Turning Alphas into Betas: Arbitrage and Endogenous Risk

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Abstract

This paper tests the idea that financial intermediaries who act as arbitrageurs in the asset market help determine the equilibrium risk of financial assets. They do this by turning "alphas" into "betas"; assets with large abnormal returns attract more arbitrage and covary correspondingly more with systematic shocks to arbitrage capital. I show that this channel explains the cross-sectional variation in the funding liquidity and the arbitrageur wealth portfolio betas of equity anomaly portfolios. My results highlight that intermediaries who act as arbitrageurs not only price cross-sections of assets given risks, but also actively shape these risks through the act of arbitrage.

JEL Classification: G11, G12, G23

Keywords: asset risk, factor beta, financial intermediaries, arbitrage, asset pricing anomalies

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1 Introduction

What determines the equilibrium risk of financial assets? This is a fundamental question in finance, as risk determines expected returns or, equivalently, the discount rates applied to future cash flows to arrive at the asset's present value.

This paper tests the implications of intermediary asset pricing for the cross-section of risk. Intermediary asset pricing models suggest that financial intermediaries that act as rational arbitrageurs—such as banks and hedge funds—play a crucial role in both pricing assets and determining asset risk.[1] Empirical evidence supports the pricing implication that betas with respect to factors that capture systematic capital shocks to arbitrageurs are valid measures of risk and explain the cross-section of returns (Adrian, Etula, and Muir, 2014; He, Kelly, and Manela, 2017; Avdjiev et al., 2019). However, the literature has not tested whether, as theory suggests, part of this risk arises endogenously as the act of arbitrage exposes assets to arbitrage capital factors.

My contribution is to test the endogenous risk prediction of intermediary asset pricing models in the cross-section of equity anomaly portfolios. Specifically, I test the prediction's cross-sectional implication that arbitrageurs turn "alphas" into "betas"; that is, assets with a larger abnormal return in the eye of arbitrageurs attract more arbitrage and covary endogenously more with arbitrage capital factors. Theory suggests that these betas generated by the act of arbitrage, henceforth called "arbitrage-driven betas," feature additional testable restrictions, which I also test. My main finding is that the cross-sectional variation in equity anomaly exposures to aggregate funding-liquidity shocks and to aggregate arbitrageur wealth portfolio shocks is mostly due to arbitrage-driven betas.

My test uses 40 equity anomaly portfolios, which have been actively traded by arbitrageurs such as hedge funds at least since the early 1990s and therefore provide a laboratory for studying arbitrage-driven betas. These anomaly portfolios are the "long" and "short" decile portfolios of 20 anomaly characteristics such as "value" and "momentum." I use two measures of arbitrage capital shocks: the funding-liquidity factor of Adrian, Etula, and Muir (2014) and an arbitrageur wealth

[1] See, for example, Gromb and Vayanos (2002, 2018), Brunnermeier and Pedersen (2009), He and Krishnmaurthy (2012, 2013), Brunnermeier and Sannikov (2014), Kozak, Nagel, and Santosh (2018), and Kondor and Vayanos (2019). Since the implications of the literature I test rely on the intermediaries being rational arbitrageurs rather than relying on frictions in intermediation, I hereafter refer to the intermediaries as arbitrageurs.

1a. **Funding βs Unrelated to CAPM α (Pre-93)** 1b. **Pre-93 CAPM α Predicts Post-93 Funding β (Post-93)** 1c. **Arbitrage Position Explains Post-93 Funding β (Post-93)**

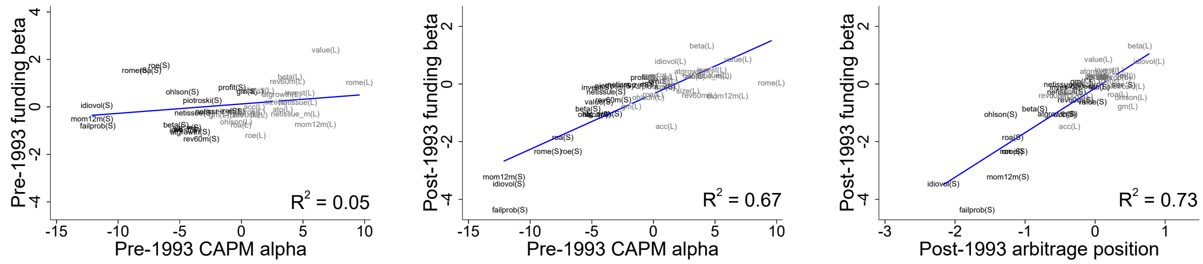

Figure 1: **Explaining the Cross-Section of Funding-Liquidity Betas**

The first figure shows that the funding-liquidity betas of anomaly portfolios in the pre-1993 period (1974–1993) cluster around zero, irrespective of their CAPM alphas. The next two figures show that the funding-liquidity betas of anomaly portfolios in the post-1993 period (1994–2016) are explained by their pre-arbitrage alphas (pre-1993 CAPM alphas) and post-1993 arbitrage position (inferred from abnormal short positions). Long-side and short-side portfolios are denoted in gray and black, respectively.

portfolio factor defined as the long-short returns to stocks in the extreme deciles of the estimated arbitrage positions. I estimate arbitrage positions using abnormal short positions, defined as the residual of the cross-sectional regression of short positions on dummy variables for size, liquidity, and convertible bonds outstanding. I look for evidence of arbitrage-driven risk primarily in the post-1993 period (1994–2016), characterized by more arbitrage on anomalies (Schwert, 2003; Chordia, Roll, and Subrahmanyam, 2008, 2011; Chordia, Subrahmanyam, and Tong, 2014). I use CAPM alpha in the pre-1993 period (1974–1993) to measure the pre-arbitrage abnormal return from the perspective of arbitrageurs (Agarwal, Green, and Ren, 2018). In all my tests, I use bootstrap standard errors that account for both cross-portfolio covariances and generated regressors.

I find strong evidence that the funding-liquidity ("funding") betas of anomaly portfolios are generated by the act of arbitrage on those portfolios. In the pre-1993 period, during which there was less arbitrage, funding betas clustered around zero, irrespective of the portfolios' CAPM alphas (see Fig. 1a). However, in the post-1993 period, during which there was more arbitrage, the portfolios attain either positive or negative funding betas, depending on whether their pre-1993 alphas were positive or negative (see Fig. 1b), consistent with the alphas-into-betas prediction. Furthermore, actual arbitrage positions explain the magnitude and the direction of the post-1993 funding betas and the large R^2 suggests that most of the cross-sectional variation in funding-liquidity exposure is an endogenous outcome of arbitrage (see Fig. 1c). I find similar patterns

2a. **Wealth βs Unrelated to CAPM α (Pre-93)** 2b. **Pre-93 CAPM α Predicts Post-93 Wealth β (Post-93)** 2c. **Arbitrage Position Explains Post-93 Wealth β (Post-93)**

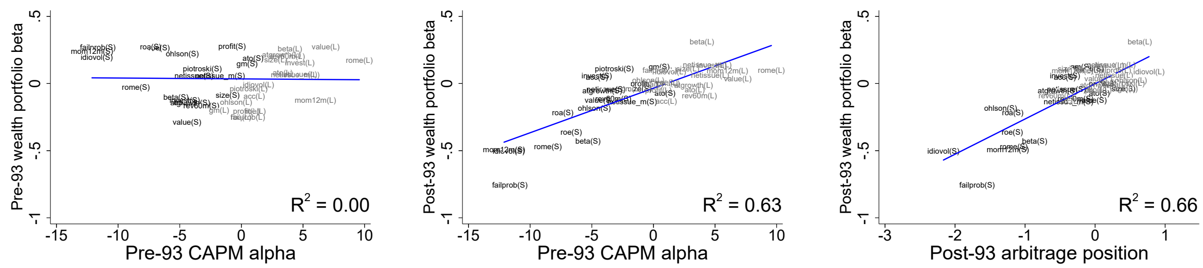

Figure 2: **Explaining the Cross-section of Arbitrageur Wealth Portfolio Betas**

The first figure shows that the arbitrageur wealth portfolio betas of anomaly portfolios in the pre-1993 period (1974–1993) cluster around zero, irrespective of their CAPM alphas. The next two figures show that the wealth portfolio betas of anomaly portfolios in the post-1993 period (1994–2016) are explained by their pre-arbitrage alphas (pre-1993 CAPM alpha) and post-1993 arbitrage position (inferred from abnormal short positions). Long-side and short-side anomaly portfolios are denoted in gray and black, respectively.

using panel regressions that allow the funding betas to vary more freely over time: funding beta increases with arbitrage position, with the academic publication of the anomaly, and with the post-1993 dummy. In contrast, fundamental characteristics, such as size and book-to-market ratio, do not contribute significantly to the variation in funding betas.

Funding betas of anomaly portfolios display additional patterns expected from arbitrage-driven betas. They strengthen or weaken in periods in which arbitrageurs are likely to be constrained or unconstrained, respectively, consistent with the predictions of Brunnermeier and Pedersen (2009) and Kondor and Vayanos (2019) among others. Furthermore, in the cross-section of anomaly portfolios, the time-series return predictability increases in the funding beta in the post-1993 period but not in the pre-1993 period. In the context of the return decomposition of Campbell and Shiller (1988) and Campbell (1991), this finding suggests that post-1993 funding betas measure discount-rate shocks generated by the act of arbitrage rather than by fundamental cash flows that happen to covary with funding-liquidity shocks.

Next, I ask if similar patterns arise in betas with respect to the arbitrageur wealth portfolio, an alternative measure of risk from arbitrageurs' point of view. I find that arbitrageur wealth portfolio betas do feature similar patterns, whether or not I control for the mechanical relation between an anomaly portfolio's percentage share in the arbitrageur wealth portfolio and its beta with respect to the wealth portfolio (see Fig. 2). Both arbitrage position and pre-1993 CAPM alpha explain more than 60% of the cross-sectional variation in exposure to arbitrageur wealth portfolio shocks in the post-1993 period. Panel regressions and auxiliary tests also confirm that the wealth portfolio betas of anomaly portfolios are arbitrage-driven.

The strong support for arbitrage-driven risk given by funding-liquidity and arbitrageur wealth portfolio betas prompts me to consider whether finding a strong cross-sectional relation between arbitrage variables and factor betas of anomaly portfolios is a low-hurdle test. I therefore calculate the likelihood that betas with respect to a random factor portfolio produce results as strong as mine. I find that only about 1 out of 500 random factors (0.2%) generate results as strong as those of funding-liquidity betas and arbitrageur wealth portfolio betas, suggesting that the odds of drawing two factors that by chance both happen to generate my strong results are extremely low.

I conduct a battery of robustness checks. First, using alternative years in the early 1990s as the sample cutoff generates results similar to those I obtain based on the 1993 cutoff. Second, controlling for pre-1993 return volatility or market liquidity does not materially affect my results, implying that my alphas-into-betas result is not a spurious result driven by pre-1993 CAPM alpha proxying for volatility or market liquidity. Third, I use the crash in arbitrage capital during the "quant" crisis of August 2007 to study the determinants of exposure to arbitrage capital shocks without relying on a factor model. I find that both pre-1993 CAPM alpha and post-1993 arbitrage positions strongly explain the cross-section of returns during the crisis, bolstering the evidence that these variables determine equilibrium exposure to arbitrage capital shocks.

Taken together, my results suggest that financial intermediaries that act as arbitrageurs contribute to the cross-section of risk. Although event study evidence suggests that the act of arbitrage exposes assets to arbitrage capital shocks (e.g., Mitchell and Pulvino, 2012; Du, Tepper, and Verdelhan, 2018), my results show that the act of arbitrage affects arbitrage capital betas more generally over a long sample period. By endogenizing the cross-sectional variation in arbitrage capital betas, my findings explain how assets become risky for arbitrageurs before arbitrageurs use these risks to determine the cross-section of expected returns. Hence, intermediary-based asset pricing is a framework that gives a complete account of not only which risks are priced in the cross-section, but also how risks are determined in the first place.

For the broader asset pricing literature, my results suggest that mispricing can persist in the form of distorted betas. As many arbitrageurs attempt to exploit abnormal return opportunities, they generate arbitrage-driven risk in the assets. This can allow the initial mispricing in the form of abnormal returns to persist in the form of risk premia associated with the arbitrage-driven betas. In this case, abnormal returns could be low in equilibrium but assets could be fundamentally mispriced due to distorted betas, which means that abnormal return can be a poor proxy for the fundamental mispricing of securities (Cohen, Polk, and Vuolteenaho, 2009). My finding on asset risk measured by factor betas is related to the evidence that the act of arbitrage affects the second and third moments of asset returns (e.g., Barberis, Shleifer, and Wurgler, 2005; Brunnermeier, Nagel, and Pedersen, 2008; Anton and Polk, 2014; Greenwood and Thesmar, 2011; Lou and Polk, 2013; Ben-David, Franzoni, and Moussawi, 2018).

My findings explain why, despite arbitrage, asset pricing anomalies persist:[2] precisely because arbitrageurs require compensation for the endogenous risk that they generate. McLean and Pontiff (2016) and Dong et al. (2018) find that correlations among anomaly portfolios change around academic publication, which the authors attribute to arbitrage trades. My results imply that changes in systematic funding-liquidity and arbitrageur wealth portfolio exposure are important drivers of this correlation change. Drechsler and Drechsler (2016) find that anomaly arbitrageurs face risk concentrated in negative-alpha stocks and require a return premium for bearing this risk. I find that the role of arbitrageurs extends beyond recognizing such risk; they also propagate it to other assets they trade. Relatedly, Liao (2019) shows that the act of arbitrage on one anomaly (such as credit spread differential) can affect an anomaly in a different market (such as covered interest parity deviation).

Finally, my findings are broadly consistent with the core message of the "adaptive market hypothesis" (Lo, 2004) that the expected returns and risks of trading strategies change over time as a new class of arbitrageurs, such as hedge funds, interacts with existing investors.[3] Evidence for this hypothesis has heretofore been qualitative; my analysis provides quantitative evidence.

[2]McLean and Pontiff (2016) document a 32% decline in the returns of 97 anomalies after their publication. Chordia, Subrahmanyam, and Tong (2014) also find that anomaly returns have not completely disappeared.

[3]The expression "alphas becoming betas" was first used to describe this hypothesis.

2 Methodology and Data

2.1 Theoretical background

I provide a simple theoretical framework from which arise the predictions I test in the data. The framework draws heavily on the continuous-time model of Kondor and Vayanos (2019), but interested readers can find the same predictions in a three-period setting in the online appendix to this paper.[4]

Consider a continuous-time economy in which uncertainty is captured by the N-dimensional Brownian motion B_t and the risk-free rate is fixed at $r > 0$. There are N risky assets in zero net supply with cash flows

$$dD_t = \overline{D}dt + dB_t, \tag{1}$$

where $\overline{D}$ is a constant $N \times 1$ vector. Hence, asset $i \in \{1, ..., N\}$ has a unit fundamental cash-flow exposure to the Brownian motion i.[5] There are two types of investors, households and arbitrageurs. Households receive a random endowment of $u^T dD_t$ at $t + dt$ for some $N \times 1$ constant vector u and are mean-variance optimizers of instantaneous changes in wealth at $t + dt$, where $A > 0$ is their coefficient of absolute risk aversion.

Arbitrageurs do not face endowment shocks, so they perceive u as distortions in asset demands that generate abnormal return opportunities. Arbitrageurs maximize power utility over consumption,

$$E_0 \left[\int_0^\infty e^{-\rho t} \frac{c_t^{1-\gamma}}{1-\gamma} dt \right], \tag{2}$$

where c_t is instantaneous consumption, $\rho > \gamma$ is the discount rate, and $\gamma \geq 0$ is the coefficient of relative risk aversion.[6] The capital of arbitrageurs k_t evolves according to

$$dk_t = rk_t dt + x_t^T dR_t - c_t dt, \tag{3}$$

where x_t is the arbitrageur's position in risky assets and dR_t denotes risky asset returns in excess

[4] Available at https://sites.google.com/site/thummimcho.

[5] All results hold analogously when $dD_t = \overline{D}dt + \sigma^T dB_t$ with $\sigma^T \neq \boldsymbol{I}_N$, but the independence assumption simplifies notation.

[6] $\rho > \gamma$ prevents arbitrageurs from accumulating infinite wealth over time.

of the risk-free rate.[7]

What does this setup imply about asset returns when the market is occupied solely by households? This proxies for a sample period in which arbitrageurs are small or for whatever reason have not engaged in arbitrage trades on assets.

Proposition 1. *In the absence of arbitrageurs, expected excess returns on assets follow*

$$\frac{E_t\left[dR_t\right]}{dt} = Au. \tag{4}$$

Proof. See Kondor and Vayanos (2019) for the proofs of this and the next propositions.

Intuitively, without arbitrageurs, assets with greater exposure to endowment shocks generate higher expected returns and equilibrium risk is determined solely by fundamental cash flows.

On the other hand, when arbitrageurs enter the market, the act of arbitrage leads asset returns to covary endogenously with arbitrage capital.

Proposition 2. *In the presence of arbitrageurs, arbitrage positions x_t, endogenous return covariances with arbitrage capital, and expected excess returns of assets are given by*

$$x_t = \tilde{x}\left(k_t\right) u, \tag{5}$$

$$\frac{Cov_t\left(dR_t, dk_t\right)}{dt} \propto u, \tag{6}$$

$$\frac{E_t\left[dR_t\right]}{dt} = \mu\left(k_t\right) u, \tag{7}$$

where $\tilde{x}\left(k_t\right) > 0$ and $\mu\left(k_t\right) > 0$ are increasing and decreasing in k_t, respectively.

Intuitively, arbitrageurs in equilibrium play a larger price-correcting role in assets with larger demand distortions and greater abnormal returns (Eq. (5)). This, however, also means that such assets are endogenously more sensitive to variation in the price-correcting role coming from arbitrage capital shocks (Eq. (6)). Arbitrageurs take this endogenous covariance into account when they determine the expected returns on assets (Eq. (7)).

[7] Although shocks to k_t come from shocks to the wealth portfolio of arbitrageurs, they can be interpreted more broadly as coming from all systematic arbitrage capital shocks, including aggregate funding-liquidity shocks.

Hence, an asset with a larger demand distortion u attracts a greater arbitrage position and develops a correspondingly larger endogenous covariance with arbitrage capital. Although u may not be observable, it is revealed by abnormal returns in the absence of arbitrageurs (Au in Eq. (4)) or by equilibrium arbitrage position in the presence of arbitrageurs ($\tilde{x}(k_t)\, u$ in Eq. (5)). Hence, holding all else fixed, abnormal return in the absence of arbitrageurs predicts endogenous risk exposure to arbitrage capital shocks; that is, "alphas" turn into "betas." When approximated as a linear relation, this implies a cross-sectional regression

$$\beta_{i,k} = b_0 + b_1 \alpha_i^{pre} + u_i, \tag{8}$$

where $\beta_{i,k} \propto \frac{Cov_t(dR_t, dk_t)}{dt}$ is the beta exposure to k_t at $t + dt$ and $\alpha_i^{pre} \equiv Au$ is "pre-arbitrage" abnormal return. Alternatively, equilibrium arbitrage position explains the contemporaneous endogenous risk exposure to k_t, motivating a regression

$$\beta_{i,k} = \tilde{b}_0 + \tilde{b}_1 x_i + \tilde{u}_i, \tag{9}$$

where x_i is the average arbitrage position on asset i over the period in which the beta is measured. These are the main cross-sectional restrictions I test in the data.

Endogenous covariance with arbitrage capital displays three additional patterns I test in the data. First, the endogenous covariance is hump-shaped with respect to arbitrage capital k_t. It is small when k_t is close to zero, since arbitrageurs only have a small impact on prices. But it is also small when k_t is close to infinity since then, the assets are priced almost exclusively by arbitrageurs, whose absolute risk aversion remains close to zero for small changes in k_t.[8] Hence, endogenous covariance with arbitrage capital tends to arise when arbitrageurs hold non-negligible capital but are constrained and disappear when arbitrageurs are unconstrained. Second, in the context of the return decomposition of Campbell and Shiller (1988) and Campbell (1991), this covariance arises from the expected returns (discount rates) of assets covarying with k_t. Hence, holding all else constant, assets with a larger endogenous covariance with arbitrage capital have more volatile expected returns and feature greater time-series predictability in returns. Third, endogenous covariance with arbitrage capital can be observed in a crash in arbitrage capital. In a

[8] This prediction also arises in Brunnermeier and Pedersen (2009).

large enough crash, the magnitude of the return response is greater in assets with a larger demand distortion u since the arbitrageur plays a larger price-correcting role in the asset.

2.2 Data and measurement

My test assets are 40 "anomaly" portfolios formed by taking the long and short portfolios (top and bottom deciles) from a univariate sorting of stocks on 20 anomaly characteristics (see the list in Table 1). These 20 characteristics, constructed based on data from the Center for Research in Security Prices and Compustat, represent a standard set of low-turnover anomaly characteristics.[9] One can arrive at this set by taking the 32 characteristics surveyed by Novy-Marx and Velikov (2016) and excluding the 5 redundant (e.g., "high-frequency combo") and 7 highest-turnover (e.g., short-term reversal) characteristics. I exclude high-turnover anomalies since arbitrage-driven betas should *not* arise in anomalies with a short mispricing horizon (Kondor and Vayanos, 2019). I use long and short portfolios as separate test assets, rather than forming long-short portfolios, for two reasons: (a) actual arbitrageurs typically do not form a long-short portfolio based on single anomaly characteristic but consider multiple anomaly characteristics of stocks; (b) it ensures a large cross-sectional variation in the right-hand variable (e.g., arbitrage position and pre-arbitrage alpha), which increases the power of the test. I determine characteristic deciles based on NYSE stocks. I compute monthly-rebalanced value-weighted portfolio returns based on domestic common stocks listed on the three major exchanges (NYSE, AMEX, and NASDAQ). For analyses requiring quarterly portfolios, I use rolled-over one-month returns to obtain quarterly returns. My sample period is from 1974 to 2016.[10]

I study two kinds of systematic shocks to arbitrage capital. The first is the aggregate funding-liquidity factor of Adrian, Etula, and Muir (2014), calculated as shocks to the book leverage of security broker-dealers as a factor capturing aggregate funding-liquidity shocks.[11] Since anomaly

[9]The online appendix to this paper provides more information on the construction of anomaly characteristics.

[10]Like Novy-Marx and Velikov (2016), I do not use data from before the early 1970s because of the poor quality of quarterly accounting data.

[11]Specifically, the factor is the change in the log of aggregate leverage of the entire broker-dealer sector obtained from the Federal Reserve Board's flow-of-funds data. The book leverage is adjusted for seasonality before taking the growth rate. Adrian et al. refer to the factor as a "leverage" factor, but I refer to it as a funding-liquidity factor since it is meant to capture aggregate funding-liquidity shocks à la Brunnermeier and Pedersen (2009). (A related paper by Asl and Etula (2012) calls it a funding factor.) I extend the quarterly funding factor to 2016q4 and standardize it over my sample period 1974q1–2016q4. See Adrian et al. (2014) and the online appendix to this paper for detailed instructions on constructing the series.

arbitrageurs such as quantitative long/short equity hedge funds rely on leverage and hence funding liquidity, they are likely to be exposed to the aggregate funding-liquidity factor (Brunnermeier and Pedersen, 2009; Aragon and Strahan, 2012; and Mitchell and Pulvino, 2012). This seems especially plausible since security broker-dealers provide funding to hedge funds as their prime brokers. The second is shocks to the aggregate arbitrage portfolio proxied by a value-weighted portfolio that goes long on the top decile and short on the bottom decile of stocks sorted on my measure of arbitrage position explained below.[12] To prevent microcaps from dominating the decile portfolios, the decile cutoffs are determined by the distribution of arbitrage positions on NYSE stocks. I estimate exposure to these shocks as the beta with respect to the shocks in a portfolio-specific time-series regression that controls for market exposure. The funding-liquidity factor and arbitrageur wealth portfolio returns have a small positive correlation of 0.075 over the sample period, implying that they capture different components of arbitrage capital shocks.

I measure arbitrage positions on portfolios using abnormal short positions on underlying stocks, following Ben-David, Frazoni, and Moussawi (2012), Boehmer, Jones, and Zhang (2013), Hanson and Sunderam (2014), and Hwang, Liu, and Xu (2018) among others.[13] Since most short positions are held by hedge funds (approximately 85%, according to Goldman Sachs, 2008), an abnormally high (low) short position on an anomaly signals a net short (long) position taken by the arbitrageurs. Each month, I estimate abnormal short position on each stock as the residual from a cross-sectional regression of short interest ratio (shares shorted divided by shares outstanding) from Compustat on ten dummy variables for size deciles, ten dummy variables for liquidity deciles (determined by Amihud's (2002) measure over the prior 12 months), and two dummy variables for convertible bonds outstanding (one for having any convertible bonds outstanding and the other for it being greater than 10% of the market capitalization of common equity).[14] I control for convertible bonds outstanding to net out the effect of convertible bond arbitrage. I

[12] I thank the anonymous referee for the idea of using my arbitrage position measure to reconstruct the arbitrageur wealth portfolio.

[13] Although Chen, Da, and Huang (2018) show that equity positions of hedge funds can also be inferred from institutional holdings (13F) data, it is difficult to infer positions of quantitative long/short equity hedge funds that trade anomalies since 13F filings are available only at the holding-company level. Using the data on long hedge fund positions kindly provided by Chen et al., I find that aggregate hedge fund long positions inferred from the 13F do not have a statistically significant relation to past alphas, implying that these are unlikely to represent the long positions of anomaly arbitrageurs.

[14] I use short interests reported in mid-month and shares outstanding on the same day (if available) or the previous trading day. The exact method used to obtain abnormal short positions, however, does not affect my results.

also remove stocks involved in mergers and acquisitions as defined in Jiang, Li, and Mei (2018) to net out the effect of merger arbitrage (risk arbitrage). Then, I compute arbitrage position on a portfolio as the *negative* (-1×100 to express it as a percentage) of the value-weighted average of abnormal short positions on underlying stocks.

Following Schwert (2003), I use the post-1993 period (1994–2016) as the period in which the anomaly portfolios are actively traded by arbitrageurs such as the quantitative equity hedge funds. The growth of arbitrage on anomalies around 1993, also observed in Chordia, Roll, and Subrahmanyam (2008, 2011), Stein (2009), and Chordia, Subrahmanyam, and Tong (2014), is likely due to a combination of factors including the growth in the hedge fund industry, publication of seminal works on cross-sectional anomalies (e.g., Fama and French, 1993; Jegadeesh and Titman, 1993), and improved market liquidity. I do not intend to differentiate among these channels but interpret my post-1993 results as driven by a combination of these factors. Fig. 3 shows that arbitrage positions on anomaly portfolios indeed did grow rapidly around 1993. Although not reported in the paper, I also find that average position on anomaly portfolios tends to fall in times of negative funding-liquidity shocks in the post-1993 period but not in the pre-1993 period.

The theoretical framework in Subsection 2.1 shows that besides arbitrage position, abnormal return in the absence of arbitrageurs is another predictor of endogenous exposure to arbitrage capital shocks. Building on the evidence that hedge fund flow chases CAPM alpha (Agarwal, Green, and Ren, 2018), I use CAPM alpha in the pre-1993 period (1974–1993) to proxy for abnormal return in the absence of arbitrageurs.[15] Table B1 shows that pre-1993 CAPM alpha strongly predicts arbitrage activity in the post-1993 period (see the coefficient on $\alpha^{pre}\times$Post-1993), suggesting that demand distortion in an anomaly portfolio revealed by pre-1993 CAPM determines the amount of post-1993 arbitrage activity on the portfolio.[16] The table also highlights the potential role of academic publication, which I include as a regressor in my panel analysis.

[15] Using a two-factor alpha that removes the possible risk premium associated with the arbitrage-related factor (funding liquidity or arbitrage portfolio) or alternative multifactor alphas generates similar results. For failure probability anomaly, I use CAPM alpha over 1981–1993 to account for the anomaly's sensitivity to sample period, emphasized in Dichev (1998).

[16] My finding on the 1993 cutoff is somewhat at odds with the finding that no return decay is observed in the anomalies following 1993 (McLean and Pontiff, 2016). The main reason for this difference is that short interest measures the arbitrage activity of a group of sophisticated arbitrageurs, whereas return decay reflects investment by all types of investors. Another contributing factor is that I use the year in which the anomaly was first published, not when it was first well publicized. For example, the academic publication of the value anomaly is Rosenberg, Reid, and Lanstein (1985) in my data, but it is Fama and French (1992) in McLean and Pontiff.

Besides the act of arbitrage, fundamental cash flows may also contribute to equilibrium risk exposure.[17] To account for cash-flow exposure to risk, I use pre-1993 factor beta or fundamental characteristics of the anomaly portfolio (size, book-to-market ratio, profitability, and investment characteristics) as additional controls. A portfolio's characteristic is defined as the value-weighted average characteristic decile of the underlying stocks, where the deciles are determined by the distribution of NYSE stocks.[18]

2.3 Standard errors

Throughout the paper, I compute standard errors based on a bootstrap procedure that takes into account both cross-portfolio covariances and generated regressors. I use bootstrapping instead of generalized method of moments (GMM) since to my knowledge, existing GMM approaches cannot be used in my case, in which different variables are estimated using data with different frequencies. However, for the main regressions in Table 6 (Columns (1) and (4)), which only use data with monthly frequency, I find that GMM standard errors are *smaller* than my bootstrap standard errors, implying that my bootstrap t-statistics are conservative. The t-statistics based on GMM are 3.05 and 3.60 for Columns (1) and (4) of Table 6, and those based on my bootstrap standard errors are 2.73 and 3.13, respectively.[19] My analysis on randomly generated factors in Table 8 also suggests that my bootstrap t-statistics are conservative; the one-sided p-values implied by my t-statistics in Columns (1) and (4) of Table 6 (0.32% and 0.09%) are higher than those implied by the random factors (0.20% and 0.05%). See Appendix A for further details on my bootstrap procedure.

3 Funding-liquidity Exposure

Anomaly portfolios display a large cross-sectional variation in funding-liquidity exposure in the post-1993 period (Fig. 1). In this section, I provide evidence that this variation arises endogenously through the act of arbitrage.

[17]In the framework presented in Subsection 2.1, this is reflected in the equilibrium asset return, $dR_t = \mu(k_t)\,udt + (g(k_t)\,u + 1)\,dB_t$ for some stochastic terms $\mu(k_t)$ and $g(k_t)$, which implies that asset return has an endogenous exposure to risk $g(k_t)\,u\,dB_t$ in addition to fundamental cash-flow exposure dB_t. See Kondor and Vayanos (2019) for further details.

[18]See the online appendix for more information about how I construct these characteristics for each stock.

[19]The MATLAB code for GMM standard errors is available upon request.

3.1 Cross-section of funding betas

The starting evidence is a strong contemporaneous cross-sectional relation between arbitrage position and funding-liquidity beta (Eq. (9) in Subsection 2.1). Columns (1)–(3) of Table 2 show that anomaly portfolios with greater arbitrage positions tend to have higher funding betas in the post-1993 period. In terms of magnitude, a 1-percentage-point ("%p") rise in the fraction of shares outstanding held by arbitrageurs (which is what the arbitrage position captures) increases the portfolio's funding beta by 1.6–1.8, which corresponds to portfolio return responding 1.6–1.8%p more to a one-standard-deviation shock in aggregate funding liquidity.[20] This is consistent with the prediction that portfolios in which arbitrage capital plays a larger price-correcting role respond more to the variation in arbitrage capital due to funding-liquidity shocks. Arbitrage position alone explains more than 70% of the cross-sectional variation in post-1993 funding betas and neither pre-1993 funding beta nor fundamental characteristics contribute to the cross-sectional fit. This suggests that the cross-sectional variation in funding-liquidity exposure is mostly arbitrage-driven.

However, using arbitrage position as the right-hand variable raises a reverse-causality concern: arbitrageurs may take larger positions on stocks with larger funding betas to earn an extra risk premium associated with funding liquidity (Jurek and Stafford, 2015).[21] A remedy is to use pre-1993 CAPM alpha as a right-hand variable, since it measures the demand distortion in the anomaly portfolio that ultimately determines the equilibrium arbitrage position and since an alpha—when correctly measured—captures the part of expected return unrelated to factor exposure.[22] Estimating the relation in Eq. (8) in Subsection 2.1, Columns (4)–(6) show that pre-arbitrage alpha strongly explains the cross-section of funding betas. A 1%p increase in pre-1993 CAPM alpha raises post-1993 funding-liquidity beta by 0.19–0.21 and pre-1993 CAPM alpha alone explains 67% of the cross-sectional variation post-1993 funding-liquidity exposure of anomaly portfolios. This, together with the result based on the arbitrage position, implies that (pre-1993 CAPM) alpha turned into (post-1993 funding-liquidity) beta through the act of arbitrage.

[20] The funding-liquidity factor I use has been standardized to have a standard deviation of 1.

[21] Relatedly, Song (2017) finds that mutual funds with lower skills increase factor exposure.

[22] One could argue that pre-1993 CAPM alpha includes a risk premium for funding-liquidity exposure, in which case pre-1993 CAPM alpha would predict post-1993 funding beta almost mechanically. However, using the pre-1993 two-factor alpha that controls for the possible risk premium associated with funding liquidity generates very similar results.

In the pre-1993 period, arbitrage position does not explain the cross-section of funding betas, consistent with my interpretation of the pre-1993 period as the period when anomaly arbitrageurs were small (Columns (9)–(11)). Instead, fundamental characteristics of anomaly portfolios explain around 70% of the cross-sectional variation in their funding-liquidity exposure. The large magnitude associated with value rank suggests that portfolios with a large value characteristic (high book-to-market ratio) tend to have large funding-liquidity exposure in the pre-1993 period, possibly because these are distressed stocks whose cash flows depend importantly on the availability of short-term funding in the financial sector. However, the effect of each individual characteristic is not statistically significant.

3.2 Panel of funding betas

An alternative to the purely cross-sectional approach is to study a panel (portfolios$\times$time) of funding betas. To do this, I use time-varying betas estimated from a moving window of ± 14 quarters (7 years) around each quarter as the left-hand variable. As a right-hand variable, I use arbitrage position, pre-1993 CAPM alpha interacted with a post-1993 dummy, and pre-1993 CAPM alpha interacted with a post-publication dummy. As additional controls, I include (a) anomaly fixed effects to control for unobserved heterogeneity across the portfolios that may be correlated with funding betas, (b) all variables used to create interaction terms (except those subsumed by anomaly fixed effect), (c) time-varying fundamental characteristics to control for changes in the characteristics that may affect the betas, and (d) quadratic time trends to control for average trends in the betas.

Table 3 shows results consistent with the cross-sectional result. A time-series increase in the arbitrage position leads to an increase in the funding beta (Columns (1)–(2)). The coefficient is around half of that implied by the cross-sectional regressions, which suggest that not taking the time-series average leads to attenuation due to the measurement error in the estimated arbitrage position. Funding beta more specifically changes around post-1993 with the direction and magnitude implied by the pre-1993 CAPM alpha, and the estimated effect of 0.18 is close to 0.19 estimated in the cross section (Columns (3)–(4)). Hence, the panel approach also suggests that alphas turned into betas through the act of arbitrage.

Albeit with slightly lower t-statistics, pre-1993 CAPM alpha also affects funding betas around the academic publication of the anomalies (Columns (5)–(6)). However, it is difficult to disentangle the effect of pre-1993 CAPM alpha around 1993 into that coming from the increase in arbitrage capacity due to the growth of hedge fund capital in the 1990s and improved market liquidity and that coming from the identification new anomalies since the early 1990s (Column (7)). This is consistent with my interpretation of the post-1993 effect as coming from a combination of those events. The two-stage least squares regressions in Columns (9)–(11) study the effect of arbitrage position changes driven by pre-1993 CAPM alphas around 1993 and by academic publication. The large estimated coefficient suggests that the time series of arbitrage position is indeed a noisy measure of actual arbitrage position and that the two-stage approach identifies the effect of estimated arbitrage position changes that are more purely driven by actual arbitrage.

It is interesting to relate my panel regression result to the finding that academic publication increases the anomaly's correlation with other published anomalies (McLean and Pontiff, 2016; Dong et al., 2018). My result shows that the increased correlation arises partly from an increased exposure to the funding factor and that the post-publication increase in the beta (correlation) has a cross-sectional pattern predicted by intermediary-based asset pricing models; the increase is larger for an anomaly with a larger pre-arbitrage alpha.

3.3 Funding betas during constrained versus unconstrained periods

What is an alternative explanation for my findings on funding-liquidity betas? Suppose that the funding-liquidity factor actually proxies for the arbitrageur wealth portfolio rather than aggregate funding-liquidity shocks. In this case, even if arbitrageurs were too small to affect the covariances of anomaly returns, a portfolio with a larger arbitrage position or pre-arbitrage alpha may mechanically have a higher beta with the factor since the portfolio would likely be a larger part of the arbitrageur wealth portfolio.

A prediction that can help refute this alternative explanation is that arbitrage-driven betas arise primarily when arbitrageurs are constrained. If funding betas were arbitrage-driven betas, they would arise primarily when arbitrageurs are constrained such that shocks to their capital that relax or tighten their constraint generate variation in arbitrage positions in the anomaly portfolios. In contrast, if funding betas were mechanical wealth portfolio betas, they would strengthen when arbitrageurs are *unconstrained* and can hold more anomalies in their portfolios.

To test this prediction, I define constrained and unconstrained periods in two ways. First, I follow Nagel (2012) to proxy constrained (unconstrained) times for institutional arbitrageurs as quarters in which the moving average of the VIX is above (below) the sample median.[23] Second, since abnormal returns are likely to be competed away in times when arbitrageurs are unconstrained, I use years in which the anomaly portfolios' alphas re-emerge (disappear) as the constrained (unconstrained) times. Specifically, I use years in which CAPM alphas estimated from daily data have a cross-sectional R^2 with pre-1993 CAPM alphas above the median.[24] Fig. 4 plots the constrained and unconstrained post-1993 quarters (or years) defined by the two methods. Despite some differences, they both identify the dot-com crash of 2000–2002 and the financial crisis of 2008–2009 as the periods in which arbitrageurs were constrained.

Table 4 strongly favors the arbitrage interpretation over the wealth-portfolio interpretation of my previous results. Funding betas during constrained times are large and cross-sectionally explained by both arbitrage position and pre-arbitrage alpha, but they tend to disappear during unconstrained times. Furthermore, although both correlation and volatility can affect beta, my finding is driven by changes in the *correlation* with the funding factor during constrained times; anomaly return correlations with the funding factor display patterns observed in funding betas (Fig. 5).

3.4 Funding betas as discount-rate betas: Cross-section of time-series return predictability

Finally, anomaly portfolios with high funding betas feature greater discount rate variations, consistent with the portfolios' funding betas arising from discount rate shocks that arbitrageurs generate. To show this, I study cross-sectional differences in the time-series predictability of returns. By definition, greater discount rate variation means greater variation in expected returns, so holding all else constant, portfolios with high funding betas should feature greater time-series return predictability. Intuitively, if funding betas arise from the act of arbitrage, high funding-beta portfolios should experience greater booms and busts induced by arbitrage capital and exhibit greater

[23]I use the exponential-weighted moving average with a smoothing factor of 0.3. However, since quarterly VIX tends to be persistent, using the original quarterly VIX series delivers similar results.

[24]Theoretically, the correct alpha to use here should additionally control for the risk premium associated with arbitrage-driven beta. Yearly alphas that additionally account for exposure to the mimicking portfolio of the funding factor does not change leads to similar classification of constrained times, so I prefer using yearly CAPM alphas for simplicity.

return predictability in the time series.[25]

I test this in a two-stage approach. The first stage is a portfolio-specific time-series predictive regression in which I predict future 12-, 18-, or 24-month cumulative excess returns using its past 3- or 5-year cumulative excess return as the predictor (DeBondt and Thaler, 1985; Moskowitz, Ooi, and Pedersen, 2012):[26]

$$r^e_{i,t\to t+s} = \theta_0 + \theta_1 r^e_{i,t-L\to t} + \epsilon_{i,t\to t+s} \;\; (s \in \{12\text{m}, 18\text{m}, 24\text{m}\}\,,\; L \in\{3\text{y}, 5\text{y}\}\;)\,. \qquad (10)$$

Past 3- or 5-year returns can proxy for valuation ratios such as the book-to-market ratio, often used in return predictability studies, when accounting data are unavailable or subject to seasonality issues, as is the case for my predictive regressions with monthly data (Fama and French, 1996; Gerakos and Linnainmaa, 2012; Asness, Moskowitz, and Pedersen, 2013). Intuitively, past return predicts future return since high (low) past return means that arbitrageurs have driven up (down) the prices of stocks in the anomaly portfolio at the expense of a lower (higher) expected return going forward. I run my portfolio-specific predictive regression using overlapping monthly data and obtain the R^2 as the measure of how predictable the time series of future portfolio return is.

The second stage is a cross-sectional regression in which I explain the first-stage R^2 using the absolute value of the funding beta, the arbitrage position, or the pre-1993 CAPM alpha of the anomaly portfolio.[27] Essentially, this approach allows me to relate funding beta and other measures of arbitrage to the fraction of return volatility coming from discount-rate shocks, which the first-stage R^2 captures.

I use my two-stage approach for the post-1993 period, where I expect to find predictability lining up with the absolute value of the funding beta and its determinants, and for the pre-1993

[25] An alternative way to check that a factor beta is a discount-rate beta is to decompose stock returns into discount-rate vs. cash-flow shocks using VAR, as in Campbell and Vuolteenaho (2004) and Campbell, Polk, and Vuolteenaho (2009) (CPV). However, as explained in CPV, this approach works most naturally for decomposing yearly returns and is not suitable for my paper, with its relatively short sample period.

[26] The return horizon over which discount-rate changes induced by arbitrage are realized is unclear, so I tried return horizons of 1 year to 3 years in the first stage. I find that my second-stage cross-sectional results are robust to using future 30-month return predictive regression and then lose statistical significance from future 36-month return prediction. The past and future returns I use as the left-hand and right-hand variables in the first-stage regression are based on the same stocks that belong to the anomaly portfolio at the time of portfolio formation. Using past and future returns on rebalanced portfolios would be an incorrect approach.

[27] I take an absolute value since predictability increases in the magnitude of the discount-rate beta, regardless of its sign.

period, which should *not* feature the same pattern unless return predictability, for whatever reason, is intrinsically correlated with the portfolio's funding beta.

Fig. 6 summarizes my finding. Return predictability increases in the absolute value of the anomaly's funding beta in the post-1993 period but not in the pre-1993 period, consistent with post-1993 funding betas being discount-rate betas arising from arbitrage trades. Table 5 shows that this cross-sectional pattern holds with respect to the absolute value of the arbitrage position and pre-1993 alpha as well (Columns (1)–(3)). That is, a portfolio with a larger abnormal return attracts a larger arbitrage position and suffers a greater booms and busts due to variation in aggregate arbitrage capital.

The economic magnitude is large. In the baseline specification, an increase of 1 in the absolute value of the funding beta increases the first-stage R^2 of the predictability regression by 0.05–0.06, depending on the return horizon. The R^2 of the second-stage cross-sectional regression reported in the brackets shows that the arbitrage variables explain as much as 58% of the cross-sectional variation in return predictability. The pre-1993 period does not display a cross-sectional relation between predictability and funding beta, suggesting that the large discount-rate variation in high-funding-beta portfolios is unique to the post-1993 period, with its increased arbitrage activity.

These results are consistent with post-1993 funding betas being discount-rate exposures—rather than cash-flow exposures—to funding liquidity, as the theory predicts. Furthermore, by showing that the time-series return predictabilities of anomaly portfolios are an equilibrium outcome of arbitrage trades, my results add to the growing literature on time-series predictability of anomaly returns. My finding is consistent with Lou and Polk (2013), Frazzini and Pedersen (2014), and Huang, Lou, and Polk (2018), who find that the act of arbitrage generates predictable time-series patterns in momentum and low-beta stocks. My finding also suggests that the strong time-series predictability of anomaly returns documented in Haddad, Kozak, and Santosh (2018) may be unique to the post-1993 sample period with greater arbitrage-driven discount-rate shocks to anomalies.

4 Exposure to Arbitrageur Wealth Portfolio Shocks

In addition to funding-liquidity exposure, the act of arbitrage can also expose assets to shocks coming from other stocks in the arbitrageur wealth portfolio. Indeed, I show that the anomaly portfolios' betas with respect to my proxy for the arbitrageur wealth portfolio display patterns we expect for arbitrage-driven exposure.

4.1 Graphical evidence

Fig. 2 in Section 1 plots the cross-section of wealth portfolio betas in the pre-1993 and post-1993 periods. In the pre-1993 period with little arbitrage on anomalies, exposures to the arbitrageur wealth portfolio clustered around zero and had no relation to their abnormal return proxied by CAPM alpha. When arbitrage on anomalies grows in the post-1993 period, however, both arbitrage position and pre-1993 CAPM alpha explain more than 60 percent of the cross-sectional variation in how much the portfolio return covaries with arbitrageur wealth portfolio shocks. That is, a portfolio with a greater pre-1993 CAPM alpha and greater arbitrage position suffers more when aggregate arbitrageur wealth goes down.

The cross-sectional patterns in the post-1993 period may, however, have an alternative interpretation. These patterns can arise mechanically if a portfolio with a large arbitrage position (i.e., a larger fraction of its market capitalization is held by arbitrageurs) also represents a larger share of the arbitrageur wealth portfolio. Although this interpretation does not explain why these cross-sectional patterns do not arise in the pre-1993 period, a more formal investigation seems helpful.

4.2 Cross-section of wealth portfolio betas

To show more formally that the post-1993 cross-sectional patterns in Fig. 2 do not arise mechanically but rather because of arbitrage, I add the portfolio's market capitalization share in the arbitrageur wealth portfolio ("share of wealth portfolio") as an additional explanatory variable in regressions explaining the cross-section of wealth portfolio betas. If my results were mechanical, the portfolio's share in the arbitrageur wealth should subsume the explanatory power of arbitrage position or pre-1993 CAPM alpha.

Table 6 shows that both arbitrage position and pre-1993 CAPM alpha robustly explain the cross-sectional variation in wealth portfolio betas, regardless of controlling for the portfolio's share in the arbitrageur wealth portfolio. The economic magnitude is large; a 1-percentage-point increase in arbitrage position (in pre-1993 CAPM alpha) is associated with an increase in the wealth portfolio beta by 0.26 to 0.35 (by 0.03 to 0.04).

While the share of arbitrageur wealth portfolio is positively related to wealth portfolio betas, its effect is statistically insignificant. In the pre-1993 period, wealth portfolio betas have little relation to arbitrage position or pre-1993 CAPM alpha, consistent with post-1993 wealth portfolio betas emerging as a consequence of the post-1993 growth in arbitrage capital.

4.3 Additional evidence

Panel A of Table 7 presents similar findings in the panel of wealth portfolio betas. An increase in the arbitrage position over time increases the anomaly's wealth portfolio betas. Wealth portfolio beta also increases around 1993 in proportion to the portfolio's pre-1993 CAPM alpha but, again, the 1993 dummy and academic publication contribute almost equally to the effect of pre-1993 alpha on wealth portfolio betas such that their relative importance cannot be easily disentangled. The share of wealth portfolio has an estimated coefficient similar to that in the cross-sectional approach but is now statistically significant.

Panel B shows that wealth portfolio betas of anomaly portfolios tend to be larger when arbitrageurs are constrained, although the reduction in betas during unconstrained times depends on the measure I use to proxy for constrained versus unconstrained times. Panel C shows that the time-series return predictabilities in the post-1993 period tend to line up with the absolute value of the wealth portfolio betas, as they do with funding betas, consistent with post-1993 wealth portfolio betas being discount-rate betas. These patterns do not hold in the pre-1993 period. Overall, these additional analyses show that arbitrageur wealth portfolio betas also display patterns expected from betas that arise endogenously through arbitrage.

Taken together, the evidence presented in this section shows that a portfolio with a larger abnormal return attracts more arbitrage and attains a larger exposure to arbitrageur wealth portfolio shocks, consistent with the predictions of intermediary-based models.

5 Robustness

Here, I provide several robustness checks to the results in the previous two sections.

5.1 Placebo factors

How likely is it that a spurious factor generates my results? To answer this, I generate 10,000 monthly placebo factors by sorting stocks on a randomly generated number at the end of each month and computing value-weighted returns on a long-short portfolio of stocks that fall into extreme deciles.[28] I also generate 10,000 quarterly placebo factors by rolling over monthly returns on monthly placebo factors.

I study the ability of placebo factors to generate the cross-sectional results in Columns (1) and (4) of Tables 2 and 6. That is, I study how well arbitrage position and pre-1993 CAPM alpha explain the cross-section of post-1993 anomaly portfolio betas with respect to a quarterly or monthly placebo factor. For each cross-sectional regression, I compute bootstrap standard errors based on the empirical distribution of 1,000 draws as I do in my original analysis. I repeat this for 10,000 placebo factors to study the distribution of t-statistics and R^2 of the regressions.

Panel A of Table 8 shows that it is unlikely for a random factor to generate the strong results I obtain with the funding-liquidity and the arbitrageur wealth portfolio factors. The odds of a random quarterly factor generating a t-statistic higher than what I obtain from funding-liquidity betas (2.31; see Column (1) of Table 2) is 0.87%, slightly lower than 1.05% implied by a t-statistic of 2.31.[29] The adjusted R^2 of 72% is even harder to achieve (0.47%), such that the chance of a random factor outperforming the funding factor in terms of both the t-statistic and the adjusted R^2 is 0.27%. My cross-sectional regression explaining post-1993 funding-liquidity betas using pre-1993 CAPM alpha (Column (4) of Table 2) is more difficult to replicate with quarterly placebo factors (0.20%).

My monthly cross-sectional regression results are equally difficult to obtain using a random factor. The odds of a random monthly factor generating a t-statistic higher than 2.73 in the cross-sectional arbitrage position to beta regression is 0.20%, slightly lower than 0.32% implied by a

[28] I use NYSE stocks to determine the decile cutoffs.

[29] This is the one-sided p-value for $t = 2.31$.

t-statistic of 2.73. The adjusted R^2 of 65% is somewhat easier to achieve (3.59%), but the chance of obtaining this fit while having a t-statistic higher than 2.73 is again 0.20%. The cross-sectional alphas-into-betas result (Column (4) of Table 6) is even harder to achieve (0.00%).

To appreciate these results, it is important to remember that my measures of arbitrage capital shocks are suggested by the literature (funding-liquidity factor) or by the estimated arbitrage positions (the arbitrageur wealth portfolio) and therefore are not "cherry picked." Hence, the joint probability that I fortuitously obtained the strong results based on funding-liquidity betas and arbitrageur wealth portfolio betas must be extremely low.

5.2 The 1993 cutoff and other robustness checks

My findings are robust to alternative choices I could have made in my empirical analysis. My cross-sectional analyses use the year 1993 to proxy for pre- versus post-arbitrage periods for anomalies, but my results are robust to using 1991, 1992, 1994, and 1995 as the end of the pre-arbitrage period. To illustrate, I repeat the main cross-sectional regressions in Tables 2 and 6 using these alternative cutoffs (Panels B and C of Table 8). Across all cutoffs, the coefficients are large and statistically significant. In fact, depending on the regression, I obtain results stronger than those based on the 1993 cutoff.

The online appendix shows that my cross-sectional results are also robust to controlling for additional market characteristics of the anomaly portfolios, such as idiosyncratic volatility and market liquidity. This suggests that my results are not a spurious result driven by both the measure of arbitrage activity (arbitrage position or pre-1993 alpha) and post-1993 funding or arbitrage portfolio beta being positively correlated with volatility or market liquidity.

5.3 A test without a factor: Evidence from the quant crisis of 2007

Prior tests based on the funding-liquidity and arbitrageur wealth portfolio factors require that these factors correctly represent shocks to the capital of anomaly arbitrageurs. Here, I provide further evidence on the cross-sectional relation between arbitrage position (or pre-1993 alpha) and exposure to arbitrage-capital shocks without taking a stand on the arbitrage capital factor. The idea is to focus on a single severe arbitrage-capital shock. Since the cross-sectional variation in returns during such an event would be mostly driven by differences in beta exposure to arbitrage capital, I can test if the cross-section of returns during the event line up with the theoretical determinants of arbitrage-driven betas. To do this, I use the crash of quantitative long/short equity hedge fund capital in August 2007, which I describe briefly before proceeding to my tests.

Over the three-day period of August 7–9, 2007, seemingly distinct equity portfolios commonly underperformed. Fig. 7a shows that anomaly portfolios that arbitrageurs typically go long on commonly posted losses (in 17 out of 20 cases) and portfolios that arbitrageurs typically go short on commonly posted gains (in 19 out of 20 cases). Hedge funds that take long-short positions on these anomalies also suffered severe losses. Fig. 7b shows that these arbitrageurs suffered a cumulative loss of almost 6% over August 7–9, then the return rebounded over the following three days (August 10–14). Remarkably, the crash and the recovery were exclusive to equity anomalies; other arbitrage strategies remained unaffected.

The primary explanation for this unusual covariance event in the anomalies is a systematic drop in arbitrage capital. It is speculated that following a portfolio underperformance since early July 2007, one or more arbitrageurs rapidly unwound their arbitrage position on anomalies, possibly due to margin calls (Khandani and Lo 2007, 2011; Pedersen, 2009; Stein, 2009). This led to losses by other arbitrageurs that in turn triggered more margin calls until anomaly arbitrageurs commonly suffered capital losses.

Treating the three-day crash period of the crisis as the period in which the level of arbitrage capital dropped severely, I ask whether returns on different portfolios during the crash can be explained cross-sectionally by the differences in their arbitrage position or pre-arbitrage alpha, analogous to my analysis on betas. Furthermore, since this drop in the asset price is a discount-rate (valuation) shock rather than cash-flow shock, I also ask whether the return during the three-day recovery period can also be explained cross-sectionally.

Fig. 8 summarizes my findings. Cumulative returns on anomaly portfolios during the crisis are cross-sectionally and strongly explained by their post-1993 arbitrage position and pre-1993 CAPM alpha. This is consistent with the key mechanism that generates a cross-section of arbitrage-driven betas: an asset with a more positive (negative) pre-arbitrage alpha and hence positive (negative) arbitrage position drops (gains) more in response to a sharp decline in arbitrage capital. An opposite pattern holds during recovery, consistent with anomaly portfolios' quant-crisis returns being discount-rate movements.[30] Table B2 shows that this result is robust to inferring arbitrage position from the month before the crash (July 2007) and to using cumulative abnormal returns instead of raw returns.

5.4 Closing remarks

I close with three additional points about my results. First, the interpretation of my results does not depend heavily on whether equity anomalies actually represent hidden risk, mispricing, or measurement error. What matters is that institutional arbitrageurs such as hedge funds trade anomalies, regardless of the debate. In fact, even if anomaly returns represent rational compensation for risk, arbitrage-driven betas would arise through risk sharing (Kondor and Vayanos, 2019). Intuitively, anomalies with larger arbitrageur positions rely more heavily on the risk-sharing role of arbitrageurs and hence become more sensitive to arbitrage capital. Also, even if some anomalies were measurement errors, a high past alpha that occurs by chance can still attract arbitrage capital and give rise to an arbitrage-driven beta. In this case, however, the arbitrage-driven beta would eventually disappear after arbitrageurs realized that the anomaly was a measurement error and stopped trading it.

Second, one may suggest that once arbitrage has driven down the anomaly alphas, arbitrage-driven betas should no longer arise. This is not the case. If the original source of the demand distortion remains, alphas can remain low only in the presence of arbitrage trades that generate the arbitrage-driven betas. In other words, in the presence of systematic shocks to arbitrage capital, low alphas and nonzero arbitrage-driven betas should coexist in equilibrium.

Third, my results do not necessarily imply that intermediaries who act as arbitrageurs make financial assets riskier. For example, it could be that equity anomalies arise because of undiversifiable risks that households face but arbitrageurs do not and that when arbitrageurs enter the market, they reduce the equilibrium risk of assets by providing risk sharing. In this case, the act of arbitrage reduces the risk of the assets for households and increases their risk for the arbitrageurs until risk premia associated with these two measures of risk are equalized. However, my results do imply that once arbitrageurs turn alphas into betas, fundamental mispricing defined

[30] The cross-sectional pattern of long anomalies earning positive returns and short anomalies earning negative returns during the recovery is clearer in abnormal returns than in raw returns.

as the deviation of price from fundamental value can persist in the form of arbitrage-driven risk rather than abnormal returns.

6 Conclusion

This paper shows that financial intermediaries who act as arbitrageurs in the asset market play a crucial role in determining the equilibrium risk of assets, consistent with the implications of asset pricing models that emphasize the role of intermediary-arbitrageurs. I show this in the context of equity anomaly portfolios, using funding-liquidity and arbitrageur wealth portfolio shocks to measure risk from the perspective of arbitrageurs.

My findings in the equity market suggest that arbitrageurs may play similar risk-determination roles in other asset classes. Understanding the sources of equilibrium risk exposure to arbitrage capital shocks in other asset markets would nicely complement the growing evidence that these risk exposures are priced in the cross-section of assets and provide a more complete account of the role of financial intermediaries in the asset market.

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Tables and Figures

Table 1: **List of 40 Anomaly Portfolios**

This table describes the 40 anomaly portfolios used in the paper. α^{pre}_{CAPM} is CAPM alpha over 1974m1–1993m12. Boldface denotes estimated alphas greater than 1.96 times the heteroskedasticity-robust standard error in absolute value. Mktcap Share is the portfolio's total market capitalization over total market capitalization of all domestic common US stocks listed on the NYSE, AMEX, and NASDAQ, averaged over 1974m1–2016m12.

	Long (top decile)				Short (bottom decile)				Academic publication	
Type	No	Label	α^{pre}_{CAPM}	Mktcap share	No	Label	α^{pre}_{CAPM}	Mktcap share	Year	Sample
Beta arbitrage	1	beta(L)	**3.9**	0.09	21	beta(S)	**-5.3**	0.09	1973	1926-1968
Return on market equity	2	rome(L)	**9.6**	0.05	22	rome(S)	**-8.6**	0.03	1977	1956-1971
Ohlson's O-score	3	ohlson(L)	-0.4	0.29	23	ohlson(S)	**-4.8**	0.01	1980	1970-1976
Size	4	size(L)	2.8	0.02	24	size(S)	-1.1	0.58	1981	1926-1975
Long-run reversals	5	rev60m(L)	3.7	0.03	25	rev60m(S)	**-3.3**	0.13	1985	1926-1982
Value	6	value(L)	**6.8**	0.04	26	value(S)	**-4.4**	0.20	1985	1980-1990
Momentum	7	mom12m(L)	**6.0**	0.10	27	mom12m(S)	**-12.1**	0.04	1990	1964-1987
Net issuance	8	netissue(L)	**4.6**	0.11	28	netissue(S)	**-3.8**	0.08	1995	1980-1990
Net issuance monthly	9	netissue_m(L)	**4.4**	0.11	29	netissue_m(S)	-1.7	0.09	1995	1980-1990
Accruals	10	acc(L)	1.0	0.06	30	acc(S)	**-4.6**	0.05	1996	1962-1991
Return on assets	11	roa(L)	-0.0	0.17	31	roa(S)	**-7.4**	0.03	1996	1979-1993
Return on book equity	12	roe(L)	1.1	0.14	32	roe(S)	**-6.7**	0.04	1996	1979-1993
Failure probability	13	failprob(L)	0.5	0.16	33	failprob(S)	**-11.6**	0.02	1998	1981-1996
Piotroski's f-score	14	piotroski(L)	0.6	0.21	34	piotroski(S)	**-3.2**	0.09	2000	1976-1997
Investment	15	invest(L)	**4.7**	0.03	35	invest(S)	**-4.6**	0.07	2004	1973-1996
Idiosyncratic volatility	16	idiovol(L)	1.4	0.25	36	idiovol(S)	**-11.7**	0.04	2006	1986-2000
Asset growth	17	atgrowth(L)	3.3	0.03	37	atgrowth(S)	**-4.2**	0.10	2008	1968-2003
Asset turnover	18	ato(L)	**3.4**	0.05	38	ato(S)	0.9	0.09	2008	1984-2002
Gross margins	19	gm(L)	-1.8	0.20	39	gm(S)	0.5	0.04	2008	1984-2002
Gross profitability	20	profit(L)	0.4	0.10	40	profit(S)	-0.8	0.07	2010	1976-2005

Table 2: **Explaining the Cross-section of Funding-liquidity Betas**

$$\text{Baseline: } \beta^{post93}_{funding,i} = b_0 + b_1 \text{ Arbitrage position}^{post93}_i + u_i$$

This table shows that the post-1993 funding-liquidity betas of 40 anomaly portfolios can be cross-sectionally explained by arbitrage position or pre-1993 CAPM alpha, whereas pre-1993 funding-liquidity betas do not display such patterns. Unless otherwise noted, the right-hand variables are calculated for the same sample period as the left-hand variable. Funding-liquidity betas are betas with respect to the funding-liquidity factor of Adrian, Etula, and Muir (2014), estimated in a two-factor model that includes the market factor. Arbitrage position is inferred from abnormal short position on underlying stocks. Characteristic ranks are value-weighted decile ranks of the underlying stocks' characteristics. Pre-1993 and post-1993 periods are 1974–1993 and 1994–2016, respectively. In the parentheses are t-statistics based on bootstrap standard errors that account for cross-portfolio covariances as well as generated regressors. Boldface denotes coefficient estimates with the absolute value of t-statistics greater than 1.96.

	$\beta^{post93}_{funding}$								$\beta^{pre93}_{funding}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Arbitrage position	**1.55**	**1.57**	**1.80**						0.68		
	(2.31)	(2.33)	(2.06)						(0.28)		
α^{pre93}_{CAPM}				**0.19**	**0.20**	**0.21**				-0.03	
				(2.62)	(2.54)	(2.27)				(-0.48)	
$\beta^{pre93}_{funding}$		0.24			-0.09		0.16				
		(1.07)			(-0.28)		(0.39)				
Size rank			0.10			-0.14		-0.41	-0.03	0.05	0.02
			(0.35)			(-0.52)		(-1.17)	(-0.11)	(0.29)	(0.10)
Value rank			0.11			-0.16		0.37	0.45	0.54	0.48
			(0.48)			(-0.48)		(1.50)	(1.57)	(1.71)	(1.82)
Profitability rank			-0.04			-0.14		0.19	0.07	0.13	0.09
			(-0.24)			(-0.65)		(0.83)	(0.37)	(0.60)	(0.46)
Investment rank			-0.06			-0.10		0.16	-0.07	-0.11	-0.09
			(-0.36)			(-0.55)		(0.99)	(-0.51)	(-0.93)	(-0.75)
Constant	-0.14	-0.16	-0.31	-0.34	-0.33	2.04	-0.56	-2.71	-2.71	-3.48	-2.89
	(-0.74)	(-0.80)	(-0.16)	(-1.13)	(-1.13)	(0.69)	(-1.56)	(-0.99)	(-1.13)	(-1.27)	(-1.30)
Observations	40	40	40	40	40	40	40	40	40	40	40
R^2_{adj}	0.72	0.75	0.75	0.67	0.66	0.71	-0.01	0.28	0.71	0.72	0.71

Table 3: **Explaining the Panel of Funding-liquidity Betas**

Baseline: $\beta_{funding,i,t} = b_0 + b_1 \text{Arbitrage position}_{i,t} + \boldsymbol{b}_3' \boldsymbol{X}_{i,t} + b_4 t + b_5 t^2 + u_i + \epsilon_{i,t}$
($\boldsymbol{X} \equiv$ time-varying characteristics)

This table uses a panel regression to show that arbitrage position and pre-arbitrage alpha explain the panel of funding-liquidity betas of anomaly portfolios (40 portfolios $\times$ 1974q1–2016q4). For each anomaly portfolio, quarterly funding-liquidity betas are estimated in a moving window of ± 14 quarters (7 years) surrounding each quarter. Pre-1993 CAPM alpha interacted with post-1993 and post-publication dummies are used as proxies or instruments for arbitrage position. Arbitrage position is inferred from abnormal short position on underlying stocks. A post-1993 dummy, a post-publication dummy, quadratic time trends (t and t^2), and a constant are included in the regression (whenever appropriate) but not reported in the table. In the parentheses are t-statistics based on bootstrap standard errors that account for cross-portfolio covariances, generated regressors, and serial correlations. Boldface denotes coefficient estimates with the absolute value of t-statistics greater than 1.96.

	OLS								2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Arbitrage position	**0.70**	**0.71**							**3.16**	3.08	3.40
	(2.09)	(2.11)							(1.99)	(1.83)	(1.84)
α^{pre93}_{CAPM} × Post-1993			**0.18**	**0.18**			0.11				
			(2.02)	(2.10)			(1.51)				
α^{pre93}_{CAPM} × Post-publication					0.21	**0.22**	0.13				
					(1.92)	(2.08)	(1.46)				
Size rank		-0.03		-0.12		-0.18	-0.15	-0.12	0.27	0.26	0.30
		(-0.20)		(-0.79)		(-1.07)	(-0.98)	(-0.73)	(0.87)	(0.79)	(0.87)
Value rank		0.17		0.18		0.15	0.20	0.14	0.28	0.28	0.29
		(0.88)		(0.99)		(0.82)	(1.07)	(0.68)	(1.54)	(1.49)	(1.59)
Profitability rank		0.22		0.20		0.21	0.21	0.21	0.23	0.23	0.23
		(1.32)		(1.23)		(1.32)	(1.33)	(1.27)	(1.29)	(1.26)	(1.29)
Investment rank		0.22		0.22		0.27	0.24	0.23	0.20	0.20	0.19
		(1.52)		(1.35)		(1.81)	(1.49)	(1.54)	(1.05)	(1.03)	(1.00)
Anomaly FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,760	5,760	5,760	5,760	5,760	5,760	5,760	5,760	5,760	5,760	5,760
R^2_{adj}	0.13	0.16	0.20	0.23	0.18	0.22	0.26	0.09	.	.	.
Instrumental variables											
α^{pre} × Post-1993									✓	✓	
α^{pre} × Post-Pub									✓		✓

Table 4: **Funding-liquidity Betas Arise during Constrained Times**

$$\text{Baseline: } \beta^{post93,\,constrained}_{funding,i} = b_0 + b_1 \text{ Arbitrage position}^{post93}_i + b_2 \beta^{pre93}_{funding,i} + u_i$$

This table shows that post-1993 funding-liquidity betas of anomalies strengthen in periods in which arbitrageurs are likely to be constrained and weaken when they are likely to be unconstrained, consistent with the predictions of intermediary-based asset pricing models. I define constrained (unconstrained) times for institutional arbitrageurs as (a) quarters in which the moving average of the VIX is above (below) the sample median ("VIX") and (b) years in which the CAPM alphas estimated from daily data have a cross-sectional R^2 with pre-1993 CAPM alphas above the median for the post-1993 period ("Alphas"). Arbitrage position is inferred from abnormal short position on underlying stocks. In the parentheses are t-statistics based on bootstrap standard errors that account for cross-portfolio covariances and generated regressors. Boldface denotes coefficient estimates with the absolute value of t-statistics greater than 1.96.

	Constrained-time $\beta^{post93}_{funding}$				Unconstrained-time $\beta^{post93}_{funding}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Arbitrage position^{post93}	**2.20**		**2.43**		0.25		0.29	
	(2.44)		(2.79)		(0.20)		(0.25)	
α^{pre93}_{CAPM}		**0.29**		**0.30**		0.03		0.05
		(3.00)		(3.27)		(0.23)		(0.38)
$\beta^{pre93}_{funding}$	0.34	-0.14	0.21	-0.29	0.20	0.15	0.27	0.19
	(1.56)	(-0.53)	(0.92)	(-1.05)	(0.67)	(0.40)	(0.98)	(0.56)
Constant	-0.12	-0.35	-0.25	-0.52	-0.15	-0.18	-0.02	-0.04
	(-0.09)	(-0.25)	(-0.20)	(-0.39)	(-0.09)	(-0.10)	(-0.01)	(-0.02)
Constrained indicator	VIX		Alphas		VIX		Alphas	
Observations	40	40	40	40	40	40	40	40
R^2_{adj}	0.71	0.69	0.79	0.67	0.14	0.12	0.20	0.25

Table 5: **Funding-liquidity Betas as Discount-rate Betas: Evidence from Return Predictability**

$$\text{1st stage time-series regression: } r^e_{i,t\to t+s} = \theta_0 + \theta_1 r^e_{i,t-L\to t} + \epsilon_{i,t\to t+s}, \quad R^2_{\text{1st stage},i} \equiv \frac{\sum_t\left(\widehat{r}^e_{i,t\to t+s} - \overline{r^e_{i,+s}}\right)^2}{\sum_t\left(r^e_{i,t\to t+s} - \overline{r^e_{i,+s}}\right)^2}$$

$$\text{2nd stage cross-sectional regression (baseline): } R^2_{\text{1st stage},i} = b_0 + b_1\left|\beta_{funding,i}\right| + u_i$$

This table shows that anomaly portfolios with a larger absolute value of funding beta feature greater return predictability than other portfolios in the post-1993 period, consistent with post-1993 funding betas being discount-rate betas arising from the act of arbitrage. Such a pattern does not arise in the pre-1993 period. The regression has 2 stages. The first stage is a portfolio-specific time-series return predictive regression in which I regress the future 12-month, 18-month, or 24-month cumulative excess return $r^e_{t\to t+s}$ on past 3-year or 5-year cumulative excess return $r^e_{t-L\to t}$. From the first stage, I obtain the coefficient of determination $R^2_{\text{1st stage}}$ as the measure of time-series predictability of returns. The second stage is a univariate cross-sectional regression in which I regress $R^2_{\text{1st stage}}$ on the absolute value of funding-liquidity beta, arbitrage position, or pre-1993 CAPM alpha that predicts the volatility of arbitrage-driven discount-rate shocks in the anomaly portfolio. Arbitrage position is inferred from abnormal short position on underlying stocks. Since there are 6 specifications of the first-stage time-series regression and 3 right-hand variables in the second-stage cross-sectional regression, each sample period has 18 univariate cross-sectional regressions in total. In the parentheses are t-statistics based on bootstrap standard errors that account for cross-portfolio covariances and generated regressors. In the brackets are the coefficient of determination (R^2) of the second-stage cross-sectional regression. Boldface denotes coefficient estimates with the absolute value of t-statistics greater than 1.96.

1st-stage prediction horizon *s:*	+12m return		+18m return		+24m return	
1st-stage predictor:	-3yr return	-5yr return	-3yr return	-5yr return	-3yr return	-5yr return
Right-hand variable	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Left-hand variable is the R^2 from 1st-stage predictive regressions in the post-1993 period						
$\lvert\beta^{post93}_{funding}\rvert$	**0.06**	**0.05**	**0.06**	**0.06**	**0.06**	**0.06**
	(2.22)	(2.19)	(2.31)	(2.27)	(2.27)	(2.23)
	[0.55]	[0.55]	[0.52]	[0.54]	[0.48]	[0.51]
$\lvert$Arbitrage position$^{post93}\rvert$	**0.12**	**0.11**	**0.13**	**0.12**	**0.12**	**0.12**
	(2.33)	(2.27)	(2.60)	(2.48)	(2.47)	(2.37)
	[0.58]	[0.56]	[0.54]	[0.53]	[0.51]	[0.51]
$\lvert\alpha^{pre93}\rvert$	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**
	(2.22)	(2.26)	(2.30)	(2.32)	(2.14)	(2.18)
	[0.47]	[0.49]	[0.41]	[0.44]	[0.39]	[0.42]
Panel B: Left-hand variable is the R^2 from 1st-stage predictive regressions in the pre-1993 period						
$\lvert\beta^{pre93}_{funding}\rvert$	0.03	0.04	0.04	0.04	0.05	0.05
	(0.87)	(1.03)	(1.09)	(1.16)	(1.31)	(1.40)
	[0.04]	[0.06]	[0.05]	[0.06]	[0.08]	[0.10]
$\lvert$Arbitrage position$^{pre93}\rvert$	-0.05	-0.04	-0.05	-0.04	-0.01	0.00
	(-0.30)	(-0.21)	(-0.28)	(-0.20)	(-0.08)	(0.02)
	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
$\lvert\alpha^{pre93}\rvert$	0.00	0.00	0.00	0.00	0.01	0.01
	(0.29)	(0.51)	(0.46)	(0.66)	(0.79)	(1.00)
	[0.01]	[0.02]	[0.01]	[0.02]	[0.04]	[0.06]

Table 6: **Explaining the Cross-section of Arbitrageur Wealth Portfolio Betas**

$$\text{Baseline: } \beta^{post93}_{wealth,i} = b_0 + b_1 \text{ Arbitrage position}^{post93}_i + u_i$$

This table shows that the post-1993 arbitrageur wealth portfolio betas of 40 anomaly portfolios can be cross-sectionally explained by arbitrage position or pre-1993 CAPM alpha. Unless otherwise noted, the right-hand variables are calculated for the same sample period as the left-hand variable. Wealth portfolio betas are betas with the arbitrageur wealth portfolio implied by estimated arbitrage positions and are estimated in a two-factor model that includes the market factor. Arbitrage position is inferred from abnormal short position on underlying stocks. Share of wealth portfolio is the portfolio's market capitalization share in the arbitrageur wealth portfolio. Characteristic ranks are the value-weighted decile rank of the underlying stocks' characteristics. Pre-1993 and post-1993 periods are 1974–1993 and 1994–2016, respectively. In the parentheses are t-statistics based on bootstrap standard errors that account for cross-portfolio covariances as well as generated regressors. Boldface denotes coefficient estimates with the absolute value of t-statistics greater than 1.96.

	β^{post93}_{wealth}								β^{pre93}_{wealth}		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Arbitrage position	**0.26**	**0.26**	**0.35**						-0.01		
	(2.73)	(2.61)	(2.16)						(-0.04)		
α^{pre93}_{CAPM}				**0.03**	**0.03**	**0.04**				-0.01	
				(3.13)	(2.80)	(2.91)				(-0.98)	
Share of wealth portfolio		0.46	0.37		0.36	0.48	1.79	1.34	0.33	0.37	0.32
		(0.75)	(0.52)		(0.55)	(0.68)	(1.84)	(1.67)	(0.60)	(0.72)	(0.61)
β^{pre93}_{wealth}		0.08			-0.24		-0.42				
		(0.41)			(-0.86)		(-1.32)				
Size rank			0.04			-0.00		-0.06	-0.03	-0.02	-0.03
			(0.61)			(-0.02)		(-0.90)	(-0.66)	(-1.13)	(-1.54)
Value rank			-0.01			-0.06		0.03	0.03	0.05	0.03
			(-0.22)			(-1.19)		(0.69)	(1.02)	(1.30)	(1.03)
Profitability rank			-0.01			-0.04		0.02	-0.03	-0.02	-0.03
			(-0.61)			(-1.12)		(0.65)	(-1.43)	(-0.75)	(-1.44)
Investment rank			-0.03			-0.04		0.00	-0.01	-0.02	-0.01
			(-1.05)			(-1.31)		(0.14)	(-0.82)	(-1.39)	(-1.11)
Constant	-0.00	0.02	0.15	-0.03	-0.01	0.65	0.02	-0.11	-0.11	-0.25	-0.11
	(-0.07)	(0.41)	(0.47)	(-0.83)	(-0.26)	(1.46)	(0.50)	(-0.23)	(-0.49)	(-0.98)	(-0.51)
Observations	40	40	40	40	40	40	40	40	40	40	40
R^2_{adj}	0.65	0.66	0.70	0.62	0.64	0.69	0.18	0.19	0.78	0.80	0.78

Table 7: **Additional Tests on Wealth Portfolio Betas**

This table repeats the tests in Tables 3, 4, and 5 on betas with respect to the arbitrageur wealth portfolio. In the parentheses are t-statistics based on bootstrap standard errors that account for cross-portfolio covariances as well as generated regressors. In Panel B, the numbers in the brackets are the coefficient of determination (R^2) of the second-stage cross-sectional regression. Boldface denotes coefficient estimates with the absolute value of t-statistics greater than 1.96.

Panel A: Explaining the panel of arbitrageur wealth portfolio betas

	OLS								2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Arbitrage position	**0.13**	**0.13**							**0.58**	**0.56**	**0.62**
	(3.58)	(3.28)							(2.95)	(2.51)	(2.73)
α_{CAPM}^{pre93} × Post-1993			**0.03**	**0.03**			0.02				
			(2.47)	(2.50)			(1.82)				
α_{CAPM}^{pre93} × Post-publication					**0.04**	**0.04**	0.02				
					(2.66)	(2.71)	(1.81)				
Share of wealth portfolio		0.15		**0.37**		**0.37**	**0.36**	**0.44**	**-0.87**	-0.82	**-0.96**
		(1.81)		(3.46)		(3.41)	(3.30)	(3.65)	(-2.05)	(-1.75)	(-1.98)
Anomaly FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control for characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17280	17280	17280	17280	17280	17280	17280	17280	17280	17280	17280
R^2_{adj}	0.15	0.17	0.18	0.21	0.18	0.20	0.23	0.09	.	.	.
Instrumental variables											
α^{pre} × Post-1993									✓	✓	
α^{pre} × Post-Pub									✓		✓

Panel B: Wealth portfolio betas tend to arise during constrained times

	Constrained-time β_{wealth}^{post93}				Unconstrained-time β_{wealth}^{post93}			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Arbitrage position	**0.24**		**0.35**		**0.25**		0.06	
	(2.07)		(2.59)		(2.26)		(0.62)	
α_{CAPM}^{pre93}		**0.03**		**0.04**		**0.03**	0.01	
		(2.33)		(2.82)		(2.50)	(0.54)	
Share of wealth portfolio	0.73	0.79	0.62	0.05	1.21	0.69	1.57	1.74
	(0.57)	(0.63)	(0.40)	(0.03)	(0.94)	(0.45)	(0.97)	(1.09)
β_{wealth}^{pre93}	0.16	-0.15	-0.08	-0.50	0.01	-0.29	0.33	0.24
	(0.65)	(-0.48)	(-0.27)	(-1.38)	(0.06)	(-0.95)	(1.26)	(0.84)
Constant	0.01	-0.00	0.02	-0.02	-0.00	-0.04	0.01	0.01
	(0.37)	(-0.10)	(0.39)	(-0.39)	(-0.00)	(-0.64)	(0.26)	(0.17)
Constrained indicator	VIX		Alphas		VIX		Alphas	
Observations	40	40	40	40	40	40	40	40
R^2_{adj}	0.58	0.58	0.63	0.62	0.63	0.59	0.22	0.20

Panel C: Wealth portfolio betas as discount-rate betas: Evidence from return predictability

	LHS: R^2 from 1st-stage predictive regressions, RHS: $\lvert\beta_{wealth}\rvert$					
1st-stage predicted variable:	+12m return		+18m return		+24m return	
1st-stage predictor variable:	-3yr return	-5yr return	-3yr return	-5yr return	-3yr return	-5yr return
Sample Period	(1)	(2)	(3)	(4)	(5)	(6)
Post-1993	**0.32**	**0.32**	**0.34**	**0.33**	**0.32**	**0.32**
	(2.10)	(2.08)	(2.25)	(2.22)	(2.11)	(2.10)
	[0.52]	[0.51]	[0.47]	[0.49]	[0.43]	[0.46]
Pre-1993	-0.12	-0.09	0.03	0.04	0.17	0.17
	(-0.77)	(-0.61)	(0.22)	(0.24)	(1.11)	(1.10)
	[0.01]	[0.01]	[0.00]	[0.00]	[0.02]	[0.02]

Table 8: **Robustness**

Panel A reports the likelihood that betas with respect to a randomly generated factor portfolio exhibit the patterns I find for funding-liquidity and wealth portfolio betas. I use 10,000 randomly generated placebo factors to caculate the likelihood. Panels B and C repeat the test in Columns (1) and (4) of Tables 2 and 6 using alternative cutoff years in the early 1990s. In the parentheses are t-statistics based on bootstrap standard errors that account for cross-portfolio covariances as well as generated regressors. Boldface denotes coefficient estimates with the absolute value of t-statistics greater than 1.96.

Panel A: What is probability that a random placebo factor generates my results?

	t-statistic	R^2	t-stat & R^2 Jointly
Arbitrage position to funding-liquidity betas:	0.87%	0.47%	0.27%
Pre-93 CAPM alpha to funding-liquidity betas:	0.47%	0.60%	0.20%
Arbitrage position to wealth portfolio betas:	0.20%	3.59%	0.20%
Pre-93 CAPM alpha to wealth portfolio betas:	0.05%	0.75%	0.00%

Panel B: Using alternatives cutoffs to explain post-cutoff funding-liquidity betas

	1991		1992		1994		1995	
Arbitrage position^{post}	**1.38**		**1.36**		**1.91**		**1.80**	
	(2.24)		(2.19)		(2.62)		(2.60)	
α^{pre}_{CAPM}		**0.16**		**0.17**		**0.24**		**0.24**
		(2.39)		(2.49)		(2.75)		(2.72)
$\beta^{pre}_{funding}$	0.34	0.14	0.34	0.13	0.27	-0.18	0.28	-0.17
	(1.71)	(0.52)	(1.82)	(0.44)	(0.99)	(-0.44)	(1.03)	(-0.44)
Constant	-0.15	-0.30	-0.15	-0.29	-0.19	-0.40	-0.18	-0.35
	(-0.85)	(-1.16)	(-0.77)	(-1.07)	(-0.82)	(-1.15)	(-0.79)	(-1.06)
Observations	40	40	40	40	40	40	40	40
R^2_{adj}	0.77	0.73	0.74	0.71	0.79	0.66	0.78	0.69

Panel C: Using alternatives cutoffs to explain post-cutoff arbitrageur wealth portfolio betas

	1991		1992		1994		1995	
Arbitrage position^{post}	**0.28**		**0.27**		**0.26**		**0.26**	
	(2.76)		(2.67)		(2.57)		(2.60)	
α^{pre}_{CAPM}		**0.03**		**0.03**		**0.03**		**0.03**
		(2.95)		(2.83)		(2.72)		(2.73)
Share of wealth portfolio	0.41	0.37	0.40	0.34	0.44	0.37	0.40	0.36
	(0.71)	(0.57)	(0.66)	(0.52)	(0.70)	(0.56)	(0.65)	(0.59)
β^{pre}_{wealth}	0.06	-0.17	0.10	-0.17	0.09	-0.22	0.10	-0.22
	(0.30)	(-0.69)	(0.50)	(-0.65)	(0.43)	(-0.77)	(0.46)	(-0.78)
Constant	0.01	-0.02	0.01	-0.01	0.01	-0.01	0.01	-0.01
	(0.23)	(-0.38)	(0.27)	(-0.32)	(0.37)	(-0.25)	(0.33)	(-0.17)
Observations	40	40	40	40	40	40	40	40
R^2_{adj}	0.68	0.69	0.66	0.65	0.66	0.62	0.67	0.64

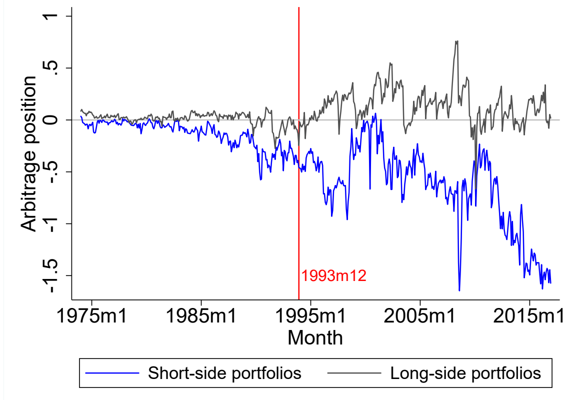

Figure 3: **Estimated Arbitrage Positions**

The figure plots the equal-weighted (cross-sectional) average of arbitrage positions in long-side and short-side anomaly portfolios over 1974m1–2016m12. Arbitrage position is inferred from abnormal short positions (see Subsection 2.2).

Figure 4a. **Constrained Quarters Implied by VIX**

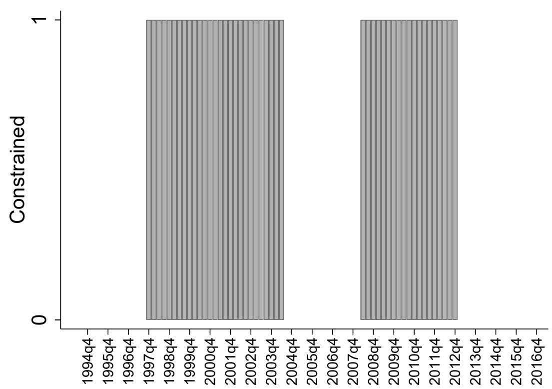

Figure 4b. **Constrained Years Implied by Alpha**

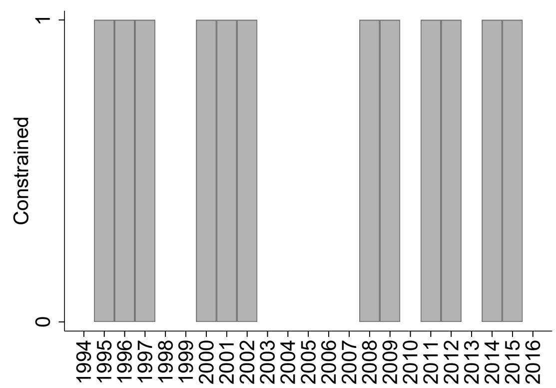

Figure 4: **Proxies for Constrained vs. Unconstrained Periods**

The first figure reports constrained (unconstrained) post-1993 quarters defined as quarters in which an exponentially weighted moving average of the VIX (smoothing factor: 0.3) is above (below) the sample median. The second figure reports constrained (unconstrained) years defined as years in which the CAPM alphas estimated from daily data are cross-sectionally explained by pre-1993 alphas with a high R^2 (above median among all year-specific cross-sectional R^2s).

Figure 5a. **Constrained Post-1993** Figure 5b. **Unconstrained Post-1993**

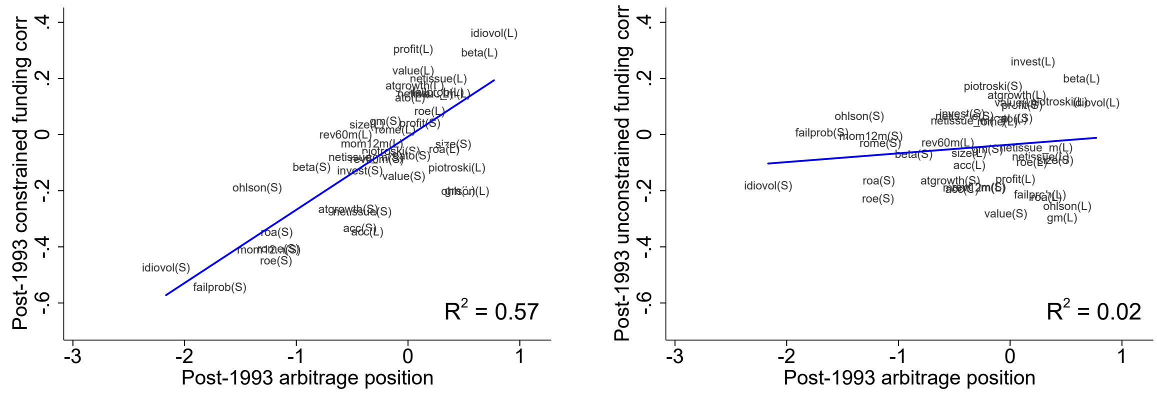

Figure 5: **Funding-liquidity Exposure Arises during Constrained Times**

The figures show that in the post-1993 period, return correlations with the funding-liquidity factor line up strongly with arbitrage position during constrained periods (left) but not during unconstrained periods (right). The result is similar if I use pre-1993 CAPM alpha as the x-axis. To compute the correlations, I first compute unexplained return as the realized return in excess of the risk-free rate and multivariate (2-factor) market beta times the excess market return. I then take the time-series correlation between the unexplained returns and the funding factor. I use constrained quarters implied by the VIX.

Figure 6a. **Post-1993 Period** Figure 6b. **Pre-1993 Period**

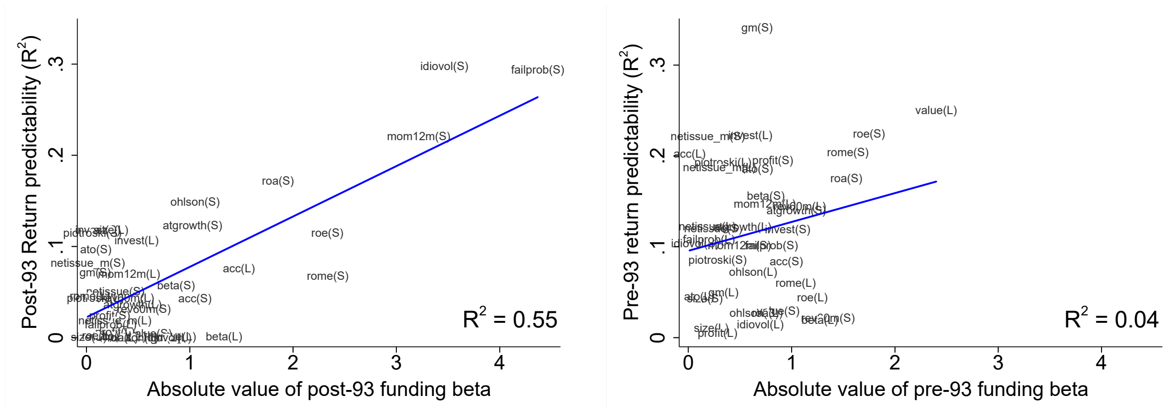

Figure 6: **Cross-section of Time-series Predictability of Returns: Post-1993 vs. Pre-1993**

The figures show that the return predictabilities of anomaly portfolios line up with the absolute value of their funding betas in the post-1993 period (left) but not strongly in the pre-1993 period (right). Return predictability is measured by the R^2 of the portfolio-specific time-series regression that explains future 1-year cumulative excess returns using the past 3-year cumulative excess returns.

Figure 7a. **Quant-Crash Returns on Anomaly Portfolios**

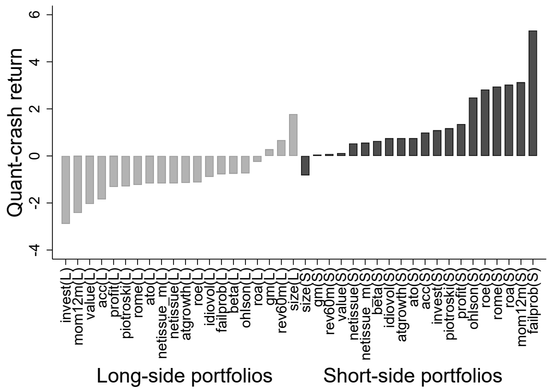

Figure 7b. **Hedge Fund Portfolio Return**

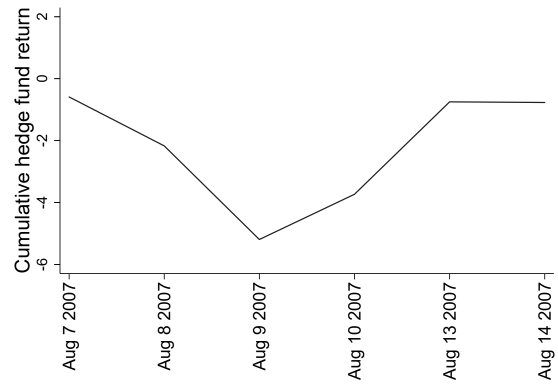

Figure 7: **Description of the Quant Crisis of August 2007**

The first figure plots the cumulative 3-day returns of long-side (first 20) and short-side (next 20) anomaly portfolios during the quant "crash" of August 7–9, 2007. The second figure plots the cumulative daily returns on equity market-neutral hedge funds during the entire quant crisis period, which includes both the crash (8/7–9) and recovery (8/10–14) periods. The hedge fund return data are from Hedge Fund Research.

Figure 8a. **Arbitrage Position Explains Quant-crash Return**

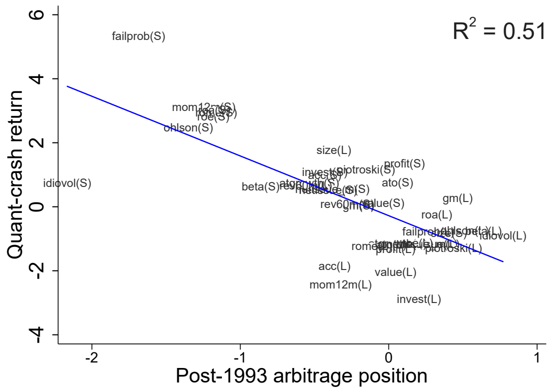

Figure 8b. **Pre-1993 CAPM α Predicts Quant-crash Return**

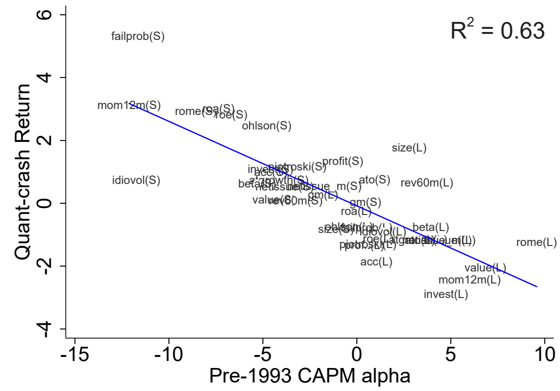

Figure 8c. **Arbitrage Position Explains Quant-recovery Return**

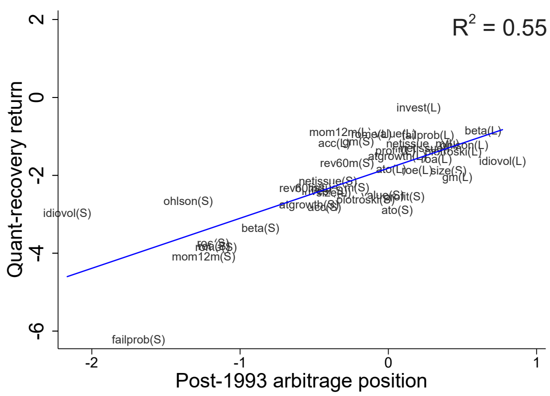

Figure 8d. **Pre-1993 CAPM α Predicts Quant-recovery Return**

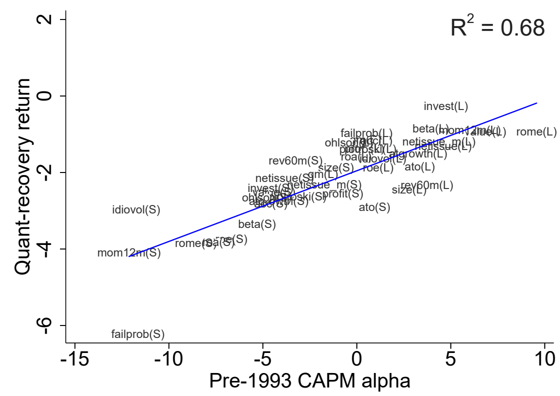

Figure 8: **Explaining the Cross-section of Returns during Quant Crash and Recovery**

The figures show that post-1993 arbitrage position and pre-1993 CAPM alpha explain the cross-section of anomaly portfolio returns during the quant crash (August 7–9, 2007; top two figures) and recovery (August 10–14; bottom two figures).

A Bootstrap Procedure

To understand my bootstrap procedure, consider a statistic

$$\hat{b}(\boldsymbol{X};G) = \hat{b}(X_1,...,X_N,F;G) = \hat{b}\left(\begin{pmatrix} x_{11} \\ \vdots \\ x_{1T} \end{pmatrix},...,\begin{pmatrix} x_{N1} \\ \vdots \\ x_{NT} \end{pmatrix},\begin{pmatrix} f_1 \\ \vdots \\ f_T \end{pmatrix};G\right),$$

where $\boldsymbol{X}$ denotes the full panel data used in my analysis, $X_i = (x_{i1}...x_{iT})'$ denotes a time series of observations for portfolio i and time periods $t = 1,...,T$, $x_{it} = (r_{it}, \text{arb position}_{it}, ...)$ is a column of observations pertaining to portfolio i at time t, and F is the time-series realizations of aggregate factors. G denotes parameters that govern the joint distribution of the sample of data $\boldsymbol{X} = (X_1,...,X_N,F)$. It contains information about the cross-sectional covariances among $(X_1,...,X_N,F)$ and about the time-series variation within X_i or F. To provide more context, $\hat{b}$ could be the OLS estimator for the slope coefficient on arbitrage position in the following cross-sectional regression (Column (1) of Table 2):

$$\beta^{post93}_{funding,i} = b_0 + b_1 \text{ Arbitrage position}^{post93}_i + u_i.$$

In the population, $Var\left(\hat{b}\right)$ is driven by both cross-sectional and time-series variations in the draw of $(X_1,...,X_N,F)$. That is, when each sample $\boldsymbol{X}_s = (X^s_1,...,X^s_N,F^s)$ is drawn from the population, (a) a set of N portfolios is chosen from a population of anomaly portfolios and (b) time-series data for the chosen portfolios and factors are drawn from a population of time-series data. This way, each sample $\boldsymbol{X}_s$ preserves the distributional characteristics summarized by G. And for each sample $\boldsymbol{X}_s$, we would compute the value of the statistic $\hat{b}^s \equiv \hat{b}(\boldsymbol{X}_s)$. $Var\left(\hat{b}\right)$ is then given by the variance of $\hat{b}^1,...,\hat{b}^\infty$ corresponding to an infinite draw of samples.

My nonparametric bootstrap approach simulates the procedure described in the previous paragraph but uses an empirical distribution G^* rather than the true population distribution G (Efron, 1979). To do this, I construct each bootstrap sample $\boldsymbol{X}^*_b$ by (a) randomly drawing a new set of 40 portfolios from the existing set of 40 anomaly portfolios with replacement and (b) randomly drawing time-series observations (with replacement) from existing time-series data on anomaly portfolios and factors. This way, each bootstrap sample $\boldsymbol{X}_b^*$ preserves the distributional characteristics G that generated the original sample and the collection of bootstrap samples $G^* = \left\{\boldsymbol{X}_1^*, ..., \boldsymbol{X}_{1,000}^*\right\}$ serves as the empirical distribution from which $Var\left(\hat{b}\right)$ is estimated. For each bootstrap sample $\boldsymbol{X}_b^*$, I compute $\hat{b}\left(\boldsymbol{X}_b^*\right)$. My bootstrap estimator for $Var\left(\hat{b}\right)$, denoted $\hat{Var}\left(\hat{b}\right)^{bootstrap}$, is then estimated as the variance of $\hat{b}\left(\boldsymbol{X}_1^*\right), ..., \hat{b}\left(\boldsymbol{X}_{1,000}^*\right)$.

To summarize, my bootstrap procedure has four steps:

1. For each bootstrap b, randomly draw with replacement the set of anomaly portfolios I_b^*: e.g.,

$$I = (1, 2, 3, 4, 5, ..., 40) \rightarrow I_b^* = (17, 4, 1, 1, 33, ..., 28)$$

2. Also randomly draw with replacement the time-series data for portfolios and factors while maintaining the cross-sectional dependence by drawing the entire row from each time period: e.g.,

$$\boldsymbol{X} = \left(\begin{pmatrix} x_{1,1} \\ \vdots \\ x_{1,33} \\ \vdots \\ x_{1,T} \end{pmatrix}, \begin{pmatrix} x_{2,1} \\ \vdots \\ x_{2,33} \\ \vdots \\ x_{2,T} \end{pmatrix}, ..., \begin{pmatrix} x_{N,1} \\ \vdots \\ x_{N,33} \\ \vdots \\ x_{N,T} \end{pmatrix}, \begin{pmatrix} f_1 \\ \vdots \\ f_{33} \\ \vdots \\ f_T \end{pmatrix}\right) \rightarrow \boldsymbol{X}_b^* = \left(\begin{pmatrix} x_{17,33} \\ x_{17,9} \\ \vdots \\ \vdots \\ \vdots \end{pmatrix}, \begin{pmatrix} x_{4,33} \\ x_{4,9} \\ \vdots \\ \vdots \\ \vdots \end{pmatrix}, ..., \begin{pmatrix} x_{28,33} \\ x_{28,9} \\ \vdots \\ \vdots \\ \vdots \end{pmatrix}, \begin{pmatrix} f_{33} \\ f_9 \\ \vdots \\ \vdots \\ \vdots \end{pmatrix}\right)$$

   The time series data are constructed by drawing the first 80 rows (240 rows for monthly data) from the pre-1993 period and the next 92 rows (276 rows for monthly data) from the post-1993 period.

3. Repeat steps 1 and 2 to construct 1,000 bootstrap samples $\boldsymbol{X}_1^*$,...,$\boldsymbol{X}_{1,000}^*$. These samples represent the empirical distribution $G^* = \left\{\boldsymbol{X}_1^*, ..., \boldsymbol{X}_{1,000}^*\right\}$.

4. Bootstrap variance of the estimator $\hat{b}$ is given by the empirical distribution of the estimator obtained from each bootstrap sample:

$$\hat{Var}\left(\hat{b}\right)^{bootstrap} = Var\left(\hat{b}\left(\boldsymbol{X}_1^*\right), ..., \hat{b}\left(\boldsymbol{X}_{1,000}^*\right)\right)$$

   The square root of the bootstrap variance is the bootstrap standard error.

For regressions involving both quarterly and monthly data, I first obtain the random draw of quarters to construct quarterly bootstrap data and then construct monthly bootstrap data based on monthly observations pertaining to the quarters used in the quarterly bootstrap. For panel regressions, I draw moving blocks of 4 quarters with replacement from each subsample of 10 years to retain time-series dependencies in the variables (Künsch, 1989) and to account for the possible publication effect in addition to the post-1993 effect.[31] For quant crisis regressions, I cannot generate bootstrap samples using in-sample data since the quant crisis is a single observation. Instead, I use 2 months surrounding the quant crisis (7/6/2007–9/14/2007) to draw 3-day returns with replacement. Alternative approaches such as using previous 1-month returns or previous 1-year returns generate stronger or similarly strong results.

In addition to standard errors, the bootstrap also provides an estimate of the downward bias in the coefficient due to generated regressors. Adjusting for these biases tend to increase the estimated coefficients and t-statistics by around 10%, but to be conservative, I report parameter estimates and t-statistics that do not adjust for the bias.

[31] Since my sample has 43 years, the last subsample of 2004–2016 has 13 years. However, the exact way I apply the moving block bootstrap does not materially affect the standard errors in my panel regressions.

B Additional Tables

Table B1: **Determinants of Arbitrage Position**

$$\text{Baseline: Arbitrage position}_{i,t} = b_0 + b_1\alpha_i^{pre} \times \mathbf{1}\,(t > 1993\text{q}4) + b_2\mathbf{1}\,(t > 1993\text{q}4) + b_3 t + b_4 t^2 + u_i + \epsilon_{i,t}$$

This table shows that pre-1993 alpha predicts post-1993 and post-publication arbitrage position in a panel regression (40 portfolios × 1974q1–2016q4). The dependent variable measures arbitrage position on portfolio i in quarter t inferred from abnormal short positions on underlying stocks (Section 2.2). The post-1993 dummy is 0 for the pre-1993 period (1974q1–1993q4) and 1 for the post-1993 period (1994q1–2016q4). A portfolio's "pre-arbitrage" alpha, denoted α^{pre}, is measured by its pre-1993 alpha with respect to the factor model specified in the column heads. For failure probability, α^{pre} is computed from 1981 onward to account for the portfolio's sensitivity to sample period, emphasized in Dichev (1998). Post-publication, Post-sample, Post-1993, and Post-1993×Post-publication (whenever appropriate) as well as quadratic time trends (t and t^2) and a constant are included in the regression but not reported in the table. In the parentheses are t-statistics based on bootstrap standard errors that account for cross-portfolio covariances, generated regressors, and serial correlations. Boldface denotes coefficient estimates with the absolute value of t-statistics greater than 1.96.

	α^{pre} = CAPM alpha					α^{pre} = FF3 alpha			α^{pre} = FF5 alpha			Long vs. short			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
α^{pre} × Post-1993	**0.076**		**0.058**	**0.051**	**0.052**	**0.058**	**0.055**	**0.045**	**0.066**	**0.061**	**0.051**				
	(3.92)		(3.12)	(1.97)	(2.52)	(3.15)	(2.14)	(2.18)	(3.56)	(2.36)	(2.47)				
α^{pre} × Post-publication		**0.076**	0.032	0.019	0.027	0.034	0.029	0.012	**0.044**	0.036	0.022				
		(3.61)	(1.78)	(0.98)	(1.11)	(1.89)	(1.52)	(0.49)	(2.47)	(1.88)	(0.90)				
α^{pre} × Post-sample				0.025			0.010			0.016					
				(0.94)			(0.36)			(0.60)					
α^{pre} × Post-1993 × Post-pub					0.010			0.034			0.036				
					(0.27)			(0.96)			(1.00)				
Long × Post-1993												**0.643**		**0.534**	**0.507**
												(3.71)		(2.97)	(2.21)
Long × Post-publication													**0.597**	0.195	0.152
													(3.28)	(1.16)	(0.92)
Long × Post-sample															0.082
															(0.35)
Anomaly FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,880	6,880	6,880	6,880	6,880	6,880	6,880	6,880	6,880	6,880	6,880	6,880	6,880	6,880	6,880
R^2_{adj}	0.20	0.16	0.21	0.21	0.21	0.27	0.27	0.28	0.27	0.27	0.28	0.16	0.13	0.16	0.17

Table B2: **Explaining the Cross-section of Quant-crisis Returns**

$$\text{Baseline: } r_i^{quant\,crash} = b_0 + b_1 \text{Arbitrage position}_i^{post93} + u_i$$

This table shows that the exposure of anomaly portfolios to arbitrage capital shocks measured by cumulative returns during the quant crash (August 7–9, 2007) is cross-sectionally explained by arbitrage position and pre-1993 CAPM alpha. Cumulative returns during the recovery from the crash (August 10–14, 2007) display an opposite pattern, suggesting that the portfolio returns during the crash were discount-rate shocks. Cumulative abnormal return is defined as the excess return net of market exposure (market excess return times the beta estimated over the 2 months surrounding the quant crisis, July 7–August 6 and August 15–September 14, using 3-day returns). Post-1993 arbitrage position is computed over the entire post-1993 period. In the parentheses are t-statistics based on bootstrap standard errors that account for cross-portfolio covariances and generated regressors. Boldface denotes coefficient estimates with the absolute value of t-statistics greater than 1.96.

	Quant-crash return			Quant-crash abnormal return			Quant-recovery return			Quant-recovery abnormal return		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Arbitrage position^{post93}	**-1.87**			**-1.99**			**1.29**			0.94		
	(-3.32)			(-3.69)			(2.13)			(1.62)		
Arbitrage position^{July2007}		**-1.28**			**-1.39**			**0.92**			0.62	
		(-3.03)			(-3.30)			(2.03)			(1.37)	
α_CAPM^{pre93}			**-0.27**			**-0.28**			**0.18**			**0.16**
			(-4.33)			(-4.87)			(2.90)			(2.62)
Constant	-0.28	-0.27	-0.08	0.34	0.34	0.56	-1.82	-1.81	-1.95	0.01	-0.01	-0.07
	(-1.15)	(-1.02)	(-0.28)	(1.37)	(1.21)	(1.92)	(-1.00)	(-0.99)	(-1.06)	(0.00)	(-0.00)	(-0.04)
Observations	40	40	40	40	40	40	40	40	40	40	40	40
R_adj^2	0.50	0.35	0.62	0.54	0.40	0.64	0.54	0.41	0.67	0.34	0.22	0.58