROE	−0.37	0.05	0.41	1.20	−1.04	1.23	4.14	9.66
Volatility	1-Month vol.	0.20	−0.28	−0.08	0.64	0.42	−4.96	−0.49	3.34
Volatility	MAX	0.00	−0.26	0.05	0.45	0.00	−4.38	0.30	2.50
Reversal	1-Month return	1.13	0.01	0.41	0.10	2.12	0.11	2.59	0.55
Turnover	12-Month turn.	0.25	−0.22	−0.43	0.74	0.69	−4.94	−3.91	5.74
Turnover	1-Mo. abn. turn.	1.24	−0.18	0.25	−0.08	3.04	−2.79	1.55	−0.43

Table 16 CH-3 alphas and factor loadings for anomalies

For each of ten anomalies, the table reports the monthly long-short return spread's CH-3 alpha and factor loadings. For each anomaly, the regression estimated is

$$R_t = \alpha + \beta_{MKT}MKT_t + \beta_{SMB}SMB_t + \beta_{VMG}VMG_t + \epsilon_t,$$

where R_t is the anomaly's long-short return spread in month t, MKT_t is the excess market return, SMB_t is CH-3's size factor, and VMG_t is the EP-based value factor. In Panel A, for the unconditional sorts, the long leg of an anomaly is the value-weighted portfolio of stocks in the lowest decile of the anomaly measure, and the short leg contains the stocks in the highest decile, with a high value of the measure being associated with lower return. In Panel B, long/short legs are neutralized with respect to size. That is, we first form size deciles by sorting on the previous month's market value. Within each size decile, we then create ten deciles formed by sorting on the anomaly variable. Finally, we form the anomaly's decile portfolios, with each portfolio pooling the stocks in a given anomaly decile across the size groups, again with value weighting. Panel B omits the size anomaly, whose alpha equals zero by construction with size-neutral sorts. Our sample period is January 2000 through December 2016. All t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980).

Category	Anomaly	α	β_{MKT}	β_{SMB}	β_{HML}	$t(\alpha)$	$t(\beta_{MKT})$	$t(\beta_{SMB})$	$t(\beta_{HML})$
Panel A: Unconditional sorts									
Size	Market cap	0.16	0.04	1.55	−0.11	1.36	1.86	34.29	−2.43
Value	EP	1.54	−0.07	−0.98	0.48	5.57	−1.63	−13.29	6.54
Value	BM	−0.28	0.00	0.12	1.60	−1.25	0.09	1.48	30.61
Value	CP	0.63	0.08	−0.49	0.43	1.40	1.31	−3.84	2.31
Profitability	ROE	1.75	−0.06	−1.01	−0.28	5.67	−1.36	−12.74	−3.08
Volatility	1-Month vol.	0.83	−0.30	−0.40	0.52	2.11	−5.41	−3.07	4.18
Volatility	MAX	0.74	−0.33	−0.28	0.28	1.85	−5.70	−1.79	1.96
Reversal	1-Month return	0.94	−0.06	0.53	0.28	1.97	−0.83	3.50	1.58
Turnover	12-Month turn.	0.83	−0.19	−1.08	0.38	2.96	−4.97	−13.10	3.72
Turnover	1-Mo. abn. turn.	1.34	−0.21	0.16	−0.20	2.86	−2.76	0.95	−0.99
Panel B: Size-neutral sorts									
Value	EP	1.76	−0.09	−0.53	0.52	5.49	−1.79	−6.52	6.17
Value	BM	−0.01	0.07	−0.10	1.39	−0.04	1.75	−1.36	20.12
Value	CP	0.52	0.06	−0.23	0.44	1.73	1.33	−2.33	4.05
Profitability	ROE	2.01	−0.04	−0.36	−0.35	5.72	−0.71	−3.75	−3.38
Volatility	1-Month vol.	0.76	−0.33	−0.33	0.40	2.06	−6.04	−2.64	3.47
Volatility	MAX	0.43	−0.30	−0.16	0.31	1.14	−5.67	−1.10	2.60
Reversal	1-Month return	1.21	−0.01	0.35	0.29	2.55	−0.09	2.63	1.78
Turnover	12-Month turn.	0.80	−0.28	−0.68	0.39	2.46	−5.89	−6.37	3.74
Turnover	1-Mo. abn. turn.	1.37	−0.17	0.21	−0.12	3.26	−2.82	1.43	−0.68

Table 17 FF-3 alphas and factor loadings for anomalies

For each of ten anomalies, the table reports the monthly long-short return spread's CH-3 alpha and factor loadings. For each anomaly, the regression estimated is

$$R_t = \alpha + \beta_{MKT}MKT_t + \beta_{SMB}FFSMB_t + \beta_{HML}FFHML_t + \epsilon_t,$$

where R_t is the anomaly's long-short return spread in month t, MKT_t is the excess market return, SMB_t is FF-3's size factor, and $FFHML_t$ is the BM-based value factor. In Panel A, for the unconditional sorts, the long leg of an anomaly is the value-weighted portfolio of stocks in the lowest decile of the anomaly measure, and the short leg contains the stocks in the highest decile, with a high value of the measure being associated with lower return. In Panel B, long/short legs are neutralized with respect to size. That is, we first form size deciles by sorting on the previous month's market value. Within each size decile, we then create ten deciles formed by sorting on the anomaly variable. Finally, we form the anomaly's decile portfolios, with each portfolio pooling the stocks in a given anomaly decile across the size groups, again with value weighting. Panel B omits the size anomaly, whose alpha equals zero by construction with size-neutral sorts. Our sample period is January 2000 through December 2016. All t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980).

Measure	Unadjusted	CAPM	FF-3	CH-3
Panel A: Unconditional sorts				
Average $|\alpha|$	0.94	1.02	0.90	0.45
Average $|t|$	1.89	2.21	2.70	1.12
GRS_{10}	7.30	7.31	6.00	1.49
p_{10}	<0.0001	<0.0001	<0.0001	0.15
GRS_7	4.40	4.45	6.86	1.74
p_7	0.0002	0.0001	0.0001	0.10
Panel B: Size-neutral sorts				
Average $|\alpha|$	1.08	1.17	0.99	0.47
Average $|t|$	2.55	2.91	2.72	1.07
GRS_9	8.24	8.08	7.97	1.97
p_9	<0.0001	<0.0001	<0.0001	0.05
GRS_7	8.15	8.10	9.11	2.33
p_7	<0.0001	<0.0001	<0.0001	0.03

Table 18 Comparing the abilities of models to explain anomalies

The table reports measures summarizing the degree to which anomalies produce alphas under three different factor models: CAPM, FF-3, and CH-3. Also reported are measures for "unadjusted" return spreads (i.e., for a model with no factors). For each model, the table reports the average absolute monthly alpha (in percent), average absolute t-statistic, the Gibbons, Ross, and Shanken (1989) "GRS" F-statistic with associated p-value, and the number of anomalies for which the model produces the smallest absolute alpha among the four models. In Panel A, for the unconditional sorts, the long leg of an anomaly is the value-weighted portfolio of stocks in the lowest decile of the anomaly measure, and the short leg contains the stocks in the highest decile, with a high value of the measure being associated with lower return. In Panel B, long/short legs are neutralized with respect to size. That is, we first form size deciles by sorting on the previous month's market value. Within each size decile, we then create ten deciles formed by sorting on the anomaly variable. Finally, we form the anomaly's decile portfolios, with each portfolio pooling the stocks in a given anomaly decile across the size groups, again with value weighting. Two versions of the GRS test are reported. In Panel A, GRS_{10} uses all ten anomalies, while GRS_7 excludes the anomalies for size, BM, and EP, which are variables used to construct factors. Panel B

omits the size anomaly, whose alpha equals zero by construction with size-neutral sorts. All t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980). The sample period is from January 2000 through December 2016 (204 months).

Category	Anomaly	α	β_{MKT}	β_{SMB}	β_{VMG}	β_{PMO}	$t(\alpha)$	$t(\beta_{MKT})$	$t(\beta_{SMB})$	$t(\beta_{VMG})$	$t(\beta_{PMO})$
Panel A: Unconditional sorts											
Size	Market cap	0.23	0.05	1.50	−0.42	0.01	1.41	3.05	39.38	−6.88	0.17
Value	EP	0.02	0.00	−0.46	1.34	0.04	0.08	0.07	−5.38	13.15	0.33
Value	BM	0.75	0.03	−0.02	0.43	−0.13	1.04	0.32	−0.09	1.55	−0.45
Value	CP	0.31	0.09	−0.26	0.65	−0.20	0.57	1.43	−1.81	3.60	−1.10
Profitability	ROE	−0.29	−0.03	−0.36	1.28	−0.10	−0.68	−0.70	−3.21	8.74	−0.96
Volatility	1-Month vol.	−0.27	−0.16	−0.27	0.59	0.72	−0.51	−2.71	−1.85	3.27	5.13
Volatility	MAX	−0.59	−0.18	−0.13	0.44	0.88	−1.64	−3.07	−0.90	2.91	7.91
Reversal	1-Month return	0.49	0.02	0.54	0.04	0.46	0.87	0.29	3.19	0.18	2.48
Turnover	12-Month turn.	0.04	−0.11	−0.94	0.64	0.43	0.11	−3.36	−10.60	5.09	3.69
Turnover	1-Mo. abn. turn.	−0.00	−0.01	0.07	−0.27	1.44	−0.01	−0.32	0.68	−2.43	16.47
Panel B: Size-neutral sorts											
Value	EP	0.43	−0.04	−0.03	1.28	−0.12	1.42	−0.79	−0.35	11.74	−1.09
Value	BM	0.57	0.12	−0.18	0.46	0.09	0.82	1.58	−1.04	1.83	0.39
Value	CP	0.19	0.08	−0.03	0.57	−0.12	0.49	1.56	−0.26	3.67	−0.92
Profitability	ROE	−0.30	0.02	0.35	1.23	−0.05	−0.76	0.51	3.67	8.99	−0.40
Volatility	1-Month vol.	−0.27	−0.21	−0.20	0.51	0.63	−0.59	−3.95	−1.37	2.87	4.90
Volatility	MAX	−0.77	−0.17	0.00	0.45	0.74	−2.05	−2.86	0.01	2.95	5.81
Reversal	1-Month return	0.71	0.07	0.40	0.12	0.42	1.28	1.14	2.62	0.68	2.60
Turnover	12-Month turn.	−0.07	−0.19	−0.53	0.61	0.44	−0.19	−4.16	−4.38	3.77	3.39
Turnover	1-Mo. abn. turn.	0.17	−0.00	0.17	−0.17	1.21	0.67	−0.05	1.83	−1.90	15.23

Table 19 Anomaly alphas under a four-factor model

For each of ten anomalies, the table reports the monthly long-short return spread's CH-4 alpha and factor loadings. For each anomaly, the regression estimated is

$$R_t = \alpha + \beta_{MKT}MKT_t + \beta_{SMB}SMB_t + \beta_{VMG}VMG_t + \beta_{PMO}PMO_t + \epsilon_t,$$

in which R_t is the anomaly's long-short return spread in month t, MKT_t is the excess market return, SMB_t is CH-3's size factor, VMG_t is the EP-based value factor, and PMO_t (pessimistic minus optimistic) is the sentiment factor based on abnormal turnover. In Panel A, for the unconditional sorts, the long leg of an anomaly is the value-weighted portfolio of stocks in the lowest decile of the anomaly measure, and the short leg contains the stocks in the highest decile, with a high value of the measure being associated with lower return. In Panel B, long/short legs are neutralized with respect to size. That is, we first form size deciles by sorting on the previous month's market value. Within each size decile, we then create ten deciles formed by sorting on the anomaly variable. Finally, we form the anomaly's decile portfolios, with each portfolio pooling the stocks in a given anomaly decile across the size groups, again with value weighting. Panel B omits the size anomaly, whose alpha equals zero by construction with size-neutral sorts. Our sample period is January 2000 through December 2016. All t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980).

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