Crowded Spaces and Anomalies

Ludwig Chincarini
Renato Lazo-Paz
Fabio Moneta*

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Abstract

This paper investigates 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 and liquidity risk. Our findings are consistent with this hypothesis and suggest that crowding adds a new consideration to the limits of arbitrage.

JEL Classification: G0
Key Words: Crowding, Institutional Investors, anomalies, crash risk, liquidity risk, limits to arbitrage

*Ludwig Chincarini is from the University of San Francisco School of Management Office MH 117, University of San Francisco, School of Management, 2130 Fulton Street, San Francisco, CA 94117. Email: lbchincarini@usfca.edu. Fabio Moneta and Renato Lazo-Paz are from Telfer School of Management, University of Ottawa, 55 Laurier Ave E, Ottawa, Ontario K1N 6N5, Canada. Emails: fmoneta@uottawa.ca and rlazopaz@uottawa.ca. We benefit from helpful comments by Anna Agapova (Discussant), Harshit Rajaiya, Tiemei Li, and seminar participants at the 2021 AFA PhD Poster session, 2022 World Finance Conference, 2022 Frontiers of Factors Investing Conference, the 2022 Crowell Prize finalist seminars, Bayes Business School, University of Bologna, University of Ottawa, and University of Venezia for their insightful comments.

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 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

[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 individual stocks liquidity.

[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).

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, institutions may follow similar strategies such as exploiting anomalies (also called factor investing).[4] This more concentrated context raises new concerns 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 and liquidity 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 particular, the interaction between crowding, crash risk, liquidity 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

[3]For instance, (Ben-David et al., 2021) 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.

both at the portfolio and stock level. We follow Brown et al. (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 et al. (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, experience 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 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. In this single sorting approach and using days-ADV as the crowding variable, we find that stocks in the highest crowding value (equal) -weighted quintile portfolio deliver a Fama and French (1993) 3-factor monthly alpha of 0.54% (0.63%), while the lowest crowding quintile is -0.90% (-0.94%). Thus, at least on average, crowded

[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 2).

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 using different factor models 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), we find that the relationship between crowding and future returns is significant across all groups and the strongest for mutual funds, transient, and short-horizon institutions.

Third, we test our hypothesis of crowding among anomaly stocks. As in Stambaugh et al. (2012), we focus on eleven well-known anomalies (see Table 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 and short the least crowded stocks exhibits significant risk-adjusted monthly return spreads of 1.78% 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 in the crowding strategy we find that it is insignificant.

The concept of crowding is inherently linked to the dynamic interaction between investors and hence time. For example, as a profitable opportunity arises, more investors of similar types pour into the space, actually creating the initial burst in returns. However, as time passes, and the space becomes saturated, the returns may dwindle. In addition, the trading space may be subject to liquidity limits as well as crash risk. We find the crowding is related to future liquidity risk and crash risk and that these effects are stronger for anomaly stocks. Our results are robust for a set of crash risk measures, the inclusion of several control variables, year and firm-level fixed effects.

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) cross-sectional regressions, while controlling for determinants of investors 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), and is absent in a sample of non-crowded stocks. 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 et al. (2021) by showing that the relationship between crowding and returns is not only specific to holdings of hedge funds, but it is present across different type of institutions. Second, we are the first to examine the relationship between crowding and returns using a large set of anomalies. We show that this relation 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. This is in line with the observed increase of factor investing (Wigglesworth, 2017). 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 and liquidity 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 et al. (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 the momentum crashes. Some investors could also lower the negative impact of crowding through diversification and keep a long-term horizon on their investments while others further enhance the problem due to short-term focus (DeMiguel et al., 2019). 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 et al. (2021) show that crowded holdings positively predict hedge fund future returns. Finally, there is scant evidence for the link 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, 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.[7] At the core of crowding is the idea that too many investors are exploiting similar investment opportunities unaware of the potential liquidity exhaustion. Some 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.[8] 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.[9] 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

[7]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 specific 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.

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

[9]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)

undertake similar *unanchored trading strategies*[10] in magnitudes that might lead to significant price dislocations when facing correlated demand shocks (Khandani and Lo, 2011).[11] They 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 ever 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 et al. (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 liquidity and crash risk, and represents an additional dimension of risk faced by arbitrageurs.

[10]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).

[11]For instance, (Yan, 2014) provides evidence that momentum crashes (e.g., Cooper et al., 2004; Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016) are influenced by crowded trades that push prices away from fundamentals leading to strong reversals.

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 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. If this risk is unknown, it might not even be priced in the market. If the risk is known, then it may be priced in the market to the extent that investors can quantify the risk.

In our empirical work, we would like to understand how crowding effects 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 incorporate information from 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 reasonable 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). 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 liquidity risk and 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 firms that have extreme changes, like moving from the 1st to 5th quintile in factor ranking, to have exaggerated price moves if there was excessive crowding at time $t-1$. Thus, the third hypothesis considers the potential influence of crowding on liquidity and crash risk.

Hypothesis 3 (Crowding and liquidity and crash risks): Crowding is positively related to liquidity and 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 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[12]. For that purpose, we follow Koijen and Yogo (2019) 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[13]. We also distinguish between short- and long-horizon institutions following Yan and Zhang (2009) and among transient, dedicated, and quasi-indexer institutions (using data from Brian Bushee's website to identify them in our sample).[14] Transient institutions are particular relevant for our research due to their active management approach to trading on anomalies.[15] 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 1 HERE]

Figure 1 depicts time-series means of cross-sectional medians of several characteristics of the 13F database over time. As shown in Figure 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 2, Panel B, plots the median number of institutional investors

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

[13]See https://koijen.net/code-and-data.html

[14]See https://accounting-faculty.wharton.upenn.edu/bushee/.

[15]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.

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 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 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 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 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 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.[16] Therefore, it is important to focus on a measure that captures crowding for all potential investment strategies while considering liquidity.

[16] 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.

4.3.1 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,

$$s_{ij} = \frac{\mathbf{w}_i' \mathbf{w}_j}{|\mathbf{w}_i||\mathbf{w}_j|} \tag{1}$$

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.[17]

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

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

where S is the similarity matrix of all managers.[18]

[17] 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.

[18] 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).

4.3.2 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 et al., 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 $t-1$.

$$\text{ActRatio}_{i,t} = \frac{\text{Shares}_{i,t-2}}{\text{AvgTurn}_{i,t-1}} \tag{3}$$

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 trading volume over the past quarter (Brown et al., 2021).

$$\text{Days ADV}_{i,j,t} = \frac{\sum_{j=1}^{N} \text{InstHold}_{i,j,t}}{\text{ADV}_{i,t}} \tag{4}$$

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 [19].

4.3.3 Aggregate Crowding Measures

In order to get a flavor of crowding in our database and sample period, we provide summary statistics in Table 2 and time series plots of the cosine similarity and Days-ADV crowding measures in Figure 2.

[INSERT TABLE 2 HERE]

[INSERT FIGURE 2 HERE]

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

In panel A of Figure 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 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

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

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 et al. (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.[20] 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 on 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).

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 5.[21]

[20] 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.

[21] 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

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

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 equation 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.

$$\text{NCSKEW}_{j,t} = -\frac{n(n-1)^{3/2} \sum R_{j,t}^3}{((n-1)(n-2)(\sum R_{j,t}^2)^{3/2})} \tag{6}$$

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 equation 7. This measure captures the asymmetric volatility of positive and negative firm-specific weekly returns.

approach is to look at *residual returns* to better assess extreme movements.

$$\text{DUVOL}_{j,t} = log\left(\frac{(n_u - 1)\sum_{DOWN} R^2_{j,t}}{(n_d - 1)\sum_{UP} R^2_{j,t}}\right) \tag{7}$$

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.

4.5 Measures of (il)Liquidity Risk

We start by estimating Amihud (2019) illiquidity measure, which is defined as:

$$\text{Illiquid}_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{j,t}} \frac{|R_{j,t,d}|}{V_{j,t,d}} \tag{8}$$

where $D_{i,t}$ is the number of observations with volume data in a given month t, $|R_{j,t,d}|$ is the absolute daily return of stock j over month d, and $V_{j,t,d}$ is the daily dollar volume for stock j over month d. For the liquidity risk measure, we estimate the *liquidity beta* as the parameter loading on quarterly regressions of the Amihud (2019) *illiquid-minus-liquid* (*IML*) factor added to the Fama and French (1993) three-factor model, as detailed in Eq. (9).

$$R_{j,t} = \alpha_{j,t} + \beta^{mkt}_{j,t} MKT_t + \beta^{size}_{j,t} SMB_t + \beta^{value}_{j,t} HML_d + \beta^{illiq}_{j,t} IML_t + \epsilon_{j,t} \tag{9}$$

Where the IML_t factor is the differential return on *illiquid-minus-liquid* stock portfolios[22]. The

[22] We apply the same filters as in Amihud (2019) and delete stock's with negative price, a trading volume of less than 100 shares and shows a return of less than -100%. Also, we delete the highest daily value of illiq in each year as well as stocks whose Illiq value are in the top 1% to control for potential outliers. Finally, we only consider NYSE and AMEX common stocks whose price is between \$5 and \$1000 and it has more than 200 days of valid return and volume data

Illiquidity of a stock j on day d is measured as in Eq. (8) and is averaged over a 12-month period . Portfolios are formed in each day and double sorted on *volatility* (standard deviation of daily returns over the same 12 months) and *Illiq*. Stocks are sorted on *volatility* into three portfolios, and within each portfolio they are sorted on *Illiq* quintiles. The IML factor return is then calculated as the average return of the highest *Illiq* quintile across the three *volatility* portfolios minus the average of the lowest *Illiq* quintile accross the corresponding *volatility* portfolios. We then proceed to run quarterly regressions of daily stock excess return on daily factor returns to obtain quarterly values of the *(il)liquidity beta*.

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 (illiquidity) 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 needed because the 13-F holdings are disclosed with an up to 45 days delay. Then, we estimate monthly excess returns over the following 3 months in 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 return which we use to regress on the Fama-French three factors and estimate the alpha.

[INSERT TABLE 3 HERE]

Panel A (Panel B) of Table 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 et al. (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 A5 in the Internet 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

[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.

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 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 4 HERE]

In Panel A of Table 4 we report the excess return and risk-adjusted return for quintile portfolio

[24]Brown et al. (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.

[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.

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 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 et al. (2021) focusing on hedge funds. We then examine whether our results are mainly driven by the

[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 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.

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). Panel B of Table 4 shows that the relationship between crowding and future returns is significant across all groups and strongest for mutual funds, transient, and short horizon institutions.

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 A7 of the Online 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). 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).

[INSERT TABLE 5 HERE]

Table 5 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.

In table 5, 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 Internet Appendix (Table **??**) we provide results where we reverse the sorting procedure and find that our results hold. If we modify our sorting procedure (Table **??**), performing independent sorting instead of conditional sorting, our main results hold although we observe lower returns and alphas in most anomalies.

[INSERT TABLE 6 HERE]

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 5 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 6, the outperformance of anomaly returns among the most (least) crowded anomaly stocks compared to the single sorted portfolios holds for all four portfolios.

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) 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; 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 monthly returns over

[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.

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 7 HERE]

Table 7 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 two set of dummy variables to identify stocks that are included only in one anomaly and whether in the long or short leg (Long-only, Short-only), and stocks that are included in at least one anomaly either in the long or short leg (long-at or short-at). That is, the Long-only and Short-only is more restrictive since stocks that appear in more than one anomaly are excluded if they appear in the opposite leg for another anomaly. 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 interaction terms with the long-only (short-only), long-at least one anomaly (short- at

[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.

least one anomaly), 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 in the two specifications we consider (included only in one anomaly leg or included at least in one anomaly leg) 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 et al. (2021) and perform 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 A10 of Internet 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 and Liquidity Risks

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 8 AND 9 HERE]

[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.

Table 8 and 9 report the results of our regression analysis. The dependent variable is stock price crash risk measured by NCSKew in Table 8 and DUVOL in Table 9. 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 8 and 9 include a post-publication dummy and its interaction with the long-only(short-only), long-at(short-at), and LADV. The average slope on (Pos-Pub x Short-only x LADV) is positive and statistically significant (t-statistic = 2.12). This suggests that crash risk is higher for stocks in the short-only group and that the relationship remains after publication dates. However, we do not observe this relationship for the (Pos-Pub x Short-at x LADV) interaction term. 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 9)

To further examine the channels through which crowding influences future expected returns we explore the effect that crowding exerts on the liquidity risk of institutional investors holdings. Following Beber et al. (2012), we include as control variables the log of market capitalization (size), the log of book-to-market ratio, a NASDAQ dummy variable, return and return volatility over the previous month. In addition, we include year and firm fixed-effects and compute t-values from firm-clustered standard errors.

[INSERT TABLE 10 HERE]

Table 10 provides the regression results for the model that relates crowding to next-quarter (il)liquidity beta. We find that crowding has predictive power for future stocks' (il)liquidity risk as there is a positive coefficient on $log(ADV_t)$, which is significant for the full sample and for the most recent sample (column 1 and 3). When we include the anomaly dummy interaction terms we find some evidence of a positive relationship coming only from the long leg.

Overall, our results show an economically and statistically significant relationship between crowding and both (il)liquidity and crash risk. This evidence is consistent with Hypothesis 3 and the idea that crowding further increases risk concerns for institutional investors.

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.

A Tables and Figures

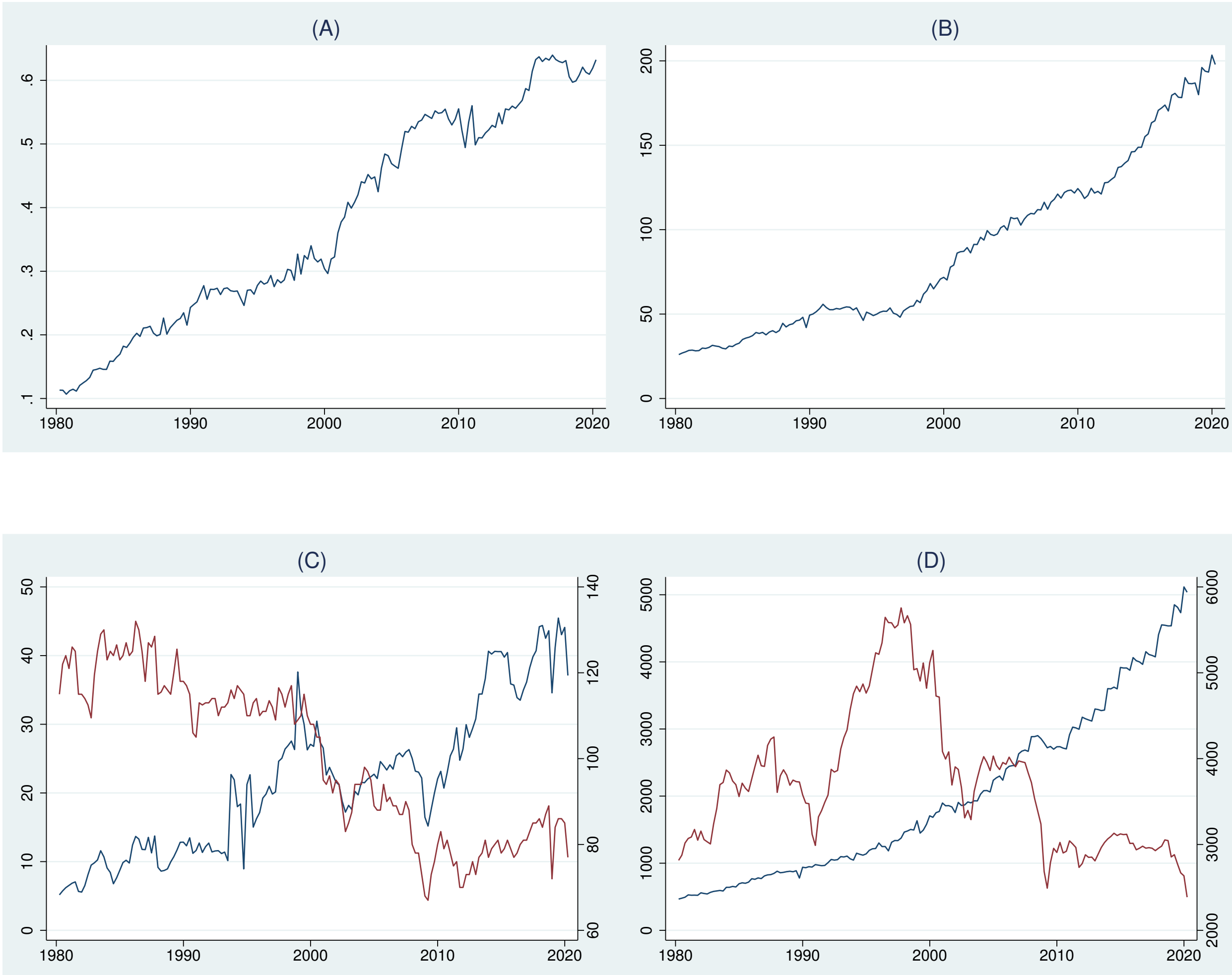

Figure 1: **13F Institutional Investors, holdings, ownership, portfolio size, and position in average security. Panel A** shows the growth of the median Institutional Ownership (IO) in percentage terms. IO is estimated for each security as the number of shares held by institutional investors divided 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

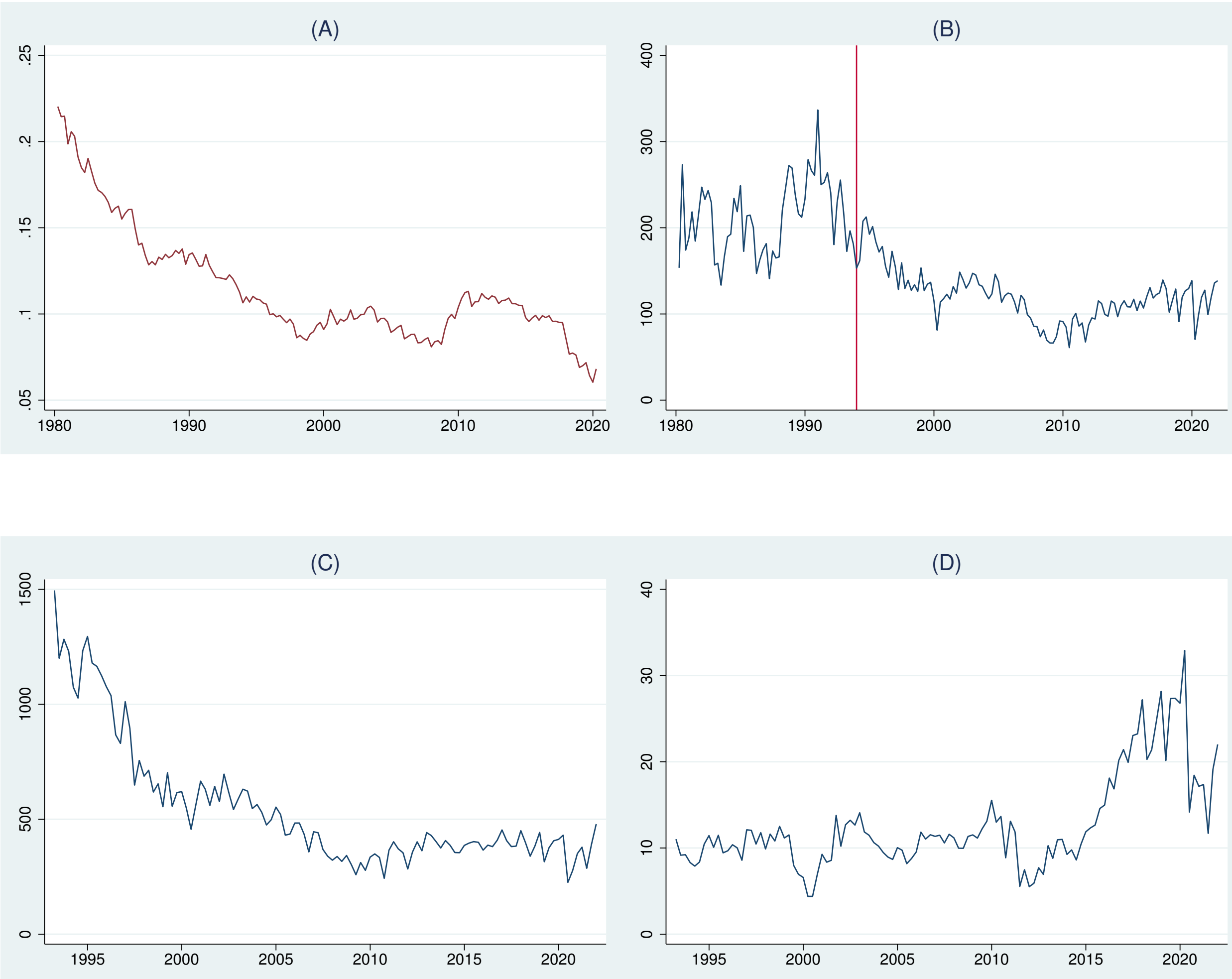

Figure 2: **Cosine similarity and Days-ADV over time** This figure plots the time Series of average Cosine Similarity of 13F institution's holdings as well as the the time-series average of cross-sectional median Days-ADV measure. Each quarter we compute cosine similarity as in equation 1 between every pair of institutional investor's holdings. Days-ADV is measured as the money value held in a security by all institutional investors relative to the 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 top-quantile while **Panel D** reports the same estimation for the bottom-quantile sample.

Table 1: **Sample Anomalies**

	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.

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

Table 2: **Descriptive Statistics**

	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

Note: This table reports descriptive statistics of the following variables: Number of Institutional Investors (NI); 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; 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, stock average daily volume relative to total market capitalization. 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. 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.

Table 3: **Crowding-sorted Portfolio returns**

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)

Note: 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 the 13F 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. In parentheses, we report the t-stat of the hypothesis test that alpha is equal to 0. In parentheses, we report the t-stat based on Newey-West standard errors.

Table 4: **Univariate portfolio sorts on Days-ADV**

Panel A: Sorted on Days-ADV

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

Panel B: Sorted on Days-ADV - by 13F Institution type

	FF3	FF5P	FF5A	FF5AM
Short Horizon	1.375	0.982	0.914	0.767
	(9.03)	(7.06)	(6.49)	(5.77)
Long Horizon	1.288	0.737	0.703	0.627
	(8.24)	(5.92)	(5.56)	(5.02)
Transient	1.336	0.955	0.913	0.766
	(9.12)	(7.16)	(6.75)	(6.04)
Dedicated	0.820	0.409	0.438	0.396
	(6.48)	(3.67)	(3.87)	(3.49)
Quase-indexer	1.387	0.872	0.805	0.716
	(8.78)	(6.58)	(6.00)	(5.43)
Mutual funds	1.367	0.908	0.865	0.771
	(9.21)	(7.06)	(6.57)	(5.99)
Invs Advisor	1.251	0.764	0.709	0.592
	(8.61)	(6.14)	(5.62)	(4.90)
Pension Funds	1.098	0.540	0.482	0.411
	(7.92)	(5.04)	(4.44)	(3.85)
Others	0.905	0.468	0.453	0.411
	(7.16)	(4.37)	(4.13)	(3.74)

Note: This table reports the risk-adjusted return 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 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*, the Fama-French five factor that includes both the IML and the Carhart (1997) momentum (MOM) factors -

Table 5: **Bivariate portfolio sorts on stock market anomalies and days-ADV**

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)
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)

Note: 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. 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

Table 5: **Bivariate portfolio sorts on stock market anomalies and days-ADV (Continued)**

	Single Sort	Double sort			
	FF3	FF3	FF5P	FF5A	FF5AM
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)

Note (continued): This table presents results of the dependent (conditional) double sort on each stock market anomalies and Days-ADV. 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.

Table 6: **Bivariate portfolio sorts: Larger sample of anomalies and Days-ADV**

	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)

Note: This table presents results of the dependent (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).

Table 7: **Fama-MacBeth regressions with interaction terms: Days-ADV and next quarter cumulative monthly returns**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LADV	0.546	0.717	0.485	0.547	0.459	0.547	0.459
	(4.31)	(2.01)	(4.75)	(4.37)	(3.66)	(5.27)	(3.61)
Long - only				-0.098		-0.018	
				(-0.15)		(-0.09)	
Long only*LADV				0.056		0.047	
				(0.32)		(0.17)	
Short - only				-1.315		-1.085	
				(-0.83)		(-0.68)	
Short only*LADV				0.231		0.058	
				(0.78)		(0.33)	
long - at					-1.690		-1.690
					(-3.13)		(-3.24)
Long at*LADV					0.287		0.206
					(3.12)		(3.01)
Short - at					-3.038		-3.037
					(-5.25)		(-5.30)
Short at*LADV					0.485		0.308
					(4.86)		(3.83)
Pos-Pub						0.905	1.041
						(0.91)	(1.12)
Pos-Pub x Long-only x LADV						0.020	
						(1.10)	
Pos-Pub x Short-only x LADV						0.137	
						(0.63)	
Pos-Pub x Long-at x LADV							0.810
							(1.62)
Pos-Pub x Short-at x LADV							0.178
							(2.92)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	294,301	79,352	213,299	294,301	294,301	294,301	294,301
Adj. R^2 (%)	8.86	10.71	8.04	8.24	9.28	9.15	9.12

Note: 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, 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 set of anomaly-stock dummy variables identify stocks that are included only in one anomaly long (short) portfolio (Long-only/ Short only), and stocks that are included in at least one anomaly long(short) portfolio (long at/short at). 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-values are based on Newey-West standard errors with four lags. Returns and alphas are in percent per month.

Table 8: **Crash risk (NCSkew), anomalies and crowding**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LADV	0.011	0.003	0.008	0.010	0.008	0.009	0.008
	(3.29)	(0.85)	(2.28)	(3.18)	(2.16)	(3.08)	(2.30)
Long - only				-0.109		-0.159	
				(-2.00)		(-2.71)	
Long only*LADV				0.010		0.016	
				(1.11)		(1.72)	
Short - only				0.050		0.019	
				(0.81)		(0.51)	
Short only*LADV				0.020		0.017	
				(1.65)		(1.11)	
long - at					-0.066		-0.075
					(-3.05)		(-3.34)
Long at*LADV					0.003		0.003
					(1.06)		(1.67)
Short - at					0.007		0.102
					(3.12)		(4.21)
Short at*LADV					0.008		0.002
					(2.16)		(1.58)
Pos-Pub						-0.049	-0.031
						(-5.29)	(-2.87)
Pos-Pub x Long-only x LADV						0.003	
						(0.63)	
Pos-Pub x Short-only x LADV						0.004	
						(0.71)	
Pos-Pub x Long-at x LADV							-0.005
							(-1.69)
Pos-Pub x Short-at x LADV							0.004
							(1.74)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	102,940	23,996	78,652	102,940	102,940	102,940	102,940
Adj. R^2 (%)	8.60	13.20	7.71	8.71	8.73	7.96	9.06

Note: 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 set of dummy variables identify stocks that are included only in one anomaly long(short) portfolio (Long-only, Short only), and stocks that are included in at least one anomaly long(short) portfolio (long at/short at). 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.

Table 9: **Crash risk (Duvol), anomalies and crowding**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LADV	0.018	0.004	0.010	0.011	0.009	0.013	0.012
	(5.13)	(0.69)	(3.93)	(5.29)	(3.36)	(6.70)	(4.64)
Long - only				-0.079		-0.105	
				(-2.36)		(-2.90)	
Long only*LADV				0.009		0.012	
				(1.65)		(1.97)	
Short - only				0.034		0.021	
				(0.89)		(0.53)	
Short only*LADV				0.011		0.002	
				(1.18)		(0.46)	
long - at					-0.046		-0.066
					(-3.34)		(-4.74)
Long at*LADV					0.015		0.005
					(1.68)		(1.81)
Short - at					0.034		0.0051
					(2.29)		(3.48)
Short at*LADV					0.005		0.002
					(1.89)		(1.47)
Pos-Pub						-0.024	-0.017
						(-3.92)	(-2.86)
Pos-Pub x Long-only x LADV						0.003	
						(1.07)	
Pos-Pub x Short-only x LADV						-0.001	
						(-0.16)	
Pos-Pub x Long-at x LADV							-0.005
							(-1.89)
Pos-Pub x Short-at x LADV							0.006
							(2.30)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	102,940	23,996	78,652	102,940	102,940	102,940	102,940
Adj. R^2 (%)	11.10	16.51	9.15	11.12	11.38	8.36	8.69

Note: 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 set of dummy variables identify stocks that are included only in one anomaly long(short) portfolio (Long-only, Short only), and stocks that are included in at least one anomaly long(short) portfolio (long at/short at). 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.

Table 10: **Crowding and next quarter stock (il)liquidity**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LADV	0.0007	0.0007	0.0007	0.000712	0.0006	0.0009	0.0009
	(10.06)	(6.91)	(7.67)	(9.87)	(7.94)	(8.78)	(7.16)
Long - only				-0.0001		0.0007	
				(-0.16)		(1.05)	
Long only*LADV				0.0001		-0.0001	
				(0.55)		(-0.49)	
Short - only				-0.0001		0.0006	
				(-0.20)		(0.89)	
Short only*LADV				0.0001		-0.0001	
				(0.52)		(-0.36)	
long - at					0.0003		0.0006
					(0.86)		(1.49)
Long at*LADV					-0.0001		-0.0002
					(-0.90)		(-2.69)
Short - at					-0.0019		-0.0012
					(-3.27)		(-2.24)
Short at*LADV					0.0003		0.0002
					(3.24)		(2.30)
Pos-Pub						0.0009	0.0006
						(0.47)	(0.34)
Pos-Pub x Long-only x LADV						-0.0001	
						(-1.15)	
Pos-Pub x Short-only x LADV						-0.0001	
						(-0.91)	
Pos-Pub x Long-at x LADV							0.0002
							(5.46)
Pos-Pub x Short-at x LADV							-0.0001
							(-2.45)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	605,662	135,334	470,066	605662	605,662	373,289	367,614
adj. R^2	0.080	0.061	0.094	0.080	0.080	0.076	0.073

Note: This table reports the results of the panel regressions of the Amihud (2019) *(il)liquidity beta* from the illiquid-minus-liquid (IML) factor added to the Fama and French (1993) three-factor model measured at quarter $t+1$ on the log of Days-ADV(LADV), a set of anomaly dummy variables, and a series of control variables. The *(il)liquidity beta* is estimated based on quarterly regressions using daily stock and factor returns data. We include the following control variables: the log of market capitalization ($Size_t$), the log of book-to-market ratio (BM_t), a NASDAQ dummy variable (NASDAQ dummy$_{t-1}$), institutional ownership, return (Ret_t) and return volatility ($Volatility_t$) over the previous year. The set of dummy variables identify stocks that are included only in one anomaly long(short) portfolio (Long-only, Short only), and stocks that are included in at least one anomaly long(short) portfolio (long at/short at). The t-stats are based on errors clustered by firm and by year.

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Internet Appendix

Table A1: **Descriptive Statistics - 13F database**

Period	NIpermno			USDpermno			NStocks		
	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

Period	Days-ADV			PSO (%)			Illiquidity		
	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

Note: 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.

Table A2: **Descriptive statistics - 13F database by Institution type**

	NInst	NIpermno		USDpermno		NStocks	
		Median	P90	Median	P90	Median	P90
Panel A: 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
Panel B: 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
Panel C: 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

Note: 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). 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. 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.

Table A3: **Descriptive statistics - 13F database by Institution type**(contd)

	NInst	NIpermno		USDpermno		NStocks	
		Median	P90	Median	P90	Median	P90
Panel A: 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
Panel B: 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
Panel C: 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
Panel D: 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
Panel E: 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
Panel F: 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

Note: 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). We identify institutional investors following Koijen and Yogo (2019). 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.

Table A4: **Days-ADV portfolio returns using different models and institution type**

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

Note: 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)

Table A5: **Descriptive statistics Days-ADV quintile portfolios stocks**

		Mkt cap (in MM)		NIpermno		ADV (In MM)		PSO (%)		Turnover (%)		Bid Ask spreads		NAnalyst
	Period	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean
5 (High)	1980-1990	1,006.7	191.8	63	26	0.29	0.03	35.0%	34.0%	0.0%	0.0%	1.0%	0.6%	7
	1991-2000	2,223.6	263.8	77	33	1.79	0.10	44.8%	44.2%	0.1%	0.0%	1.3%	0.9%	6
	2001-2010	2,085.3	251.3	78	45	2.99	0.26	51.6%	50.4%	0.1%	0.1%	1.0%	0.7%	3
	2011-2021	4,887.6	334.5	123	66	7.78	0.45	62.4%	65.0%	0.2%	0.1%	0.7%	0.6%	3
4	1980-1990	722.1	149.9	54	23	0.66	0.08	30.7%	28.8%	0.1%	0.1%	1.1%	0.7%	7
	1991-2000	2,126.5	279.3	82	41	4.27	0.35	43.4%	42.4%	0.2%	0.1%	1.3%	0.9%	6
	2001-2010	4,367.8	556.0	141	91	15.86	1.94	59.4%	63.7%	0.4%	0.3%	0.9%	0.7%	6
	2011-2021	9,393.3	1033.8	240	137	31.98	4.07	68.7%	73.8%	0.4%	0.4%	0.7%	0.6%	6
3	1980-1990	481.5	114.5	44	20	0.94	0.12	27.4%	23.7%	0.1%	0.1%	1.1%	0.8%	6
	1991-2000	1,335.5	220.3	67	35	4.68	0.48	39.0%	36.2%	0.3%	0.2%	1.4%	1.0%	6
	2001-2010	4,042.8	764.5	153	109	24.13	4.58	59.9%	64.2%	0.6%	0.6%	0.9%	0.7%	7
	2011-2021	6,990.4	1311.1	238	153	38.4	8.23	66.7%	71.6%	0.6%	0.6%	0.7%	0.5%	6
2	1980-1990	292.1	73.9	28	12	0.95	0.12	19.7%	15.1%	0.2%	0.2%	1.3%	1.0%	5
	1991-2000	817.6	134.9	43	22	5.32	0.47	28.9%	23.4%	0.5%	0.3%	1.6%	1.3%	4
	2001-2010	2,341.5	484.7	114	74	25.6	3.75	48.7%	47.5%	1.0%	0.8%	0.9%	0.7%	5
	2011-2021	3,698.9	617.5	165	93	33.62	4.42	54.2%	52.4%	0.9%	0.8%	0.7%	0.5%	5
1 (low)	1980-1990	158.3	48.4	13	5	2.58	0.12	8.6%	3.8%	0.8%	0.2%	1.4%	1.2%	2
	1991-2000	347.1	97.0	19	9	12.23	0.39	11.3%	3.8%	1.7%	0.4%	1.6%	1.3%	2
	2001-2010	1,398.7	191.2	51	17	39.81	1.19	23.2%	8.3%	3.2%	0.8%	0.8%	0.6%	2
	2011-2021	2,791.4	249.6	85	26	52.59	3.65	30.7%	19.0%	3.6%	1.5%	0.8%	0.5%	3

Note: This table presents summary statistics on the following variables: Market capitalization(Mkt Cap) in millions of US dollars; the number of 13F institutional investors holding the same stock (NIpermno); the average daily trading volume (ADV) over a quarter in millions of US dollar; stock percentage of shares outstanding owned by the 13F investors (PSO); Turnover (in %) estimated as the stock average daily volume relative to total market capitalization; stock's bid-ask spread estimated following Abdi and Ranaldo (2017); and the number of analyst following a firm. 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.

Table A6: **Returns on Days-ADV and Activity Ratio sorted portfolios**

	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)

Note: 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.

Table A7: **Days-ADV sorted portfolios: Subperiod analysis**

	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)

Note: 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.

Table A8: **Bivarate portfolio sorts: Alternative sorting procedures**

	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)

Note: 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.

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

	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)

Note: 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 meausre 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)

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

	(1)	(2)	(3)	(4)	(5)	(6)
Long-only	-0.638		-1.669			
	(-1.02)		(-2.05)			
Long-only x Illiq	0.125		0.273			
	(1.15)		(1.82)			
Long-only x PSO	-0.235		-0.283			
	(-0.93)		(-0.80)			
Short-only		-2.629	-3.577			
		(-2.77)	(-3.03)			
Short-only x Illiq		0.383	0.594			
		(2.40)	(3.01)			
Short-only x PSO		0.566	0.924			
		(1.99)	(2.51)			
Long-At				-2.502		-1.316
				(-4.73)		(-2.48)
Long-At x Illiq				0.409		0.200
				(4.70)		(2.26)
Long-At x PSO				0.009		-0.335
				(0.06)		(-1.85)
Short-At					-3.754	-3.098
					(-6.20)	(-5.25)
Short-At x Illiq					0.565	0.472
					(6.28)	(5.32)
Short-At x PSO					0.253	0.526
					(1.74)	(3.51)
Obs.	294,747	294,747	213,674	294,747	294,747	294,747
Adj. R^2 (%)	11.0	10.9	10.1	11.2	11.1	11.4

Note: 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 dummy variables, 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, 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 set of dummy variables identify stocks that are included only in one anomaly long(short) portfolio (Long-only, Short only), and stocks that are included in at least one anomaly long(short) portfolio (long at/short at). The t-values are based on Newey-West standard errors with four lags. Returns and alphas are in percent per month.