Essays on Empirical Asset Pricing

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Thesis submitted to the University of Ottawa
in partial Fulfillment of the requirements for the
PhD degree in Management

Telfer School of Management
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Abstract

In this dissertation, I investigate important questions related to the impact of non-fundamentally driven demand shocks on asset prices (first chapter) and crowding by institutional investors (second chapter). The first chapter is single-authored, and the second chapter is a joint work with Ludwig Chincarini and Fabio Moneta.

In the first chapter, I revisit the *stock price fragility* measure of Greenwood and Thesmar (2011) and propose a different approach to estimate it using exchange-traded funds (ETFs) data rather than mutual funds data as in the original paper. Previous literature employs equity mutual fund flows to measure a stock's exposure to non-fundamental demand risk - stock price fragility. However, this approach may be biased by confounding fundamental information, potentially leading to underestimation of risk exposure. Moreover, I document a significant decrease in the forecasting power of the mutual fund-based fragility for future stock return volatility in the most recent sample period. I propose an alternative approach that incorporates readily available primary market data from ETFs. This approach significantly enhances the predictive power of fragility in forecasting stock return volatility. Moreover, this approach captures the influence of increased ETF activeness while partially capturing the effect of non-fundamental institutional demand on return volatility.

In the second chapter, we investigate the relation between crowded trades, those in which many investors hold the same stocks possibly exhausting their liquidity provision, and future stock returns on a set of well-known stock market anomalies. We find that anomaly risk-adjusted returns appear to be concentrated among the most (least) crowded stocks for the long-leg (short-leg) portfolio. Moreover, we find that our results remain significant after publication dates. We hypothesize that crowded equity positions in anomaly

stocks increase institutional investor's exposure to crash risk. Our findings are consistent with this hypothesis and suggest that crowding adds a new consideration to the limits of arbitrage.

Acknowledgements

Foremost, I extend my heartfelt gratitude to God for the abundance of blessings in my life. I wish to express profound appreciation to all those who contributed in various capacities throughout my journey in the PhD program.

A special acknowledgment is reserved for my thesis supervisor, Dr. Fabio Moneta. His continuous support has been integral to my progress in the PhD program. I am sincerely indebted to him for his guidance, support, and invaluable lessons that have enhanced my academic prowess and fostered personal growth. Thanks so much, Professor Fabio!

I thank my fellow PhD colleagues, Mian Wei, Andrew Scarffe, Chen Li, and Xiayiou Sun. Their encouraging words and companionship have rendered this journey truly memorable. Special thanks to Laura Steadman and Heather Vitkuske, their help and words of encouragement were essential during crucial times, thanks for being so kind and helpful! I also want to thank my Peruvian colleagues, Hamilton Galindo, Jan Sandoval, and Jose Berrospide. They provided an inspiring environment where we could share both personal and academic ideas.

My heartfelt appreciation goes out to my parents, Lourdes and Edgar; my brothers, Rodrigo and Edgar; and my nephews, Mateo, Tomas, and Catalina. Special mention is reserved for my doppelganger, Diego. Their unconditional support has been invaluable for me. I want to express profound thanks to my wife, Paola, for consistently supporting me through the highs and lows of this challenging journey.

Recognition is extended to my previous professors at the Federal University of Minas Gerais (UFMG), namely Robert Iquiapaza, Aureliano Bressan, and Wagner Lamonier, for their impactful lessons during my time in Belo Horizonte. Their encouragement has propelled me to embrace academic life and continually challenge myself to achieve higher goals.

Also, I am grateful for the enduring friendship of my Brazilian friends, Joyce Cavalcanti, and Ewerton Avelar.

Lastly, I want to express my gratitude to the numerous individuals I had the pleasure of meeting during conferences and presentations, with a special mention to Maurizio Montone, Agustin Hurtado, and Matthew Ringgenberg.

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Chapter 1

An ETF-based measure of stock price fragility

1 Introduction

Classical asset pricing theories state that stock prices fluctuate because of fundamental shocks, such as news. This argument is based on the assumption that trading unrelated to a firm's fundamentals triggers a response by arbitrageurs who take the opposite side of the trade, canceling out any potential impact on security prices (e.g., Fama, 1965; Ross, 1976). However, extensive research has documented that trading driven by non-fundamental information (e.g., sentiment, noise, liquidity) can influence stock prices and that arbitrage activity faces various limitations that contribute to the persistence of mispricing.[1] While evidence shows that *non-fundamental demand shocks* influence asset prices, scholars continue to debate how to empirically measure a stock's exposure to these shocks.

Earlier research shows that stocks bought by mutual funds experiencing substantial inflows tend to underperform in the long run, whereas those sold by funds facing outflows

1 Seminal theoretical papers model the effect of noise traders (De Long et al., 1990), trading motivated by informational and noninformational motives (Wang, 1996) and the limits to arbitrage activity (Shleifer and Vishny, 1997) on stock prices and trading volume.

tend to outperform (e.g., Coval and Stafford, 2007; Frazzini and Lamont, 2008). Moreover, Lou (2012) finds that price pressure resulting from mutual fund flow-driven trades contributes to the persistence of stock return momentum and mutual fund performance. This evidence has motivated a large body of literature to use investor flows to and from mutual funds as sources of exogenous non-fundamental price pressure.[2]

Building on this previous work, Greenwood and Thesmar (2011) developed the concept of *stock price fragility*. This measure combines information on an asset's ownership composition with data on the correlation between owners' non-fundamentally driven trades. These trades are proxied by mutual fund flows to capture firm-level exposure to non-fundamental demand risk. Therefore, a stock is considered *fragile* if a few owners hold a large percentage stake (i.e., concentrated ownership) or if its owners face highly correlated non-fundamental demand shocks. This intuitive interpretation has prompted researchers to use this measure extensively.[3] Nonetheless, recent evidence has raised doubts about the empirical validity of mutual fund flows as instruments for non-fundamentally driven price pressure. Specifically, recent studies demonstrate that mutual fund flows motivate fund managers to perform discretionary trades[4] (Huang et al., 2022; Berger, 2022) and that such flows attract time-varying specialized demand from other mutual funds (Rzeznik and Weber, 2022).[5] Additionally, mutual fund managers actively hedge against the impact of common flows on fund size by tilting their portfolios toward low-flow-beta stocks, even at the expense of providing lower risk-adjusted returns (Dou et al., 2022). Theoretical mod-

2 Wardlaw (2020) and Berger (2022) provide excellent recent discussions about the literature that relies on mutual fund flows as exogenous shocks to stock prices.

3 In empirical corporate finance settings, studies have related stock price fragility to firm's financing costs (Francis et al., 2021), cash holdings, and investment policies (Friberg et al., 2023), and equity issuance and repurchase activity (Massa et al., 2020). In the context of asset pricing factors, Huang et al. (2021) estimates the stock price fragility at the factor level to analyze the component of stock pricing factors returns that are driven by noise trading.

4 *Discretionary* trades refer to those that contain fundamental information. This is, trades motivated by the fund managers' beliefs about stock mispricing that represent opportunities to generate alpha. Contrary to discretionary trades, *expected* trades assume that fund managers only expand (contract) their current portfolio in response to inflows (outflows) proportionally to the current weights of each asset in their portfolios.

5 This refers to the demand from funds familiar with a specific set of assets that better allows them to price them adequately.

els such as the influential model of Berk and Green (2004) argue that mutual fund flows reflect learning about mutual fund manager skills and thus do not necessarily reflect only non-fundamental demand. Overall, it is likely that the impact of mutual fund flows on prices cannot be exclusively attributed to non-fundamental demand. It also encompasses trades motivated by fundamental information.

The focus of this study is to provide an alternative method for estimating stock price fragility by employing data on exchange-traded funds (ETFs). Brown, Davies and Ringgenberg (2021) introduce a model that links ETF primary market flows (i.e., the creation and redemption of ETF shares) to non-fundamental demand shocks.[6] The authors provide empirical evidence that supports their theoretical predictions. In light of this evidence, we propose an alternative method to estimate stock price fragility by employing ETF primary market flows and ownership composition data. This approach effectively overcomes many limitations associated with relying on mutual fund data while offering a more comprehensive scope by including a broader set of non-fundamental-driven sources of price variation. This is because ETFs are traded by a broad cross-section of market participants (i.e., retail traders, institutional investors, and Hedge funds), while mutual funds are mostly held by retail investors and households.

Our methodology provides three significant improvements over the existing method: 1) it relies on observable signals of non-fundamental demand not confounded by information about fund manager skills or fundamentally motivated trades (i.e., ETF flows); 2) it captures the impact of ownership and demand from both retail and institutional investors; and 3) it provides additional insights into the impact of the ETF industry's growth on asset prices.[7] Furthermore, in light of recent discussions concerning the impact of growing

6 An important distinction exists between primary and secondary ETF trading markets. The primary market refers to the creation and redemption of ETF shares between the authorized participants (AP) and the financial institutions. The secondary market refers to the intraday trading that occurs among investors, which could be due to many different reasons. Madhavan (2014) and Ben-David et al. (2017) provide excellent reviews of the ETF industry.

7 Another potential advantage of an ETF-based fragility measure is that it can be estimated for a higher frequency (i.e., monthly), as opposed to the traditional mutual fund approach that relies on quarterly data. This approach could offer valuable insights into short-lived price dislocations, making it a promising avenue for future research.

activeness in the ETF industry and the emergence of specialized attention-grabbing thematic ETFs (e.g., Easley et al., 2021; Ben-David et al., 2023), our study contributes by further exploring the effects of increased ETF activeness on asset prices.

Our analysis consists of two main parts. In the first part, we test the validity of our proposed methodology and compare it with the original estimation method. We begin by estimating the stock price fragility measure as in Greenwood and Thesmar (2011), G^{MF}, for the sample period used in that study (*in-sample*) and extend it until the last quarter of 2018 (*out-of-sample*). We then proceed to estimate the fragility measure employing only ETF data, G^{ETF}. Finally, in a regression setting, we test the ability of each measure to forecast future return volatility. In the second part of our analysis, we explore the factors that potentially make G^{ETF} superior measure and investigate the determinants of our prior findings. Specifically, we examine whether G^{ETF} captures the previously documented impact of institutional investors' ownership on volatility and whether increased ETF activeness helps explain our results.

We highlight four main empirical results. First, we find that the statistical and economic significance of G^{MF} in forecasting the next quarter's stock return volatility has significantly declined in the second part of our sample (2009-2018) - *out-of-sample*. Greenwood and Thesmar (2011) document that for the period between 1989 to 2008, an increase in G^{MF} fragility from the 25th to the 75th percentile predicts an increase in daily volatility by 0.5%. Nevertheless, during the *out-of-sample* period, our estimation suggests that a comparable increase in fragility is associated with an expected rise in daily volatility of approximately 0.25%. While we do not focus on studying the determinants of this decline, we observe that this behavior coincides with a period during which the equity mutual fund industry has experienced significant outflows, as shown in Figure I.1. Simultaneously, there has been substantial growth in the ETF industry in terms of trading volume and trading by a broader set of market participants (Dannhauser and Pontiff, 2019; Glosten et al., 2021; Easley et al., 2021). For instance, we estimate that by the last quarter of 2021, approximately 70% of Mutual funds and Investment advisors in the 13F institutional investors holding database included ETFs in their portfolios.

Second, we show that G^{ETF} strongly predicts the next quarter's stock return volatility in the later part of our sample period (2009 - 2018). Moreover, we find that when we include both G^{MF} and G^{ETF} in our regression model, only the coefficient of G^{ETF} remains positive and statistically significant. This evidence supports the conjecture that G^{ETF} provides information on fragility above and beyond that included in the G^{MF} measure. Our results align with evidence of an increase in ETF trading volume (Ben-David et al., 2017) and the integration of ETFs into both institutional and retail investors' portfolios (Dannhauser and Pontiff, 2019). Furthermore, our findings support the empirical evidence of Brown, Davies and Ringgenberg (2021) and Davies (2022), indicating that ETF primary flows are indicators of non-fundamental demand shocks.

Third, we present evidence that G^{ETF} captures the influence of mid and small-sized institutional ownership on stock price volatility. In a recent study, Ben-David et al. (2021*a*) show that increased ownership by large- and mid-sized institutional investors predicts higher volatility and noise in stock prices. This effect arises from the granular nature of these institutions, where subunits within large institutional investors tend to exhibit correlated trading behavior. This phenomenon, in turn, reduces the ability of institutional investors to diversify idiosyncratic demand shocks since correlated trades result in larger trading volumes, ultimately leading to more substantial price impacts We follow Ben-David et al. (2021*a*) specification and find that G^{ETF} remains statistically significant even when accounting for the impact of institutional investors' ownership on future stock price volatility. Furthermore, when G^{ETF} is incorporated into our regression analysis, the coefficient of mid-sized institutional ownership becomes statistically insignificant. We interpret this finding to be a consequence of the distinct ETFs ownership structure. Unlike mutual funds, which retail investors primarily own, ETFs are roughly equally owned by both retail and institutional investors (Dannhauser and Pontiff, 2019). Moreover, we present additional evidence of the widespread adoption of ETFs by 13F institutional investors over time, particularly among investment advisors and transient institutions, that tend to have higher activity levels and shorter investment horizons. This fact can help explain why including G^{ETF} subsumes the explanatory power of mid-sized institutions.

Fourth, we document that the forecasting power of G^{ETF} on the next quarter's stock price volatility is mostly explained by *active* ETFs. It is possible that our results may be influenced by the comparison of two fundamentally distinct investment vehicles owing to their differing investment mandates. Equity mutual funds are actively managed, whereas ETFs were originally designed as passive vehicles with the primary objective of replicating a benchmark. We address this concern by estimating the activeness index of Easley et al. (2021) using our sample of ETFs. We corroborate the authors' findings in a broader sample of ETFs and show that ETFs have become, on average, more active in recent years.[8] Additionally, motivated by Easley et al. (2021) concerns that increased ETF activeness might negatively affect price informativeness by channeling active bets, we decompose the G^{ETF} into active and non-active components following the methodology outlined by Greenwood and Thesmar (2011). Our findings indicate that our results primarily stem from the active ETFs component. These results are consistent with Ben-David et al. (2021*a*), who demonstrate that the expansion of the ETF industry has given rise to a multitude of specialized ETFs designed to cater to investors' extrapolation beliefs and prevailing investment trends. This phenomenon has led investors to allocate their wealth to already overvalued underlying stocks, exacerbating mispricing. When this mispricing is eventually corrected, it results in negative alphas for investors. Importantly, this evidence indicates that G^{ETF} measure can capture recent trends in the ETF industry that influence a stock's exposure to non-fundamental demand—an aspect largely overlooked by the G^{MF} measure.

Overall, our results are consistent with the argument that ETF primary markets flows provide valid signals of non-fundamental demand shocks (Brown, Davies and Ringgenberg, 2021) and that not only retail ownership but institutional investors' ownership contribute to stock return volatility (Bushee and Noe, 2000; Koijen and Yogo, 2019*a*; Ben-David et al., 2021*a*). Recent developments in the asset management industry, such as the rise of passive investing, increased accessibility to broader datasets, and advancements in theoretical frameworks and empirical evidence, call for a reevaluation of stock price fragility estimation. In this study, we address these developments and propose a revised fragility estimation method.

8 Easley et al. (2021) defines ETF activeness as being either in *form* or in *function*. A fund is active in *form* if it is designated to deliver out-performance or alpha. In *function* suggests that whether a fund is passively or actively managed, it can serve as a foundational component of an actively managed portfolio.

Our paper contributes to the ongoing discussion on the validity of mutual fund flows as instruments for non-fundamentally driven price variations. Specifically, we add to the growing literature that uses ETFs as a laboratory to study non-fundamental demand. Recent research has cast doubt on the empirical validity of two widely used approaches that rely on mutual fund data: one involving extreme outflows and the other employing a normalized measure, MFFLOWS. These approaches have been found to fail to satisfy the conditions necessary to be considered valid instruments and are not entirely orthogonal to fundamentals. Regarding the first approach, Huang et al. (2022) document that fire sales (i.e., those in which fund managers are forced to sell part of their holdings because of large outflows) contain fundamental information.[9] In essence, fund managers actively select which assets to sell rather than mechanically reducing all their positions, as previously assumed. Rzeznik and Weber (2022) document that the impact of fire sales on stock prices is negligible when mutual funds that hold the same stocks receive inflows. This suggests that specialized demand from these other funds mitigates the negative effects of fire sales by counteracting and purchasing these stocks. This evidence implies that the effects of fire sales are observable only in the absence of specialized demand. This conditional effect limits the suitability of fire sales as an adequate measure for capturing non-fundamental demand shocks In an influential paper, Wardlaw (2020) demonstrates that a widely used measure, the MFFLOWS of Edmans et al. (2012), is a direct function of realized returns during the outflow quarter. Moreover, the author shows that several documented results no longer hold once MFFLOW is corrected for this mechanical relationship. Similarly, Berger (2022) shows that the assumption that managers sell firms in proportion to portfolio weights induces selection bias in studies that employ the MFFLOW measure.[10] That is, it misallocates large

9 Huang et al. (2022), show that when faced with large outflows, fund managers decrease only 43.9% of their holdings, and 37.4% of their positions remain unchanged. Surprisingly, the authors find that following large outflows, fund managers expand their holdings in 18.7% of securities, and such buys are more likely related to fundamentals since they can forecast future positive returns.

10 This refers to the *proportional trading assumption*. For mutual fund flows to serve as a valid instrument for non-fundamental demand, it is essential that the information they convey remains independent and unrelated to any fundamental trading motive. This is possible if we assume that mutual funds trade (buy or sell) such that their initial allocation proportion does not change when faced with flows. This should be especially stronger when faced with extreme outflows or fire sales (Coval and Stafford, 2007; Edmans et al., 2012).

price impacts to poorly performing illiquid firms with lower growth, which are, in fact, firms that fund managers avoid selling. Thus showing that the assumption does not hold true. Our study adds to this discussion by providing evidence that is in line with Brown, Davies and Ringgenberg (2021) and Davies (2022). Specifically, our results reveal that when included in the estimation of price fragility, ETF primary market flows exhibit properties and outcomes consistent with reliable proxies for non-fundamental demand shocks.

Furthermore, our work adds to the growing body of literature investigating the effects of ETF activity on the volatility of their underlying assets (Ben-David et al., 2018) and the consequences of increased ETF activeness and heterogeneity of ETF products on stock prices (Easley et al., 2021; Davies, 2022; Ben-David et al., 2023). While extensive evidence exists on how ETFs can amplify the volatility of underlying stocks, our analysis extends these findings by considering ownership structure as a complementary factor. Our findings align with the insights of Israeli et al. (2017) regarding uninformed traders and ETFs and Davies (2022) regarding the role of ETFs, especially leveraged ETFs, in channeling investor gambling behavior. Our measure effectively captures these effects, which are often overlooked when relying solely on mutual fund data.

Recent studies emphasize the role of investor demand in explaining asset return patterns. In a pioneering work, Koijen and Yogo (2019*a*) studied the impact of institutional investors and household ownership in determining stock demand elasticity and associated stock price volatility. Their findings indicate that while large institutional investors account for a substantial portion of market capitalization, mid- and small-sized institutional investors, as well as households, significantly contribute to stock price volatility. We believe that our measure contributes to this discussion by showing that an ETF-based fragility measure potentially captures the joint effect of retail and institutional stock ownership and demand shocks, channeled through ETF trading, on stock volatility. In this context, our results contribute to the current literature by revealing the role that institutional investor demand plays in non-fundamental demand shocks that ultimately influence stock prices.

The remainder of this paper is organized as follows. Section 2 describes the conceptual framework supporting our empirical approach. Section 3 describes the mutual funds and ETF data sources. Section 4 presents our main empirical results. Section 5 concludes the study and briefly discusses the implications of our results.

2 Conceptual framework

This section outlines the theoretical framework that motivates our empirical methodology. First, we review the literature that relates ETF primary market flows to non-fundamental demand shocks. Second, we provide an overview of recent studies that revisit the relationship between firms' ownership structure and non-fundamental demand risk, drawing links to our proposed methodology. Finally, we describe recent studies that discussed the limitations of mutual fund flows as a proxy of non-fundamental demand shocks and explain how an estimation of stock price fragility based on ETF data could effectively address and mitigate these concerns.

2.1 Non-fundamental demand shocks

Non-fundamental demand shocks cause market participants to trade an asset without regard to fundamental information about changes in future growth prospects or risk factors. Although the classic asset pricing theory regards these trades as *noise*, they can lead to deviations in asset prices from their intrinsic or fundamental values (De Long et al., 1990). The financial economics literature that investigates the factors behind such trades is extensive, and it can be broadly categorized into two main groups: noise/liquidity-driven (De Long et al., 1990; Wang, 1994) and sentiment-driven (Baker and Wurgler, 2006).[11] While the influence of non-fundamental demand shocks on asset prices has been extensively explored, identifying shocks orthogonal to any fundamental information remains an empirical challenge because fundamental values are unobservable. Many empirical studies have traditionally used mutual fund flows as a proxy for non-fundamental shocks. However,

11 The literature on investor sentiment encompasses explanations grounded in concepts of both overreaction and underreaction (Barberis et al., 1998), gambling-like behavior (Kumar and Lee, 2006), and the disposition effect (Barber and Odean, 2000), among various other phenomena explored by the behavioral finance literature.

as discussed earlier, this approach relies on assumptions that have faced scrutiny in recent studies (e.g., Berger, 2022; Huang et al., 2022). To understand why ETF primary market flows offer clear and distinct signals of non-fundamental demand shocks, we briefly describe the redemption/creation mechanism underlying ETF trading. We then describe the link between this mechanism and the key insights from Brown, Davies and Ringgenberg (2021) model.

ETFs are regarded as one of the most significant innovations in the asset management industry (Madhavan, 2014; Huang et al., 2020). Their remarkable success is commonly attributed to their cost efficiency and intraday liquidity.[12] However, a less recognized driver behind the rapid growth of the ETF industry is its superior tax efficiency compared to mutual funds, primarily because of the advantage of lower capital gain taxes (Moussawi et al., 2020).[13] These advantages led to the explosive growth of the ETF industry, resulting in the creation of a diverse range of investing products that track a wide array of benchmarks. This development provides investors with opportunities to gain exposure to both the broad market and specific sectors and themes (Ben-David et al., 2023). As a result of the tremendous growth of the ETF Industry, roughly 35% of U.S. equity trading volume is attributable to ETFs (Glosten et al., 2021).

Adding to this distinguishing feature of offering investors intraday liquidity is the redemption/creation mechanism, which sets ETFs apart from other investment vehicles. This mechanism ensures that ETF shares expand or contract based on investors' demand. Because of the interaction between ETF share supply and investor demand, ETF share values may deviate from the Net Asset Value (NAV) of the underlying securities that compose the benchmark (i.e., ETF premium or discount). When such disparities occur, a specialized group of investors, referred to as Authorized Participants (AP), engage in trading activities involving the purchase and sale of large blocks of ETF shares with the ETF sponsor. The trading activity of APs corrects any arbitrage opportunities, ensuring

12 As of 2021, the US ETF market comprised around 2,570 funds, collectively accounting for a total of \$7.2 trillion in net assets. In a global context, the total value of the worldwide ETF market reached \$10.1 trillion (ICI, 2022 - available at https://www.icifactbook.org/pdf/2022_factbook.pdf)

13 Moussawi et al. (2020) document that the tax efficiency of ETFs relative to mutual funds increases long-term investors' after-tax returns by an average of 0.92% per year.

that ETF intraday prices closely approximate the NAV of the underlying portfolio. This process is known as the creation-redemption mechanism or ETF primary market.

The creation/redemption process of ETFs on the primary market indicates excess demand from investors. When there is an increased demand for ETF shares, which causes an ETF premium, APs acquire a block of new ETF shares from the ETF sponsor. This transaction involves transferring the basket of underlying securities to the sponsor and subsequently selling the newly acquired ETF shares in the secondary market. Conversely, the opposite process occurs when excess selling pressure on ETF shares results in an ETF discount. Brown, Davies and Ringgenberg (2021) argue that this temporary dislocation between the ETF's share value and the NAV of their underlying assets signals the appearance of a non-fundamental demand shock. Moreover, since these discrepancies are corrected through the redemption (creation) of ETF shares by APs, these changes in ETF shares (i.e., *ETF flows*) allow researchers to observe these non-fundamentally driven trades. The authors' model shows that, in equilibrium, ETF flows do not contain information about fundamental information shocks.[14] Instead, they are the product of net excess demand in either the ETF shares or the ETF underlying assets. In other words, ETF flows act as a proxy for the magnitude and direction of non-fundamental demand shocks.

Brown, Davies and Ringgenberg (2021) corroborate the predictions of their theoretical model by empirically showing that ETF flows forecast future asset returns that later reverse, and that this effect is stronger among leveraged and high-activity ETFs (those with more active primary markets). More recently, Davies (2022) expands this model to estimate a market-level Speculation Sentiment Index that captures aggregate speculative trades channeled through the trading activity of leveraged ETFs. His results are consistent with speculation sentiment causing market-wide price distortions that later revert.

Brown, Davies and Ringgenberg (2021) relate their model to the well-known Berk and Green (2004) model which states that mutual fund flows indicate investors' learning about manager's skill. Nevertheless, a significant distinction arises, given that ETFs are passively

14 This is because, even though both the demand for ETF shares and the demand for the underlying assets contain fundamental information, this particular component does not directly contribute to the relative mispricing observed when the ETF premium emerges.

managed vehicles. Consequently, ETF flows do not reflect investors' learning of managerial skills. Instead, they reflect the arbitrage activity of APs who exploit any misalignment between the value of ETF shares and their underlying NAV. This distinction serves as one of the primary advantages of an ETF-based fragility measure compared to that derived from mutual fund data. ETF flows lack discretionary skill-revealing information and stem from mispricing between ETF share price and NAV, which induces arbitrage trading.

Overall, motivated by the above theoretical and empirical evidence, we argue that the arbitrage mechanism that characterizes the ETF primary market provides two main benefits for the fragility measure: (i) *observable non-fundamental demand shocks*: The creation and redemption process of ETF shares in the primary market offer distinct signals of non-fundamental demand shocks, which can be observed in data that tracks the number of outstanding ETF shares; (ii) *we do not need to rely on assumptions regarding fund managers behavior*: the mechanical correction of the misalignments between ETF share price and underlying assets alleviates concerns regarding fund managers' discretionary decisions that might introduce fundamental information in fund flows.

2.2 Ownership structure and non-fundamental risk

Stock price fragility measures a security's exposure to *shifts* in non-fundamental demand by capturing the joint influence of ownership composition and the variance-covariance matrix of non-fundamentally-driven trades (i.e., *flows*) of asset owners. Greenwood and Thesmar (2011) introduced this measure based on a model that represents changes in an investor's portfolio assets as a function of two key motivations: i) those attributable to active rebalancing and ii) those arising from flow-driven trading. Then, assuming a stable relationship between aggregate flow-driven trades, a security's returns can be modeled as a function of price pressure due to flow-driven trades and an error term that captures information about the security fundamentals. If flow-driven demand cancels out across owners, prices should reflect only fundamental information. However, if non-fundamental demand is not solved, it has the potential to exert temporary non-fundamental pressure on prices.

Under the assumption of orthogonality between flow-driven trades and fundamental information, Greenwood and Thesmar (2011) concluded that the two key determinants of a security's return variance due to non-fundamental demand are: i) a vector representing the weight of each investor in that security (i.e., *ownership concentration*) and ii) the conditional variance-covariance matrix of flows originating from security owners (i.e., n*on-fundamental demand shocks*).

More recently, Ben-David et al. (2021*a*) studied the relationship between large institutions' ownership and return volatility. In principle, demand by large institutional investors influences stock return behaviors whenever shocks to these agents' portfolios are not easily diversified across their constituent subunits, influencing aggregate market outcomes (Gabaix, 2011). In other words, if funds under the same investment management firm exhibit some level of correlation in their trading activities when faced with external shocks to their holdings, then these institutions are considered granular. Their capacity to internally diversify these shocks is limited, ultimately resulting in a more pronounced market impact of their trades. Ben-David et al. (2021*a*) developed a model that relates asymmetric information and risk-averse market makers, linking asset managers' behavior to price dynamics. In their model, the variation in stock prices is represented as a function of three components: i) systematic aggregate shocks driving institutional trades, ii) fundamental idiosyncratic shocks, and iii) the effect of the ownership structure. Their main finding suggests that increased ownership by large institutional investors predicts higher volatility and noise in stock prices. Moreover, the authors find that institutional ownership has an impact on return volatility that is different from that of ownership concentration.

Overall, the above theoretical models and empirical evidence reveal that stock return volatility is influenced by two key factors: ownership concentration and ownership by institutional investors. These variables have distinct effects on market dynamics. It is important to note that ownership by institutional investors, which constitutes the second element has been largely overlooked in Greenwood and Thesmar (2011) stock price fragility measure. This is because mutual funds are primarily held by households, while ETFs are owned and traded by a combination of institutional and retail investors (Dannhauser and

Pontiff, 2019).[15] Non-fundamental demand can stem from both retail and institutional investors. We argue that an ETF-based fragility measure is able to partially capture both effects, given the characteristics of investor ownership of ETF shares being split between retail and institutional investors.

2.3 An ETF-based stock price fragility (G^{ETF})

Estimating stock price fragility presents two empirical challenges: i) identifying a source of independent shocks to stock prices that are orthogonal to firm fundamentals and are fully observable, and ii) access to comprehensive data on the ownership structure of assets. The first challenge, theoretically the most relevant, has been extensively explored in the financial economics literature. Beginning with Coval and Stafford (2007), numerous studies employ flow pressure from mutual fund sales as a proxy for non-fundamental price shocks.[16] Among the reasons for using mutual fund data were initial evidence showing that mutual funds mechanically reduce their portfolio holds when faced with significant outflows (i.e., fire sales) and the well-known fact that the vast majority of mutual fund share owners are households that are typically considered less financially sophisticated.[17] Motivated by this evidence, Greenwood and Thesmar (2011) relied on mutual fund data to estimate stock fragility.[18] Although using mutual fund flows as a proxy for non-fundamentally driven demand shocks has been a traditional approach in several empirical studies, as

15 On Appendix 0A4 shows the progressive inclusion of ETFs in 13F institutional investors' portfolios. We also include data on the adoption of leveraged and inverse-leveraged ETFs. We confirm the findings in the literature by showing the widespread use of ETFs by institutional investors.

16 A non-comprehensive list of related studies in empirical asset pricing area include Lou (2012); Edmans et al. (2012); Huang et al. (2021); Dong et al. (2021); Li (2022). See Wardlaw (2020) for a complete discussion of the related literature in empirical corporate finance.

17 According to the 2022 Investment Company Institute (ICI) Fact Book, more than 89% of mutual fund assets in the US were held by households.

18 It's important to highlight that the fragility measure incorporates all mutual fund flows and does not depend on the most commonly used MFFLOW measure introduced by Edmans et al. (2012). MFFLOW aims to capture forced selling activity following large mutual fund outflows. However, Wardlaw (2020) points out that this measure induces a mechanical relation between the measure and raw returns. While Greenwood and Thesmar (2011) approach does not directly suffer from this limitation, concerns that mutual funds flow convey fundamental information remain.

discussed earlier, recent papers have raised concerns about the assumptions we rely on when employing such an instrument. More specifically, i) the proportional trading assumption and ii) the absence of discretionary trades.

For mutual fund flows to serve as an adequate instrument for exogenous price changes, non-fundamental demand shocks should be transmitted to all securities within the fund portfolio. Thus, mutual fund holdings should expand and contract their current positions in response to a demand shock, thereby influencing the prices of their underlying securities. Berger (2022) shows that mutual fund managers, when faced with large outflows, do not sell shares of their portfolio firms in proportion to their current portfolio weights, as assumed by the MFFLOW measure of Edmans et al. (2012). Thus, when empirically tested in a regression framework, the *proportional trading assumption* does not hold and leads to biased coefficient that overstate the effect of mutual fund flows on stock prices. Berger (2022) show that mutual fund managers *systematically* avoid selling poorly performing, illiquid firms with lower growth.

Closely tied to the proportional trading assumption is the assumption that mutual fund flows do not incorporate fundamental information from discretionary trades of fund managers. Huang et al. (2022) reveal that during fire sales[19], mutual fund managers use fundamental information to direct a portion of their sales toward stocks with limited growth prospects (i.e., stocks with high short interest) while opting to sell fewer shares in stocks expected to beat earnings expectations in the next quarter. In line with these findings, Rzeznik and Weber (2022) find evidence that the negative impact of mutual fund fire sales on stock prices is negligible when specialized demand from other funds meets fire sale pressure. In other words, when active mutual funds hold a high valuation of a specific stock affected by fire sales from other funds, they opt to purchase that stock, effectively mitigating the adverse impact of selling pressure.

Overall, recent empirical evidence documents that even when mutual fund managers face selling pressure from significant outflows, they employ discretionary trades as a strategic response. In this process, fund managers introduce a blend of both fundamental (i.e.,

19 In the mutual fund literature, a fire sale event is typically defined as occurring when the fund experiences a net outflow equal to 5% or more of its total net assets (TNA).

discretionary trades) and non-fundamental (i.e., expected or mechanical trades) information into their subsequent trades, ultimately influencing stock prices.

Recent studies suggest that, at most, mutual fund flows are noisy indicators of non-fundamental demand shocks. Motivated by this evidence and the theoretical and empirical findings of Brown, Davies and Ringgenberg (2021), we argue that an ETF-based stock price fragility (G^{ETF}) are unaffected by the documented concerns associated with mutual fund flows because i) ETF primary flows act as reliable signals for non-fundamental demand shocks, and ii) the mechanical arbitrage processes inherent to the creation and redemption of ETF shares mitigate concerns about discretionary trades conveying fundamental information. Furthermore, as previously discussed, this measure can capture the influence of institutional demand on asset prices — a factor that is overlooked by the current methodology.

We follow Greenwood and Thesmar (2011) and propose a fragility measure that employs only information (i.e., fund flows and ownership composition) from the ETFs.

$$G_{it}^{k} = \left(\frac{1}{\theta_{i,t}}\right)^{2} W_{i,t}^{k}\Omega_{t}^{k}W_{it}^{k}, \tag{1.1}$$

Where W_{it}^{k} is the vector of weights of each ETF (Mutual fund) in security i at time t, Ω_t is the conditional variance-covariance matrix of investors' dollar flows at time t, and θ_{it} is a scaling factor, usually proxied by the security's market capitalization.

We further expand the expression in Equation (1.1) to explicitly differentiate between Active and Passive ETFs using the classification of Easley et al. (2021). In this approach, we rewrite the fragility measure to include a term for each type of ETF (i.e., $W^k = W^{Act} + W^{Pas}$ and $\Omega^k = \Omega^{Act} + \Omega^{Pas}$), and a component that considers the holdings-weighted covariance between the two (i.e., $\Omega^{Act,Pas}$), as detailed in the following Equation.

$$G_{it}^{ETF} = \left(\frac{1}{\theta_{it}}\right)^{2} (W^{Act}\Omega^{Act}W^{Act} + W^{Pas}\Omega^{Pas}W^{Pas} + 2W^{Act}\Omega^{Act,Pas}W^{Pas}) \tag{1.2}$$

This specification enables us to empirically investigate the concerns raised by Easley et al. (2021) regarding the impact of the increased activeness of the ETFs on price discovery. This is a key aspect to consider, given that the evolution of the ETF industry has been marked by the introduction of a wide variety of heterogeneous products (Ben-David et al., 2023). We argue that our measure helps to shed light on these open questions regarding the impact of ETF trading activity on overall market efficiency. While G^{ETF} represents a potentially significant improvement in the estimation of stock price fragility, we are aware that it still has some limitations. Similarly, as Greenwood and Thesmar (2011), we rely on the assumption of uncorrelated liquidity-driven trades from investors outside our sample.

3 Data and variable construction

We first estimate the original measure of Greenwood and Thesmar (2011) to assess whether an ETF-based fragility measure proves to be a better measure. To create the required database of mutual funds and ETFs, we collected and combined data from several sources, as discussed in detail in the following section.

3.1 Mutual funds data

Our sample consists of US mutual funds from 1989 to 2018. Furthermore, in several tests, we partition the sample period into two distinct periods: from 1989 to 2008 and 2009 to 2018. To determine the sample periods, we followed two criteria. First, we closely follow Greenwood and Thesmar (2011) and begin our sample period from the last quarter of 1989 to the last quarter of 2008. This allowed us to replicate their estimations (i.e., *in-sample results*). Second, although the first US-listed ETF, the SPDR, was launched in 1993, ETFs became relevant investment vehicles in terms of the number of funds, assets under management (AUM), and participation in total volume traded in the period 2007-2009 (Madhavan, 2014). This period matches the end of Greenwood and Thesmar (2011) sample period. Thus, to test the explanatory power of our proposed measure, we focus on the latter part of our sample, starting in 2009, which allows us to capture the increase in ETF activity and perform an *out-of-sample* test of the original fragility measure in the context of the rise of passive investing.[20]

We collect fund returns and total net assets (TNA) from the Center for Research in Security Prices (CRSP) Mutual Fund Database, We then collect mutual funds' quarterly holdings data from the Thomson/Refinitiv Mutual Fund Database (*s12*). We merged both databases by using the MFLinks database. We follow Doshi et al. (2015) to identify and select US domestic equity mutual funds and Pavlova and Sikorskaya (2023) to create the mutual funds holdings database.[21] Mutual funds with less than $ 5 million dollars in total net assets were excluded.[22] Our fund sample includes 3,871 distinct US domestic equity mutual funds with 138,316 fund-quarter observations from the 1989-2018 period.

As commonly done in previous studies, we limit our holdings sample to include only stocks whose market capitalization is equal to or above NYSE market capitalization decile 5.[23]

20 For instance, Madhavan (2014) highlights that the US ETF industry assets under management rose from $70 billion in 2000 to $1.7 trillion by mid-2014. Glosten et al. (2021) mention that an increase in market participation has accompanied the rise in AUM since approximately 30% of US equity trading volume is attributable to ETFs. Regarding relocation from other investment vehicles, in 2017, the demand for equity ETFs resulted in $186 billion net share issuance, whereas domestic equity mutual funds had net redemptions of $236 billion.

21 We describe the merging of holdings databases and selecting mutual funds process in detail in Section OA1. of the Appendix.

22 While Greenwood and Thesmar (2011) do not explicitly impose this filter, we follow Fama and French (2010) and include the 5 million in TNA to control for the effects of incubation bias Evans (2010).

23 Greenwood and Thesmar (2011) highlight two advantages of applying this filter: (1) Simplifies matrix computations (2) ensures that the estimation focuses on stocks of greater dollar importance more likely to be affected by liquidity-driven trades. Similarly, Francis et al. (2021) highlights that an empirical issue in fragility estimation is that it becomes highly noisy if a stock has low mutual fund ownership, which is precisely the case for stocks with smaller market capitalization. Thus, limiting the sample of stocks included in the holdings data reduces the possibility of distortions introduced by those noisy estimations.

3.2 Exchange-traded funds (ETFs) data

To create our primary ETF database, we begin by reviewing the list of ETF identifiers from Brown, Davies and Ringgenberg (2021).[24] We extend this database to include ETFs up to the last quarter of 2018. We combined these data with information from Bloomberg and CRSP. From Bloomberg, we obtain data on outstanding shares and funds' net asset value (NAV). When data were missing or incomplete, we supplemented them with data from CRSP. Additionally, we account for any splits or reverse splits conducted by ETFs, making adjustments based on historical stock split information provided by Bloomberg.

We collect data on ETFs' prices and returns from CRSP. We obtain data on ETFs portfolio holdings using the Thomson/Refinitiv Mutual Fund Holdings (*s12*) and complement it with CRSP Mutual Fund Database data. Our ETF data sample covers the period from 2000 to 2018. In total, our sample includes 1,096 distinct ETFs for which we have both holdings and price/return data.

We impose the same filters on stocks in the ETF holdings database as those used in the mutual funds' sample to ensure comparability. Specifically, we retain stocks with market capitalization falling within the 5th decile or above of the NYSE breakpoint size deciles.

3.3 Estimating Fragility

We estimate stock price fragility as detailed in Equation (1.1). The two main components of the fragility measure are the security ownership composition and the variance-covariance matrix of investors' non-fundamentally driven trades. The ownership structure is proxied by a vector of each mutual fund (ETF) portfolio allocation to stock i relative to the fund's total net assets (net asset value), as described in the following expression:

$$w_{i,j,t} = \frac{n_{i,j,t} P_{it}}{a_{j,t}}$$

24 We thank David Brown for providing us with these data.

where $n_{i,j,t}$ is the number of securities i held by mutual fund (ETF) j at time t, P_{it} is the price of security i, and $a_{j,t}$ is the total j mutual fund (ETF) total net assets (net asset value).

MF-based Fragility (G^{MF})

For our mutual fund sample, we calculate the *percentage flows* for each mutual fund i at the end of quarter t as follows:

$$MFFlow_{j,t} = \frac{TNA_{j,t} - TNA_{j,t-1}(1 + R_{j,t})}{TNA_{j,t-1}}$$

where $TNA_{j,t}$ is the mutual fund j Total Net Asset at the end of quarter t and $R_{j,t}$ is the fund's total return over that same quarter. We winsorize this variable at the 1%. Because we employ the dollar positions of each fund in each security in matrix W, we require the covariance matrix Ω_t to be expressed in dollar terms.We follow Greenwood and Thesmar (2011) and rescale the Ω_t matrix by funds assets at time t to obtain an estimate $\hat{\Omega}_t$:

$$\hat{\Omega}_t^{MF} = diag(TNA_{j,t})\Omega_t diag(TNA_{j,t})$$

For each quarter t, we calculate $\hat{\Omega}_{j,t}$ using a five-year rolling window estimation starting from 1984:Q1. Finally, fragility is estimated as shown in the following equation:

$$G^{k_{it}} = \left(\frac{1}{\theta_{i,t}}\right)^2 W_{i,t}^k \Omega_t^k W_{it}^k, \tag{1.3}$$

where K refers to either mutual fund or ETF data.

ETF-based Fragility (G^{ETF})

The elements of matrix W are estimated in the same way as with the mutual fund data. Thus, this vector represents the ETFs portfolio allocation weights to each stock i multiplied by the stock's i price and divided by the total net assets of ETF k. Similar to the methodology applied for MF-based fragility, we estimate ETF flows as percentage changes. In the context of the ETF primary market, this involves calculating the change in shares outstanding for each ETF k at each time t,

$$ETFFlow_{k,t} = \frac{SharesOutstanding_{j,t}}{SharesOutstanding_{j,t-1}} - 1$$

As performed with the mutual fund data, we normalize the ETF fund flows covariance matrix $\Omega_{k,t}$ as follows:

$$\hat{\Omega}_k^{ETF} = diag(NAV_{k,t})\Omega_{k,t}diag(NAV_{k,t})$$

To ensure consistency with the *MF-based* fragility estimation process, we estimated $\hat{\Omega}_k$ using a five-year rolling window[25]. Before 2005, ETF holdings represented only a negligible percentage of a stock's outstanding shares (Da et al., 2020). Consequently, utilizing data from this period would likely result in imprecise values for our measure. To address this concern and ensure the reliability of our estimations, we start reporting ETF-based fragility values from 2009 onwards. This approach guarantees the inclusion of a more substantial dataset and helps mitigate the potential for noisy results. We estimate the *ETF-based* fragility (G^{ETF}) based on the specification as in Equation (1.1).

[INSERT FIGURE I.1 HERE]

Figure I.1 depicts the total new cash flows to mutual funds and ETFs. In the early sample period, mutual funds mostly experienced inflows. However, beginning in 2006,

25 This specification differs from the one used by Greenwood and Thesmar (2011). They calculate the $\Omega_{k,t}$ variance-covariance flow matrix at time t by including all data from 1989 to each quarter t. We adopt a methodology in line with Francis et al. (2021) and Huang et al. (2022) and employ a five-year rolling window to estimate $\hat{\Omega}_k$. This approach accounts for the time-varying nature of the flow variance-covariance matrix and ensures the inclusion of the most up-to-date information. Huang et al. (2022) shows that varying the rolling-window estimation to two, three, or five years has little effect on the results.

mutual funds on aggregate experienced outflows, as shown in Panel A. In contrast, as shown in Panel B, ETFs experienced significant inflows over the years, especially in the later part of the sample period. Our results are consistent with those of Dannhauser and Pontiff (2019).

[INSERT TABLE I.1 HERE]

Table I.1 presents the descriptive statistics of our Mutual Funds (Panel A) and ETF (Panel B) samples. In any given year, our sample includes more mutual funds (1,134) than ETFs (334). The average ETF is larger in terms of assets under management (AUM) and holds a larger number of stocks. This difference is most likely driven by the presence of very large ETFs.[26] Thus, the median fund size provides a more accurate picture, showing that the median mutual fund ($58 million) is slightly larger than the median ETF ($ 48 million) Also, as detailed in previous studies, we observe a significant increase in ETF ownership over time (Da and Shive, 2018; Glosten et al., 2021). Specifically, it increased from 0.63% on average in the first part of the ETF sample period to 3.96% in the later part of our sample, as shown in Panel B of Table I.1. As described by Greenwood and Thesmar (2011), for fragility to be a reliable forecaster of future volatility, a firm's ownership composition should not be too volatile from one quarter to the next. We test this assumption by estimating the autocorrelation coefficient of the number of owners. This is the number of funds that own the same stock. Panel C of Table I.1 shows that the one-quarter-autocorrelation coefficient for the number of mutual fund owners is 0.861, while for ETFs is 0.832. Moreover, we observe that the autocorrelation coefficient value stays above 0.70 for both samples up to a lag of four quarters. Our results for the mutual fund sample closely follow those reported by Greenwood and Thesmar (2011). Moreover, we provide evidence that the ownership structure is highly persistent *also* for our sample of ETFs. These results provide additional evidence in favor of the suitability of ETF data for estimating stock price fragility.[27]

26 Easley et al. (2021) document that by 2020, the three largest ETFs were: Vanguard Total Stock Market Shares Index ETF (VTI), the iShares S&P 500 Index ETF, and the SPDR (SPY) with assets under management of $216.4, $253.4, $337.2 billions, respectively.

27 This requirement on the *persistence of ownership* of sample firms can also means that if we observe a

Table I.2 shows the descriptive statistics of the variables that compose the fragility measure as well as for the square root of MF-based and ETF-based fragility.[28] Panel A of Table I.2 shows that the number of mutual funds and ETFs holding the same stocks increased over time, particularly in the ETF sample for the later part of our sample period. On average, stocks within the mutual fund sample are held by 50 funds, whereas in the ETF sample, this figure averages approximately 25 funds.

[INSERT TABLE I.2 HERE]

Panel B of Table I.2 provides insights into the time-series variation of flow volatility, estimated as the standard deviation of percentage mutual fund (ETF) flows. The volatility of mutual fund flows exhibited an increase in the initial segment of our sample period from 1989 to 2009, which is consistent with the findings of Greenwood and Thesmar (2011). However, volatility shows a notable decline in the out-of-sample period from 2010 to 2018. Conversely, the volatility of ETF flows experienced a substantial increase over the entire sample period, particularly in the later period of 2014-2018. A potential explanation for this behavior is the *flow hedging* activity of active equity funds. Dou et al. (2022) find that active equity funds hedge against common flows by tilting their portfolios toward low-flow beta stocks.

Concerning the correlation between fund flows, Panel C of Table I.2 shows a decrease in the mean values for the mutual funds and ETF sample. Nonetheless, after an initial decrease, the correlation among ETF flows remained fairly stable for 2009-2018. It is worth mentioning that both the bottom (p25) and top (p75) quintiles of flow correlation are considerably similar for both mutual fund flows and ETF flows over the full sample.

fund's ownership of stock i on quarter t, we require that same stock i to be part of the funds portfolio on quarter $t+1$. Thus in principle, this is less of a concern for ETFs since index-tracking ETFs hold most of the securities than compress the benchmark index. This should be a major concern also for active ETF since most of such funds deviate from their benchmarks by changing their weighting scheme rather than the selection of stocks to hold (**?**Easley et al., 2021)

28 Greenwood and Thesmar (2011) prefer to use the square-root of fragility because it is proportional to variance. Moreover, the authors define fragility as the conditional expected variance of flow-driven net buys into a stock.

Panel D of Table I.2 summarizes the square root value of fragility. Notably, from 1989 to 2009, the mean value for mutual fund fragility exhibited a substantial increase, soaring from 0.039 to 0.143. However, in the later part of our sample period, this value declined averaging 0.102. In contrast, the mean $\sqrt{G}$ continued to rise steadily for the ETF sample.

A potential concern is that the estimated fragility values may be influenced by potential differences in the characteristics of the stocks included in each sample. We address this concern in Table I.A1 of the Appendix. In this analysis, we sorted stocks into five quintile portfolios based on their MF-based G^{MF} (Panel A) and ETF-based G^{ETF} (Panel B) for each quarter t. Subsequently, we calculated the time-series averages of the cross-sectional means for various stock-level characteristics. Our findings confirm several results of Greenwood and Thesmar (2011). We observe that fragility does not exhibit a monotonous correlation with the number of owners. This underscores the notion that fragility is contingent on both the composition of ownership and the correlation between owners' trading decisions. Surprisingly, while we confirm that smaller firms and growth stocks with lower B/M ratios exhibit higher MF fragility, we do not find the same pattern when examining the quintiles for ETF fragility. This aligns with the findings of Brown, Davies and Ringgenberg (2021), who noted that ETF flows convey information distinct from mutual funds, as ETFs are utilized by a diverse cross-section of investors, including retail investors, institutional investors, and hedge funds, thereby reflecting a broader range of trading decisions.

4 Empirical Results

In this section, we present our primary analysis to validate the proposed ETF-based fragility as a measure of non-fundamental risk. To this end, we test whether the measure is useful for forecasting flow-induced trading volatility in a regression framework. Additionally, we expand our initial setting to incorporate the influence of institutional investors' ownership on stock price volatility and explore the implications related to the proposed ETF-based fragility measure. Finally, we consider the heterogeneity of the ETF industry and decompose ETF-based fragility to explore the role of active and passive ETFs in our earlier findings.

4.1 Fragility and stock return volatility

For fragility to be a useful measure of non-fundamental risk, it must forecast mutual fund (ETF) induced trading stock return volatility. We test this predictive power by estimating the following Fama and MacBeth (1973*a*) regression.[29]

$$\sigma_{i,t+1} = \alpha + \beta\sqrt{G}_{i,t} + \delta Z_{i,t} + \mu_{i,t+1} \tag{1.4}$$

Equation (1.4) follows the main specification employed by Greenwood and Thesmar (2011), where $\sigma_{i,t+1}$ is the one-quarter-ahead standard deviation of daily stock returns. $Z_{i,t}$ represents the vector of control variables, including the log of unadjusted stock price, the natural logarithm of market capitalization, the ratio of book equity to market equity, the past 12-month stock return, lagged skewness of stock returns, the log of firm's age (in months) and share turnover. The coefficient β measures the relationship between the current quarter's fragility and the next quarter's stock return volatility. Therefore, a positive and statistically significant value of β indicates that an increase in stock fragility in the current quarter would forecast an increase in stock return volatility in the next quarter. Table I.3 presents the results from the regression model. We first predict future volatility using $\sqrt{G^{MF}}$ and its components across the entire sample period. The results of this test are presented in the first four columns of the table. To evaluate the *out-of-sample* performance of $\sqrt{G^{MF}}$, we replicate these four regression specifications for the latter portion of the sample period, spanning from 2009 to 2018. For comparability and to test our proposed ETF-based fragility measure, we run the same regression specifications on $\sqrt{G^{ETF}}$ for the same period.

[INSERT TABLE I.3 HERE]

Column (1) of Table I.3 provides a first formal test of the relationship between fragility and future volatility for the sample period between 1989 and 2018. Consistent with previous findings, a positive and statistically significant relationship exists between $\sqrt{G^{MF}}$

29 We perform Fama and MacBeth (1973*a*) regressions to control for the effect of common trends like increasing ownership of Mutual Funds and ETFs (Da et al., 2020).

and next-quarter daily return volatility. Nonetheless, it's worth noting that the reported coefficient is smaller than the value documented by Greenwood and Thesmar (2011) who reported a value of β equal to 0.696. In our analysis, we find this coefficient to be 0.459. Furthermore, when focusing on the latter part of our sample, as reported in Column (5), we observe a substantially reduced coefficient of 0.325, almost half of the coefficient reported by Greenwood and Thesmar (2011).

In columns (2) and (3), we examine the relationship between specific components of fragility, namely ownership (IO) and concentration, and expand the initial specification by introducing additional control variables. The results indicate a positive relationship between mutual fund ownership and future volatility[30], and that the explanatory power of fragility extends beyond pure ownership concentration, as proxied by the Herfindahl index. In column (4), we check whether the predictive power of $\sqrt{G^{MF}}$ remains robust when accounting for a comprehensive set of control variables, including the lagged dependent variable. This is important because volatility tends to exhibit a high persistence over time. The results reveal that the coefficient of fragility decreases significantly to 0.072 (t-stat = 2.75). Moreover, if we focus on the latter part of our sample, the coefficient drops further to 0.018, reaching only marginal significance at the 10% level (t-stat = 1.70). These findings suggest that the forecasting power of $\sqrt{G^{MF}}$ on volatility significantly diminishes over time.

We repeat the analysis conducted in columns (1) to (4) using the ETF-based fragility and report our findings in columns (9) to (12). Our initial test shows that $\sqrt{G^{ETF}}$ is a strong positive predictor of the next-quarter standard deviation of daily stock returns with a β equal to 0.825 (t-stat = 7.76). Notably, this coefficient is significantly higher than that of $\sqrt{G^{MF}}$ for the same period, which stands at 0.325. In column (10), we corroborate the findings of Ben-David et al. (2017) regarding the positive relationship between higher ETF ownership and increased volatility. Interestingly, even when we incorporate the full set of control variables, as shown in column (12), the relationship between $\sqrt{G^{ETF}}$ and future volatility remains strongly positive and statistically significant, as we obtain a coefficient value of 0.338 (t-stat = 5.93) Our results provide evidence that an ETF-based measure of fragility is a strong predictor of next quarter volatility. Moreover, our estimates indicate

30 As previously documented by Sias (1996) and Bushee and Noe (2000).

that the original measure of Greenwood and Thesmar (2011) lost forecasting power over time.

[INSERT TABLE I.4 HERE]

Next, we more directly investigate the conjecture that ETF-based fragility is a robust measure of non-fundamental demand risk. To this purpose, Table I.4 presents an analysis of the volatility predictors for the later part of the sample period. We report the results of regressions in which we assess the influence of both $\sqrt{G^{MF}}$ and $\sqrt{G^{ETF}}$, along with a set of control variables, on the next-quarter daily return volatility. As previously mentioned, ETFs exhibit a distinct ownership composition to mutual funds, held nearly equally by households and institutional investors. Therefore, the effect of non-fundamentally driven demand captured by G^{ETF} is likely to differ from that of G^{MF}. In other words, while the ETF-based measure may capture a similar component to the MF-based fragility, namely, retail investors' demand, it is also possible that it incorporates the influence of institutional investors' demand.

To explore these differences, we repeat the analysis reported in Table I.3 including both $\sqrt{G^{ETF}}$ and $\sqrt{G^{MF}}$ simultaneously. In Column (1) of Table I.4, we test the joint effect of both fragility measures on future volatility. While we observe that daily volatility is positively and statistically significantly correlated with both measures, the coefficient of $\sqrt{G^{ETF}}$ is significantly larger than that of $\sqrt{G^{MF}}$. Moreover, the coefficient of $\sqrt{G^{MF}}$ is smaller than that reported in Column (5) of Table I.3. This finding suggests that the ETF-based fragility measure captures, at least to some extent, an effect similar to but above and beyond that measured by the MF-based fragility. Column (2) shows that the mutual funds and ETF ownership are both positively correlated with future volatility. Columns (3) and (4), include control variables to test the robustness of our findings. The results show that, with the full suite of controls, the coefficient on $\sqrt{G^{MF}}$, 0.009, is no longer statistically different from zero (t-stat = 1.03). In contrast, the coefficient of $\sqrt{G^{ETF}}$, 0.426, remains highly significant (t-stat = 7.95).

[INSERT TABLE I.5 HERE]

To address concerns regarding the possibility that the regression settings influence our results, we also present panel fixed effects estimates, consistent with previous studies (Ben-David et al., 2021*a*; Friberg et al., 2022). We include firm and year-quarter fixed effects and adjust the standard errors for clustering at the firm level. The sample period employed in this analysis spans from the first quarter of 2009 to the last quarter of 2018. We follow Friberg et al. (2022) specification and test the relationship between stock price fragility and future stock return volatility within three subsets: (i) the full sample, (ii) a subset comprising observations with a minimum of 20% institutional ownership, and (iii) a sample of firms with market capitalization above the median. These subsets are designed to assess the robustness of our findings and ensure that they are not influenced or concentrated in firms with dispersed and relatively low levels of institutional ownership or by smaller firms. We report the results of this analysis in Table I.5.

Our findings reported in columns (1), (5), and (9) closely match those of Friberg et al. (2022).[31] We observe that $\sqrt{G^{ETF}}$ is positive and statistically significant in all three subsets, as detailed in columns (2), (6), and (11). Moreover, in line with our previous findings, the magnitude of the coefficient of $\sqrt{G^{ETF}}$ is significantly larger than that of $\sqrt{G^{MF}}$. We then include two sets of control variables: those used by Friberg et al. (2022) (natural log of market capitalization and the inverse of stock price) and those employed by Greenwood and Thesmar (2011) as specified in Table I.4. In columns (4), (8), and (12) we observe that when including the set of controls specified by Greenwood and Thesmar (2011) in the regressions, our results are similar to those obtained in the Fama-Macbeth regressions: $\sqrt{G^{MF}}$ loses all statistical significance while $\sqrt{G^{ETF}}$ remains positively and statistically significantly related to future stock price fragility. In summary, this analysis provides further evidence that the proposed ETF-based fragility measure is a robust and strong predictor of future return volatility.

Lou (2012) was among the first to propose a capital-flow-based explanation for some return predictability patterns. By aggregating flow-induced trading by mutual funds, the

31 The disparities we observe might potentially be attributed to differences in sample periods since Friberg et al. (2022) conducted their analysis spanning from 2001 to 2017. In untabulated results, we replicated our analysis for this identical time frame and obtained results that closely mirror those reported.

author finds that such demand shocks can partially explain stock price momentum. More recently, Li (2022) documents that price pressure from mutual fund investor demand explains approximately 30% of fluctuations in the Fama-French size and value factors. Thus, fragility may predict the volatility of risk factors themselves.[32] Thus, we also explore the relationship between fragility and volatility of returns in excess of several asset pricing factors. For excess return volatility, we estimate risk-adjusted returns using three models: (1) market-adjusted returns, (2) the Fama and French (1993) three factors model, and (3) the Fama and French (1993) model augmented with the Carhart (1997) momentum factor. Additionally, we estimate the DGTW-adjusted returns as in Daniel et al. (1997). The results of this analysis are shown in Table I.6.

[INSERT TABLE I.6 HERE]

In Panel A, our results corroborate those of Greenwood and Thesmar (2011) as we observe that the coefficient of $\sqrt{G^{MF}}$ is slightly smaller than that obtained when analyzing total return volatility. Furthermore, we note a significant decrease in the magnitude of this coefficient in the latter part of our sample period, 2009-2018. We observe a similar pattern in the ETF sample, as shown in the first part of Panel B. Subsequently, we examine the relationship when we include both fragility measures simultaneously. We see that the coefficients of $\sqrt{G^{ETF}}$ are significantly higher than those of $\sqrt{G^{MF}}$. Moreover, the inclusion of $\sqrt{G^{MF}}$ only marginally reduced the coefficient of $\sqrt{G^{ETF}}$. These results highlight the statistically significant association between fragility and excess return volatility for both fragility measures. However, it is worth noting that the ETF-based measure exhibits a stronger predictive power.

In summary, the analysis carried out in this section is consistent with the argument that an ETF-based fragility measure strongly predicts future stock return volatility. These empirical observations are consistent with the evidence that shows that ETF primary market flows reflect non-fundamental demand shocks.

32 Following this rationale, Greenwood and Thesmar (2011) argue that the predictability of fragility on *excess return volatility* is expected to yield weaker results.

4.2 Fragility and institutional investors' ownership

In this section, we study the determinants of the superior forecasting power of G^{ETF} on stock return volatility. We argue that ETF primary market flows potentially channel excess demand not mainly from one class of investors, as is the case with mutual fund flows, but from a broader cross-section of market participants including retail investors, institutional investors, and hedge funds.

[INSERT FIGURE I.2 HERE]

Figure I.2 shows a significant increase in 13F institutional investors over the years, paralleled by a corresponding rise in the adoption of ETFs in their portfolios. By the end of 2000, approximately 20% of institutional investors included at least one ETF in their holdings. However, by the end of 2020, this proportion had surged to approximately 70% of all institutional investors.

[INSERT FIGURE I.3 HERE]

In Figure I.3, we expand this evidence and analyze the time-series adoption of ETFs in 13F institutional investors' holdings. Moreover, considering different investor types, we observe that investment advisors, mutual funds, quase-indexers, and transient institutions are among the institutional investors that have the most extensively incorporated ETFs in their portfolios. Interestingly, both short- and long-horizon investors, as defined by Yan and Zhang (2009*a*), have similarly integrated ETFs into their portfolios, with a recent trend of heightened adoption by long-term investors. In Appendix 7, we present data on leveraged and inverse-leveraged ETFs. We document that long-term investors, investment advisors, and quasi-indexers have consistently incorporated this investment vehicle into their portfolios over the years. By the end of 2021, nearly 50% of investors in each of these categories reported having at least one leverage or inverse-leveraged ETF in their portfolios. In summary, ETFs are widely included in 13F institutional investors' holdings.

In a recent study, Ben-David et al. (2021*a*) shows that increased stock ownership by large institutional investors induces higher return volatility and greater noise in stock prices. This heightened volatility is primarily attributed to investors' inability to diversify idiosyncratic shocks among their subunits. In other words, subunits within large institutional investors tend to exhibit correlated behavior when faced with such shocks, amplifying their impact on asset price volatility. Considering the widespread inclusion of ETFs in the portfolios of 13F institutional investors, it is plausible that an ETF-based fragility measure may capture the price pressure resulting from institutional investors trading ETFs.

Prior literature shows that institutional investors engage in ETF trading for diverse reasons. For instance, Huang et al. (2020) show that hedge funds regularly implement a *long-the-stock/short-the-ETF* strategy relying on industry ETF to hedge their industry risk exposure. Similarly, Karmaziene and Sokolovski (2022) and Li and Zhu (2022) find evidence that arbitrageurs employ ETFs to circumvent short-sale bans and constraints. On the contrary, Sherrill et al. (2017) document a negative association between large ETF positions and mutual fund performance. The authors find that underperformance is mostly due to mutual funds' poor timing ability to implement investment strategies based on ETFs. Sherrill et al. (2020) show that many active mutual funds hold passive ETFs to reduce their cash holdings while relying on active ETFs to enhance fund performance. Nevertheless, the evidence supporting the latter proposition is somewhat limited.

In this section, we test the hypothesis that an ETF-based measure of stock price fragility to some extent captures the impact of institutional investor trading. We introduce variables within a regression framework that considers ownership by large-, mid-, and small-sized institutional investors based on their assets under management. Our objective is to assess the influence of these variables on the predictive power of G^{MF} and G^{ETF} on future return volatility. We follow Ben-David et al. (2023) specification and perform the following panel regression:

$$\sigma_{i,t+1} = \beta_1 \text{TopIO}_{i,t} + \beta_2 \text{MidIO}_{i,t} + \beta_3 \text{BottomIO}_{i,t} + \delta Z_{i,t} + \beta_4 G_{i,t} + \alpha_i + \theta_t + \mu_{i,t+1} \quad (1.5)$$

where $\sigma_{i,t+1}$ is the next quarter t stock i volatility. $\text{TopIO}_{i,t}$ is the fraction of shares outstanding collectively held by the top institutions ranked based on the money value of portfolio holdings over the previous four quarters. $\text{BottomIO}_{i,t}$ represents the aggregate stock's i ownership of the smallest institutional investors whose aggregate money holdings value equals that of the top institutions. $\text{MidIO}_{i,t}$ is collective ownership by institutions not classified as top neither as bottom. $Z_{i,t}$ is the vector of control variables that include the log of market capitalization, book-to-mark ratio, past 6-month momentum returns, the inverse of price ratio (1/price), and the Amihud illiquidity measure (Amihud, 2002). α_i is the stock fixed effect, and θ_t is the time (calendar year-quarter) fixed effect.

[INSERT TABLE I.7 HERE]

Table I.7 shows the results for two specifications: considering the Top 3 and Top 10 institutional investors. *Top IO* represents the aggregate ownership of the largest institutional investors in a given stock. For the *top 3 Institutions* specification, we sum the ownership of the top 3 institutions, whereas for the *top 10 Institutions* we sum the ownership of the top 10 institutions. We also perform the regression for the full sample and repeat the analysis for the later part, 2009 - 2018. In columns (1) and (2), our results closely follow those reported by Ben-David et al. (2021*a*). We observe a positive and statistically significant association between ownership by large and medium-sized institutional investors and stock volatility. This relationship is negative for bottom institutional ownership, consistent with the view that large investors affect volatility. Additionally, the coefficient on G^{MF} is also positive and significantly related to future stock price volatility.

Ben-David et al. (2021*a*) argue that including stock price fragility has little impact on their analysis because each measure captures two partially independent effects. In other words, the influence of concentration (i.e., fragility) and large institutional investors' limitations in diversifying away demand shocks to their holdings (i.e., granularity) have different impacts on stock price volatility. As previously discussed, we argue that an ETF-based fragility measure partially channels the effect of Institutional Ownership on stock price volatility given that ETFs are owned and traded by both retail and institutional investors. In Column (4), we test this hypothesis and replace G^{MF} with G^{ETF}. For comparability, we limit our analysis to the second part of our sample (2009-2018). We find that the coefficient on large institutional ownership and G^{ETF} are positive and statistically significant. However, the coefficients of the *mid* and *bottom IO* are smaller and indistinguishable from zero. This effect is observable if we change our setting and observe the top 10 institutional ownership, as detailed in Column (7).

[INSERT TABLE I.8 HERE]

In columns (5) and (8) we add both to our main regression model and find results similar to those documented previously. That is, the coefficient of G^{MF} loses statistical significance, while G^{ETF} remains economically and statistically significant. We replicate the results for the alternative grouping of top institutional investors, specifically the Top 5 and Top 7 Institutions in Table I.8. Our results remain qualitatively the same.

Our evidence confirms our hypothesis that G^{ETF} measure partially captures the effect of institutional investors' demand on volatility, whereas G^{MF} does not capture. This analysis suggests that only using G^{MF} and overlooking the impact of institutional ownership on return volatility could introduce a significant bias in estimating stock price fragility.

4.3 ETF activeness and stock price volatility

A valid concern in our empirical analysis is that we combine data from two *distinct* investment vehicles. In terms of their investment mandates, we compare *active* mutual funds while ETFs are, in principle, passively managed. We follow Easley et al. (2021) and estimate their *Activeness Index* to determine which fraction of our sample of ETFs can be considered active. According to Easley et al. (2021), the activeness of an ETF can be classified into two categories: *active-in-form* and *active-in-function.* The former refers to ETFs designed to generate alpha by selecting holdings that deviate from a chosen benchmark. The latter pertains to funds used as building blocks of active portfolios by choosing benchmarks that differ from the market. This classification allows us to consider both ETFs marketed by fund sponsors as seeking to outperform the market and those utilized by investors as components of their active strategies.

$$\text{ActivenessIndex}_{\text{i,t}} = \sum_{s=1}^{N} w_{i,s,t} - w_{market,s,t} \tag{1.6}$$

Where $w_{i,s,t}$ is the weight of stock s in fund's i's portfolio at time t and $w_{market,s,t}$ is the weight of stock s in the value-weighted portfolio of all US listed stocks (i.e., the market portfolio).

We illustrate the composition of ETFs and their trading activity based on the median level of their *activeness index*. ETFs with activeness index values above the median value are considered active. Those below the median value are classified as passive. ETFs with values located in the top (bottom) quintile are considered very active (passive). In Table I.9 we report descriptive statistics on the activeness index value for our full sample, for several subsets, and grouped by number of funds and aggregate assets under management (AUM).

[INSERT TABLE I.9 HERE]

The mean activeness index value is between 87% to 90%. In other words, the mean ETF in our sample is highly active. If we focus on the number of funds, over 94% are classified as either moderately active or very active. In terms of AUM, approximately 70% is managed by active ETFs. For our larger sample of ETFs, we corroborate the findings of Easley et al. (2021) and show that most ETFs can be classified as active investment vehicles. Furthermore, our findings align with those of **?**, who documented that the evolution of the ETF industry has been marked by the emergence of niche, highly specialized products, including sector, thematic, industry, and smart-beta ETFs.

Is it possible that more active ETFs drive our results?. While Brown, Davies and Ringgenberg (2021) do not distinguish between ETFs based on their activeness index value, Easley et al. (2021) expressed concerns about the potential negative impact of the increasing activeness of ETFs on price discovery. Thus, it is plausible to consider that more active ETFs could play a particularly significant role in propagating fragility, as they may attract a greater number of short-term, speculative trades. We follow Easley et al.

(2021) and split our sample according to the activeness index (50% threshold), since this cutoff most likely includes both *active-in-form* and *active-in-function* ETFs. Then, we re-estimate the ETF fragility as detailed in Equation 2 and replicate the main specifications of Tables I.4 and I.6, considering the decomposition of G^{ETF} into active and passive parts.

[INSERT TABLE I.10 HERE]

Column (1) of Table I.10 shows that most of the observed relationship between G^{ETF} and volatility stems from the active ETFs component. Column (2) examines the same relationship if we include G^{MF} while Column (3) shows the results when we include the full set of control variables. Our results confirm the concerns raised by Easley et al. (2021) regarding the role of increased ETF activeness in price informativenes. We show that the active ETF component of the ETF-based fragility measure is responsible for most of the observed relationship between fragility and future stock return volatility.

5 Conclusion

Wardlaw (2020) advocates reevaluating the empirical approach employed to measure non-fundamental price changes. The author raises concerns about the use of noisy, low-frequency data, such as mutual fund flows, for this purpose. Moreover, recent studies challenge assumptions supporting the use of mutual fund flows.

In our study, we turn to ETF primary market flows. Motivated by empirical and theoretical evidence showing that they clearly signal non-fundamentally driven demand shocks (Brown, Davies and Ringgenberg, 2021), we document that relying on this data significantly improves the estimation of stock price fragility (Greenwood and Thesmar, 2011) while avoiding the criticism and limitations surrounding the use of mutual fund flows data. We find that an ETF-based fragility measure strongly predicts stock return volatility. Moreover, given the growing concentration of equity holdings in a few institutional investors, whose ownership ties closely to stock return volatility as evidenced in the literature (Koijen and Yogo, 2019*a*; Ben-David et al., 2021*a*), it is plausible that a fragility measure based on mutual funds may fail to account for this effect. Our findings show that an ETF-based fragility measure partially captures the effects of institutional ownership on stock volatility. These results are supported by evidence of increased ownership of ETFs by institutional investors (Dannhauser and Pontiff, 2019). Additionally, we address recent concerns about the effect of increased ETF activeness on return's volatility (Easley et al., 2021) and show that most documented effects stem from active ETFs. Overall, our findings offer a comprehensive view of the underlying dynamics of stock price fragility.

Our results have implications for empirical asset pricing studies. In particular, they inform the debate on the impact of non-fundamentally driven demand shocks on stock return volatility. Although our approach does not completely resolve the limitations associated with empirically estimating stock fragility, it represents a method not affected by many criticisms surrounding the use of mutual fund flows, thus offering researchers a more accurate proxy for assessing firm-level exposure to non-fundamental demand risk. In the broader context, our findings contribute to the ongoing discussion within the literature examining the repercussions of the rise in passive investments on overall market efficiency, a matter of great interest to policymakers and investment managers.

6 Tables and Figures

Figure I.1: Flows to Equity Mutual Funds and Exchange-Traded Funds (ETFs)

This figure plots the total new cash flows to our sample of equity mutual funds in Panel A and to the exchange-traded funds (ETFs) in Panel B. We include only stocks whose CRSP share code is 10 and 11 (ordinary common shares). Also, we exclude firms with stock prices less than USD $5 to reduce the effects of microcaps. The variables Days-ADV, PSO, and turnover are winsorized at the 1% and the 99% levels. The sample period is from 1989:Q4 to 2018:Q4. The sample period for mutual fund data covers the period from 1989:Q4 to 2018:Q4. For the ETF data, the sample is from 2000:Q1 to 2018:Q4

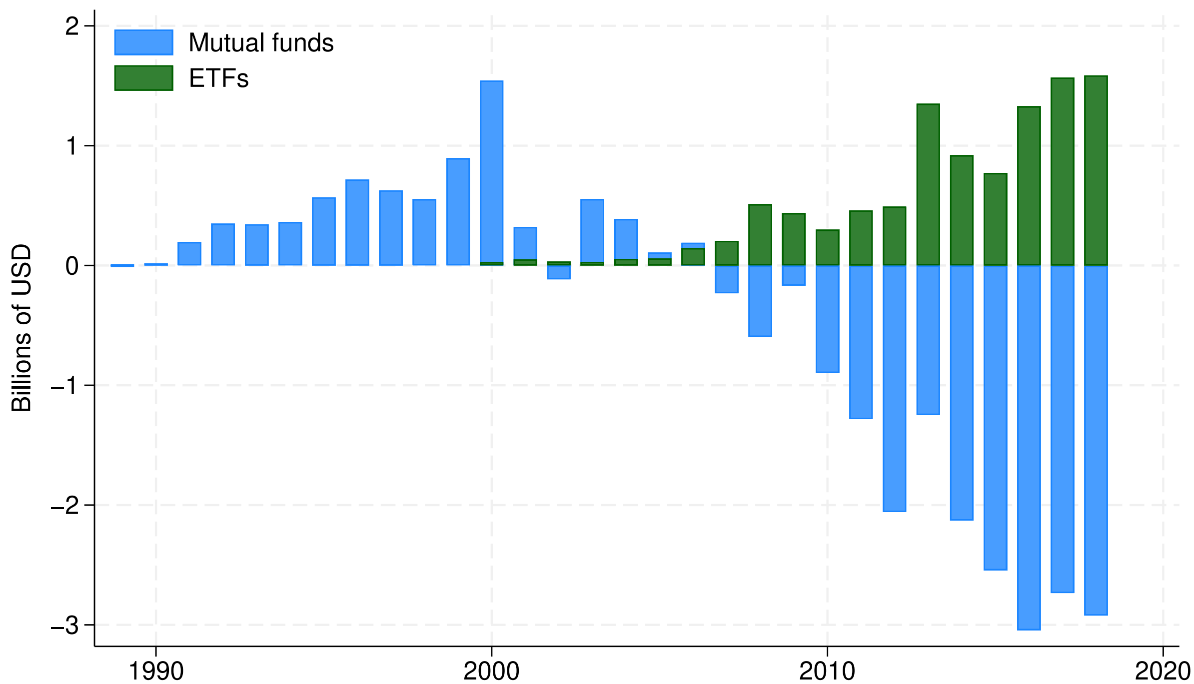


Figure I.2: 13F Institutional Investors holding ETFs

This figure plots the total number of 13F institutional investors, the number of 13F institutional investors that held ETFs and leveraged/inverse-leveraged ETFs in their portfolios in the last quarter of five different years.

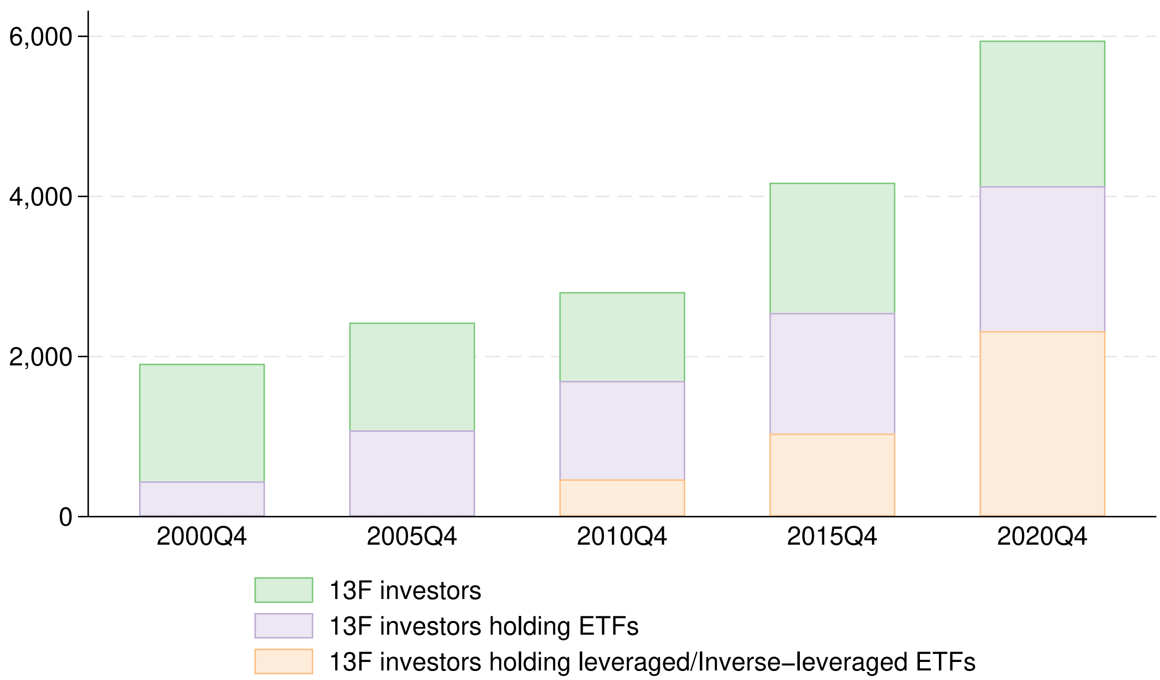
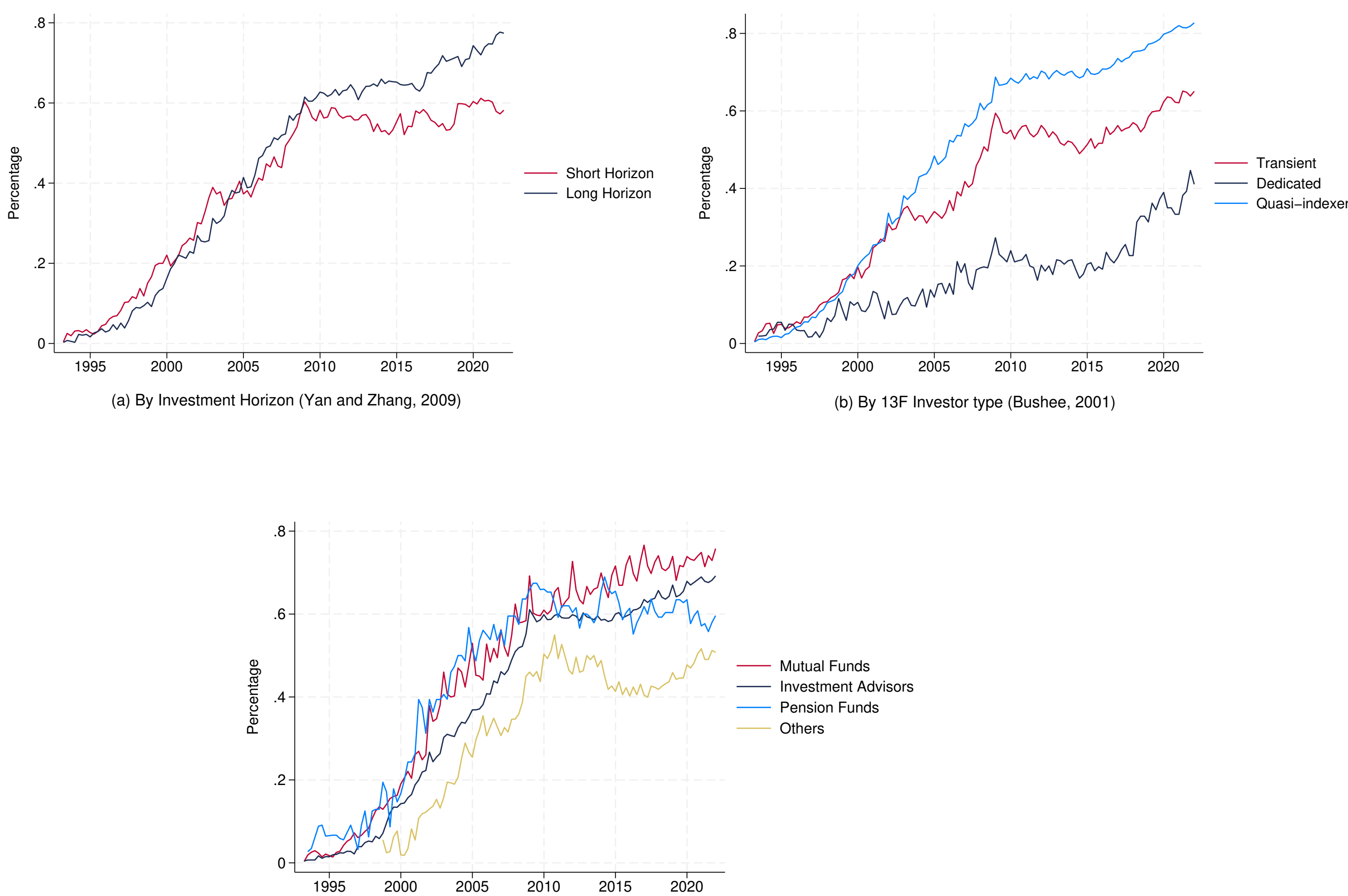


Figure I.3: The evolution in the adoption of ETFs in 13F Institutional Investors holdings

This figure shows the time series of the percentage of 13F institutional investors holding exchange-traded funds (ETFs) in their portfolios from 1993 to 2021. The 13F institutional investors are classified based on three criteria. In Panel A, investors are classified into short- and long-horizon based on the *average churn ratio* of Yan and Zhang (2009*a*). In Panel B, we group investors into transient (i.e., those with high portfolio turnover and highly diversified portfolios), dedicated (i.e., those characterized by large investments in portfolio firms and low portfolio turnover), and quasi-indexer (i.e., those with low portfolio turnover but more diversified portfolios) using the classification provided by Bushee (2001). In Panel C, we classify investors according to Koijen and Yogo (2019*a*). The 13F holdings data is obtained from Thomson/Refinitiv, while ETF data is collected from Bloomberg and CRSP.



(a) By Investment Horizon (Yan and Zhang, 2009)

(b) By 13F Investor type (Bushee, 2001)

(c) By Investor type (Koijen and Yogo, 2019)

Table I.1: Descriptive statistics

This table reports the time-series average of the cross-sectional mean, median, standard deviation, and first and third quartiles of several variables for our sample of mutual funds and exchange-traded funds (ETFs). The *number of funds* is the average of the total number of funds per quarter. *Number of holdings* represents the average number of stocks in the fund's portfolio. *TNA* is the fund's total net assets at the quarter end, in millions of US dollars. *Ownership* is the percentage of shares outstanding owned by all equity mutual funds (ETFs) in our sample. The *NYSE Decile* is the average NYSE size decile of a mutual fund (ETF) stock portfolio. Panel A reports the descriptive statistics for the sample of mutual funds. Panel B shows the results for the sample of ETFs. Panel C reports the autocorrelation coefficient for one-quarter (Q_{t-1}) to four-quarters (Q_{t-4}) lags in the number of owners. This is, the total number of mutual funds (ETFs) holding the same stock. Only stocks with market capitalization equal to or higher than NYSE size decile 5 are included. The *Full sample* covers the period from 1989:Q4 to 2018:Q4.

Panel A: Mutual Funds

	Full Sample					Mean by period		
	Mean	Std	p25	Median	p75	1989-1999	2000-2009	2010-2018
Number of funds	1,138	501	690	1352	1537	524	1494	1441
Number of holdings	80	85.071	36	58	90	66	80	85
TNA (in MM of USD)	879.82	3764.83	30.80	132.78	532.74	467.22	733.43	1219.15
Ownership (%)	8.71	12.29	1.49	5.15	11.86	4.28	10.95	11.20
NYSE decile	8.05	0.11	7.99	8.03	8.11	8.08	8.10	7.97

Panel B: ETFs

	Full Sample					Mean by period	
	Mean	Std	p25	Median	p75	2000-2009	2010-2018
Number of funds	334	276	94	112	571	89	606
Number of holdings	116	188	18	48	110	93	120
TNA (in MM of USD)	1,760.5	9,280.1	34.3	157.8	689.1	1,000.3	1,766.9
Ownership (%)	2.27	2.97	0.14	0.91	3.64	0.63	3.96
NYSE decile	7.41	1.73	6.00	7.00	9.00	7.46	7.37

Panel C: Autocorrelation

	Mutual Funds				ETFs			
	Q_{t-1}	Q_{t-2}	Q_{t-3}	Q_{t-4}	Q_{t-1}	Q_{t-2}	Q_{t-3}	Q_{t-4}
Number of owners	0.861	0.851	0.786	0.78	0.832	0.807	0.791	0.701

Table I.2: Fragility and fragility components descriptive statistics

This table reports the time-series statistics of cross-sectional averages mean, median, standard deviation, and first and third quartiles of the following variables: *Number of owners* is the total number of funds holding the same stock. *Flow volatility* represents the standard deviation of mutual fund (ETF) flows. *Flow correlation* is the Pearson correlation of fund flows at the fund-pair level for each quarter. *Fragility* (sqrt) is the square root of the fragility measure estimated as in Equation 1.3. Only stocks whose market capitalization is equal to or higher than NYSE size decile 5 are included. The sample period for equity mutual funds is from 1989:Q4 to 2018:Q4, while for the exchange-traded funds (ETFs) is from 2000:Q1 to 2018:Q4. Fragility is winsorized at the 1% and 99% levels.

	Mutual funds						ETFs				
	Mean	Std	p25	Median	p75		Mean	Std	p25	Median	p75
Panel A: Number of owners											
1989-1999	22	26	7	15	27	2000-2008	5	4	2	4	7
2000-2009	76	71	28	59	100	2009-2013	31	24	7	31	50
2010-2018	82	65	40	72	108	2014-2018	51	31	29	48	73
Full sample	50	61	7	27	73	Full sample	25	29	4	9	44
Panel B: Flow volatility											
1989-1999	4.664	11.505	0.399	0.870	2.749	2000-2008	0.351	0.491	0.058	0.177	0.369
2000-2009	5.498	17.178	0.408	0.895	3.933	2009-2013	0.824	0.963	0.342	0.493	0.741
2010-2018	4.248	11.093	0.279	0.541	1.388	2014-2018	1.755	2.648	0.431	0.693	1.273
Full sample	4.821	13.500	0.331	0.650	2.472	Full sample	0.858	1.586	0.187	0.389	0.746
Panel C: Flow correlation											
1989-1999	0.097	0.646	-0.384	0.133	0.653	2000-2008	0.066	0.633	-0.441	0.058	0.615
2000-2009	0.069	0.485	-0.215	0.069	0.386	2009-2013	0.027	0.460	-0.238	0.004	0.306
2010-2018	0.035	0.417	-0.179	0.033	0.260	2014-2018	0.025	0.433	-0.225	-0.006	0.273
full sample	0.072	0.432	-0.149	0.063	0.319	Full sample	0.028	0.426	-0.206	-0.002	0.262
Panel D: Fragility (sqrt)											
1989-1999	0.039	0.207	0.000	0.001	0.005	2000-2008	0.001	0.006	0.000	0.000	0.000
2000-2009	0.143	0.434	0.001	0.006	0.051	2009-2013	0.010	0.041	0.000	0.000	0.000
2010-2018	0.102	0.217	0.001	0.022	0.114	2014-2018	0.064	0.130	0.000	0.001	0.047
Full sample	0.105	0.303	0.001	0.011	0.064	Full sample	0.028	0.089	0.000	0.001	0.001

Table I.3: Fragility and stock return volatility

The standard deviation of daily stock returns over quarter $t+1$ (σ_{t+1}) is regressed on squared fragility $\sqrt{G}$ at quarter t and a set of lagged control variables as detailed in Equation (1.1) using the Fama and MacBeth (1973*a*) methodology. This table reports the average slope coefficients and the Newey-West t-statistics in parentheses. Fragility is measured by employing only mutual fund flows and holdings data ($\sqrt{G}^{MF}$), and ETF data only ($\sqrt{G}^{ETF}$). The control variables included are: the log of stock price, the log of market capitalization, the ratio of book equity to market equity, the past 12-month cumulative stock return, lagged skewness of monthly stock returns, the log of age, share turnover, and the lagged dependent variable (σ_t). ***, **, or * indicate significance at the 1%, 5%, or 10% level, respectively.

	Mutual funds								ETFs			
	Full sample				2009 - 2018				2009 - 2018			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\sqrt{G}^{MF}$	0.459***		0.305***	0.072**	0.325***		0.189***	0.018*				
	(11.82)		(8.57)	(2.75)	(8.75)		(6.26)	(1.70)				
$\sqrt{G}^{ETF}$									0.825***		0.722***	0.338***
									(7.76)		(7.10)	(5.93)
IO		0.015***				0.014***				0.003*		
		(15.64)				(14.27)				(2.35)		
log(numb owners)		0.027				-0.033**				-0.032***		
		(1.26)				(-2.82)				(-3.37)		
Own Herfindahl			-0.002***	-0.001			-0.004***	-0.002***			-0.001	-0.011
			(-4.27)	(-1.14)			(-6.51)	(-5.03)			(-1.00)	(-1.06)
Add Controls	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes
N	148,342	148,342	148,342	137,283	58,377	58,377	58,377	54,633	45,078	45,078	44,808	42,776
adj. R^2	0.010	0.049	0.045	0.486	0.007	0.045	0.043	0.376	0.013	0.025	0.024	0.373

Table I.4: MF and ETF Fragility and stock return volatility

The standard deviation of daily stock returns over quarter *t+1* (σ_{t+1}) is regressed on squared fragility $\sqrt{G}$ at quarter t and a set of lagged control variables using the Fama and MacBeth (1973*a*) methodology. This table reports the average slope coefficients and the Newey-West t-statistics in parentheses. Fragility is measured employing only mutual fund flows and holdings data ($\sqrt{G}^{MF}$), and ETF data only ($\sqrt{G}^{ETF}$). The control variables included are: the log of stock price, the log of the number of owners, the Herfindahl index, the log of market capitalization, the ratio of book equity to market equity, the past 12-month cumulative stock return, lagged skewness of monthly stock returns, the log of age, share turnover, and the lagged dependent variable (σ). ***, **, or * indicate significance at the 1%, 5%, or 10% level, respectively.

	2009 - 2018			
	(1)	(2)	(3)	(4)
$\sqrt{G}^{MF}$	0.067*		0.015	0.009
	(1.99)		(1.16)	(1.03)
$\sqrt{G}^{ETF}$	0.790***		0.795***	0.426***
	(7.77)		(8.20)	(7.95)
IO^{MF}		0.014***	0.012***	0.005***
		(11.11)	(12.37)	(7.47)
IO^{ETF}		0.002**	0.012***	0.007***
		(2.03)	(6.58)	(4.96)
Add Controls	No	No	No	Yes
Obs.	44,956	44,956	44,956	44,956
adj. R^2	0.015	0.025	0.034	0.376

Table I.5: Panel regression: Stock return volatility and fragility

This table presents the results of a panel regression of the average daily return volatility over the next quarter on the square root of mutual fund fragility and ETF fragility following Friberg et al. (2023). We define it as *Controls FB*, which includes control variables employed by Friberg et al. (2023) and includes the log of market capitalization and the inverse of stock price. *Controls GT* refers to the control variables used by Greenwood and Thesmar (2011), which are the log of market capitalization, the ratio of book equity to market equity, the past 12-month cumulative stock return, lagged skewness of monthly stock returns, the log of age, share turnover, and the lagged dependent variable (σ). t-statistics are reported in parentheses and are based on standard errors clustered at the stock levels. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively. We include year-quarter and firm fixed effects. Standard errors are clustered at the firm level. The sample period is from 2009:Q1 to 2018:Q4.

	All firms				IO >0.2				Mkt cap >Median			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(11)	(11)	(12)
$\sqrt{G^{MF}}$	0.065***		0.032*	0.01	0.06***		0.046**	0.031	0.064		0.046***	0.034
	(3.60)		(1.86)	(0.70)	(3.37)		(2.57)	(1.56)	(3.58)		(2.59)	(1.61)
$\sqrt{G^{ETF}}$		0.187**	0.176**	0.152**		0.191**	0.179**	0.139**		0.193**	0.178**	0.147**
		(2.24)	(2.10)	(2.06)		(2.26)	(2.20)	(2.05)		(2.34)	(2.13)	(2.22)
Controls FB	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Controls GT	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	98,304	69,776	69,776	69,776	95,923	68,744	68,744	68,744	98,283	69,772	69,772	69,772
adj. R^2	0.662	0.683	0.689	0.725	0.661	0.683	0.688	0.711	0.662	0.683	0.691	0.748

Table I.6: Fragility and excess return volatility

The standard deviation of *excess stock returns* over quarter *t+1* (σ_{t+1}^{exc}) is regressed on squared fragility $\sqrt{G}$ at quarter t. Excess returns are estimated based on the single-factor market model (1-Factor σ) the Fama and French (1993) three-factor model (3-Factor σ), and the Fama and French (1993) three-factor model augmented with the momentum factor of Carhart (1997) (4-Factor σ). This table reports the average slope coefficients and the Newey-West t-statistics in parentheses. In panel A, Fragility is measured based only on mutual fund flows and holding data ($\sqrt{G}^{MF}$). In panel B, Fragility is estimated as detailed in Eq. (1.1) based on ETF data only ($\sqrt{G}^{ETF}$). $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Mutual fund Fragility

	Full sample				2009 - 2018			
	1-Factor σ	3-Factor σ	4-Factor σ	DGTW	1-Factor σ	3-Factor σ	4-Factor σ	DGTW
$\sqrt{G}^{MF}$	0.530***	0.526***	0.527***	0.407***	0.400***	0.391***	0.397***	0.331***
	(7.86)	(7.81)	(7.96)	(7.49)	(12.01)	(11.81)	(11.65)	(9.77)
Obs.	148,337	148,337	148,337	111,704	58,373	58,373	58,373	41,459
adj. R^2	0.010	0.010	0.010	0.010	0.011	0.010	0.010	0.012

Panel B: ETF and Mutual fund Fragility (2009-2018)

	ETF				MF and ETFs			
	1-Factor σ	3-Factor σ	4-Factor σ	DGTW	1-Factor σ	3-Factor σ	4-Factor σ	DGTW
$\sqrt{G}^{MF}$					0.245***	0.238***	0.245***	0.231***
					(5.46)	(5.35)	(5.28)	(5.67)
$\sqrt{G}^{ETF}$	0.831***	0.804***	0.814***	0.774***	0.767***	0.744***	0.748***	0.619***
	(9.18)	(9.08)	(9.27)	(7.48)	(8.62)	(8.73)	(8.86)	(6.74)
Obs.	45,076	45,076	45,076	32,677	45,076	45,076	45,076	32,677
adj. R^2	0.020	0.018	0.018	0.026	0.022	0.020	0.020	0.029

Table I.7: Stock return volatility, ownership by 13F institutional investors, and stock price fragility

This table presents the results of a panel regression of next quarter's stock volatility on a set of different aggregations of Institutional Ownership and stock price fragility estimated based on mutual fund data only (G^{MF}) or ETF data only (G^{ETF}). We estimate stock volatility as the standard deviation of daily stock returns within each quarter. *Top IO* represents the aggregate ownership of the largest institutional investors in a given stock. For specifications (1), (3), (4), and (5), we sum the ownership of the top 3 institutions, whereas for specifications (2), (6), (7), and (8), we take the top 10 institutions. The *bottom IO* represents the combined ownership of the smaller institutional investors whose equity holdings equal that of the top IO. The *middle IO* is the aggregated ownership of all institutional investors not considered in either the top or bottom group of investors. The control variables include the Amihud (2002) illiquidity measure, the inverse of the stock price at quarter-end, book-to-market ratio, the log of the market capitalization of each stock estimated at quarter end, and past 6-month momentum return over the previous two quarters. t-statistics are reported in parentheses and are based on standard errors clustered at the stock and quarter levels. $***$, $**$, and $*$ represent the statistical significance at the 1%, 5%, and 10% levels, respectively. The *full* sample period is from 2009:Q1 to 2018:Q1.

	Full Sample		2009-2018					
	Top 3 Inst	Top 10 Inst	Top 3 Inst			Top 10 Inst		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Top IO	0.471**	0.263**	0.568*	0.617**	0.530**	0.406***	0.424***	0.328**
	(2.71)	(2.37)	(5.00)	(4.37)	(3.50)	(4.29)	(4.44)	(3.40)
Mid IO	0.163**	0.184**	0.164**	0.115	0.100	0.158*	0.048	-0.064
	(2.23)	(2.06)	(2.06)	(1.32)	(0.89)	(1.75)	(0.46)	(-0.45)
Bottom IO	-0.466***	-0.157*	0.086	0.069	0.018	0.106	0.076	-0.039
	(-2.90)	(-1.75)	(0.72)	(0.58)	(0.13)	(1.08)	(0.72)	(-0.28)
G^{MF}	0.034***	0.022**	0.020**		0.019	0.025**		0.016
	(2.88)	(2.08)	(2.15)		(1.54)	(2.17)		(1.15)
G^{ETF}				0.308**	0.206**		0.288**	0.200*
				(2.25)	(1.98)		(2.17)	(1.90)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	131,040	131,040	77,421	69,217	69,217	77,421	69,217	69,217
adj. R^2	0.659	0.667	0.652	0.689	0.689	0.652	0.689	0.703

Table I.8: Stock return volatility, ownership by 13F institutional investors, and stock price fragility - alternative aggregation of institutional investors

This table presents the results of a panel regression of next quarter's stock volatility on a set of different aggregations of Institutional Ownership and stock price fragility estimated based on mutual fund data only (G^{MF}) or ETF data only (G^{ETF}). We estimate stock volatility as the standard deviation of daily stock returns within each quarter. *Top IO* represents the aggregate ownership of the largest institutional investors in a given stock. For specifications (1), (3), (4), and (5), we sum the ownership of the top 5 institutions, while for specifications (2), (6), (7), and (8), we take the top 7 institutions. The *bottom IO* represents the combined ownership of the smaller institutional investors whose equity holdings equal that of the top IO. The *middle IO* is the aggregated ownership of all institutional investors not considered either in the top or bottom group of investors. The control variables include the Amihud (2002) illiquidity measure, the inverse of the stock price at quarter-end, book-to-market ratio, the log of the market capitalization of each stock estimated at quarter-end, and past 6-month momentum return over the previous two quarters. t-statistics are reported in parentheses and are based on standard errors clustered at the stock and quarter levels. $***$, $**$, and $*$ represent the statistical significance at the 1%, 5%, and 10% levels, respectively.

	Full Sample		2009-2018					
	Top 5 Inst	Top 7 Inst	Top 5 Inst			Top 7 Inst		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Top IO	0.467***	0.429***	0.652***	0.678***	0.616**	0.567***	0.594***	0.526**
	(3.35)	(3.45)	(5.62)	(5.84)	(4.01)	(5.65)	(5.83)	(4.38)
Mid IO	0.131*	0.125*	0.116*	0.053	0.038	0.095*	-0.003	0.024
	(1.87)	(1.74)	(1.70)	(0.52)	(0.79)	(1.79)	(-0.04)	(0.45)
Bottom IO	-0.284**	-0.227*	0.139	0.106	0.088	0.155	0.124	-0.029
	(-2.18)	(-1.91)	(1.42)	(1.00)	(0.83)	(1.60)	(1.20)	(-0.28)
G^{MF}	0.061***	0.052***	0.041*		0.031	0.037*		0.028
	(2.89)	(2.88)	(1.94)		(1.54)	(1.97)		(0.92)
G^{ETF}				0.284**	0.229**		0.244**	0.201*
				(2.33)	(2.01)		(2.16)	(1.99)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	131,040	131,040	77,421	69,217	69,217	77,421	69,217	69,217
adj. R^2	0.659	0.667	0.652	0.689	0.689	0.652	0.689	0.703

Table I.9: Activeness of ETF sample

This table reports the time-series averages of the cross-sectional mean, median, standard deviation, and 90th percentile of the activeness index (%) for the full sample period covering the period from 2000:Q1 to 2018:Q4 as well as for three subperiods: before 2009, between 2009 and 2014, and from 2014 to 2018. For the same subperiods, the table shows the breakdown of the number of funds and assets under management (AUM) by the following four levels of activeness: Very Passive (VP) (activeness index < 25%), Moderately Passive (MP) (25% < activeness index < 50%), Moderately Active (MA), (50% < activeness index < 75%), and Very Active (VA) (activeness index > 75%).

	Activeness index (%)				Number of funds (%)				AUM(%)			
	Mean	Median	Std	P90	VP	MP	MA	VA	VP	MP	MA	VA
Full sample	89.41	97.38	17.48	99.95	0.92	4.69	10.27	84.53	19.91	11.98	6.99	62.09
Before 2009	87.31	93.63	15.11	99.41	1.49	3.60	14.12	82.09	18.22	9.04	9.01	59.20
2009-2014	89.36	97.23	17.21	99.94	0.93	4.15	9.13	86.07	18.94	10.26	6.40	66.68
2014-2018	89.90	97.67	17.46	99.96	0.81	5.96	6.10	87.13	24.42	20.59	8.21	46.78

Table I.10: Stock return volatility, excess return volatility, and activeness of ETFs

This table presents the results of Fama and MacBeth (1973*a*) regressions of next quarter's total return volatility and excess return volatility on the squared fragility of the current quarter. We estimate Fragility as detailed in Equation (1.1). Following Easley et al. (2021), we classify ETFs according to their activeness index value into passive (Activeness index < 50%) and active (Activeness index > 50%) ETFs. The control variables included in the specification (3) are: the log of stock price, the log of market capitalization, the ratio of book equity to market equity, the past 12-month cumulative stock return, lagged skewness of monthly stock returns, the log of age, share turnover, and the lagged dependent variable (σ). $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from 2009:Q1 to 2018:Q4

	Total return volatility			Excesss return volatility					
	(1)	(2)	(3)	1-Factor σ	3-Factor σ	4-Factor σ	1-Factor σ	3-Factor σ	4-Factor σ
$\sqrt{G}^{ETF(Active)}$	0.801**	0.727**	0.381**	0.887**	0.817**	0.745***	0.783**	0.623**	0.648***
	(2.89)	(2.91)	(2.26)	(2.88)	(3.07)	(3.30)	(2.91)	(3.12)	(3.38)
$\sqrt{G}^{ETF(Passive)}$	0.128*	0.130	-0.170**	0.164*	0.162*	0.116*	0.127	0.0848	0.0873
	(1.92)	(0.32)	(-1.97)	(2.10)	(1.85)	(2.06)	(0.32)	(0.11)	(0.22)
$\sqrt{G}^{MF}$		0.387***	0.003				0.236***	0.223***	0.230***
		(8.12)	(0.20)				(5.32)	(5.11)	(4.96)
Add Controls	No	No	Yes	No	No	No	No	No	No
Obs.	18,563	18,563	18,016	18,563	18,563	18,563	18,563	18,563	18,563
adj. R^2	0.013	0.026	0.471	0.014	0.012	0.011	0.029	0.026	0.025

7 Appendix

A1.Mutual Fund database construction procedure

1. Mutual Funds Holdings

   Following Pavlova and Sikorskaya (2023), to create the database of mutual fund holdings we use data from CRSP Mutual fund Database (CRSP, from June 2010 to December 2018) and Thomson Refinitiv S12 (TRS12, from March 1980 to December 2018). We mostly rely on CRSP data for the second part of the sample since its relatively more reliable and timely (Ben-David et al., 2023).

   - To merge both databases we employ the MFLINKS file.
   - As in Doshi et al. (2015) we first process TRS12 database and stay only with those observations where FDATE and RDATE are equal. To avoid employing stale data, we keep the first reported FDATE-FUNDNO observation per fund.
   - For the funds that report data more than once in a month, we keep the last reported information for that given month.
   - We use the MFLINKS file to include the WFICN identifier. Whenever the merging process produces non unique WFCIN-RDATE observations, we keep that with the highest assets.
   - We proceed to merge the S12type3 file with the holdings database to obtain CUSIP data that we use to include PERMNO from CRSP for each stock.
   - We split-adjust the shares variable.
   - to Include the CRSP holdings data we match WFICN to csrp fundno variable from MFLINKS.
   - Finally, we check for possible duplicated observations and keep the last reported data for each reported month.

2. Selecting Equity Mutual Funds

   - Based on the crsp obj cd variable, we exclude those funds whose names include: international, balanced, sector, bond, money market, and index.
   - Similarly, as with the holdings database, we keep the most recent entry for each fund.

- If a fund changes its style during the sample period, we drop that fund from our sample.

A2. Additional results

Table I.A1: Stock Characteristics

For quarter t, stocks in our sample are sorted into 5 quintile portfolios based on their mutual fund (ETF) stock price fragility value. Fragility is defined as the conditional expected variance of flow-driven net buys into a stock. This table reports the time-series mean of the cross-sectional average of several stock-level characteristics for each fragility quintile portfolio. *Volat* is the standard deviation of daily stock returns in the next quarter (t+1); *BM* is the book-to-market ratio; *Ret12* is the past 12-month stock return; *Turnover* is the average monthly share turnover (monthly volume traded over total shares outstanding) over the previous 3 months; *Age* is the firm's Age is calculated as the number of years (months/12) since the first return appears in CRSP; *Mkt Cap* is the average stock's market capitalization (end-of-quarter share price times the total number of shares outstanding), expressed in millions of US dollars. *NYSE* is the NYSE market capitalization decile breakpoint; *NOwn* is the average number of mutual funds (ETFs) that hold the same stock; *MOM* is the firm's stock return momentum decile; *Analysts* is the number of Analyst following the firm collected from I/B/E/S. Panel A shows the results for quintile portfolios sorted on fragility estimated as in Eq. (1.1) that consider flows and holdings data from mutual funds only (G^{MF}). Similarly, Panel B reports the average values for the characteristics sorted on fragility calculated using ETF data exclusively (G^{ETF}). The sample covers the period from 1989:Q4 to 2018:Q4 for Panel A and from 2009:Q1 to 2018:Q4 for Panel B.

Panel A: MF fragility (G^{MF})

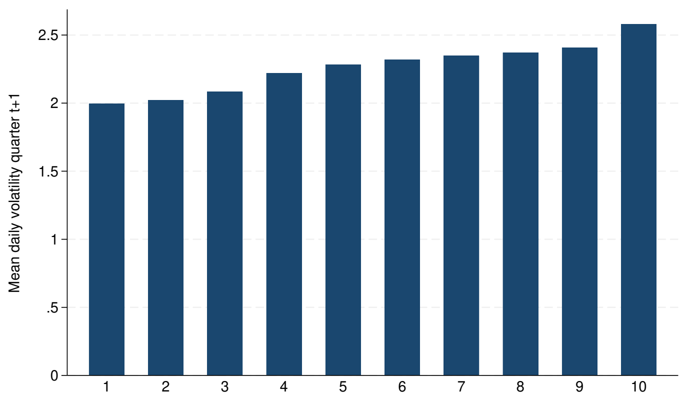
Quintile	Volat	BM	Ret12	Turnover	Age	Mkt cap	NYSE	NOwn	MOM	Analysts
1(low)	2.010	0.719	0.247	0.238	21.7	16,423.9	7.3	40.5	4.7	8.7
2	2.152	0.608	0.264	0.202	25.4	18,696.1	8.0	90.6	4.9	14.3
3	2.301	0.605	0.278	0.228	22.4	7,978.9	7.4	71.6	4.9	12.3
4	2.359	0.623	0.242	0.243	20.9	4,645.8	6.8	60.7	4.8	10.8
5 (high)	2.494	0.632	0.207	0.266	19.7	3,095.3	6.4	55.5	4.6	10.1

Panel B: ETF fragility (G^{ETF})

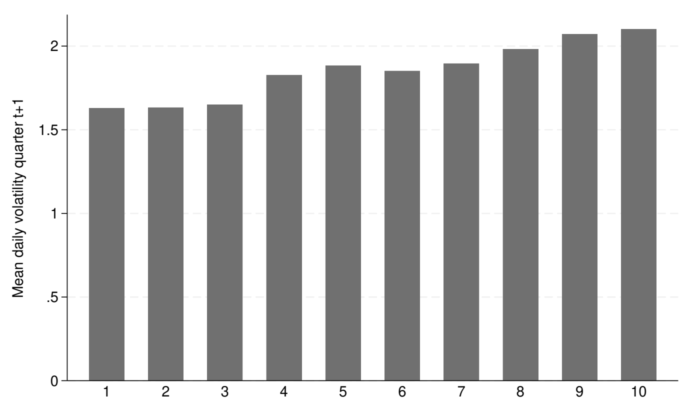
Quintile	Volat	BM	Ret12	Turnover	Age	Mkt cap	NYSE	NOwn	MOM	Analysts
1(low)	1.648	0.676	0.174	0.208	24.4	17,070.2	7.6	36.6	4.7	10.5
2	1.704	0.573	0.191	0.194	30.1	29,573.6	8.5	64.5	4.8	16.8
3	1.874	0.590	0.218	0.225	24.9	15,935.4	7.7	38.5	4.9	13.5
4	2.007	0.595	0.236	0.215	23.6	9,718.1	6.9	47.6	5.0	11.5
5 (high)	2.096	0.670	0.176	0.224	24.9	12,771.7	6.7	28.9	4.7	10.9

Figure I.A1: Fragility and volatility

This figure shows, for each decile of Mutual fund and ETF fragility, the time series average of cross-sectional mean daily stock return standard deviation in the next quarter t+1. The sample covers the period from 1989:Q4 to 2018:Q4 for MF fragility deciles and from 2009:Q1 to 2018:Q4 for ETF fragility deciles.



MF fragility decile.



ETF fragility deciles

A3. Institutional investors leveraged/inverse ETF holdings

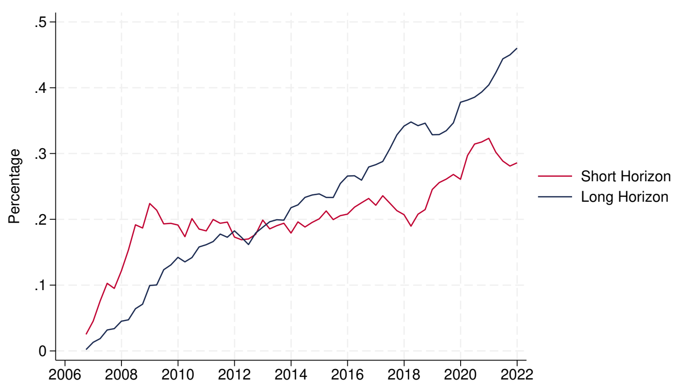
While the first ETF was launched on the Toronto Stock Exchange (TSX) in March 1990, the first US domestic ETF, the SPDR S&P 500, was introduced in January 1993. Since their inception, ETF attracted the attention of investors due to their hybrid design that combined characteristics of open and closed-end mutual funds while offering broad diversification at a lower cost and equity-like liquidity.

Leverage ETFs were first launched to the market in 2006. Similarly to traditional ETFs, these funds offered exposure to a wide set of benchmarks, however, their replication method includes using derivatives. This mechanism allows ETF fund managers to leverage the performance of the fund. While a positive exposure is possible (obtaining 1.5x or 2x the return of a specific benchmark), it is also possible to obtain a negative exposure. This is, investors can also buy ETFs that offer negative exposure by obtaining a negative multiplier of the benchmark return, for instance -1.5x -2x of the return.

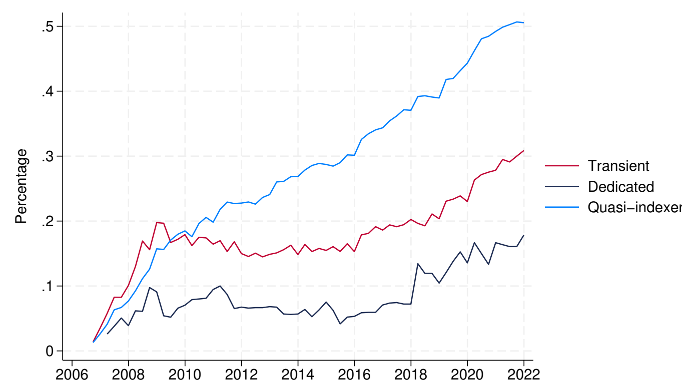
We identify leverage and inverse-leverage ETFs as those that include the following terms in their names: leverage, inverse, Double, Short, Ultra, UltraShort, 4x, 3x, 2.5x, 2x, 1.5x, 1.25x.

Figure I.A4: 13F Institutional Investors holding leveraged/inverse-leveraged ETFs

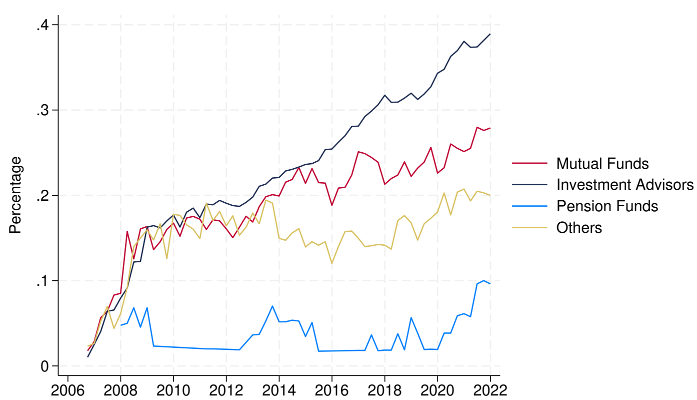
This figure shows the time series of the percentage of 13F institutional investors that held leverage or inverse-leveraged exchange-traded funds (ETFs) in their portfolios from 1993 to 2021. 13F institutional investors are classified based on three different criteria. In panel A, investors are classified into short-horizon and long-horizon based on the average churn ratio of Yan and Zhang (2009*a*). In panel B, we group investors into transient (i.e., show high portfolio turnover and highly diversified portfolios), dedicated (i.e., characterized by large investments in portfolio firms and low portfolio turnover), and quasi-indexer (i.e., those with low portfolio turnover but more diversified portfolios) Bushee (2001). In panel C, we classify investors following Koijen and Yogo (2019*a*). The 13F holdings data is obtained from Thomson/Refinitiv, while leveraged and inverse-leveraged ETF data is collected from Bloomberg and CRSP.



(a) By Investment Horizon (Yan and Zhang, 2009)



(b) By Investor type (Bushee, 2001)



(c) By Investor type (Koijen and Yogo, 2019)

Chapter 2

Crowded Spaces and Anomalies

1 Introduction

A cornerstone of modern financial theory is the role that arbitrageurs play in creating efficient markets by ensuring prices reflect fundamental values (Grossman and Stiglitz, 1980). However, finding and exploiting mispricing can prove to be a risky challenge. Even if arbitrageurs can implement long (short) positions in under (over) priced securities in a timely and cost-efficient way, they need to consider a set of limitations and risks such as transaction and holding costs (Pontiff, 2006), information uncertainty (Edmans et al., 2015), noise trader risk (De Long et al., 1990), short sales, and capital constraints (Shleifer and Vishny, 1997; Lam and Wei, 2011). In this paper we focus on an additional risk called *crowding*, which is driven by the increased participation of investors in exploiting market inefficiencies (Chincarini, 1998; Stein, 2009).

According to Chincarini (2018), *crowding* occurs when the number of investors chasing a similar strategy is too large given the available liquidity or typical turnover.[1] Moreover, crowding has the potential to persist over time especially for non-fundamentally

1 A closely related concept is herding. Herding occurs when a group of investors trade in the same direction over a period of time (Nofsinger and Sias, 1999), or applying similar trading styles (Wermers, 1999). The main difference is that crowding is directly linked to the individual stocks' liquidity.

anchored investment strategies. These are strategies for which "arbitrageurs do not base their demand on an independent estimate of fundamental value" (Stein, 2009, p.1520). For instance, momentum has the potential to be very profitable at times but this strategy is not subject to a price-based mechanism that signals when overpricing might be occurring.[2] Ultimately, crowding can create a coordination problem that can negatively influence risk and return dynamics, making the risk of a trade endogenous to the trade itself (Lou and Polk, 2021; Antón and Polk, 2014).

Between 1980 and 2020, the number of institutional investors included in the 13F database increased more than ten times from around 400 in 1980 to more than 4,000 in 2020. More investors are actively participating, but fewer institutions now own a significant proportion of the market.[3] In contrast, the number of publicly listed companies included in that same database continuously decreased over the last 20 years after reaching its peak of 5,756 in the late 1990s to a total of 2,386 in 2020. Furthermore, there are a host of institutions that are increasingly creating factor-based investing strategies related to exploiting anomalies.[4] This coordinated trading could raise crowding and be a concern for investors and regulators.

In this paper, we argue that crowded equity positions pose additional risks to arbitrage trading through increased exposure to crash risk. Moreover, we hypothesize that this relationship is more pronounced in a set of well-known asset pricing anomalies. Intuitively, investment strategies based on stock market anomalies are good candidates to become crowded as investors are aware of their existence once they are published (Mclean and Pontiff, 2016), and institutional investors trade to exploit them (Calluzzo et al., 2019). We aim to better understand the risks involved in the trading of anomaly stocks, in particu-

2 Although some argue in favor of using a relative valuation measure to assess whether an anomaly might be overpriced (see Arnott et al., 2017).

3 For instance, (Ben-David et al., 2021*b*) document that as of December 2016, the largest institutional investor in the US market was responsible for managing a portfolio equivalent to 6.3% of the total equity market while the top 10 institutional investors managed 26.5% of that same market.

4 During the past decade, factor investing has experienced rapid growth of approximately 11% per annum, reaching an estimated $1.9 trillion in assets under management by 2017 (Wigglesworth, 2017). This growth has been heightened by the launch of several investment products (e.g., smart-beta exchange-traded funds) that aim to exploit anomalies.

lar, the interaction between crowding, crash risk, and the cross-section of anomaly stock returns. This focus on both crowding and a large set of anomalies, to the best of our knowledge, has not been explored in previous literature.

For our empirical analysis, we use Thomson/Refinitiv 13F Institutional investors holdings database for our measure of institutional positions in equities over the period 1980:Q1-2021:Q4. We use this data in conjunction with other data to estimate a broad set of crowding measures. We follow Brown, Howard and Lundblad (2021) and adopt days-ADV as our main measure of crowding. Days-ADV is estimated as the sum of investors' holdings in dollars in a given stock divided by the average daily trading volume in dollars of that same stock. It represents how many days it would take institutions to exit all their positions. As explained by Brown, Howard and Lundblad (2021), by incorporating both the magnitude of the ownership and the (il)liquidity, this measure captures the key idea of crowding risk. An analogy is that of a crowded room of people. The time it will take to exit the room will depend on both the number of people in the room and the size of the exit door.

Our analysis provides several results. First, we find that our main measure of crowding, days-ADV, experiences a decline in the first half of the sample driven by the dramatic increase of trading volume at the end of the 1990s.[5] However, there is a positive increasing trend since the end of the 2000s.[6]

Second, we examine the relationship between crowding and stock returns in the context of institutional investors' holdings. Every quarter we sort stocks into quintile portfolios based on the crowding variable and then proceed to build long and short portfolios selecting the top and bottom quintiles as those most and least crowded, respectively. Next, we examine the returns of these portfolio in the quarter after portfolio formation. In this single sorting approach and using days-ADV as the crowding variable, we find that a value (equal)

5 Among the explanations put forward by French (2008) are the development of electronic trading networks, decimalization of stock prices in the year 2000, as well as the progressive implementation of several SEC rules designed to increase market liquidity.

6 When we compute a measure of similarity among institutional investors' portfolio, in line with the results of Sias et al. (2016), we find little evidence of a significant level of overlap at the aggregate level. Nonetheless, we find that the similarity among portfolios significantly increased during specific periods of history such as during the dot-com bubble and the financial crisis (See Panel A of Figure II.2).

-weighted quintile portfolio of the most crowded stocks delivers a Fama and French (1993) 3-factor monthly alpha of 0.54% (0.63%), whereas the alpha of the lowest crowding quintile is -0.90% (-0.94%). Thus, at least on average, crowded stocks are associated with future superior returns, while the least crowded stocks provide inferior returns. The difference is economically and statistically significant. This finding is also robust to different factor model specifications, including the Fama-French 5-factor model (Fama and French, 2015) and liquidity factors. We also examine whether the relationship between crowding and stock returns varies across different institution types. Previous studies have documented that some institutions such as hedge funds and transient institutions are more active as arbitrageurs (e.g., Akbas et al., 2015; Calluzzo et al., 2019). When we distinguish among mutual funds, investment advisors (mostly hedge funds), pension funds and others, and among transient, dedicated, and quasi-indexers as in Bushee (2001), and short- vs. long-horizon institutions as in Yan and Zhang (2009*b*), we find that the relationship between crowding and future returns is stronger for stocks mostly held by investment advisors, transient, and short-horizon institutions.

Third, we test the relationship between crowding and returns among anomaly stocks. As in Stambaugh et al. (2012), we focus on eleven well-known anomalies (see Table II.1). We begin by analyzing our full institutional investor's holdings sample from the first quarter of 1980 to the first quarter of 2020. We find a strong relationship between our anomaly returns and crowding. Specifically, a portfolio that is long the most crowded stocks in the long leg of the anomalies and short the least crowded stocks in the short leg of the anomalies exhibits significant risk-adjusted monthly return (3-factor alpha) of 1.7% across all 11 anomalies. We also observe a decay in the alpha of the anomalies after publication as in Mclean and Pontiff (2016) and Calluzzo et al. (2019), but the alpha remains statistically significant for crowded stocks. Interestingly, when we examine the performance of a portfolio of anomaly stocks that are not part of the crowding portfolio we find that the alpha is insignificant, which indicates that the abnormal returns of the anomalies are driven by the crowded stocks.

Next, we want to explain why crowding is associated with higher return. One possible explanation suggested by Brown, Howard and Lundblad (2021) is that institutional investors are better informed. The findings that the results are stronger for stocks mostly held by sophisticated and better informed institutions such as hedge funds, transient, and short-term institutions provide some support for this explanation. However, we find that results are weaker when we only examine the level or the change of institutional ownership without taking into account the liquidity of the stocks. Another explanation is that crowding constitutes another limit to arbitrage reducing the correction of mispricing and/or institutions require to be compensated for investing in crowded stocks because more exposed to crash risk. Indeed, as more investors pour into the same stocks the space may become saturated and subject to crash risk. We find that crowding is related to future crash risk and that these effects are stronger for anomaly stocks. Our results are robust to different crash risk measures, the inclusion of several control variables, and year and firm-level fixed effects. A further alternative explanation is that the high return of crowded stocks is driven by a temporary price impact of institutions purchasing the same stocks. If this is the case we should observe a reversal not long after portfolio formation. However, we find that the performance of the crowding portfolio persists over the next six quarters after portfolio sorting.

We also conduct several additional tests. First, we confirm that the relationship between crowding and returns is still present and stronger for anomaly stocks, when we perform Fama and MacBeth (1973*b*) cross-sectional regressions, while controlling for determinants of investor demand. Second, we perform a structural break analysis of the days-ADV measure and find a common break in 1995. Therefore, we split the sample and verify that the main results hold across the two samples. Third, we verify that the relationship between crowding and future returns is not driven by liquidity and that both the numerator and denominator of the days-ADV measure are important drivers of our crowding findings. Fourth, we verify that our results are robust to alternative specifications of the number of lags included in the estimation of the days-ADV measure. Also, we find that the observed relationship between days-ADV measure and returns hold for alternative sorting procedures (dependent and independent sorting), is robust across different states of the economy (non-crisis periods, expansionary and recessionary periods). Last, our results are robust if we expand the number of anomalies using the sample of 97 anomalies analyzed by Mclean and

Pontiff (2016).

Our paper contributes to several strands of prior research on the influence of institutional investors on asset prices and crowding. First, we expand the finding of Brown, Howard and Lundblad (2021) by showing that the relationship between crowding and returns is not only specific to holdings of hedge funds, but it is present across all institutions. Second, we are the first to examine the relationship between crowding and returns using a large set of anomalies. We show that this relationship is stronger for anomalies and still significant after publication. Recent evidence (e.g., Calluzzo et al., 2019) shows that institutional investors increase their anomaly-related trading once the required accounting information is available. Thus, the increasing attractiveness of such investment strategies may create additional concerns due to crowded trading spaces that might limit mispricing correction. Third, we study crash risk as a channel through which crowded holdings influence stock returns. In this respect, we also contribute to the literature on crash risk and stock returns (Chabi-Yo et al., 2019; Ruenzi and Weigert, 2018). We also extend the work of Ruenzi and Weigert (2018) on the effects of crash risk on momentum and show that this relationship holds for a broader set of stock market anomalies and it is related to crowding.

There is still debate about the impact that crowding has on market efficiency. For instance, it is still unclear if the trading behavior of institutional investors further increases or alleviates concerns of excessively crowded equity positions. Brown, Howard and Lundblad (2021) provide evidence that hedge fund exposure to crowdedness amplify tail risk in times of market distress. By contrast, a recent paper by Barroso et al. (2022) cast doubt that crowding is an explanation of momentum crashes.[7] Moreover, evidence is mixed regarding the impact that crowded holdings have on the performance of institutional investors' portfolios. Zhong et al. (2017) find a strong negative association between crowding and future mutual fund returns. Brown, Howard and Lundblad (2021) show that crowded holdings positively predict hedge fund future returns. Finally, there is scant evidence for the link

7 Some investors could also lower the negative impact of crowding through diversification and having a long-term investment horizon while others further enhance the problem due to short-term focus (DeMiguel et al., 2019).

between crowding and anomaly performance, as well as other risks that investors might face when trading to exploit stock market anomalies.

Increasingly crowded equity investments are a rising concern among investors and regulators. In particular, investors in a crowded space could be exposed to pronounced price declines during market turmoil, consequently impacting their performance and overall market stability, which is an important focus of regulators. To the extent that crowding is associated with higher risks, which can be more severe with the use of leverage, then monitoring our crowding measure will allow regulators to anticipate conditions that might elevate market risk.

The remainder of the paper is organized as follows. Section 2 presents a brief discussion of the previous literature on crowding and links it to previous studies on the limits to arbitrage. In Section 3 we develop the hypotheses that we test in our empirical analyses. Section 4 describes both the data and our empirical methodology. Section 5 presents and discusses the main empirical results, and Section 6 concludes.

2 Related Literature on Crowding

The term *crowded-traded problem* was described early on as an explanation of the woes of the hedge fund Long-Term Capital Management (Chincarini, 1998). It is unclear when a proper name was given to the concept, but David Rocker elaborated on Chincarini (1998) with an article in Barron's in March 1999 entitled "A Crowded Trade". The academic world did not specifically focus on this concept until Stein (2009) and Chincarini's elaboration of the original LTCM concept in the book *The Crisis of Crowding* (2012). In the years since 2012, the crowded-traded phenomenon has been highlighted as a potential new risk consideration to investing. Many investment institutions have committees devoted to monitoring crowding and many academic papers have been published trying to understand the topic fully.[8] At the core of crowding is the idea that too many investors are exploiting similar investment opportunities unaware of the potential liquidity exhaustion. Some

8 For instance, in June 2018 MSCI introduced their "MSCI integrated factor crowding models" as means to offer investors a model that allows to quantitatively assess the degree of crowding in spe-

of these investors use leverage and so the crowding literature is related to the fire sale literature as well (e.g., Coval and Stafford, 2007; Chernenko and Sunderam, 2020).

From the perspective of investor's following each other's trading decisions, the crowded-trade problem is related to literature on informational cascades, reputational interactions, social learning, and herding.[9] However, crowding adds a different approach to the discussion on why portfolios might become more similar by arguing that investors may collectively, intentionally or unintentionally, undertake the same trading strategies characterized by their disconnection from price-regulated mechanisms.

Recent studies have further considered additional reasons that might lead to crowding, specifically regulatory changes, copycat trading, and the rise of quantitative trading.[10] Increased disclosure requirements regarding institutional investors' holdings, like the SEC 2004 regulation on the frequency of portfolio disclosure and the Dodd-Frank Act following the financial crisis of 2008, could lead to increased crowding in the market place (see Hong (2016b)). Recent research has shown that some investors have incentives to free-ride on institutional investors' strategies and try to mimic the trades of past winners (e.g., Verbeek and Wang, 2013; Phillips et al., 2014). Another strand of literature examines how the type of trade impacts crowding. For example, when more investors undertake similar *unanchored trading strategies*[11], these strategies may experience significant price dislocations when facing correlated demand shocks (Khandani and Lo, 2011).[12] They

cific factor strategies and help them make a timely decision when facing increasingly crowded positions. See https://www.msci.com/www/research-paper/msci-integrated-factor-crowding/01025037754 for a detailed description of the model.

9 Hirshleifer and Hong Teoh (2003) provide an excellent review on those topics and its relation to the behavior of capital markets.

10 See Chincarini (2012) for a comprehensive analysis of these phenomena. For the problems related to copycat trading amongst quantitative funds, see Chincarini (1998), Rothman (2007, 2008), Khandani and Lo (2011)

11 The idea of non-anchored strategies can be better understood by focusing on the most common example of this kind of strategy: momentum. Lou and Polk (2021) argue that momentum makes the most interesting case to study due to (i) the inability of traditional asset pricing models to explain it, and (2) its positive-feedback nature, which means that investors do not base their demand on an independent estimate of fundamental value. As more investors engage in momentum trading they further exacerbates the return signals possibly leading to more investors undertaking similar positions. See also Baltas (2019).

12 For instance, (Yan, 2014) provides evidence that momentum crashes (e.g., Cooper et al., 2004; Barroso

argue that the quant meltdown of August 2007 was driven by a set of quantitative-driven strategies simultaneously signaling sell orders which exhausted liquidity provisions and led to a sharp decline of some stock prices. Although the authors do not call it crowding, Hong et al. (2016b), find that arbitrageurs require a premium for trading stocks for which closing or covering their short positions is more difficult. Chincarini (2017) and Bruno et al. (2018) find that crowding can even occur from portfolio construction techniques or transaction costs considerations which are entirely independent of the alpha model.

Our paper is related to the work of Brown, Howard and Lundblad (2021), which analyses a sample of hedge funds holdings during the period 2006-2017. They find that hedge funds take on highly concentrated positions that outperform less crowded ones, indicating possible skill in identifying profitable risk-adjusted opportunities. They also find that crowding is a relevant component of hedge funds' tail risk as funds exposed to more crowded positions suffer larger drawdowns especially during periods of market distress. We differ from this paper in several aspects. First, by focusing on all institutional investors rather than just hedge funds we extend their contribution by examining the relationship of crowding and returns in other type of institutions. Second, we focus specifically on the relationship between crowding and anomaly returns. Finally, we show that crowding is related to crash risk, and represents an additional dimension of risk faced by arbitrageurs.

3 Hypotheses Development

In this section, we develop our main hypotheses for the empirical analysis. Arbitrageurs play an important role in making markets efficient and ensuring prices reflect fundamental values (Grossman and Stiglitz, 1980). However, finding and exploiting mispricing opportunities can prove to be a risky challenge. Even if we assume that arbitrageurs can take long (short) positions in under (over) priced securities in a timely and cost-efficient way, they need to consider a set of additional limitations and risks. Some of those limitations include transaction and holding costs (Pontiff, 2006), information uncertainty (Edmans

and Santa-Clara, 2015; Daniel and Moskowitz, 2016) are influenced by crowded trades that push prices away from fundamentals leading to strong reversals.

et al., 2015), noise trader risk (De Long et al., 1990), short sales, and capital constraints (Shleifer and Vishny, 1997; Lam and Wei, 2011). An additional risk to exploiting or attempting to exploit statistical arbitrage positions or any other type of positions is the absence of knowledge of the *types* of investors and the *quantity* of investors in a trading space. Since trading spaces may have limited capacity, the concentration of ownership of particular investors might expose the trading space to unwanted risk in the future.

In our empirical work, we would like to understand how crowding affects asset pricing. This is not straightforward, since crowding may have different effects over time due to the dynamic nature of asset pricing and supply and demand imbalances. Ultimately, the relationship between crowding and returns is an empirical question that we test with the first hypothesis.

Hypothesis 1 (Crowding and expected returns): Investors require compensation for trading in a crowded space and therefore crowding is positively associated with stock expected returns.

While institutional investors on an aggregate level mostly hold the market portfolio (Lewellen 2011), there is evidence that some of them conduct financial research, pay attention to academic publications, and engage in anomaly-based trades ((Mclean and Pontiff, 2016; Calluzzo et al., 2019). For instance, Calluzzo et al. (2019) document a shift on the portfolio holdings of some institutional investors toward anomaly-ranked stocks, especially after their publication. As previously discussed, some anomaly-based trades (e.g., momentum) do not base their demand on an independent estimate of fundamental value. Investors might keep their positions as long as they are profitable. Therefore, if institutional investors implement similar trading strategies and in particular rely on a similar set of anomaly stock characteristics (e.g., past year returns, gross profitability, return on assets) when trading, it is plausible to assume that market anomalies are the prime candidates for crowding. Investors then would require a compensation for investing in crowded anomaly stocks, which leads to our second hypothesis.

Hypothesis 2 (Crowding and anomaly returns): The relation between crowding and returns is higher for anomaly stocks.

Crowding surges when investors have imperfect information on the number of other investors actively implementing the same investment strategies and the liquidity characteristics of those positions. If the demand for a specific stock is uncorrelated among investors, then many investors holding the same stock would not lead to price volatility since their demands would mostly cancel out (Ben-David et al., 2021*b*). In contrast, if buy (sell) signals are correlated, as when investor implement similar strategies, demand shocks have the potential to impact asset prices through "asset acquisition (buildup phase)" and fire sales (e.g., Coval and Stafford, 2007; Chernenko and Sunderam, 2020). Moreover, the impact is conditional on the liquidity characteristics of each position. These conditions impose greater risk to arbitrageurs holding these securities by increasing concerns about exposure to crash risk due to correlated demand shocks (Chang et al., 2017). For example, if we screen for a certain anomaly attribute at time t, we might expect stocks that have extreme changes, like moving from the 1st to 5th quintile in factor ranking, to have exaggerated price moves, upon revelation of the change, if there was excessive crowding at time $t-1$. Thus, the third hypothesis considers the potential association between crowding and crash risk.

Hypothesis 3 (Crowding and liquidity and crash risks): Crowding is positively related to crash risk.

4 Data and Methodology

4.1 Institutional Investors' Holdings

We use Thomson/Refinitiv (TR) 13F database to collect data on Institutional Investors' portfolio holdings. The Security Exchange Commission (SEC) regulation requires all institutional investors that exercise investment discretion on assets under management over \$100 million to report their end-of-quarter holdings greater than 10,000 shares or \$200,000 on Form 13F within 45 days of each quarter-end. We then proceed to merge our holdings database with data on stock prices, volume, total shares outstanding for each stock from the Center for Research in Security Prices (CRSP). As commonly performed in previous studies, we capped institutional ownership to 100% whenever the number of shares held was greater than the number of shares outstanding (Calluzzo et al., 2019). We excluded microcap stocks with a share price of less than \$5 as well as utilities and financial firms from our sample. The exclusion of microcaps alleviates concerns about anomaly-returns being driven by penny stocks and reduces the effect of potential market microstructure noises.

In our base sample, we include all institutional investors considered in the 13F database. However, there is vast evidence on the differences in trading behavior among institutional investors[13]. For that purpose, we follow Koijen and Yogo (2019*b*) procedure and divide our sample into different types of institutional investors, such as mutual funds, investment advisors, which include mostly hedge funds after mutual funds are separated out, pension funds, and others[14]. We also distinguish between short- and long-horizon institutions following Yan and Zhang (2009*b*) and among transient, dedicated, and quasi-indexer institutions (using data from Brian Bushee's website to identify them in our sample).[15] Transient institutions are particular relevant for our research due to their active management approach to trading on anomalies.[16] Moreover, this classification allows us to extend the analysis of previous studies that focused only on hedge funds by including additional institutional investors that actively look for arbitrage opportunities.

[INSERT FIGURE II.1 HERE]

13 See, for example, Calluzzo et al. (2019) and Edelen et al. (2016) for recent discussion on the topic.

14 See https://koijen.net/code-and-data.html

15 See https://accounting-faculty.wharton.upenn.edu/bushee/.

16 According to Calluzzo et al. (2019), the quarterly average portfolio turnover of transient institutions is 66.8% while for non-transient investors is 25%. Regarding which institutions are considered as transient, according to the authors, 34.1% are hedge funds, 58.6% mutual funds and the remaining 7.3% includes bank trusts, insurance companies, pension funds, and endowments.

Figure II.1 depicts time-series means of cross-sectional medians of several characteristics of the 13F database over time. As shown in Figure II.1, Panel A, the proportion of shares outstanding owned by institutional investors (IO) has steadily increased over the years reaching its peak of almost 79% around the year 2019. However, more surprising is the sharp decline, and subsequent rebound, on IO at the end of the year 2019 and the first quarter of 2020. This might be arguable the effect of the world's covid-19 pandemic. This V-shaped behavior at the end of our sample is also observed in the other figures. Figure II.2, Panel B, plots the median number of institutional investors that hold the same security. At its peak, in the year 2019, a typical security in our sample was owned by 160 different institutional investors. Figure II.2, Panel C, shows the decline in the median number of stocks held in a typical institutional investor's portfolio (red line) contrasted to the increase in the amount of money, in millions of USD, allocated to the average security (blue line). Finally, as shown in Figure II.2, Panel D, institutional investors now face a context of an increased number of investors (blue line) that have access to a smaller pool of available securities (red line). Between 1980 and 2020, the number of institutional investors included in the 13F Institutional holdings database grew more than 10 times from around 400 to more than 4,000. By comparison, the number of publicly listed companies included in that database reached 5,756, its peak, in the late 1990s, and has continuously decreased over the last 20 years to a total of 2,386 in 2020.

4.2 Stock Anomalies

We used Compustat and CRSP databases to obtain the financial data needed to estimate each of the anomaly variables. For the anomalies constructed with accounting data, we used information from the last fiscal year in calendar year ($t-1$) to ensure that we employed information available to investors at the time of the portfolio formation. We considered 11 well-known stock market anomalies following Stambaugh et al. (2012). Table II.1 describes each stock anomaly and reports the year of publication. We create the anomaly portfolios by ranking stocks in our sample based on the anomaly variables (see Table II.1) on June 30 of each year and sorting them into quintiles. One exception is momentum where we sort the data at the end of each quarter. After sorting the data, we examine the returns of the stocks over the next 12 months, from July to June of the following year (next 3 months for momentum). The anomaly returns are constructed by subtracting the returns of quintile 5 from the returns of quintile 1 using both value-weighting and equal-weighting to construct the portfolio returns.

[INSERT TABLE II.1 HERE]

For our main results, we analyzed annually ranked anomaly portfolios. Nonetheless, recent studies (Han et al., 2021) have documented increased performance of several anomalies portfolios when rebalanced at a higher frequency. Those studies argue that rebalancing anomaly portfolios once a year does not adequately incorporate valuable information produced during the year. Quantitative hedge funds and other similar investors may rebalance their portfolios on a more frequent basis, like monthly or more frequently as data becomes available. In order to address these issues, in untabulated tests we also performed our analysis on a quarterly basis and obtained results that are similar to the main results in this paper.

4.3 Measures of Crowding

One major challenge in measuring crowding in equity markets is capturing the simultaneity in capital allocation to specific strategies while considering liquidity concerns. Moreover, given the restrictions that many institutional investors (e.g., mutual funds) face entering short positions, it is most likely that many investment strategies are based on long-only mandates. On the other hand, investors such as hedge funds, are significantly less restricted to include complex investment strategies involving the use of derivatives, leverages, and holding short positions.[17] Therefore, it is unlikely that a single measure can capture

17 It is worth noting that, as documented by Calluzzo et al. (2019), although restricted on holding short positions, there has been an increase in allowance at mutual funds accessing leverage, derivatives, and holding illiquid assets.

crowding for all potential investment strategies while including considerations about liquidity provisions. We plan to consider different measures and institutions to mitigate the above concerns.

Similarity

One way to measure crowding or the similarity in holdings between investors is to examine the degree of overlap between investors' portfolio holdings (Sias et al., 2016; Chincarini, 2018; Blocher, 2016)). Following Chincarini (2018) and Bruno et al. (2018), we can measure the similarity between two portfolios as s_{ij}, which is the dot product between the position weight vectors ($\mathbf{w}$) of each portfolio i and j divided by the product of the Euclidean norm of each vector. Thus,

$$s_{ij} = \frac{\mathbf{w}_i' \mathbf{w}_j}{|\mathbf{w}_i||\mathbf{w}_j|} \tag{2.1}$$

This measure will have a value between 0 and 1 for portfolios that can only be long securities (i.e. long-only portfolios). This measure will have a value between -1 and 1 for portfolios that can have negative weights.[18]

In order to measure the crowding for a large group of portfolios, say M portfolios, we define the N-by-M portfolio holdings matrix as the matrix, H, which consists of columns of position weight vectors on N assets for each of M portfolios, we follow Chincarini (2018) and measure crowding as

$$C = \frac{\sum_{i=1}^{M} \sum_{j=1}^{M} S_{i,j} - M}{M^2 - M} \tag{2.2}$$

18 This measure is related to a more commonly used measure known as Pearson correlation. One can think of Pearson correlation as a de-meaned version of Cosine Similarity.

where S is the similarity matrix of all managers.[19]

Stock-level Crowding Measures

The previous measure is useful, but it is at the portfolio level and it does not explicitly consider the liquidity of the securities. A stock-level measure of crowding would relate the amount of ownership in a particular security to the level of normal trading in the security. This measure might indicate the potential pricing pressure on the security at time t and the potential pricing pressure on the security in the future assuming some level of persistence. An approach used in previous studies is to relate investor's holdings with securities daily trading activities (Zhong et al., 2017; Brown, Howard and Lundblad, 2021). Intuitively, three possible measures of ownership concentration are the total number of institutional investors invested in an individual security at time, the security's percentage of shares outstanding owned by a particular group of investors in a given period t, and the total amount of money invested in security i at time t. One measure of crowding that we use in this paper relates the percentage of shares held by a particular class of investor at time t with the average turnover of the stock. In particular, the ActRatio (Zhong et al., 2017) is defined as the percentage of shares held by active investors at $t-2$ divided by the average share turnover of the stock i at time $t-1$.

$$\text{ActRatio}_{i,t} = \frac{\text{Shares}_{i,t-2}}{\text{AvgTurn}_{i,t-1}} \tag{2.3}$$

where higher values of $\text{ActRatio}_{i,t}$ signals more crowded position in a given stock.

Another measure of crowding used in this paper is called Days-ADV, which is defined as the total amount of dollars invested in a security relative to the security's average daily

19 That is, $S = (H'H) \circ \hat{\hat{H}}$. The matrix S contains the similarities of each portfolio with every other portfolio. For example, element S_{12} represents the similarity of the portfolios of managers 1 and 2. For a specific set of portfolios, this measure of crowding is given by the average of the off-diagonal elements of this matrix. The diagonal elements are the similarity of each portfolio with itself, which are irrelevant. For more information, Chincarini (2018) or Bruno et al. (2018).

trading volume over the past quarter (Brown, Howard and Lundblad, 2021).

$$\text{Days ADV}_{i,j,t} = \frac{\sum_{j=1}^{N} \text{InstHold}_{i,j,t}}{\text{ADV}_{i,t}} \tag{2.4}$$

Although we mainly focus on the days-ADV measure in this paper, both measures attempt to measure the excess ownership in a security that given its typical trading volume might cause price distortions or demand-supply imbalances [20].

Aggregate Crowding Measures

In order to get a flavor of crowding in our database and sample period, we provide summary statistics in Table II.2 and time series plots of the cosine similarity and Days-ADV crowding measures in Figure II.2. In Table II.2 we also provide the mean and the median of relevant variables when we create portfolios sorting stocks into quintiles based on the Days-ADV measure. We find that the most crowded stocks with high Days-ADV relative to the least crowded stocks tend to be larger, have less turnover and smaller bid-ask spread, but have higher number of analysts following the stocks.

[INSERT TABLE II.2 HERE]

[INSERT FIGURE II.2 HERE]

Figure II.2 depicts the time-series of the aggregate cosine similarity as well as the days-ADV measures over time.

In panel A of Figure II.2 we plot the aggregate cosine similarity for the complete 13F holdings database for the sample period between 1980:Q1 and 2021:Q4. Consistent with

20 We estimate the correlation between both the days-ADV and Actratio measures (See Panel A of Table II.A4 in the Appendix). The results indicate that the measures are quite similar, thus they are most likely measuring the same effect.

Sias et al. (2016) we observe a decay in the overall similarity among institutional investors' portfolios. We extend their findings and provide evidence that the decrease in overlap among hedge funds occurs also in the broader sample of 13F institutional investors. However, starting in the year 2000 we observe a cyclical behavior. First, there is a progressive decay in overall similarity until the year 2009, coinciding with the financial crisis of 2008-2009. In the following years we observe a sharp increase in overall aggregate similarity that remained fairly stable until it began decreasing again around the year 2018. Concerning the days-ADV (see Panel B), it experiences a sharp decline in the first half of the sample driven by the dramatic increase of trading volume at the end of the 1990s (see Panel C). However, there is a positive increasing trend since the end of 2000s, which mirrors the finding documented by Brown, Howard and Lundblad (2021) for hedge funds during the period between the years 2004 and 2017.

A limitation of holding-level measures such as the cosine similarity is that it does not fully captures the impact of crowding on prices unless it is linked to a liquidity provision measure (Beber et al., 2012). Additionally, this approach is somehow limited by the inability to observe other portfolio components such as short positions widely used by hedge funds.[21] It is due to these limitations that we focus on the crowding measures at the stock level since it is possible that, although two portfolios have very low cosine similarities, they might still hold very concentrated positions in specific securities.

4.4 Measures of Crash Risk

Crash risk proxy variables aims at capturing higher moments of the stock return distribution with a special interest on extreme negative returns (Habib et al., 2018). Theoretically, crash risk is based on the notion that investors expect higher returns for stocks with more negative skewness, implying that skewness is a priced risk factor (Harvey and Siddique, 2000).

21 A remarkably exception is the work of Girardi et al. (2021) who study portfolio holdings similarity in the insurance industry. With this more complete view of insurers holdings, the authors conclude that insurers whose portfolios are more similar experience larger common sales that impact prices when shocks to their assets or liabilities occur.

Following (Hutton et al., 2009) and (Callen and Fang, 2015) we define crash risk using *weekly* firm-specific returns using the residuals from the following equation:[22]

$$r_{j,t} = \alpha_j + \beta_{1,j} r_{m,t-1} + \beta_{2,j} r_{i,t-1} + \beta_{3,j} r_{m,t} + \beta_{4,j} r_{i,t} + \beta_{5,j} r_{m,t+1} + \beta_{6,j} r_{i,t+1} + \epsilon_{j,t} \quad (2.5)$$

where $r_{j,t}$ is the return on stock j in week t, $r_{m,t}$ is the return on the CRSP value-weighted market index in day t, and $r_{i,t}$ is the return on the value-weighted industry index based on the two-digit SIC code. The inclusion of both lead and lag terms of the value-weighted market and industry indices aims at correcting the effect of non-synchronous trading (Dimson, 1979). However, the estimated residuals from Eq. (2.5) are highly skewed. Since several crash risk measures are based on the difference in the number of standard deviations above or below a reference return we log transform the residual returns $[\log(1 + \epsilon_{j,t})]$ to allow for a more symmetrical distribution.

Following the common practice in the literature we estimate two measures of crash risk. The first is the negative conditional skewness of firm-specific returns, NCSKEW, estimated as the negative of the third moment of firm's specific weekly returns divided by their cubed standard deviation.

$$\text{NCSKEW}_{j,t} = -\frac{n(n-1)^{3/2} \sum R_{j,t}^3}{((n-1)(n-2)(\sum R_{j,t}^2)^{3/2})} \quad (2.6)$$

where n is the number of observations per firm j during the fiscal year, t. Since an increase in NCSKEW points out to a stock's return having more left-skewed distribution, we follow the convention that higher NCSKEW value implies a higher *crash risk*.

The second measure of crash risk that we use *down-to-up volatility* (DUVOL) and is estimated as shown in Eq. (2.7). This measure captures the asymmetric volatility of positive and negative firm-specific weekly returns.

22 As stated by Hutton et al. (2009) using actual returns would lead to biased inference since many crashes would be expected during times of market turmoil as well as jumps during recovery periods. A more suitable approach is to look at *residual returns* to better assess extreme movements.

$$\text{DUVOL}_{j,t} = log\left(\frac{(n_u - 1)\sum_{DOWN} R^2_{j,t}}{(n_d - 1)\sum_{UP} R^2_{j,t}}\right) \tag{2.7}$$

For a given firm j we count the number of weeks with returns above (n_u) and below (n_d) the daily mean. Then, we proceed to estimate the log ratio of the standard deviation of the sample of *up weeks* and the sample of *down weeks*. Similar to the NCSKEW measure, an increase in DUVOL indicates that a firm is prone to crash risk.

5 Empirical Analysis

In this section, we test our hypotheses about the relationship between crowding and stock returns for the full sample and conditional on anomalies. We run two type of tests, one based on portfolio sorting and one based on Fama-MacBeth regressions. In the last part, we examine the relationship between crowding and crash risk.

5.1 Crowding and the Cross-Section of Stock Returns: Portfolio Analysis

To test our first hypothesis that crowding is positively associated with expected returns, we first use a single portfolio sorting approach. We begin by forming quintile portfolios of stocks at the end of each calendar quarter based on each of the four crowding measures measured at the end of previous quarter: *IO*, *NINST*, Days-ADV, and *ActRatio*. The one quarter lag in the measures is used because the 13-F holdings are disclosed with an up to 45 days delay. Then, we estimate monthly excess returns over the following three months for both equal and value-weighted portfolios and form a spread portfolio by taking long (short) positions on stocks with high (low) crowding values, according to each proxy variable. We repeat this process every quarter and obtain a time-series of excess returns which we use to regress on the Fama-French three factors and estimate the alpha.

[INSERT TABLE II.3 HERE]

Panel A (Panel B) of Table II.3 reports the FF3 alpha of the value-weighted (equal-weighted) quintile portfolios, and *high-minus-low*, Q5-Q1, portfolios in our sample period from 1980:Q1 to 2021:Q4 for our various crowding measures. Consistent with Brown, Howard and Lundblad (2021), we find a significant annualized alpha for the value (equally) weighted portfolios sorted on days-ADV. On average, a value-weighted portfolio composed of highly crowded stocks (quintile 5) delivers a monthly alpha of 0.54% (6.48% annualized) with a t-stat of 8.87, whereas one that includes the least crowded stocks (quintile 1) offers a monthly alpha of -0.90% (-10.80% annualized) with a t-stat of 7.86. The spread portfolio (*high-minus-low*) has a monthly alpha of 1.44% (17.28% annualized) with a t-stat of 9.67. Our results for portfolios sorted on the *ActRatio* measure are similar, however, the economic magnitude of the alpha of the spread portfolio is lower than that obtained in the *days-ADV* sorted portfolios.[23] In addition to $t-1$ crowding measures on $t+1$ portfolio returns, we also examined to what extent the lags matter for these results. Table II.A5 in the Appendix summarizes these results and indicates that the results are robust to changes in lags.

Additionally, we fail to find significant alphas for portfolios sorted on either institutional ownership (IO) or *NInst*. These results suggest that securities held by many institutional investors are not necessarily crowded unless it is related to the specific security liquidity provision. It is important then to consider a crowding measure such as days-ADV that captures both the magnitude of the investors involved in a security as well as the liquidity of the stocks. For the remainder of the paper we focus on the days-ADV measure as our main crowding measure.[24]

We further expand the test of hypothesis 1 about whether crowding is related to the cross-section of expected returns. To do so, we focus on the excess-return of the portfolio

23 Our results differ from those of Zhong et al. (2017) who report that a low-minus-high portfolio sorted on their *ActRatio* can generate an annualized risk-adjusted return of 14.53%. We argue that one main difference with our empirical design, specifically their focus on active mutual funds only, might contributing to such differences.

24 Brown, Howard and Lundblad (2021) highlights three advantages of the days-ADV measure: (i) widely used by practitioners , (ii) it is a measure with an intuitive interpretation, and (iii) can be further decomposed into illiquidity and size components.

sorted on days-ADV measure while controlling for a wider set of factors included in several widely known asset pricing models. Specifically, in addition to the Fama and French (1993) three-factor model (FF3) we consider the Fama and French (2015) five-factor model that additionally controls for profitability and asset growth (FF5); the FF5 model augmented with the Pastor and Stambaugh (2003) traded liquidity factor [25]; and the FF5 model augmented with the Amihud (2019) illiquid-minus-liquid (IML) factor [26]. Finally, to alleviate the concern that our results might be driven by the *momentum* effect, we include the results for the FF5 model augmented with the IML factor and the momentum (MOM) factor [27].

[INSERT TABLE II.4 HERE]

In Panel A of Table II.4 we report the excess return and risk-adjusted return for quintile portfolio sorted on days-ADV for our full sample period. The results in the first column show that, on average, the most crowded stocks (quintile 5 - high) earn a monthly excess return of 1.20% (t-stat = 6.47), whereas the least crowded stocks (quintile 1 - low) have a monthly excess return of -0.10% (t-stat = -0.36). The Q5-Q1 portfolio earns a monthly excess return of 1.30% (t-stat=7.46). The return of the most crowded portfolio (Q5) is lower but remains significant after controlling for the risk factors considered in each asset pricing model. The portfolio that holds the least crowded stocks (Q1) earns lower adjusted returns. The monthly alphas for the high-crowding portfolio range from 0.54% with FF3, to 0.36%, with the FF5 augmented with the Pastor and Stambaugh or Amihud liquidity

25 We obtain the values for the liquidity factor from Lubos Pastor's website http://finance.wharton.upenn.edu/~stambaug/

26 We follow Amihud (2019) and estimate the IML factor as the differential return on *illiquid-minus-liquid* stock portfolios. The Illiquidity of a stock j on day d is measured by $Illiq_{j,d} = |return_{j,d}|/dollarvolume_{j,d}$ and is averaged over a 12-month period ending in November of each year. Portfolios are formed in each year and double sorted on *volatility* (standard deviation of daily returns) and *Illiq*. Stocks are sorted on *volatility* into three portfolios, and within each portfolio they are sorted on *Illiq* quintiles. The IML is then calculated as the average of monthly returns of the highest *Illiq* quintile acroos the three *volatility* portfolios minus the average of the lowest *Illiq* quintile accross the corresponding *volatility* portfolios.

27 Factor returns from Fama and French (1993), Fama and French (2015) factors as well as the momentum (MOM) factor were collected from Kenneth French's online data library.

factor, whereas the alphas of the least crowded portfolio span from -0.90%, FF3, to -0.53%, with FF5 augmented with the Amihud liquidity factor. Accordingly, the alphas for the high-minus-low portfolio span from 1.43%(t-stat = 9.67) , in the FF3 model, and to 0.89% (t-stat=6.89) in the FF5 augmented with the Amihud liquidity factor model. The adjustment for liquidity risk, in the FF5 with liquidity factor, does not significantly reduce the performance of the Q5-Q1 portfolio. Similarly, the inclusion of the momentum factor (see the last column), does not significantly affect results. This result is informative about the role that crowding might play for institutional investors trading, that although related to liquidity, seems to represent a distinct risk concern, in line with our first hypothesis.[28]

The relationship between days-ADV and expected returns is also documented by Brown, Howard and Lundblad (2021) focusing on hedge funds. We then examine whether our results are mainly driven by the hedge fund sample. We find that this is not the case. We distinguish among different type of investors such as mutual funds, investment advisors (mostly hedge funds), pension funds and others. We also distinguish among transient, dedicated, and quasi-indexers as in Bushee (2001), and short- vs. long-horizon institutions as in Yan and Zhang (2009*b*). To focus on the differential information and avoid that our findings are driven by overlaps of stocks held by different type of institutions, we follow Lan et al. (2023) and examine the stocks mostly held by each type of institution. For instance, to distinguish between stocks mostly held by short horizon and long horizon institutions, we first estimate a measure of relative holdings by aggregating the holdings of stocks by long horizon funds and short horizon funds and normalize it by number of shares outstanding. Then, we calculate the difference between such holdings and proceed to group stocks into terciles. Thus, in this case, the top (bottom) tercile contains stocks that are held mostly by long (short) horizon funds. Finally, within each top and bottom tercile we sort stocks into quintiles based on Days-ADV measure. Finally, we proceed to estimate the performance

28 It is possible to argue that our results may be driven by the first part of our sample in which we observe significantly higher values of the days-ADV measure. In Figure II.2 is possible to identify two distinct periods that may indicate changes in the trading behavior over our sample period. Since our main crowding measure, days-ADV, its a function of the daily trading volume, these changes may influence our results. We perform a structural break analysis of the time-series mean and median of days-ADV measure and find a common break in 1992:Q4. In an untabulated analysis we find that the alpha of the spread portfolio is statistically significant in both subperiods.

(risk adjusted return) of a spread portfolio that is long the most crowded stocks and short the least crowded ones. Table II.5 shows that the relationship between crowding and future returns is stronger for stocks mostly held by investment advisors, transient, and short-horizon institutions. Yan and Zhang (2009*b*) document that short-term institutions' trading is positively related to future stock returns and future earnings surprises and that this predictability does not revert in the long run. The authors argue that those results arise from short-term investors having access to better information than long-term institutions. Other studies have highlighted similar informational advantages reflected in hedge funds trades (Von Beschwitz et al., 2022) and, generally, in active managers's positions (Anton et al., 2010). Our finding that the relation between crowding and returns is stronger for stocks mostly held by hedge funds and short-term investors is consistent with these informational advantages.

[**INSERT TABLE II.5 HERE**]

We also explore the possibility that our results are sensitive to the state of the economy by examining the performance of the days-ADV sorted portfolios for different sample periods. Specifically, we analyze the NBER expansionary and recessionary periods and also a sample that does not include the most recent financial crisis period of 2008 (non-crisis period). Our results hold for all subperiods, which suggest that the relationship between days-ADV and expected return is robust to different states of the economy (See Table II.A6 of the Appendix for details).

5.2 The Effect of Crowding on Anomaly Returns

In this section, we test Hypothesis 2 about the cross-sectional interaction between crowding and anomaly returns. First, we conditionally sort the stocks in our sample first by each of the anomaly variables (using quintiles) and then according days-ADV . As a robustness check, we switched the order of the sorting variables to make sure our results were not driven by the order of the sorting (see Table II.A8 of the Appendix). Next, among stocks in the long and short anomaly portfolios, we focus on those with the highest and lowest days-ADV values. We classify an anomaly stock to be most (least) crowded if it is in the top (bottom) 30% of days-ADV values. Given our interest in measuring the impact of crowding on anomaly returns, we compare our estimations with the performance of single-sorted portfolios of each anomaly variable. Finally, we repeat our analysis for the period before and after the publication date of each anomaly to take into account the previously documented alpha decay once anomalies are broadly publicized (Mclean and Pontiff, 2016; Calluzzo et al., 2019).

Table II.6 reports the results for each anomaly in our sample (Panel A) as well as for an equally-weighted portfolio invested across the 11 anomalies (Panel B). Strikingly, anomaly returns appear to be concentrated among the most and least crowded stocks and this finding is consistent across all the anomalies in our sample. For all of the 11 anomalies, the three-factor alpha of the spread portfolio (high crowding and long-leg anomaly minus low crowding and short-leg anomaly) is much higher than that obtained in the single sorting portfolio. In line with other research ((Mclean and Pontiff, 2016) and (Calluzzo et al., 2019)) most alphas decline in the period after publication, but, with only one exception (AG), they remain economically and statistically significant.

[INSERT TABLE II.6 HERE]

In Table II.6, Panel B, we estimate an aggregate anomaly portfolio by taking the equally weighted average each quarter across all available anomaly returns. The monthly three-factor alpha of the spread equally-weighted portfolio is 1.78% annualized with a t-value of 10.94. When we consider the FF5 model augmented with the liquidity factors, the alphas is reduced but still highly significant with a t-value of 8.92 and 7.99. Similarly, the addition of the momentum factor to the FF5 model augmented with the liquidity factors (see the last column), does not significantly change the results. In the Appendix (Panel A of Table II.A8) we provide results where we reverse the sorting procedure and find that our results hold. If we modify our sorting procedure (Panel B of Table II.A8), performing independent sorting instead of conditional sorting, our main results hold although we observe lower returns and alphas in most anomalies.

Next, we test whether the observed relationship between days-ADV and anomaly returns is limited to our sample of eleven anomalies. We address this concern and replicate the results of Table II.6 for a broader set of anomalies. We select the 97 anomalies analyzed by Mclean and Pontiff (2016) and estimate the double sorted portfolio returns for the same subsamples (full sample, in-sample, and post-publication). Following Mclean and Pontiff (2016) we group the set of anomalies into four equally-weighted portfolios: event, market, valuation, and fundamental. As shown in Table II.7, the outperformance of anomaly returns among the most (least) crowded anomaly stocks compared to the single sorted portfolios holds for all four portfolios.

[INSERT TABLE II.7 HERE]

The fact that abnormal returns are significantly higher (lower) among anomaly stocks within the top (bottom) days-ADV group supports Hypothesis 2 and the view that crowded positions include additional risk considerations for arbitrage trading. Our results complement those of (Chen et al., 2019) who find that arbitrage trading is not able to correct mispricing in anomalies by showing that crowded equity positions might pose additional limits to arbitrage.

5.3 Fama-MacBeth Analysis

Next, we perform Fama and MacBeth (1973*b*) cross-sectional regressions to examine the influence of crowding on future stock returns, while controlling for other variables identified to influence institutional investors demand (Yan and Zhang, 2009*b*; Calluzzo et al., 2019). For each quarter we run a cross-sectional regression of cumulative monthly returns over the next quarter on the *log of the days-ADV* measure along with control variables.[29]

The control variables include institutional ownership, market capitalization (size), the number of months since stock's first appears in CRSP (age), the standard deviation of

29 We take the log of days-ADV due to the skewed distribution of days-ADV and reduce the effect of outliers on the estimated coefficients.

monthly returns over the previous two years, book-to-market ratio, dividend yield, average monthly turnover over the past three months, cumulative return over the past three months, cumulative return over the past nine months preceding the beginning of the quarter. We use the natural log of all control variables with the exception of cumulative returns.

[INSERT TABLE II.8 HERE]

Table II.8 reports the results of the Fama-Macbeth regressions using as dependent variable next quarter returns. We consider three different samples: a full sample in column 1, and two different subperiods in column 2 and 3 according to the previously estimated structural break in the days-ADV series. We find the regression coefficient on the log(ADV) measure to be significant with the expected signs for the full sample and for each subperiod.[30] These results provide further support for Hypothesis 1. To test Hypothesis 2 we next include the crowding variable interacted with dummy variables that capture whether a stock is in the long or short leg of an anomaly. We use a *Long* (*Short*) dummy that equals one if a stocks is included in at least one anomaly long (short) portfolio. The coefficients associated with the dummies are generally statically significant indicating that the relationship between crowding and future stock returns is stronger for anomaly stocks. In columns 6 and 7 we include a post-publication dummy as well as an interaction terms with the long (short) dummy, and the log of the days-ADV measure (LADV). Results show the average slope coefficient on the interaction terms is positive and significant for both long (short) legs after publication dates. Our evidence suggest that the relationship between days-ADV and stock returns is stronger among anomaly returns and that this effect remains after publication dates. This results provide further evidence in line with Hypothesis 2.

A potential concern is that our results are driven either the numerator or denominator of the days-ADV measure. We follow Brown, Howard and Lundblad (2021) and perform

30 In an untabulated analysis we address the question of whether crowding has a short-lived impact on future stock returns. Although the magnitude of the parameter coefficients is reduced in the cross-sectional regression of cumulative returns (from 0.559 to 0.312 and 0.599 to 0.303 for each subperiod, respectively), these values remain highly significant.

the Fama-Macbeth regressions on the separate components of the days-ADV measure (PSO - security's percentage of shares outstanding and ILLIQ - inverse of turnover). Our results (Table II.A10 of the Appendix) show that the observed relationship between crowding and future returns is not driven by only one component of the days-ADV measure.

5.4 The Relationship between Crowding and Crash Risk

Large fluctuations in stock prices, especially large sudden drops, are a main concern of investors and regulators. A strand of literature on the cross-section of stock returns shows that investors dislike tail sensitive assets (e.g., Kelly and Jiang, 2014; Chabi-Yo et al., 2019), and that security return's skewness is a priced risk factor (Harvey and Siddique, 2000). These large, negative, market-adjusted returns are labelled crash risk. Most of the literature on *crash risk* relates different aspects of information asymmetries between corporate insiders and external stakeholders (Habib et al., 2018) as determinants of a firm's exposure to crash risk. However, recent studies analyze this risk in the context of its relation to investor's factor exposure (Chabi-Yo et al., 2019). In Hypothesis 3 we conjecture that crowding increases institutional holdings' exposure to stock price crash. Moreover, it is possible that the rise of capital allocated to specific strategies, such as market anomalies, and the use of leverage by the arbitrageurs increase the exposure to crash risk due to liquidity exhaustion.

We empirically investigate the impact of crowding on crash risk to shed light on the potential increased risk that crowded holdings pose to institutional investors. We measure stock crash risk using two variables. First, we calculate the negative coefficient of skewness of firm-specific weekly returns (NCSkew). Second, we estimate DUVOL (down-to-up volatility) as in Hutton et al. (2009). This measure is the log ratio of the standard deviation of the down sample returns to the standard deviation of the up sample returns. Up (down) sample includes all weeks with firm-specific weekly returns above (below) the mean of the fiscal year. We proceed to regress these crash risk measures on the log of the Days-ADV measure and a set of control variables. The control variables we include are the cumulative firm-specific daily returns, the kurtosis and the standard deviation of firm-specific daily returns, market-to-book ratio, book value of all liabilities divided by total assets, ROA ratio, log of market capitalization (size), average monthly share turnover, the number of analyst following the firm, aggregated at the month level, and estimated as the average over the past 3 months. The control variables are measured at a quarterly frequency using the most recent data with one quarter lag with respect the dependent variable. All regressions control for year and firm fixed-effects.[31] Standard errors are corrected for firm clustering.

[INSERT TABLE II.9 AND II.10 HERE]

Table II.9 and II.10 report the results of our regression analysis. The dependent variable is stock price crash risk measured by NCSKew in Table II.9 and DUVOL in Table II.10. We estimate the crash risk measures using the next year weekly returns. Column 1 shows the estimation of the effect of crowding, the log of Days-ADV (LADV), on crash risk for the complete sample period. Columns 2 and 3 show that relationship for the sample period between 1980:Q1 to 1992:Q4 and 1993:Q1 to 2021:Q4, respectively. These specifications allows us to consider the structural break in the time-series of the Days-ADV measure. The coefficient on the LADV variable is significant for the complete sample period (t-statistic = 3.29) and the most recent sample. The results provide support for Hypothesis 3 and suggest that crowding increases the 13f portfolio holdings exposure to crash risk. Next, we investigate if the relationship is stronger for anomalies using the same dummies used in the Fama MacBeth regression. The relationship between crowding and crash risk appears to be stronger in the short leg of anomalies as the coefficient of the interaction term with the short leg dummy is significant.

Columns 6 and 7 of Tables II.9 and II.10 include a post-publication dummy and its interaction with the long (short) dummy, and LADV. Overall, the insignificance of most interaction terms suggests that the relationship between days-ADV and crash risk on anomaly stocks do not vary or are reduced after publication dates. These results are similar for the alternative crash risk measure DUVOL (columns 6 and 7 of Table II.10).

31 We follow Callen and Fang (2015) who argue that the inclusion of the implementation of firm fixed-effects in crash risk regressions help mitigate the concern that omitted time-invariant firm characteristics may be driving the results.

It is possible that some institutional investors (e.g., transient and short-horizon institutions) may engage in more frequent trading. As a result, the observed relationship between crowding and crash risk could vary when examining shorter time intervals, such as quarterly data. Moreover, it's important to consider that some institutional investors simultaneously employ multiple investment strategies, potentially leading certain stocks to become more (less) crowded if they are considered in more than one long (short) anomaly portfolios. We address this aspect in Tables II.A11 and II.A12 in the Appendix. We first construct quarterly versions of each one of the initial 11 anomalies as well as for each crash risk proxy. We also estimate the NET variable of Engelberg et al. (2020). NET represents the difference between the number of long and short anomaly portfolios that a stock is in for quarter t. A positive value of NET indicates that a stock is part of more long anomaly portfolios than short ones, thus we define a NET dummy variable that equals 1 if the NET value is positive and 0 otherwise. We run similar regressions as in Tables II.9 and II.10 and include an interaction term between post-publication, the NET dummy, and the log of Days-ADV variables. Our findings verify the positive relationship between Days-ADV and future crash risk at the quarterly level. The magnitude of the LADV coefficient is higher than that obtained in the yearly regressions. Furthermore, we document a positive and significant coefficient of the interaction term, indicative of an increase exposure to crash risk for NET long stocks after publication.

Overall, our results show an economically and statistically significant relationship between crowding and crash risk. This evidence is consistent with Hypothesis 3 and the idea that crowding further increases risk concerns for institutional investors. This finding is consistent with a risk-based explanation of the higher returns associated with crowding. An alternative explanation is that the higher return is driven by a temporary price impact of institutions purchasing crowded stocks. To test this explanation we examine the returns of the crowding portfolio over longer periods of time than just the next quarter after portfolio sorting. In Table II.A7 in the Appendix we find that the performance of the crowding portfolio does not revert in the short run but persists over the next six quarters after portfolio sorting. There is still the possibility that the price impact of institutions crowding some particular type of stocks is more permanent in nature, which is consistent with recent research on demand system Koijen and Yogo (2019*b*). We leave this investigation to future research.

6 Conclusion

Intuitively, an increased participation of sophisticated investors will have a positive influence on market efficiency by enhancing arbitrage trading that quickly corrects mispricing. However, there may be negative externalities when too many investors chase the same inefficiency without adjusting for the presence of other investors. Dating back to the late 1990s and reemerging after the quant crisis of 2007, this phenomenon has been coined the "crowded-trade problem". While there is no doubt that stock markets are increasingly dominated by institutional investors, there is conflicting evidence on the influence of crowding in equity price dynamics and the role that arbitrageurs play in increasing or mitigating this potential problem. Our paper contributes to this current debate by examining crowding for a set of well-known stock anomalies and using holdings of institutional investors. We present several empirical findings that support the view that crowding influences anomaly returns, is positively related to crash risk, and plays a role in the limits of arbitrage by adding risk considerations.

We find that, while in aggregate, crowdedness has decreased over time in our sample of institutional holdings, crowded equity positions in anomalies remain and have significant impacts in terms of risk and return dynamics. If crowded positions impose additional risk for arbitrageurs, we expect to find increased abnormal returns among the most crowded anomaly stocks. Based on the days-ADV measure of crowding over the period 1980-2021 we observe that crowding is positively related to future abnormal returns across all the anomalies in our sample. Moreover, we find that these anomaly returns conditional on crowding remain significant after publication dates. Our findings are relevant for practitioners and regulators concerned about the crash risk exposure in highly concentrated positions related to anomaly trading.

7 Tables and Figures

Figure II.1: 13F Institutional Investors, holdings, ownership, portfolio size, and position in average security.

Panel A shows the growth of the median Institutional Ownership (IO) in percentage terms. IO is estimated for each security as the number of shares held by institutional investors divided by the total number of shares outstanding. Panel B illustrates the growth in the mean number of institutional investors ($NumbInst$) holding the same security. Panel C shows, in the red line, the median number of shares in a typical portfolio of an institutional investor in our sample. This graph also shows, in the blue line, the growth in the average amount of money invested, expressed in millions of USD, by an institutional investor in a typical security. Panel D illustrates, in the red line, the total number of distinct securities existing in our 13F institutional investors' holdings dataset in each quarter. Additionally, in the blue line, we show the total number of distinct 13F institutional investors in our sample. The security universe is constructed as securities identified in SEC 13F filings and CRSP. We include only common shares (CRSP share codes 10 and 11) and securities whose price is higher than \$5. The sample period is from 1980:Q1 to 2021:Q4.

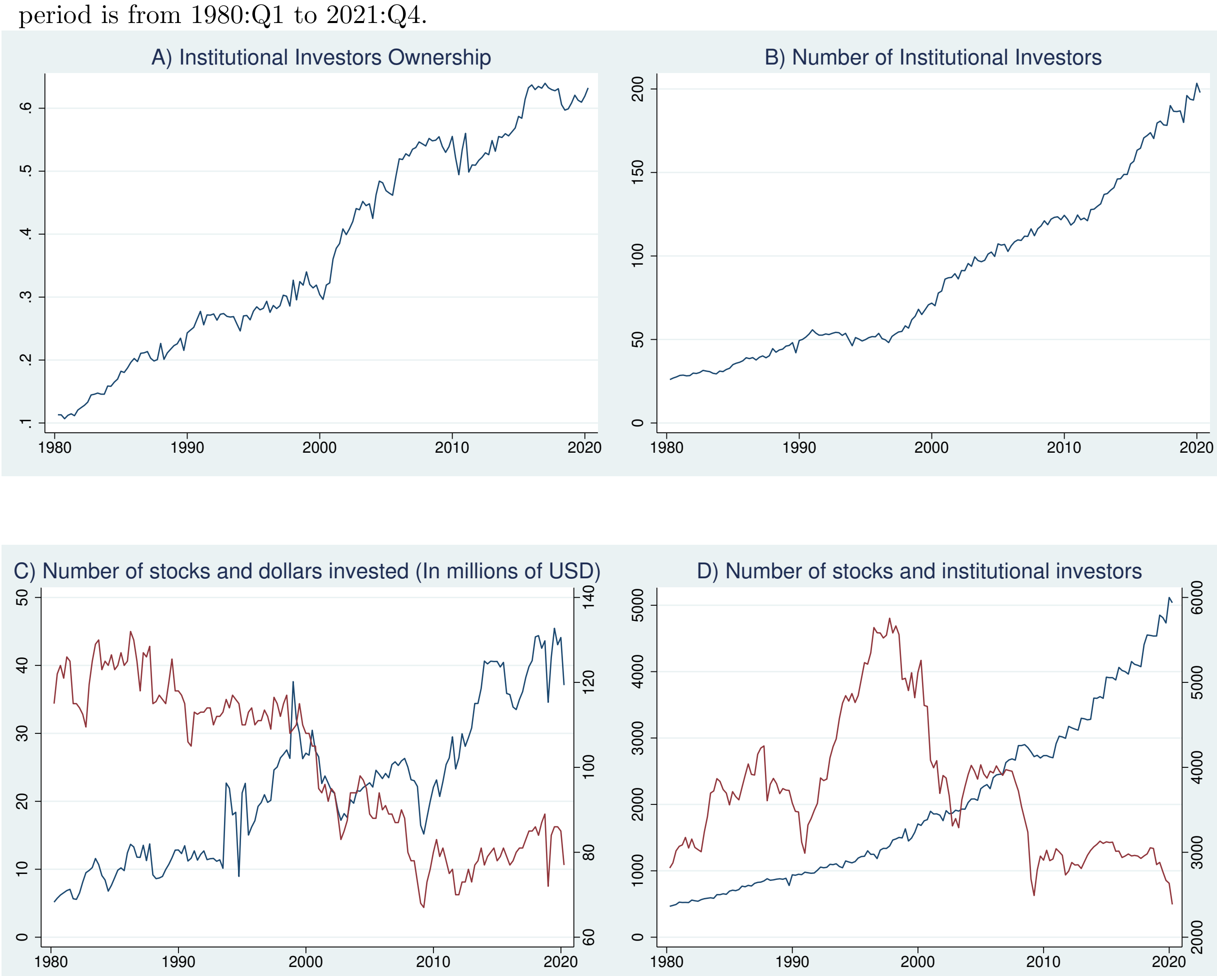


Figure II.2: Cosine similarity and Days-ADV over time

This figure plots the time-series of average Cosine Similarity of 13F institution's holdings as well as the the time-series average of cross-sectional median Days-ADV measure. Each quarter we compute cosine similarity as in Eq. (2.1) between every pair of institutional investor's holdings. Days-ADV is measured as the money value held in a security by all institutional investors relative to a security's average daily money volume. The sample period is from 1980:Q1 to 2021:Q4. Panel A shows the evolution of average cosine similarity over time. Panel B plots the time-series median Days-ADV for the complete sample period. We performed a structural break analysis of this time-series find a common break in the year 1995 (horizontal red line). Panel C shows the time-series for the subsample of stocks in the Days-ADV bottom-quantile, while Panel D reports the same estimation for the top-quantile sample.

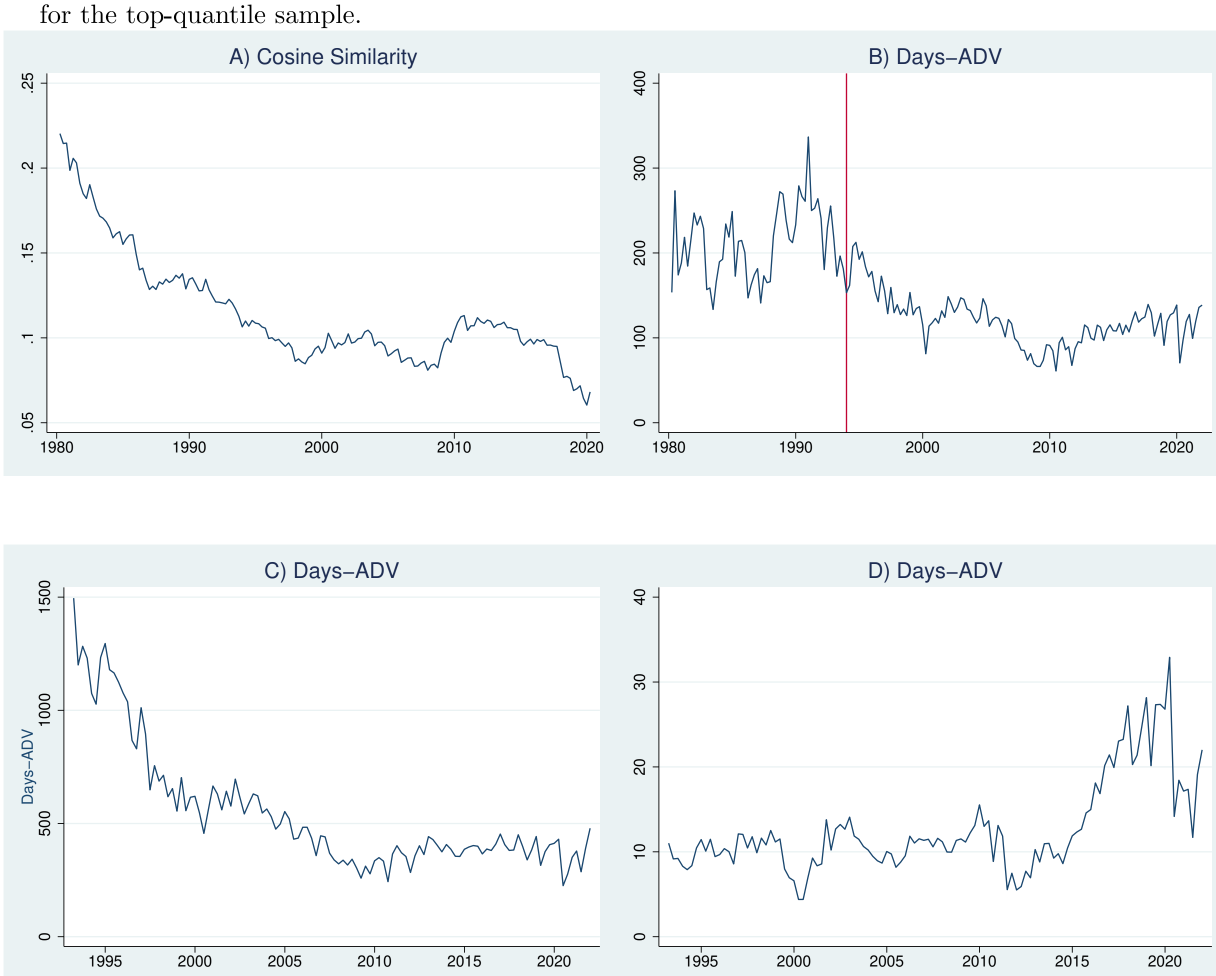


Table II.1: Sample Anomalies

This table describes the eleven asset pricing anomalies studied by (Stambaugh et al., 2012), providing details of the paper in which they were first identified, nd a brief explanation of the anticipated relationship between the stock characteristic and expected risk-adjusted returns.

	Anomaly	Label	Paper	Description
1	Composite equity issuance	CEI	Daniel and Titman (2006)	CEI measures the amount of equity a firm issue or retires in exchange for cash or services. Firms with higher CEI earn lower risk-adjusted returns
2	Net stock issuance	NSI	Loughran and Ritter (1995)	Issuing firms underperform compared to the overall market and such performance lasts for up to three years.
3	Total accruals	ACC	Sloan (1996)	Stock prices may not reflect the accrual component of earnings. Firms with higher total accounting accruals underperform those with lower accounting accruals
4	Net operating assets	NOA	Hirshleifer et al. (2004)	NOA is negatively related to firm's future long-run risk-adjusted return.
5	Gross profitability	GP	Novy-Marx (2013)	Profitable firms earn significantly higher risk-adjusted returns than unprofitable ones
6	Asset growth	AG	Cooper et al. (2004)	Firms with higher asset growth rates subsequently underperform those with lower growth rates.
7	Capital investments	CI	Titman et al. (2004)	Increases in firms capital investments strongly predicts future lower risk adjusted returns.
8	Investment-to-assets	IVA	Xing (2008)	Firms with low investment-to-assets ratios show higher risk-adjusted returns compared to those with higher ratios
9	Momentum	MOM	Jegadeesh and Titman (1993)	A profitable strategy is to buy shares of firms with positive performance in the past six months, skip one month, and hold it for the following six months.
10	Ohlson O-score	OSC	Dichev (1998)	Higher bankruptcy risk, measured by the O-score Ohlson (1980), is not rewarded with higher returns. Firms facing increased bankruptcy risk earn subsequently lower returns.
11	Failure probability	FP	Campbell et al. (2008)	Financial distress, estimated based on a dynamic logit model, negatively predicts firm's future return.

Table II.2: Descriptive Statistics

This table reports descriptive statistics of the following variables: Number of stocks held in the institutional investor's portfolio (NStocks); Total Assets under management (AUM) in millions of USD dollars; Number of institutional investors holding the same stock (NIpermno); Total amount of money invested by all 13f institutional investors in a given stock (USDpermno) in millions of US dollars; stock average daily volume relative to total market capitalization (Turnover); Number of Institutional Investors (NI); stock percentage of shares outstanding owned by the 13F investors (PSO); Days-ADV, defined as the money value held in a security by all institutional investors relative to the security's average daily money volume; And, Activity ratio (Actratio) which is the percentage of shares held by all institutions at at quarter (*t-2*) divided by the stock's average turnover during previous quarter (*t-1*); the bid-ask spread estimated as suggested by Abdi and Ranaldo (2017) (Bid-Ask); and the number of analyst following the firm (NAnalyst) collected from I/B/E/S. Panel A reports summary statistics for the full sample of 13F institutional investors. Panel B reports the mean and the median of these variables across stocks in each quintile portfolio that is sorted on the Days-ADV measure. The data on institutional holdings is obtained from Thomson Reuters (TR) 13F database. Stock price, trading volume, and total shares outstanding data is from CRSP. The number of analysts is from IBES. Number of institutional investors is a counter of the number of distinct institutional investors holding the same stock. We include only stocks whose CRSP share code is 10 and 11 (ordinary common shares). Also, we exclude firms with stock prices less than USD $5 to reduce the effects of microcaps. The variables Days-ADV, PSO, and turnover are winsorized at the 1% and the 99% levels. The sample period is from 1980:Q1 to 2021:Q4.

Panel A: Stock Characteristics - 13F Institutional Investors holdings

	Full Sample			1980-1992			1993-2021		
	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std
NStocks	232	100	411	244	120	265	206	91	477
AUM ($ Million)	6,489.1	933.2	33,640.1	6,298.0	1,708.3	13,335.5	6,574.7	585.8	42,742.1
NIpermno	93	47	139	40	15	67	117	62	171
USDpermno ($ Million)	1,599.7	130.43	7,229.9	221.36	16.42	925.5	2,217.6	181.5	10,056.1
Turnover (%)	0.74	0.28	1.97	0.26	0.09	1.07%	0.96	0.37	2.38
NI	2,209	1,815	1,512	764	775	181	2,857	2,717	1391
PSO (%)	40.25	38.77	27.11	24.16	19.49	19.88	47.47	47.41	30.34
Days-ADV	377.6	150.5	700.0	660.1	213.7	1,167.9	251.0	122.2	490.7
Actratio	29.2	7.6	290.7	54.5	10.2	437.4	17.9	6.4	224.9

Table II.2: Descriptive Statistics (Continued)

Panel B: Stock Characteristics - Days-ADV sorted portfolios

		Mkt cap		NIpermno		ADV		PSO		Turnover		Bid-ask		NAnalyst	
	Period	Mean	Med	Mean	Med	Mean	Med	Mean	Med	Mean	Med	Mean	Med	Mean	Med
5 (High)	1980-1992	636.62	143.36	44	21	0.74	0.08	34.82	32.99	0.07	0.06	1.35	0.81	5	3
	1993-2021	2,432.01	219.24	76	42	3.82	0.23	49.03	47.74	0.13	0.11	1.18	0.85	3	2
4	1980-1992	1,083.71	209.37	71	33	2.11	0.29	34.78	33.58	0.15	0.14	1.06	0.65	8	5
	1993-2021	6,080.15	578.55	162	93	16.77	1.72	57.22	60.06	0.29	0.28	1.00	0.76	7	5
3	1980-1992	743.77	142.98	59	26	2.21	0.27	30.08	26.90	0.22	0.19	1.14	0.75	8	4
	1993-2021	5,982.10	759.50	183	109	24.83	3.70	58.53	62.77	0.45	0.46	1.04	0.79	8	6
2	1980-1992	403.84	83.68	38	16	1.77	0.19	22.71	17.66	0.29	0.24	1.31	0.95	5	2
	1993-2021	4,530.92	670.37	171	103	29.53	5.00	56.32	60.20	0.69	0.70	1.17	0.92	8	6
1 (low)	1980-1992	168.69	41.94	20	6	1.29	0.11	11.40	5.62	0.43	0.27	1.62	1.27	3	1
	1993-2021	2,357.24	297.18	112	45	30.60	3.25	39.18	27.82	1.21	1.02	1.51	1.24	6	3

Table II.3: Crowding-sorted Portfolio returns

This table reports monthly portfolio performance (expressed in percentage) measured by the Fama and French (1993) three-factor alpha quintile portfolios sorted on several crowding measures. The alpha is the intercept of a regression of monthly portfolio returns on the three Fama-French factors. Number of institutions (NI) is a counter of the number of distinct institutional investors holding the same stock. The percentage of shares outstanding owned by 13F Institutional investors (PSO) is estimated for each stock as the number of shares held by institutional investors divided by the total number of shares outstanding. Days-ADV is the money value held in security by all institutional investors relative to the security's average daily money volume. Activity ratio (Actratio) is the percentage of shares held by an institution at the end of each quarter (t-2) divided by the stock's average turnover during the quarter (t-1). We only include stocks whose CRSP share code is 10 and 11 (ordinary common shares). Also, we exclude firms with stock prices less than USD \$5 to reduce the effects of microcaps. Panel A reports the performance of value-weighted portfolios while Panel B shows the results for equal-weighted portfolios. We report t-statistics computed using Newey-West standard errors.

Panel A: FF3 alphas - Value-weighted

	5 (High)	4	3	2	1 (Low)	5 - 1
NI	-0.03	-0.07	-0.16	-0.01	-0.02	-0.01
	(-0.65)	(-1.63)	(-3.28)	(-0.20)	(-0.29)	(-0.10)
PSO	-0.11	-0.04	-0.06	-0.01	-0.11	0.00
	(-1.94)	(-0.89)	(-1.20)	(-0.13)	(-1.45)	(0.05)
Actratio	0.54	0.25	-0.01	-0.29	-0.70	1.26
	(8.20)	(1.85)	(-3.15)	(-6.51)	(-7.42)	(8.44)
Days-ADV	0.54	0.04	-0.16	-0.55	-0.90	1.44
	(8.87)	(0.87)	(-4.11)	(-6.69)	(-7.86)	(9.67)

Panel B: FF3 alphas - Equally-weighted

	5 (High)	4	3	2	1 (Low)	5 - 1
NI	-0.02	-0.11	-0.15	-0.10	-0.10	0.09
	(-1.40)	(-2.11)	(-2.54)	(-1.21)	(-0.94)	(0.80)
PSO	-0.06	-0.01	0.00	-0.04	-0.29	0.23
	(-1.21)	(-0.27)	(-0.04)	(-0.60)	(-2.94)	(2.08)
Actratio	0.55	0.07	-0.12	-0.49	-0.80	1.38
	(10.20)	(5.14)	(-0.21)	(-4.51)	(-8.19)	(11.92)
Days-ADV	0.63	0.29	0.02	-0.69	-0.94	1.57
	(10.64)	(4.96)	(0.21)	(-3.08)	(-9.40)	(12.23)

Table II.4: Univariate portfolio sorts on Days-ADV using various factor models

This table reports the excess returns (*ExcRert*) and risk-adjusted returns (alpha) for quintile portfolios and a spread portfolio (5-1) that buys the quintile 5 (high) and sells the quintile 1 (low) of stocks sorted on the Days-ADV measure. We adjust risk exposures using the three factor model of Fama and French (1993) - *FF3*, the five factor model of Fama and French (2015) augmented with the traded liquidity measure proposed by Pastor and Stambaugh (2003) - *FF5P*, the Fama-French five factor augmented with the *illiquid-minus-liquid* (IML) factor of Amihud (2019) - *FF5A*, and the Fama-French five factor that includes both the IML and the Carhart (1997) momentum (MOM) factors - *FF5AM*. Returns and alphas are expressed in percentages. The sample period is from 1980:Q1 to 2021:Q4. We report t-statistics computed using Newey-West standard errors.

	ExcRet	FF3	FF5P	FF5A	FF5AM
5 (high)	1.198	0.536	0.358	0.362	0.312
	(6.47)	(8.87)	(6.46)	(6.37)	(5.71)
4	0.722	0.037	-0.078	-0.094	-0.152
	(3.89)	(0.87)	(-1.74)	(-2.31)	(-3.65)
3	0.584	-0.159	-0.149	-0.160	-0.148
	(2.90)	(-4.11)	(-3.67)	(-3.86)	(-3.81)
2	0.311	-0.554	-0.287	-0.244	-0.186
	(1.24)	(-6.69)	(-3.93)	(-3.29)	(-2.59)
1 (low)	-0.097	-0.898	-0.600	-0.530	-0.484
	(-0.36)	(-7.86)	(-5.74)	(-4.96)	(-4.54)
5 - 1	1.295	1.435	0.958	0.892	0.796
	(7.46)	(9.67)	(7.52)	(6.89)	(6.29)

Table II.5: Bivariate portfolio sorts on stocks *mostly held* by institutions and Days-ADV

This table reports risk-adjusted returns (alphas) of the Days-ADV sorted spread portfolio (5-1) for stocks *mostly held* by each type of institutional investors following the procedure of Lan et al. (2023). Alphas are expressed in percentages. The sample period is from 1980:Q1 to 2021:Q4. We report t-statistics computed using Newey-West standard errors.

	FF3	FF5	FF5A	FF5AM
Short horizon	0.946	0.862	0.841	0.464
	(5.48)	(4.92)	(4.73)	(3.48)
Long horizon	0.236	0.205	0.201	0.007
	(1.79)	(1.49)	(1.46)	(0.06)
Transient	1.284	1.243	1.151	0.845
	(5.13)	(4.42)	(4.66)	(3.64)
Quase-indexer	0.431	0.369	0.360	0.063
	(2.86)	(2.35)	(2.24)	(0.50)
Transient	0.863	0.815	0.802	0.546
	(3.67)	(3.32)	(3.19)	(2.73)
Dedicated	0.301	0.182	0.204	0.027
	(1.99)	(1.16)	(1.27)	(0.18)
Invs Advisor	0.759	0.822	0.801	0.610
	(4.20)	(4.29)	(4.27)	(3.39)
Mutual funds (MF)	0.440	0.374	0.375	-0.036
	(2.11)	(1.72)	(1.68)	-(0.20)
Invs Advisor + MF	0.709	0.696	0.684	0.345
	(3.39)	(3.74)	(3.01)	(2.43)
The rest	0.362	0.334	0.301	0.146
	(3.01)	(2.70)	(2.41)	(2.03)

Table II.6: Bivariate portfolio sorts on stock market anomalies and Days-ADV

This table presents results of single sort on each stock market anomaly as well as the bivariate dependent sort on each stock market anomaly and Days-ADV. We sort anomalies at the end of every June (with the exception of momentum which is sorted every quarter). When sorting based on days-ADV, we rebalance every quarter. In Panel A, we report the results for each anomaly. In Panel B, we report the results for a portfolio that takes the equally-weighting (EW) average each month across all the available anomaly returns. We adjust risk exposures using the three factor model of Fama and French (1993) - *FF3*, the five factor model of Fama and French (2015) augmented with the traded liquidity measure proposed by Pastor and Stambaugh (2003) - *FF5P*, the Fama-French five factor augmented with the *illiquid-minus-liquid* (IML) factor of Amihud (2019) - *FF5A*, the Fama-French five factor that includes both the IML and the Carhart (1997) momentum (MOM) factors - *FF5AM*, and the Fama-French five factor augmented with the multivariate crash risk factor of Chabi-Yo et al. (2019) - *FF5C*. For each anomaly, we consider three sample periods. The complete sample period from 1980:Q1 to 2021:Q4 (first row); a sample period starting in 1980:Q1 until the end of the original anomaly publication sample period (in-sample); and the sample period starting from the year of publication up to the end of our the sample period 2021:Q4 (post-publication).

Panel A: Risk-adjusted returns (alpha) for each anomaly

	Single Sort	Double sort			
	FF3	FF3	FF5P	FF5A	FF5AM
FP	0.373	1.584	1.546	1.418	1.289
	(2.52)	(7.51)	(7.04)	(6.43)	(5.92)
In-sample	0.762	2.058	1.977	1.873	1.695
	(3.88)	(7.38)	(6.72)	(6.52)	(5.87)
Post-publication	0.003	1.070	1.221	0.942	1.002
	(0.01)	(2.73)	(3.26)	(2.44)	(2.67)
OSC	0.500	2.010	1.541	1.399	1.268
	(3.87)	(9.75)	(8.14)	(7.38)	(6.89)
In-sample	0.656	2.216	1.811	1.648	1.601
	(3.74)	(8.06)	(6.45)	(5.72)	(5.54)
Post-publication	0.537	1.873	1.221	0.997	0.946
	(3.40)	(6.27)	(4.42)	(3.66)	(3.61)
NSI	0.463	1.417	0.920	0.833	0.734
	(4.45)	(6.20)	(4.24)	(3.75)	(3.33)
In-sample	0.558	1.806	1.618	1.834	1.734
	(3.10)	(4.72)	(3.63)	(3.83)	(3.90)
Post-publication	0.495	1.429	0.963	0.882	0.815
	(3.52)	(4.80)	(3.31)	(2.97)	(2.76)
CEI	0.485	1.827	1.418	1.304	1.080
	(4.21)	(8.21)	(6.39)	(5.80)	(5.08)
In-sample	0.317	2.140	1.386	1.437	1.015
	(1.91)	(6.55)	(4.54)	(4.71)	(3.59)
Post-publication	0.692	1.183	0.971	0.950	1.049
	(3.64)	(2.97)	(2.44)	(2.32)	(2.62)
ACC	0.171	1.403	0.815	0.814	0.681
	(1.32)	(6.48)	(3.90)	(3.82)	(3.26)
In-sample	0.135	1.915	1.232	0.982	0.981
	(0.55)	(6.10)	(3.99)	(3.05)	(3.08)
Post-publication	0.083	1.136	0.461	0.500	0.436
	(0.50)	(3.63)	(1.53)	(1.63)	(1.46)

Table II.6: Bivariate portfolio sorts on stock market anomalies and days-ADV (continued)

	Single Sort	Double sort			
	FF3	FF3	FF5P	FF5A	FF5AM
NOA	0.594	2.109	1.836	1.900	1.664
	(5.07)	(10.31)	(8.69)	(8.85)	(8.51)
In-sample	0.700	2.697	2.383	2.547	1.981
	(4.05)	(8.40)	(7.06)	(7.72)	(7.20)
Post-publication	0.477	1.376	1.336	1.215	1.222
	(2.82)	(4.89)	(4.64)	(4.18)	(4.26)
MOM	0.309	1.172	1.298	1.001	
	(1.98)	(4.16)	(4.43)	(3.48)	
In-sample	0.711	1.340	0.702	0.518	
	(2.31)	(2.17)	(0.94)	(0.68)	
Post-publication	0.180	1.009	1.207	0.993	
	(0.88)	(2.81)	(3.25)	(2.77)	
GP	0.768	2.032	1.491	1.401	1.228
	(5.86)	(9.00)	(7.13)	(6.64)	(6.02)
In-sample	0.753	2.104	1.444	1.455	1.269
	(4.89)	(7.75)	(5.82)	(5.85)	(5.25)
Post-publication	0.977	1.402	1.374	1.364	1.338
	(2.60)	(2.28)	(2.52)	(2.44)	(2.43)
AG	0.256	1.593	0.889	0.784	0.615
	(2.03)	(6.85)	(4.25)	(3.68)	(3.01)
In-sample	0.334	1.965	1.018	0.982	0.580
	(1.76)	(5.48)	(3.22)	(3.11)	(1.99)
Post-publication	0.124	0.617	0.348	0.238	0.218
	(0.53)	(1.75)	(1.13)	(0.74)	(0.69)
ROA	0.626	2.040	1.380	1.185	0.986
	(3.53)	(8.05)	(6.26)	(5.35)	(4.65)
In-sample	0.818	2.353	1.444	1.383	0.936
	(2.84)	(5.74)	(4.29)	(4.14)	(3.00)
Post-publication	0.425	1.309	0.926	0.842	0.867
	(1.79)	(3.81)	(2.87)	(2.57)	(2.64)
IVA	0.176	1.426	0.857	0.689	0.512
	(1.58)	(6.15)	(3.90)	(3.09)	(2.39)
In-sample	0.265	1.784	0.965	0.875	0.443
	(1.78)	(4.94)	(2.98)	(2.69)	(1.50)
Post-publication	0.172	0.622	0.489	0.317	0.275
	(0.81)	(1.78)	(1.42)	(0.90)	(0.82)
Panel B: Alpha for the EW-portfolio across anomaly returns					
EWPort	0.390	1.693	1.267	1.149	0.969
	(6.42)	(11.09)	(9.05)	(8.20)	(7.69)
In-sample	0.536	1.957	1.415	1.352	1.099
	(5.24)	(9.32)	(7.38)	(7.04)	(6.50)
Post-publication	0.301	1.609	1.154	1.037	0.914
	(3.89)	(7.67)	(5.76)	(5.18)	(4.88)

Table II.7: Bivariate portfolio sorts: Larger sample of anomalies and Days-ADV

This table presents results of the bivariate (conditional) double sort on stock market anomalies and Days-ADV. We extend our sample of anomalies and estimate the 97 anomalies studied by Mclean and Pontiff (2016). We follow the authors and classify the anomalies into four groups: event (32 anomalies), market (25 anomalies), valuation (13 anomalies), and fundamentals (27 anomalies). We report the results for each portfolio that takes the equally-weighting (EW) average each month across all the available anomaly returns in each group. We adjust risk exposure using the three factors of Fama and French (1993) - *FF3*, the Fama-French five factor augmented with the traded liquidity measure proposed by Pastor and Stambaugh (2003) - *FF5P*, the Fama-French five factor augmented with the *illiquid-minus-liquid* (IML) factor of Amihud (2019) - *FF5A*, and the Fama-French five factor that includes both the IML and the Carhart (1997) momentum factors - *FF5AM*. For each anomaly, we consider three sample periods. The complete sample period from 1980:Q1 to 2021:Q4 (first row); a sample period starting in 1980:Q1 until the end of the original anomaly publication sample period (in-sample); and the sample period starting from the year of publication up to the end of our the sample period 2021:Q4 (post-publication).

	Single Sort	Double sort			
	FF3	FF3	FF5P	FFF5A	FF5AM
Panel A: Event					
Full sample	0.170	1.250	0.892	0.822	0.680
	(6.54)	(10.57)	(8.06)	(6.90)	(6.72)
In-sample	0.186	1.299	0.900	0.873	0.667
	(2.84)	(7.79)	(5.99)	(5.41)	(4.46)
Post-publication	0.127	1.083	0.777	0.689	0.508
	(2.54)	(8.88)	(6.70)	(5.59)	(5.46)
Panel B: Market					
Full sample	0.393	1.550	1.115	0.999	0.755
	(5.43)	(10.66)	(7.98)	(6.61)	(6.72)
In-sample	0.466	1.913	1.281	1.222	0.905
	(3.99)	(8.70)	(5.84)	(5.01)	(4.69)
Post-publication	0.369	1.530	1.082	0.971	0.775
	(4.95)	(10.84)	(8.07)	(6.97)	(6.71)
Panel C: Valuation					
Full sample	0.121	1.306	0.974	0.927	0.853
	(2.48)	(10.18)	(8.14)	(7.47)	(7.02)
In-sample	0.276	1.429	1.087	1.106	1.030
	(4.74)	(9.81)	(7.23)	(7.13)	(6.66)
Post-publication	0.109	1.190	0.890	0.723	0.638
	(1.39)	(8.58)	(6.46)	(5.78)	(5.29)
Panel D: Fundamental					
Full sample	0.289	1.408	1.061	0.930	0.796
	(7.45)	(10.79)	(9.09)	(7.30)	(7.22)
In-sample	0.367	1.492	1.055	1.024	0.895
	(5.54)	(9.44)	(7.67)	(7.42)	(6.85)
Post-publication	0.152	0.982	0.603	0.480	0.365
	(2.02)	(6.47)	(4.64)	(3.64)	(2.90)

Table II.8: Fama-MacBeth regressions with interaction terms: Days-ADV and next quarter cumulative monthly returns

This table presents the results from Fama-Macbeth regressions of cumulative monthly returns over the next quarter on the log of Days-ADV (LADV), a set of anomaly-stock dummy variables, a post-publication dummy, several interaction terms, and a series of control variables. We include the following control variables: market capitalization (size), the number of months since stock's first appears in CRSP (age), the standard deviation of monthly returns over the previous two years, book-to-market ratio, dividend yield, average monthly turnover over the past three months, cummulative return over the past three months, cumulative return over the past nine months preceding the beginning of quarter. We use natural log of all control variables with the exception of cumulative returns. The *Long* (*Short*) dummy equals one if a stocks is included in at least one anomaly long (short) portfolio. The post-publication dummy (*Pos-Pub*) is equal to one if the month is after the publication date of the anomaly paper and zero otherwise. The t-statistics are based on Newey-West standard errors with four lags. Returns and alphas are in percent per month.

	(1)	(2)	(3)	(4)	(5)
LADV	0.546	0.717	0.485	0.460	0.460
	(4.31)	(2.01)	(4.75)	(3.66)	(3.61)
Long				-1.690	-1.691
				(-3.13)	(-3.24)
Long x LADV				0.287	0.206
				(3.12)	(3.01)
Short				-3.038	-3.038
				(-5.25)	(-5.30)
Short x LADV				0.485	0.308
				(4.86)	(3.83)
Pos-Pub					1.042
					(1.12)
Pos-Pub x Long x LADV					0.810
					(1.62)
Pos-Pub x Short x LADV					0.178
					(2.92)
Controls	Yes	Yes	Yes	Yes	Yes
Obs	294,301	79,352	213,299	294,301	294,301
Adj. R^2	8.86	10.71	8.04	9.28	9.12

Table II.9: Crash risk (NCSkew), anomalies and crowding

This table estimates the cross-sectional relation between the log of Days-ADV (LADV), future stock price crash risk, a set of anomaly-stock dummy variables, a post-publication dummy, several interaction terms, and a series of control variables. The dependent variable is the one-year-ahead NCSkew (Negative coefficient of firm-specific daily returns.). We include the following control variables: the kurtosis and the standard deviation of firm-specific weekly returns, market-to-book ratio, book value of all liabilities divided by total assets, ROA ratio, log of market capitalization (size), average monthly share turnover, the number of analyst following the firm, and the lag of the NCSkew variable. All control variables are measured over the previous fiscal year *t-1*. The *Long* (*Short*) dummy equals one if a stocks is included in at least one anomaly long (short) portfolio. The post-publication dummy (*Pos-Pub*) is equal to one if the month is after the publication date of the anomaly paper and zero otherwise. The *t*-statistics are based on errors clustered by firm.

	(1)	(2)	(3)	(4)	(5)
LADV	0.011	0.003	0.008	0.008	0.009
	(3.29)	(0.85)	(2.28)	(2.16)	(2.30)
Long				-0.066	-0.075
				(-3.05)	(-3.34)
Long x LADV				0.003	0.003
				(1.06)	(1.67)
Short				0.007	0.102
				(3.12)	(4.21)
Short x LADV				0.008	0.002
				(2.16)	(1.58)
Pos-Pub					-0.031
					(-2.87)
Pos-Pub x Long x LADV					-0.005
					(-1.69)
Pos-Pub x Short x LADV					0.004
					(1.74)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	102,940	23,996	78,652	102,940	102,940
Adj. R^2	8.60	13.20	7.71	8.73	9.06

Table II.10: Crash risk (Duvol), anomalies and crowding

This table estimates the cross-sectional relation between the log of Days-ADV (LADV), future stock price crash risk, a set of anomaly-stock dummy variables, a post-publication dummy, several interaction terms, and a series of control variables. The dependent variable the one-year-ahead DUVOL ("*Down-to-up volatility*"). We include the following control variables: the kurtosis and the standard deviation of firm-specific weekly returns, market-to-book ratio, book value of all liabilities divided by total assets, ROA ratio, log of market capitalization (size), average monthly share turnover, the number of analyst following the firm, and the lag of the NCSkew variable. All control variables are measured over the previous fiscal year *t-1*. The *Long* (*Short*) dummy equals one if a stocks is included in at least one anomaly long (short) portfolio. The post-publication dummy (*Pos-Pub*) is equal to one if the month is after the publication date of the anomaly paper and zero otherwise. The t-statistics are based on errors clustered by firm.

	(1)	(2)	(3)	(4)	(5)
LADV	0.018	0.004	0.001	0.009	0.012
	(5.13)	(0.69)	(3.93)	(3.36)	(4.64)
Long				-0.046	-0.066
				(-3.34)	(-4.74)
Long x LADV				0.015	0.005
				(1.68)	(1.81)
Short				0.034	0.051
				(2.29)	(3.48)
Short x LADV				0.005	0.002
				(1.89)	(1.47)
Pos-Pub					-0.017
					(-2.86)
Pos-Pub x Long x LADV					-0.005
					(-1.89)
Pos-Pub x Short x LADV					0.006
					(2.30)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	102,940	23,996	78,644	102,940	102,940
Adj. R^2	11.10	16.51	9.15	11.38	8.69

8 Appendix

Table II.A1: Descriptive Statistics - 13F database

This table reports descriptive statistics of the following variables: Number of 13F institutional investors holding the same stock (NIpermno); Total amount of money invested by all 13F institutional investors in a given stock(USDpermno), in millions of US dollars; Number of stocks held in 13F institutional investor's portfolio (NStocks); Days-ADV, defined as the money value held in a security by all institutional investors relative to the security's average daily money volume; stock percentage of shares outstanding owned by the 13F investors (PSO); And, Illiquidity as the inverse of the stock average daily volume relative to total market capitalization. We include only stocks whose CRSP share code is 10 and 11 (ordinary common shares). Also, we exclude firms with stock prices less than USD $5 to reduce the effects of microcaps. The variables Days-ADV, PSO, and Illiquidity are winsorized at the 1% and the 99% levels. The sample period is from 1980:Q1 to 2021:Q4.

	NIpermno			USDpermno			NStocks		
Period	Mean	Median	P90	Mean	Median	P90	Mean	Median	P90
1980-1990	38	13	101	199.1	13.9	392.3	205.4	121	472
1991-2000	58	25	143	704.9	42.8	1,094.3	261.4	111	622
2001-2010	107	62	250	1,792.2	169.9	3,326.6	237.4	85	540
2011-2021	170	88	404	3,779.8	279.3	7,044.7	233.6	82	565

	Days-ADV			PSO (%)			Illiquidity		
Period	Mean	Median	P90	Mean	Median	P90	Mean	Median	P90
1980-1990	1,129.5	205.2	1,722.8	23.7	18.4	52.4	7,733.5	1197.8	9,522.2
1991-2000	627.1	156.6	925.8	43.8	29.1	70.2	3,286.8	611.7	4,027.8
2001-2010	269.6	105.4	441.6	52.0	48.7	91.5	1,018.3	270.8	1,821.3
2011-2021	309.3	111.2	383.4	60.3	59.5	95.8	1,456.6	210.3	915.3

Table II.A2: Descriptive statistics - 13F holdings database by Institution type

This table reports descriptive statistics of the following variables: Number of 13F institutional investors (NInst); the number of 13F institutional investors holding the same stock (NIpermno); total amount of money invested by all 13F institutional investors in a given stock (USDpermno), in millions of US dollars; Number of stocks held in 13F institutional investor's portfolio (NStocks). In Panel A, we identify institutional investors following Brian Bushee's classification (Bushee, 2001). *Dedicated* and *quase-indexer*s provide long-term, stable ownership to firms because they are geared toward longer-term dividend income or capital appreciation. *Dedicated* institutions are characterized by large average investments in portfolio firms and very low turnover. *Quase-indexers* are also characterized by low turnover, but they tend to have diversified holdings, consistent with passive buy-and-hold strategies. *Transient* institutions are characterized by having short investment horizons and high portfolio turnover. In Panel B, we identify institutional investors following Koijen and Yogo (2019*b*). We include only stocks whose CRSP share code is 10 and 11 (ordinary common shares). Also, we exclude firms with stock prices less than USD $5 to reduce the effects of microcaps. The sample period is from 1980:Q1 to 2021:Q4.

Panel A: Brian Bushee's classification (Bushee, 2001)

	NInst	NIpermno		USDpermno		NStocks	
		Median	P90	Median	P90	Median	P90
Dedicated							
1980-1990	58	2	11	3.6	68.5	96	451
1991-2000	60	2	7	3.9	134.9	49	499
2001-2010	70	1	4	4.2	236.9	15	145
2011-2021	82	1	3	9.4	309.4	16	103
Quase-indexer							
1980-1990	511	11	76	10.3	286.8	127	492
1991-2000	884	18	102	29.5	752.9	117	646
2001-2010	1,462	41	170	114.1	2,396.9	99	584
2011-2021	2,536	59	289	171.5	5,051.6	112	676
Transient							
1980-1990	126	4	22	4.8	107.3	135	464
1991-2000	291	7	39	10.9	287.3	127	645
2001-2010	726	20	77	42.1	776.1	76	554
2011-2021	995	23	97	72.5	1,472.3	71	584

Table II.A3: Descriptive statistics - 13F holdings database by Institution type (continued)

Panel B: Koijen and Yogo (2019*b*) classification

	NInst	NIpermno		USDpermno		NStocks	
		Median	P90	Median	P90	Median	P90
Banks							
1980-1990	208	6	47	4.6	135.7	191	598
1991-2000	190	7	41	5.9	196.0	232	1111
2001-2010	160	12	39	20.1	455.9	223	1,506
2011-2021	155	13	44	36.5	1124.4	276	2,006
Insurance companies							
1980-1990	65	3	13	3.6	64.3	103	457
1991-2000	72	3	17	3.8	114.5	155	974
2001-2010	55	6	18	8.0	189.7	235	1955
2011-2021	51	6	16	9.9	286.7	165	2443
Investment Advisors							
1980-1990	226	4	22	5.4	103.5	80	236
1991-2000	632	6	34	10.5	196.9	78	236
2001-2010	1,703	22	114	51.2	857.4	72	286
2011-2021	3,039	45	230	117.7	2,382.1	77	424
Pension Funds							
1980-1990	31	2	13	2.6	79.9	137	637
1991-2000	33	3	15	5.2	118.2	419	1,449
2001-2010	40	7	23	10.7	206.5	664	2,223
2011-2021	54	9	31	15.3	397.7	616	1,787
Mutual Funds							
1980-1990	151	5	25	6.4	143.0	148	487
1991-2000	344	11	52	25.0	600.1	168	754
2001-2010	295	20	64	86.2	1,733.4	206	1238
2011-2021	226	16	52	102.7	2,992.2	230	1458
Other							
1980-1990	35	1	6	2.2	31.9	54	172
1991-2000	33	1	4	1.4	35.0	54	152
2001-2010	145	3	12	4.2	97.5	38	306
2011-2021	206	5	20	6.5	260.9	33	581

Table II.A4: Descriptive statistics: Correlation matrix

This table presents average correlation between different crowding measures and among anomalies. Panel A shows the correlation between: the number of 13F institutional investors holding the same stock (NI), the Days-ADV, defined as the money value held in a security by all institutional investors relative to the security's average daily money volume (Days-ADV), the stock percentage of shares outstanding owned by the 13F investors (PSO), and the Activity ratio, estimated as the percentage of shares held by an institution at the end of each quarter (*t-2*) divided by the stock's average turnover during the quarter (*t-1*) (Actratio). The separately estimate the correlation among those variables for the period before and after the structural break (1992:Q4). Panel B reports the correlation for the set of eleven anomalies for the period before the structural break in the Days-ADV time series while Panel C shows the same estimation for the sample period after that same structural break (1993-2021).

Panel A: Correlation - Crowding measures

	1980-1992					1993-2021			
	NI	Days-adv	PSO	Actratio		NI	Days-adv	PSO	Actratio
NI		0.15	0.53	0.15	NI		-0.03	0.45	-0.06
Days-ADV			0.30	0.99	Days-adv			0.12	0.99
PSO				0.29	PSO				0.07

Panel B: Correlation - Anomalies (Pre-structural break in Days-ADV time series (1980-1992))

	Days-ADV	FP	OSC	NSI	CEI	ACC	NOA	GP	AG	ROA	IVA	MOM
Days-ADV		-0.20	-0.25	-0.13	-0.23	-0.04	-0.04	-0.11	-0.05	-0.15	-0.04	-0.06
FP			0.63	0.06	0.09	-0.04	0.22	0.21	-0.10	0.49	0.02	0.08
OSC				0.05	0.15	-0.10	0.24	0.31	-0.13	0.47	-0.01	0.00
NSI					0.36	0.13	0.17	0.05	0.29	0.02	0.21	0.05
CEI						0.09	0.16	0.06	0.21	0.06	0.17	0.06
ACC							0.30	-0.12	0.38	-0.11	0.33	0.06
NOA								0.03	0.46	0.02	0.51	0.06
GP									-0.07	0.37	-0.06	0.06
AG										-0.22	0.68	0.04
ROA											-0.13	0.13
IVA												0.06

Panel C: Correlation - Anomalies (Post-structural break in Days-ADV time series (1993-2021))

	Days-ADV	FP	OSC	NSI	CEI	ACC	NOA	GP	AG	ROA	IVA	MOM
Days-ADV		-0.09	-0.11	-0.15	-0.17	0.02	0.04	-0.07	-0.06	-0.09	-0.06	-0.07
FP			0.55	0.04	0.06	-0.05	0.16	0.16	-0.11	0.31	0.04	0.03
OSC				0.16	0.19	-0.14	0.13	0.34	-0.16	0.48	-0.03	-0.03
NSI					0.49	0.07	0.05	0.13	0.33	0.21	0.16	0.02
CEI						0.06	0.09	0.17	0.21	0.23	0.14	0.01
ACC							0.14	-0.02	0.22	-0.08	0.16	0.03
NOA								0.07	0.33	-0.10	0.40	0.03
GP									-0.01	0.38	-0.01	0.03
AG										-0.14	0.54	0.04
ROA											-0.09	0.07
IVA												0.05

Table II.A5: Returns on Days-ADV and Activity Ratio sorted portfolios: different lags

This table shows the return in excess of three risk-free rate (Ex ret) and risk-adjusted return for a *High-minus-low* portfolios sorted on alternative specification of Days-ADV and ACTratio measures. We adjust returns using the three factors of Fama and French (1993). To alleviate concerns about discretionary selection on the number of lags employed to estimate both Days-ADV and ACTratio, we estimate portfolio returns for different specifications on the variables construction. We employ, contemporanoeus (t), lagged one-quarter (t-1), and lagged two-quarters (t-2) of both the numerator and denominator of the ratio construction. We employ either total value invested in money terms (Days-ADV) or in number of shares owned (ACTratio) as the numerator (H). Similarly, we use either the average daily volume in money (unit) terms to estimate Days-ADV (ACTratio). We include only stocks whose CRSP share code is 10 and 11 (ordinary common shares). Also, we exclude firms with stock prices less than USD $5 to reduce the effects of microcaps. The sample period is from 1980:Q1 to 2021:Q4.

	Days-ADV				Actratio			
	Ex_ret	t-stat	FF3	t-stat	Ex_ret	t-stat	FF3	t-stat
H_t/V_t	1.230	(6.36)	1.385	(8.50)	1.243	(6.75)	1.411	(9.03)
H_t/V_{t-1}	1.316	(7.27)	1.483	(9.21)	1.317	(7.84)	1.497	(10.18)
H_t/V_{t-2}	1.421	(8.80)	1.250	(7.14)	1.245	(7.62)	1.401	(9.68)
H_{t-1}/V_{t-1}	1.296	(7.46)	1.435	(9.67)	1.285	(7.37)	1.466	(9.80)
H_{t-1}/V_{t-2}	1.204	(7.28)	1.357	(9.24)	1.253	(7.42)	1.414	(9.64)
H_{t-2}/V_{t-2}	1.251	(7.30)	1.388	(9.41)	1.233	(7.06)	1.396	(9.29)
H_{t-1}/V_t	1.136	(5.96)	1.242	(7.84)	1.225	(6.63)	1.386	(8.77)
H_{t-2}/V_{t-1}	1.192	(6.42)	1.297	(8.37)	1.233	(7.06)	1.396	(9.29)
H_{t-2}/V_t	1.106	(5.73)	1.199	(7.55)	1.179	(6.69)	1.334	(8.90)

Table II.A6: Days-ADV sorted portfolios: Subperiod analysis

This table shows the return in excess of three risk-free rate (Ex ret) and risk-adjusted return for a *High-minus-low* portfolios sorted on Days-ADV. Column "Non-crisis period" cover the period from March 1980 to December 2021 and excludes the financial crisis period, June 2007 - June 2009; the "recessionary" and "expansionary" periods are based on the NBER business cycle periods. We adjust returns using the three factors of Fama and French (1993). We adjust risk exposure using the three factors of Fama and French (1993) - FF3, the Fama-French five factor augmented with the traded liquidity measure proposed by Pastor and Stambaugh (2003) and the momentum factor - FF5PM, and the Fama-French five factor augmented with the *illiquid-minus-liquid* (IML) factor of Amihud (2019) and the momemntum factor - FF5AM. We include only stocks whose CRSP share code is 10 and 11 (ordinary common shares). Also, we exclude firms with stock prices less than USD $5 to reduce the effects of microcaps.

	Non-crisis periods				Recessionary periods				Expansionary periods			
Quintile	Exc Ret	FF3	FF5PM	FF5AM	Exc Ret	FF3	FF5PM	FF5AM	Exc Ret	FF3	FF5PM	FF5AM
5 (high)	1.205	0.542	0.276	0.267	1.425	0.643	0.329	0.274	1.171	0.521	0.255	0.291
	(6.64)	(8.82)	(5.92)	(5.61)	(1.80)	(2.88)	(2.08)	(1.67)	(6.35)	(8.24)	(5.31)	(5.46)
1 (low)	0.014	-0.816	-0.448	-0.424	-0.068	-1.372	-0.618	-0.518	-0.099	-0.773	-0.507	-0.428
	(0.06)	(-7.13)	(-4.84)	(-4.47)	(-0.07)	(-3.43)	(-2.31)	(-1.83)	(-0.37)	(-6.57)	(-5.44)	(-3.95)
5 - 1.	1.191	1.358	0.724	0.690	1.504	2.015	0.947	0.792	1.271	1.294	0.762	0.719
	(7.39)	(8.89)	(6.24)	(5.85)	(2.85)	(4.53)	(2.96)	(2.42)	(6.90)	(8.23)	(6.58)	(5.48)

Table II.A7: Alpha Persistence: Days-ADV sorted portfolio

This table reports the return in excess (*alpha*) of the spread portfolio sorted on Days-ADV measure. The long portfolio contains high crowded stocks while the short portfolio includes low crowded stocks. We then estimate the *alpha* of the spread portfolio for different holding: 2 (Q2), 3(Q3), 4(Q4), 5 (Q5), and 6 (Q6) quarters. We adjust risk exposure using the three factors of Fama and French (1993) - FF3, the Fama-French five factor augmented with the traded liquidity measure proposed by Pastor and Stambaugh (2003) - FF5P, the Fama-French five factor augmented *illiquid-minus-liquid* (IML) factor of Amihud (2019) - FF5A, and the Fama-French five factor augmented with the *illiquid-minus-liquid* (IML) factor of Amihud (2019) and the momemntum factor - FF5AM. We include only stocks whose CRSP share code is 10 and 11 (ordinary common shares). Also, we exclude firms with stock prices less than USD $5 to reduce the effects of microcaps.

	Q2	Q3	Q4	Q5	Q6
FF3	1.398	1.395	1.207	1.224	1.049
	(9.19)	(9.70)	(8.70)	(9.52)	(9.08)
FF5P	0.891	0.977	0.814	0.872	0.853
	(6.82)	(7.58)	(6.58)	(7.58)	(7.43)
FF5A	0.831	0.961	0.792	0.823	0.809
	(6.24)	(7.31)	-(6.28)	(7.06)	(6.91)
FF5AM	0.725	0.831	0.671	0.695	0.629
	(5.60)	(6.66)	(5.57)	(6.36)	(6.23)

Table II.A8: Bivariate portfolio sorts: Alternative sorting procedures

This table presents double-sorted portfolio returns employing alternative sorting procedures. In panel A, we perform a dependent (conditional) double sort first on days-ADV and then on each stock market anomaly, At the end of each quarter, we assign each stock in our sample in each quintile portfolios based on the Days-ADV measure. Next, we sort into three Anomaly portfolios (H, M, or L) within the bottom (Q1) and top (Q5) days-ADV quintiles. In panel B, we independently double sort on Days-ADV and on each stock market anomaly.

	Single Sort	Double sort				
	FF3	FF3	FF5P	FF5A	FF5AM	FF5C
Panel A: Dependent (Conditional) sorting: Days-ADV and Stock market anomalies						
Full-sample	0.390	1.780	1.330	1.179	1.015	1.314
	(6.42)	(10.94)	(8.92)	(7.99)	(7.40)	(8.86)
In-sample	0.536	1.885	1.355	1.274	1.060	1.252
	(5.24)	(8.36)	(6.48)	(6.07)	(5.39)	(5.92)
Post-publication	0.301	1.679	1.167	0.994	0.878	1.143
	(3.89)	(7.08)	(5.20)	(4.51)	(4.16)	(5.02)
Panel B: Independent sorting: stock market anomalies and days-ADV						
Full sample	0.390	1.682	1.246	1.137	0.941	1.130
	(6.42)	(11.18)	(9.08)	(8.26)	(7.45)	(9.11)
In-sample	0.536	1.792	1.266	1.225	1.005	1.141
	(5.24)	(9.04)	(6.92)	(6.71)	(6.09)	(6.91)
Post-publication	0.301	1.455	1.048	1.056	0.982	1.085
	(3.89)	(8.46)	(6.43)	(5.93)	(5.64)	(5.92)

Table II.A9: Conditional Double-sorted portfolios: Non-Crowded-sorted Portfolio returns

This table presents results of the dependent (conditional) double sort on stock market anomalies and on Days-ADV. At the end of each quarter, we assign the stocks in our sample according to each anomaly variable into three portfolios based on the bottom 30%, middle 40%, and top 30%. Next, we sort the stocks in the top (bottom) 30% anomaly portfolios into quintile (Q1,Q2,Q3,Q4,Q5) portfolios based on the Days-ADV measure. We compute the value-weighted monthly return of the spread portfolio that for the long leg contains stocks in the top anomaly tercile *not-included* in the Days-ADV Q5 quintile. Thus, we form a portfolio of stocks included in the Q1,Q2,Q3,Q4 Days-ADV quintiles. Similarly, for the short leg we consider stocks in the bottom anomaly tercile **not-included** in the Days-ADV Q1 quintile. This is, we form a portfolio consisting of stocks in the Q5,Q4,Q3,Q2 Days-ADV quintiles. Finally, we create a portfolio that takes the equally-weighting (EW) average each month across all the available anomaly returns. We adjust risk exposures using the three factors of Fama and French (1993) - FF3, the Fama-French five factor augmented with the traded liquidity measure proposed by Pastor and Stambaugh (2003) - FF5P, the Fama-French five factor augmented with the *illiquid-minus-liquid* (IML) factor of Amihud (2019) - FF5A, and the Fama-French five factor that includes both the IML and momentum (MOM) factors - FF5AM. We show the results for three sample periods. The complete sample period from 1980:Q1 to 2021:Q4 (first row); a sample period starting in 1980:Q1 until the end of the original anomaly publication sample period (in-sample); and the sample period starting from the year of publication up to the end of our the sample period 2021:Q4 (post-publication)

	Single sort	Double sort			
	FF3	FF3	FF5P	FF5A	FF5AM
Full-sample	0.390	0.009	-0.076	-0.101	-0.105
	(6.42)	(0.18)	(-1.63)	(-2.14)	(-2.21)
In-sample	0.536	0.071	-0.022	-0.080	-0.082
	(5.24)	(0.85)	(-0.27)	(-0.95)	(-0.97)
Post-publication	0.301	0.004	-0.004	-0.031	-0.039
	(3.89)	(0.05)	(-0.04)	(-0.34)	(-0.41)

Table II.A10: Fama-MacBeth regressions: Days-ADV components (PSO and Illiq) and next quarter cumulative returns

This table presents the results from Fama-Macbeth regressions of cumulative monthly returns over the next quarter on the components of the Days-ADV measure PSO and Illiq. As in Brown, Howard and Lundblad (2021), we use the decomposition Days-ADV = PSO x Illiq. PSO is the percentage shares outstanding held by 13F institutional investors. Illiq is the stock's market capitalization relative to its average daily trading volume over the previous quarter. We include the following control variables: market capitalization (size), the number of months since stock's first appears in CRSP (age), the standard deviation of monthly returns over the previous two years, book-to-market ratio, dividend yield, average monthly turnover over the past three months, cummulative return over the past three months, cummulative return over the past nine months preceding the beginning of quarter. We use natural log of all control variables with the exception of cummulative returns. The *Long* (*Short*) dummy equals one if a stocks is included in at least one anomaly long (short) portfolio. The t-values are based on Newey-West standard errors with four lags.

	(1)	(2)	(3)
Long	-2.502		-1.316
	(-4.73)		(-2.48)
Long x Illiq	0.409		0.200
	(4.70)		(2.26)
Long x PSO	0.009		-0.335
	(0.06)		(-1.85)
Short		-3.754	-3.098
		(-6.20)	(-5.25)
Short x Illiq		0.565	0.472
		(6.28)	(5.32)
Short x PSO		0.253	0.526
		(1.74)	(3.51)
Obs.	294,747	294,747	294,747
Adj. R^2 (%)	11.2	11.1	11.4

Table II.A11: Crash risk (NCSkew), NET anomalies and crowding

This table estimates the cross-sectional relation between the log of Days-ADV (LADV), future stock price crash risk, a NET dummy variable, a post-publication dummy, several interaction terms, and a series of control variables. The dependent variable is the one-quarter-ahead NCSKEW (Negative coefficient of firm-specific daily returns.). We include the following control variables: the kurtosis and the standard deviation of firm-specific daily returns, market-to-book ratio, book value of all liabilities divided by total assets, ROA ratio, log of market capitalization (size), average monthly share turnover, the number of analyst following the firm, and the lag of the NCSkew variable. All control variables are measured over the previous quarter t-1. To estimate the NET dummy variable we first calculate the difference between the number of long and short anomaly portfolios (based on quintiles) that a stock is in for each quarter. The NET dummy equals 1 if the NET value is positive (i.e., the stock is in more long than short anomaly portfolios) and 0 otherwise. The post-publication dummy (*Pos-Pub*) is equal to one if the quarter is after the publication date of the anomaly paper and zero otherwise. The t-statistics are based on errors clustered by firm.

	(1)	(2)	(3)	(4)	(5)
LADV	0.031	0.027	0.039	0.035	0.035
	(6.32)	(4.90)	(3.60)	(6.41)	(6.43)
Net				0.065	0.063
				(2.06)	(1.99)
Net * LADV				-0.0114	-0.016
				(-1.48)	(-1.54)
Pos-Pub					-0.289
					(-2.04)
Pos-Pub * Net * LADV					0.012
					(3.74)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Obs.	197,958	34,493	163,348	197,946	197,946
adj. R^2	0.029	0.026	0.073	0.029	0.029

Table II.A12: Crash risk (Duvol), NET anomalies and crowding

This table estimates the cross-sectional relation between the log of Days-ADV (LADV), future stock price crash risk, a NET dummy variable, a post-publication dummy, several interaction terms, and a series of control variables. The dependent variable is the one-quarter-ahead DUVOL ("Down-to-up volatility"). We include the following control variables: the kurtosis and the standard deviation of firm-specific daily returns, market-to-book ratio, book value of all liabilities divided by total assets, ROA ratio, log of market capitalization (size), average monthly share turnover, the number of analyst following the firm, and the lag of the Duvool variable. All control variables are measured over the previous quarter year t-1. To estimate the NET dummy variable we first calculate the difference between the number of long and short anomaly portfolios (based on quintiles) that a stock is in for each quarter. The NET dummy equals 1 if the NET value is positive (i.e., the stock is in more long than short anomaly portfolios) and 0 otherwise. The post-publication dummy (*Pos-Pub*) is equal to one if the quarter is after the publication date of the anomaly paper and zero otherwise. The t-statistics are based on errors clustered by firm.

	(1)	(2)	(3)	(4)	(5)
LADV	0.036	0.033	0.047	0.036	0.038
	(3.07)	(2.88)	(3.75)	(3.80)	(3.81)
Net				0.002	0.001
				(0.12)	(0.08)
Net * LADV				0.001	0.001
				(0.47)	(0.13)
Pos-Pub					-0.104
					(-1.03)
Pos-Pub * Net * LADV					0.009
					(2.18)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Obs.	197,784	34,462	163,203	197,772	197,772
adj. R^2	0.043	0.035	0.092	0.043	0.043

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