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The Race to Exploit Anomalies and the Cost of Slow Trading

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Abstract

Studying 71 anomalies, we show how the discovery of anomaly reshapes out-of-sample returns, thereby creating a contrarian effect to the general decay in returns. As a result, the average contribution of the first-day return to the portfolio value increases from 3% before the anomaly is discovered to 12% afterward and 30% in case of momentum anomalies. The effect exists in long-side and short-side portfolios and in the bought and sold stocks of both portfolios. The long-lasting effect indicates that arbitrage capital plays a key role in retaining market efficiency in the long run, implying a persistent mispricing component in anomalies.

Keywords: market efficiency, cross-section anomalies, arbitrage capital, asset mispricing, contrarian return effect

JEL classification codes: G12, G14

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In efficient markets, once an anomaly is discovered, it is expected to decay as long as it does not reflect risk. Comparing in-sample and out-of-sample returns, Chordia, Subrahmanyem, and Tong (2014) find that returns on 12 prominent anomalies decline by half on average, in line with the efficient market hypothesis. Mclean and Pontiff (2016) show that the average return on 97 anomalies declines by more than a third after the anomalies are published in academic journals. Studying 241 anomalies in 39 stock markets, Jacobs and Müller (2020) show that only the U.S. market displays a reliable post-publication decay. They attribute the magnitude of the post-publication anomalies to the cost of arbitrage. Chu, Hirshleifer, and Ma (2020) reinforce this explanation, showing a causal effect of limits to arbitrage (Shleifer and Vishny, 1997) on 11 well-known anomalies. This study complements those and other works on market response to anomaly discovery and limits to arbitrage by directly examining the trading activity of arbitrageurs and studying how arbitrage capital reshapes out-of-sample returns and trade volume. This extends the analysis of the size of such decay to its dynamic, process, and source.

Focusing on the impact of arbitrage trading activity, this study identifies permanent patterns in returns that emerge only after the anomalies are discovered. The long-lasting effect shows that arbitrage capital plays a key role in retaining market efficiency in the long run, suggesting a persistent mispricing component in anomalies. Examining 71 cross-section anomalies, we show that after the anomalies are published, a shift of returns to the beginning of the month occurs as the result of a rush of arbitrageurs to exploit anomalies. This shift creates a strong and persistent return effect at the beginning of each month. This is contrary to the general decay in returns after the anomalies are discovered, as observed in other studies. To illustrate, the average annualized return (without compounding) on the first trading day of the month on the long-side anomalies portfolio jumps from 13.4% before the anomalies are discovered to 19.6%

after they are discovered and 36.3% after they are published in academic journals. A very similar pattern in the opposite direction is observed in the short-side anomalies portfolio.

The analysis shows that after the anomaly is published, the average returns on the first and second days of the month are significantly larger than those on other days. Consistent with the research of Chordia, Subrahmanyem, and Tong (2014), who attribute the decline in returns after 1993 to the reduction in costs of arbitrage, the effect is significantly stronger in early years. Prior to 1994, the post-discovery first-day average return is about 18 times larger than the daily average return on the post-discovery anomalies portfolio. It is still significant and 6.5 times larger after 1993. The effect is significant in long-side and short-side portfolios as well as in the bought and sold stocks of both portfolios. While the differences are not significant across short-side and long-side portfolios, the evidence is in line with the limits-to-arbitrage hypothesis. Prior to 1994, the effect is significantly stronger in stocks that are more difficult to arbitrage, where the costs of arbitrage are estimated via stock liquidity, turnover, idiosyncratic volatility, bid–ask spread, and size. The differences diminish after 1993 along with the general reduction in costs of arbitrage.

If the post-discovery increase in returns is a result of a rush of less sophisticate arbitrageurs and perhaps also noise traders to exploit anomalies at the beginning of each month, the volume of trade may also be affected. The evidence is generally in line with this argument. Prior to 1994, the volume at the beginning of the month significantly increases with the demand for arbitrage stocks and decreases with the supply of such stocks. This asymmetry implies that arbitrageurs' buying and selling trading strategies are not identical, which, in the case of short-selling, may be explained by the additional complexity of the transaction.

We stress at the outset that the results do not imply that most of arbitragers trade on a monthly basis. The results show that the marginal arbitrage capital that is concentrated at the beginning of the month, perhaps of less sophisticate arbitrageurs, is sufficient to generate a long-lasting pattern in returns. This marginal arbitrage capital is traded on a monthly basis mainly because major anomalies like momentum require full-month data to predict stock returns. Moreover, even in case of fundamental anomalies wherein stock predictors are updated at different days of the month, cross-section ranking of stocks relative to each other is often made on a monthly basis. This common approach in the literature considers relative strength of stocks at a certain point of time when market situation is the same, usually at the end of each month. Thus, it is sufficient that marginal arbitragers rank stocks and correspondingly update their portfolios on a monthly (or quarterly) basis to generate the effect. Indeed, while the effect is persistent over time and robust across different types of anomalies it is substantially stronger in the monthly-based market and momentum anomalies. Anomalies which are also easier to be applied and therefore more exposed to less sophisticated arbitrageurs. The effect is less profound in fundamental anomalies, in line with the assumption of weaker incentives to trade at the beginning of each month in case of anomalies that are based on annual financial statements. It is stronger in fundamental anomalies that are based on quarterly financial statements as well as in particularly strong and persistent fundamental anomalies that are based on earnings and profitability.

To illustrate the importance of this effect, we estimate the accumulated loss from the delay of a single day each month in updating the anomalies portfolio. The loss is close to zero most of the time and accumulates to about 3% of the portfolio value in case of pre-discovered anomalies. This value is close to the loss predicted from a naive model, which assumes a loss that is proportional to the length of the delay and the portion of the outdated portfolio. In a sharp contrast, the loss in the case of post-publication anomalies is high throughout the sample period and accumulated to 12.3% of the portfolio value. The accumulated loss is as high as 15.4% and 29.7% in case of market and momentum anomalies, respectively. Those losses are several times larger than those predicted from a naive model. This confirms that after the anomalies are discovered, a large portion of their abnormal returns is realized at the beginning of the month, mainly on the first day. As a result, the first-day returns on anomalies account for more than 12% of the portfolio value, which increases to almost 30% in case of momentum anomalies.

Despite the tempting similarities, the post-discovery anomalies effect in this study is not related to the turn-of-the-month (TM) effect of Ariel (1987), wherein the average returns on the last two and first three days of the month are higher than those on other days. First, the TM effect implies positive returns at the beginning of the month, whereas the post-discovery anomalies effect displays an almost identical negative effect in the short-side portfolio. Second, while the TM effect is persistent over time (e.g., McConnell and Xu, 2008), the post-discovery anomalies effect emerges only after the anomalies are published. Moreover, unlike the TM effect, the post-discovery anomalies effect in returns is accompanied by a simultaneous effect in the volume of trade, which is significant in the early years of the studied sample. Finally, no association is found between the interaction of the TM effect and anomalies and the post-discovery returns. Very similar results are obtained for the weekend effect (French, 1980) and the turn-of-the-year effect (Rozeff and Kinney, 1976), indicating that those effects are also not related to the post-discovery anomalies effect.

The results in this study contribute to the literature on market anomalies in several respects. First, in line with Yan and Zheng (2017), Engelberg, Mclean, and Pontiff (2018), Jacobs and Müller (2020), Bartram and Grinblatt (2018, 2021), and others, this study strongly supports the existence of a mispricing component in anomalies. As the association between many anomalies and risk premia is ambiguous, several studies warn of *p*-hacking and data snooping in identifying new anomalies (e.g., Fama, 1998; Harvey, Liu, and Zhu, 2016; Martin and Nagel, 2019). In response, this study presents strict evidence for a persistent trading activity of arbitrageurs in out-of-sample returns on anomalies. The chances that spurious patterns found within in-sample returns by coincidence create long-lasting out-of-sample arbitrage profits are very small. Identifying the continuous trading activity of arbitrageurs indicates that arbitrageurs find anomalies to be profitable in the long run in terms of risk and reward. Thus, the results in this study support the existence of a mispricing component in anomalies.

The analysis also sheds more light on the process by which returns on anomalies decay after the anomalies are discovered. The results support the view of arbitrage price pressure in line with the research of Green, Hand, and Soliman (2011), Kokkonen and Suominen (2015), Akbas, Armstrong, Sorescu, and Subrahmanyam (2014), McLean and Pontiff (2016), Jacobs and Müller (2020), and others. The main contribution lies in identifying how this pressure strengthens each month, with a pick on the first day of the month. The analysis shows that this pressure not only decreases returns on anomalies in general but also is sufficiently large to generate a contrarian effect. Taken together, the process by which arbitrage capital retains market efficiency conforms to Lo's (2004) adaptive market hypothesis.

This research also contributes to the strand of studies that explore whether anomalies produce profits after accounting for actual costs (e.g., Pontiff, 1996; Conrad, Gultekin, and Kaul, 1997; Korajczyk and Sadka, 2004; Lesmond, Schill, and Zhou, 2004; Hanna and Ready, 2005; McLean, 2010; Novy-Marx and Velikov, 2016; Patton and Weller, 2020). The main take is that the ability and costs involved in timing the transaction are major factors that affect actual profits.

Unless one trades at the end-of-the-month closing price, any profitability analysis must incorporate actual prices of stocks at the exact time of the transaction while accounting for the substantial loss involved in any real-time delay. Considering that many of the abovementioned studies find that profits are close to zero after accounting for transaction costs, even very short real-time delays may be critical and completely disastrous for anomalies' abnormal profits.

The results of this study determine two major implications for arbitrageurs. First, arbitragers who rank stocks on a monthly basis should strive to execute their transactions as early as possible because the loss implied from any delay is substantially larger than the time of the delay relative to the investment horizon. Second—and in line with McLean and Pontiff's (2016) results—arbitragers should consider exploiting anomalies before publication to increase profits. According to the evidence, after discovery but before publication, the impact of arbitrageurs is smaller, implying weaker competition during this interim period. Finally, although the effect is not related to calendar anomalies such as the TM and weekend effects (for a review, see Ziemba, 2012), the results have an important implication to studies on this subject. Specifically, as the post-discovery anomalies effect occurs at the beginning of each month, any calendar analysis must control for this effect to avoid cross-biases between the two phenomena.

The rest of the paper is organized a follows. Section 2 presents the data and the aggregate anomaly variables that are used in the analysis. Section 3 explores the changes in returns and volume of trade caused by the trading activity of arbitrageurs after the anomalies are discovered. Section 4 estimates the loss from slow trading on the anomalies. Section 5 concludes the study. The list of 71 cross-section anomalies is given in Appendix A.

2. Data and Methodology

The analysis considers all U.S. firms listed on the NYSE, AMEX, and NASDAQ with share codes 10 and 11. The sample excludes stocks with end-of-month prices below $5, stocks that are not traded during the month, stocks that do not have monthly returns or quarterly earnings for the previous 12 months, and stocks with negative equity book values for the previous year. These uniform filters conform to conventional filters in the literature on cross-section anomalies. They are also consistent with the goal of this study to explore the effect of anomaly discovery on stocks characterized by normal trading activity rather than stocks that suffer from severe trading frictions, major liquidity problems, and the absence of information. Problems that may create unique trading patterns which are unrelated to anomaly discovery. We assume that the majority of arbitrageurs who exploit anomalies prefer to trade stocks that do not suffer from such problems as long as those problems are not directly related to the anomaly under consideration.

To explore and compare patterns in both returns and trading volume over identical samples, stocks with no monthly volume data are excluded. To mitigate backfilling biases (Fama and French, 1993), a firm must be listed on Compustat (annual) for at least two years before it is included in the sample. Based on financial statements data from 1971, the firm-month sample starts in January 1973. The next-month returns start in February 1973 and end in December 2018, with 29,535,334 firm-day observations across 14,111 firms.[1]

For the financial statements data, the previous fiscal year's annual data is updated at the end of June every year to make sure that the information for predicting future stock returns is available in real time. For the quarterly data, the previous quarter's financial statements data is updated each month provided that the release date was in the past. If the release date is not given,

[1] Omitting stocks with end-of-month prices below $5 also removes daily observations within a month with prices above $5. This removal is consistent with the majority of studies in the literature that implement anomalies strategies on a monthly basis. Including days within a month during which the price is above $5 while excluding others during which the price is below $5 is also impractical given the large trading costs involved in daily trading strategies.

it is assumed to be public by the end of the fourth month after the reporting period to guarantee data availability for a real-time information set. Following Shumway (1997), delisting returns are incorporated based on the CRSP daily delisting file.

To explore the impact of the discovery of anomalies on trading activity, we construct a comprehensive anomalies net trading (*ANT*) index. *ANT* is constructed from 71 cross-sectional anomalies reported in the academic literature to predict stock returns. Appendix A lists those anomalies and provides information about journal publications and how those anomalies are constructed.[2] The list is limited to anomalies that produce continuous (non-binary) predictors that can be calculated from CRSP, Compustat, and IBES databases or data from the original study, which is publicly available. It is also restricted to anomalies that have been published in academic journals after February 1973 to guarantee pre-published observations for all anomalies.

ANT aggregates net changes in stock holdings in all anomalies portfolios based on changes in holdings rather than the holdings themselves to identify actual trading in anomalies stocks. For instance, consider a stock that belongs to a portfolio for two months in a row. While this stock affects returns on the anomaly over two months, arbitrageurs buy this stock mainly in the first month because it is already in their portfolio in the second month. By the same line of reasoning, arbitrageurs sell this stock only in the third month when the stock is excluded from the portfolio. Thus, *ANT* represents the net demand from the rebalance trading activity of anomalies portfolios.

To construct *ANT*, each month's stocks are sorted on each anomaly. The long and short portfolios of each anomaly are composed of stocks that belong to extreme quintiles. *ANT* is equal

[2] Focusing on the post-discovery period, the anomalies replications in this study, which are described in Appendix A, do not necessarily adhere to those in the original study but rather adopt a more uniform approach. For instance, a few early studies limit their sample to NYSE stocks, probably because of data availability considerations. Using a more uniform approach, this study assumes investing in all three stock exchanges regardless of the anomaly under consideration. As Mclean and Pontiff (2016) note, making replications that are identical to the original anomalies is virtually unrealistic considering the changes in CRSP, Compustat, and IBES records, definitions, and methodologies.

to the sum of changes in long-side minus changes in short-side anomalies portfolios that the firm-month observation belongs to. According to this definition, *ANT* measures the monthly net change in the number of anomalies portfolios that the firm-month observation belongs to. For instance, if a stock is added to three long portfolios and one short portfolio and omitted from one long portfolio, then long-side $ANT = 3 - 1 = 2$, short-side $ANT = 1$, and $ANT = 2 - 1 = 1$. The analysis also considers net trading in long-side and short-side anomalies portfolios separately while distinguishing between positive and negative *ANT* values to examine buy and sell activities in each portfolio separately.

To compare the *ANT* results to the general performance of investing in the anomalies, we also construct an anomalies portfolios index (*API*). *API* is calculated as the sum of long-side minus short-side anomalies portfolios that the firm-month observation belongs to. This index is identical to the aggregate anomalies index of Engelberg, McLean, and Pontiff (2018). The *ANT* index can be seen as the first difference in *API*.

The upper part of Table 1 provides descriptive statistics for *ANT*. As expected, the average *ANT*, which stands for mean net trading, is close to zero. It is not exactly zero because the anomalies portfolios are not empty at the end of the sample period. The maximum value of *ANT* is 39, and the minimum value is −34. The lower part of Table 1 provides descriptive statistics for *API*. The average stock belongs to 11.09 long portfolios and 11.08 short portfolios. These values are lower than the value implied from 71 anomalies ($71 \times 0.20 = 14.2$) because several predictors are based on the intersection between two anomalies (e.g., momentum and LT reversal and momentum–volume anomalies in Appendix A). Hence, they add only $0.20 \times 0.20 = 0.04$ stocks, on average, to long and short anomalies portfolios. The mean value of *API* is 0.01, the maximum value is 31, and the minimum value is −38.

To estimate the time of anomaly discovery, we adopt Mclean and Pontiff's (2016) clearly defined two points in time: the end of the original study's sample period and the publication date. The anomaly pre-discovery period starts at the beginning of the sample and lasts until December of the last year in the original study's sample period. The post-discovery period starts immediately afterward, in January of the subsequent year. The assumption here is that once the authors of the original study discover the anomaly, the information about it may start propagating and affecting the market. To test this hypothesis, the post-discovery period is further divided into two sub-periods. The post-discovery pre-publication period starts in January following the last year of the original study's sample period and ends in December of the publication year, which is the year on the cover of the journal. The post-publication period starts immediately afterward, in January of the subsequent year.

3. Patterns Following Anomaly Discovery

This section shows how the discovery of anomalies affects trading activity and, thus, the returns on relevant stocks. The hypothesis is that many arbitrage strategies are implemented monthly, in line with the majority of studies in the literature. Arbitrageurs who exploit anomalies make their portfolio rebalance decisions on the first day of the calendar month, when the previous month's data is first available, and implement them immediately afterward. Comparing pre- and post-discovery anomalies, the evidence suggests that once the anomalies are discovered, they generate persistent patterns in the return and volume at the beginning of the calendar month.

Figure 1 illustrates how the discovery of an anomaly reshapes returns. It compares annualized mean returns on pre- and post-discovery anomalies portfolios, as defined above. Annualized returns are daily returns multiplied by a factor of 252 without compounding. As previously explained, the analysis employs 71 cross-section anomalies to construct *ANT*. Mean returns in the figures are calculated separately for the first day and all other days of the month on stocks that their holdings in anomalies portfolios increase (*ANT* > 0) or decrease (*ANT* < 0). Each figure also plots the values for the remaining stocks that their holdings do not change (*ANT* = 0), which serve as a benchmark.

The figure on the left-hand side plots the mean returns on stocks with positive *ANT*, implying a net increase in holdings of those stocks in anomalies portfolios. The mean return on the benchmark stocks, in which their holdings are unchanged (in light-gray bars), slightly increases from 13.7% on pre-discovery anomalies to 14.7% and 15.7% on post-discovery pre- and post-publication anomalies. As expected, the differences in mean returns are small because the underlying stocks are not supposed to be directly affected by the relevant anomalies arbitrage capital. The non–first-day mean return on stocks that their holdings increase (in gray bars) decreases from 15.9% to 14.8% and 13.8%, respectively. This decrease is also expected and in line with the research of Chordia, Subrahmanyam, and Tong (2014) and Mclean and Pontiff (2016), who found that the returns on anomalies decline after discovery. In a sharp contrast to the general decline, the first-day mean return (in black bars) soars, rising from 13.4% before discovery to 19.6% after discovery and 36.3% after publication. The figure on the right-hand side, with mean returns on stocks with negative *ANT*, mirrors those results with a trend toward the opposite direction. The differences in non–first-day mean returns (in gray bars) on stocks that their holdings decrease are, again, very small. However, the first-day mean return (in black bars) falls from 28.3% to 26.8% after discovery and 11.5% after publication. Figure 1 shows a substantial change in monthly first-day mean returns after the anomalies are discovered. This change is opposite the general decay in returns after such discovery.

3.1 Patterns in Returns after Anomaly Discovery

The first set of tests estimate the following regression equation:

$$R_{i,t} = a_t + \beta_1 ANT_{i,t} + \beta_2 PostANT_{i,t} + \sum_{j=1}^{2} \beta_{3,j}(ANT_{i,t} \times Dj_t) + \sum_{j=1}^{2} \beta_{4,j}(PostANT_{i,t} \times Dj_t) + \sum_{j=1}^{2} \beta_{5,j} Dj_t + \sum_{j=1}^{10} \beta_{6,j} R_{i,t-j} + \sum_{j=1}^{10} \beta_{7,j} R_{i,t-j}^2 + \sum_{j=1}^{10} \beta_{8,j} V_{i,t-j} + \varepsilon_{i,t}, \quad (1)$$

where $R_{i,t}$ is the daily return of stock i on day t; α_t accounts for the fixed effect of day t; $ANT_{i,t}$ is the stock i anomalies net trading index; $PostANT_{i,t}$ is the post-discovery *ANT*; and Dj_t (j = 1, 2) are dummy variables for the first two trading days of the month. The control variables include lagged values over the last 10 days for returns ($R_{i,t-j}$), volatility ($R^2_{i,t-j}$), and volume ($V_{i,t-j}$). As shown in the research of Engelberg, McLean, and Pontiff (2018), those control variables are used to assess the robustness of the results. For brevity, the coefficients are not reported. At a later stage, the regression also includes control variables for *API* and post-discovery *API* (*PostAPI*) to compare the *ANT* results to the performance on all anomalies and post-discovery anomalies, respectively. In all regressions, standard errors are clustered on time and firm.

Equation (1) includes two sets of interaction variables to test the main hypotheses. *ANT* × *D1* and *ANT* × *D2* in the first set capture returns on *ANT* in the first two trading days of the month regardless of whether the anomalies have been discovered or not. The second set of interaction variables focuses on post-discovery anomalies. *PostANT* × *D1* and *PostANT* × *D2* capture return effects in the first two trading days of the month that are unique to post-discovery anomalies (*PostANT*). *PostANT* is calculated similar to *ANT* except that it is constructed only from anomalies that have already been discovered. As explained in the previous section, an anomaly's post-discovery period starts immediately after the end of the original publication's sample period, when information on the anomaly may start affecting market trading.

Table 2 reports the regression results. The values in the table are in terms of basis points. The first test does not include control variables. The *PostANT* × *D1* coefficient of 2.56 is highly significant (t = 5.05), and the *ANT* × *D1* coefficient of −1.26 is also significant (t = −4.32). A similar pattern, albeit weaker, is observed on the second trading day. The *PostANT* × *D2* coefficient is 0.93 (t = 2.40), and the *ANT* × *D2* coefficient is −0.65 (t = −2.38). These significant coefficients show that pre-discovery negative returns on *ANT* in the first two trading days of the month turn significantly positive after the anomalies are discovered. The next three tests confirm that the first-day results do not depend on model specifications. The *PostANT* × *Dj* (j = 1, 2) coefficients in the second test with time-fixed effects are 2.42 and 0.88, and they are significant (t = 5.19 and 2.69). The coefficients are 1.57 and 0.66 (t = 3.39 and 1.93) in the third test with time-fixed effects and lagged control variables, where the first coefficient remains significant. They are 1.53 and 0.63 in the fourth test with time- and firm-fixed effects as well as lagged control variables, where the significance of the first-day coefficient is intact (t = 3.30 and 1.83).

The returns on *ANT* are not the same as those on anomalies. This is because *ANT* represents the monthly change in anomalies portfolios and hence does not account for holdings stocks over a period longer than one month. To compare the first-day effect to returns on anomalies, the last test repeats the third test with additional control variables for *API* and *PostAPI*. The *PostANT* × *D1* and *PostANT* × *D2* coefficients of 1.57 (t = 3.37) and 0.66 (t = 1.92) are almost identical to the coefficients in Test 3. This confirms that the significant first-day effect in returns is above and beyond the all-month daily mean return on anomalies portfolios. Moreover, the first-day coefficient is more than three times larger than the *API* coefficient of 0.48 (t = 11.09), which stands for returns on all anomalies. It is more than five times larger than the sum of the *API* and *PostAPI* coefficients of 0.48 − 0.17 = 0.31, which represents a mean return on post-discovery anomalies.

Meanwhile, the significantly negative *PostAPI* coefficient of −0.17 (t = −2.69) indicates that returns on post-discovery anomalies decline by more than a third. This decline is consistent and similar in magnitude to the decay reported in the studies of Chordia, Subrahmanyam, and Tong (2014) and Mclean and Pontiff (2016). Obtaining all-month results that are fully consistent with those in previous studies further confirms that the methodology in this study is robust.

To sum, the results in Table 2 show a shift of returns on post-discovery anomalies to the beginning of the month. As a result, the post-discovery first- and second-day mean returns are about five and three times larger, respectively, than the mean returns on post-discovery anomalies portfolios. The first-day post-discovery effect is robust to serial correlations in returns, volatility, and volume of trade as well as to time- and firm-fixed effects. Presumably, after the anomalies are discovered, arbitrageurs rush to exploit them mainly on the first day of each month.

3.2 Characteristics of the Post-Discovery Effect

The previous section reports on a significant increase in first-day returns on anomalies portfolios after the anomalies are discovered. This section explores the characteristics of this effect by running regressions similar to those in Table 2. For brevity, the first set of tests concentrates on the first day while excluding the second-day variables, which show mixed results in Table 2. The regressions include all lagged control variables and time-fixed effects. The results of regression with other specifications are not reported because, as shown in Table 2, the effect only strengthens under other specifications.

Table 3 reports the first set of regression results. The first test explores whether the post-discovery effect starts immediately after the end of the original study's sample period, presumably when the authors of the study discover the anomaly, or only after the study is published. Mclean and Pontiff (2016) noted and provided supportive evidence that more investors know about a predictor after the publication date compared with before the publication date. Some arbitrageurs, perhaps less sophisticated ones, may also curb their investments until the anomaly is rechecked and obtains formal publication approval. To test this hypothesis, in the next tests, the post-discovery period is further divided into pre- and post-publication sub-periods. The pre-publication (*Prep*) sub-period starts in January of the year following the last year of the original study's sample period and ends in December of the publication year. The post-publication (*Postp*) sub-period starts in January immediately afterward. The post-discovery *ANT* indices, termed *PrepANT* and *PostpANT*, are calculated the same way as *ANT* except that the anomalies are confined to the two post-discovery sub-periods.

The first test of Table 3 shows that the first-day effect in returns starts only after the anomalies are published. The *PostpANT* × *D1* significant coefficient of 1.98 (t = 3.56) indicates a large increase in first-day returns after publication. No similar effect is observed in the post-discovery pre-publication sub-period as the *PrepANT* × *D1* coefficient of −0.08 is negative and insignificant (t = −0.15). This does not rule out the possibility that some arbitrageurs exploit anomalies before they are published. One can see this from the negative values of *PrepAPI* and *PostpAPI* at the bottom of the table. A significantly positive *API* coefficient of 0.48 (t = 11.20), which stands for returns on anomalies portfolios, is offset after the anomalies are discovered, as implied from the *PrepAPI* negative coefficient of −0.11 (t = −0.98). This offset intensifies and becomes significant after publication according to the *PostpAPI* coefficient of −0.19 (−2.64).

The next tests in Table 3 run separate regressions for long-side and short-side *ANT* portfolios and positive and negative *ANT* values to determine whether buying and selling stocks generate different effects. The regression in the second test in Table 3 is similar to that in the first test with *ANT* and *API*, which are constructed only from long-side anomalies portfolios. *ANT* in the following two tests is restricted to either positive or negative values of long-side *ANT*, which corresponds to buying and selling stocks that belong to the long-side portfolio, respectively. The *PostpANT* × *D1* coefficient of 2.12 in the second test is significantly positive (t = 3.31), showing a large first-day effect in returns on the long-side portfolio. The *PostpANT* × *D1* coefficients in the following two tests of 2.88 and 2.35 are also significant (t = 3.43 and 2.51), indicating a significant effect in both bought and sold stocks. *ANT* and *API* in the last three tests are constructed only from short-side portfolios. The short-side *PostpANT* × *D1* coefficient of −1.92 is significantly negative (t = −3.17). Breaking short-side *ANT* in the last two tests into negative and positive values—which stand for stock buying and (short-)selling, respectively—the *PostpANT* × *D1* coefficients of −2.85 and −2.01 are also significant (t = −2.47 and −2.79). Finally, according to the significant *PostpAPI* coefficients of −0.28 and 0.29 (t = −3.28 and 3.03), at the bottom of the second and fifth columns, the decline in returns on both long-side and short-side portfolios becomes significant only after publication.

To sum, consistent with the literature, returns sharply decline after the anomalies are discovered, where this decline becomes significant after publication. In a sharp contrast, the rush to exploit anomalies shifts returns to the beginning of the month, which creates a positive first-day effect in returns, opposite the general decline in returns. This post-discovery effect is significant only after the anomalies are published. The effect exists in long-side and short-side portfolios as well as in bought and sold stocks of both portfolios. A Wald test in an unreported regression that includes all variables shows that the effect is not significantly different across short-side and long-side portfolios.

Chordia, Subrahmanyem, and Tong (2014) show that after 1993, the returns on 12 anomalies decline by half, on average. They attribute this decline to the growing hedge funds industry and the reduction in trading costs, in particular short-selling trading costs. This remarkable market change may also affect the post-discovery effect. First, if the effect is linked to the anomalies' mispricing, it is expected to weaken with the decline in returns and the underlying mispricing. In addition, any difference between the long-side and short-side portfolios is expected to diminish with the reduction in short-trading costs. To test these predictions, the next tests distinguish between early and more recent years by splitting post-publication *ANT* (*PostpANT*) into two variables. Early *PostpANT* (*E-PostpANT*) is calculated the same way as *ANT* with post-publication anomalies for the years 1973–1993. Late *PostpANT* (*L-PostpANT*) is calculated the same way for the years 1994–2018.

Table 4 reports the results of regressions similar to those in Table 3 with separate early and late *PostpANT*. The regressions also include the second-day dummy (*D2*) and its interaction variables to check whether the length of the effect has changed over time. For brevity, the tests do not include the pre-publication post-discovery variable (*PrepANT*), which is found to be insignificant in all the tests of Table 3. For consistency, we excluded pre-publication *API* (*PrepAPI*) after we verified that this exclusion does not change the results of the effect. In the first test with all the anomalies, the *E-PostpANT* × *D1* coefficient of 5.13 is highly significant (t = 5.17), and the *L-PostpANT* × *D1* coefficient of 1.82 is also significant (t = 3.22). These values are more than 18 and 6.5 times larger, respectively, than the sum of the *API* and *PostpAPI* coefficients at the bottom of the table of 0.46 − 0.18 = 0.28, which stands for the post-publication daily mean return on anomalies. The second-day *E-PostpANT* × *D2* coefficient of 2.48 is also large and significant (t = 2.38), while the *L-PostpANT* × *D1* coefficient of 0.42 is not significant

(t = 0.48). Wald tests reject the null hypothesis of equal early and late interaction coefficients of both the first and second days ($P < 0.005$).

The other tests in Table 4 repeat the regression with long-side and short-side portfolios and the bought and sold stocks of each portfolio separately. Similar patterns are observed in all the tests. First, in all the tests, both the *E-PostpANT* × *D1* and *L-PostpANT* × *D1* coefficients are significant, indicating that the first-day effect is robust and persistent. It exists during the early and more recent years in both the bought and sold stocks of both the long-side and short-side portfolios. The long-side *E-PostpANT* × *D1* coefficient in the second test is 6.50 (t = 4.63) in comparison to the *L-PostpANT* × *D1* coefficient of 2.00 (t = 3.16). The numbers rise to 10.02 (t = 4.27) and 2.64 (t = 3.17), respectively, in the case of long-side bought stocks in the third test. The short-side portfolio coefficients in the fifth test are −5.58 (t = −4.57) and −1.83 (t = −2.98). They are −7.17 (t = −3.38) and −1.86 (t = −2.57) in the case of (short-)sold stocks in the last test. Wald tests confirm that in all cases, the *E-PostpANT* × *D1* coefficient is significantly larger in absolute terms than the *L-PostpANT* × *D1* coefficient ($P \leq 0.05$). A similar, albeit weaker, tendency of larger early coefficients in absolute terms is observed on the second day. The long-side *E-PostpANT* × *D2* coefficient in the second test is 2.50 (t = 1.67) in comparison to the *L-PostpANT* × *D1* coefficient of 0.02 (t = 0.05), where both coefficients are not significant. The numbers are −3.42 and −0.89 in the case of short-side portfolios, where the former is significant (t = −2.78 and −0.89). Finally, Wald tests in a regression that includes both long-side and short-side variables did not reject the null hypothesis of equal magnitude in absolute terms of long-side and short-side *E-PostpANT* × *D1* and, separately, long-side and short-side *L-PostpANT* × *D1* coefficients.

The results in Table 4 show a significant and persistent post-discovery first-day effect before and after 1994. The effect exists in both the bought and sold stocks of both the long-side and short-side portfolios. No significant differences in the magnitude of the effect were observed across the long-side and short-side portfolios. In line with the findings of Chordia, Subrahmanyem, and Tong (2014), the effect is significantly stronger prior to 1994, but it remains significant afterward. The spillover of the effect to the second day diminishes after 1993, demonstrating how markets have become more efficient over time.

3.3 Post-Discovery Effect and Anomaly Type

In this section, the association between the post-discovery effect and the type of anomaly is explored. The type of anomaly is defined according to the underlying data, as reported in Appendix A. Market anomalies are calculated from market data, such as prices, returns, and volume of trade. Momentum anomalies are market anomalies that are calculated from monthly past returns. Fundamental anomalies are based on data from financial statements, where quarterly anomalies are fundamental anomalies that are calculated from quarterly financial statements. Earnings anomalies are fundamental anomalies that are linked directly to the earnings, revenues, and profitability of the firm, all of which are associated with strong and persistent anomalies. Finally, valuation anomalies are based on ratios between fundamental figures and market value.[3]

Assuming that the effect is driven by arbitrage capital, we make the following predictions. First, the post-discovery effect is expected to be stronger in anomalies that show higher in-sample returns because those anomalies attract more arbitrage capital. The effect is expected to be particularly strong in momentum anomalies because they are inherently defined monthly.

[3] Changes in recommendations are also included in valuation anomalies based on the assumption that analysts use such ratios and consider both fundamental and market variables in making recommendations.

Hence, they are the most likely anomalies to be traded monthly at the beginning of the month. Market anomalies in general and momentum anomalies in particular are also relatively easy to apply. This may expose them to the slower trading activity of less sophisticated arbitrageurs, which, in turn, is expected to strengthen and extend the effect.

Data on fundamental anomalies is updated substantially less frequently than data on market anomalies, where firms may release financial statements during all days of the month. Therefore, the incentives to trade monthly and on the first day of each month are smaller, implying a weaker effect. Nonetheless, portfolios that are based on quarterly data rather than annual data are expected to be traded more frequently, implying a stronger effect. This is due to a substantially more frequent inflow of information that continues all year long. Finally, the most commonly followed earnings and revenues data items are associated with particularly strong and persistent fundamental anomalies. Prominent examples are the earnings surprises anomaly (Foster, Olsen, and Shevlin,1984), which is also profitable in more recent years (Ali, Chen, Yao, and Yu, 2020), as well as the return-on-equity (Haugen and Baker, 1996), revenue surprises (Jegadeesh and Livnat, 2006), return-on-assets (Cooper, Gulen, and Schill, 2008), profitability (Balakrishnan, Bartov, and Faurel, 2010), gross profitability (Novy–Marx, 2013), and earning acceleration (He and Narayanamoorthy, 2020) anomalies. These robust fundamentals anomalies are expected to create a stronger effect.

To test the hypotheses above and the robustness of the effect in general, we run regressions similar to the first regression in Table 4 with *ANT* that is restricted in each test to a certain type of anomaly. Table 5 reports the results. The first two tests include market and momentum anomalies. We first confirm a positive association between in-sample returns and a post-discovery decline in returns. This is notable from the association between the *API* and *PostpAPI* coefficients at the bottom of the table, which represent in-sample returns and a post-discovery decline in returns, respectively. The market and momentum significant *API* coefficients are 0.67 and 1.46 (t = 6.42 and 9.55) versus the all-anomaly *API* coefficient in the first test in Table 4 of 0.46 (t = 10.68). The corresponding *PostpAPI* significant coefficients are −0.26, −0.78, and −0.18 (t = −1.98, −3.48, and −2.54).

The first-day and second-day post-discovery coefficients (*E-PostpANT* × *Dj* and *L-PostpANT* × *Dj, j* = 1, 2) are 6.80, 2.47, 3.01, and 0.33, respectively, where the first three coefficients are significant (t = 5.60, 2.91, 2.50, and 0.59). The significant values are larger than the all-anomaly values in the first test of Table 4 of 5.13, 1.82, 2.48, and 0.42 (t = 5.17, 3.22, 2.38, and 1.06). The coefficients increase to 9.51, 3.10, 4.32, and 0.63 in the second test with momentum anomalies, where the first three coefficients remain significant (t = 5.73, 2.79, 2.48, and 0.68). These results are generally in line with the aforementioned predictions. First, higher in-sample returns on *API* are accompanied by a stronger first-day effect throughout the sample period and a stronger second-day effect prior to 1994. In addition, the effect is substantially stronger in anomalies that are prone to monthly trading and exposed to less sophisticated arbitrageurs.

As expected, the effect in fundamental anomalies in the third test is weaker. The *E-PostpANT* × *D1* and *L-PostpANT* × *D1* coefficients are 0.14 and 1.54, respectively, where only the latter is significant (t = 0.12 and 3.17). The standalone *ANT* coefficients (*E-PostpANT* and *L-PostpANT*) are 1.97 and −0.06, where the former is highly significant (t = 7.00). This switch over time between significant coefficients is in line with the assumption of lower incentives to trade on fundamental anomalies at the beginning of each month. Prior to 1994, returns on *ANT* were spread over the entire month, as implied from the *E-PostpANT* significant coefficient.

From 1994 onward, returns shift to the first day of the month, as implied from the insignificantly negative *L-PostpANT* coefficient and the significantly positive *L-PostpANT* × *D1* coefficient. Presumably, the frequency of trading fundamental anomalies increased and shifted to the beginning of the month only after trading costs declined and competition among arbitrageurs intensified.

The effect is strengthened in the fifth test with quarterly anomalies. The *L-PostpANT* × *D1* coefficient of 3.43 is more than twice larger than the coefficient of all fundamental anomalies, and it is highly significant (t = 4.39). Similar results are observed in the next test with the prominent earnings and profitability anomalies. The *L-PostpANT* × *D1* coefficient is 3.57 and highly significant (t = 4.69). In both tests, the *E-PostpANT* coefficients of 1.07 and 1.59 are significant (t = 3.30 and 5.22), indicating a similar shift of returns to the beginning of the month after 1993.

In the last test, no evidence of the post-discovery effect was found in the valuation anomalies. Instead, the significant *ANT* × *D1* coefficient of 3.14 (t = 2.70) implies a first-day effect that exists in all anomalies regardless of whether have been discovered or not. This all-anomaly effect may be due to investors who rebalance their portfolios monthly while following similar valuation measures at the base of the valuation anomalies or for any other reason that makes their trading correlated with those measures. Unless the valuation anomalies were known to the arbitrageurs before they are published, the all-time first-day effect, which is unique to valuation anomalies, cannot be explained by anomalies post-discovery trading activity.

To sum, the post-discovery effect exists in all types of anomalies apart from valuation anomalies. The effect is stronger in market anomalies and momentum anomalies in particular. This is in line with the assumption of increasing arbitrage capital with in-sample returns and with the notions that market and momentum anomalies are traded more often at the beginning of each month and are more exposed to less sophisticated arbitrageurs. The effect is weaker in fundamental anomalies. As expected, it is stronger in anomalies that are based on quarterly data and earnings and profitability data.

3.4 Post-Discovery Effect and Limits to Arbitrage

This section explores the question of whether limits to arbitrage (Pontiff, 1996; Shleifer and Vishny, 1997) play a role in the post-discovery effect. If the effect is driven by arbitrage capital, it is expected to increase with costs of arbitrage. The hypothesis is that limits to arbitrage make market correction more difficult and create contrarian patterns. Alternatively, if the effect is not related to market mispricing and arbitrage capital, the effect is not expected to be sensitive to costs of arbitrage.

Table 6 reports the results of regressions similar to those in Table 5 with two additional variables for the interaction between the effect interaction variables (*E-PostpANT* × *D1* and *L-PostpANT* × *D1*) and a dummy variable for high costs of arbitrage (*HCA*). Each month, stocks are sorted according to end-of-month illiquidity, idiosyncratic volatility, bid–ask spread, turnover, or size. *HCA* is equal to one if a stock belongs to the top quintile of the first three variables or the bottom quintile of the last two variables, all of which serve as proxies for *HCA*. Illiquidity is estimated via the annual average of Amihud (2002) daily illiquidity measure, idiosyncratic volatility is the standard deviation of the residuals from regressing daily returns on the daily innovations of the Fama–French three-factor model over a 60-month rolling window (Ang, Hodrick, Xing, and Zhang, 2006), bid–ask spread is based on Corwin–Schultz (2012) estimates, turnover is the monthly volume of shares scaled by shares outstanding (Haugen and Baker, 1996; Datar, Naik, and Radcliffe, 1998), and size is the price times shares outstanding (for size and limits to arbitrage, see Baker and Wurgler, 2006). For brevity, we exclude the second-day variables.

The results in Table 6 are very similar regardless of how the costs of arbitrage are estimated. Prior to 1994, when the trading costs were generally high, the post-discovery effect was significantly stronger in stocks that are more costly to arbitrage. This is observed from the relatively large and significant *E-PostpANT* × *D1* × *HCA* coefficients of 7.82, 4.67, 4.91, 3.70, and 5.85 (t = 3.98, 2.66, 2.50, 2.05, and 3.26) for illiquidity, turnover, idiosyncratic volatility, size, and bid–ask spread, respectively. From 1994 onward, the *L-PostpANT* × *D1* × *HCA* coefficients were close to zero and insignificant. This indicates that in the more recent years, the effect, which is still significant according to the significantly positive *L-PostpANT* × *D1* coefficients, is not significantly different among stocks that are more costly to arbitrage. Apparently, the general decline in costs of arbitrage in the last few decades eliminates the differences in the effect across stocks.

3.5 Patterns in Volume Following Anomaly Discovery

If the post-discovery first-day increase in returns on *ANT* is a result of arbitrage capital, the volume of trade may also be affected on the same days. To test this hypothesis, Table 7 reports the results of the regression similar to that in Equation (1), with dollar volume as the dependent variable. Dollar volume is the product of the daily number of traded shares and the closing price.[4] The values in the table are expressed in terms of millions of dollars. The model specifications in the table correspond to those in Table 6.

Several conclusions emerge from the results. First, a volume effect is evident in all cases

[4] Prior to 1993, the number of traded shares of NASDAQ stocks was divided by a factor of two to account for differences in reporting schemes.

during the early years in both the first and second days of the month. For example, the *E-PostpANT* × *D1* and *E-PostpANT* × *D2* coefficients in the first test with *ANT* are 0.25 and 0.22, respectively, and they are highly significant (t = 5.97 and 5.44). The same pattern is observed in both the long-side and short-side *ANT* portfolios. The effect becomes insignificant in the more recent years. The *L-PostpANT* × *D1* and *L-PostpANT* × *D2* coefficients are about half in magnitude, in absolute terms, and insignificant. This is accompanied by a tendency for the volume in other days to decrease as the *E-PostpANT* coefficients on a standalone basis are larger than the corresponding *L-PostpANT* coefficients.

Another major result is the opposite sign of the effect depending on whether the anomaly strategy implies stock buying or selling. The long-side *E-PostpANT* × *D1* and *E-PostpANT* × *D2* coefficients are significantly positive for buying (*ANT* > 0) and selling (*ANT* < 0), indicating an increase and a decrease of volume, respectively, with long-side *ANT*. The short-side *E-PostpANT* × *D1* and *E-PostpANT* × *D2* coefficients are significantly negative for buying (*ANT* < 0) and (short-)selling (*ANT* > 0), indicating, once again, an increase and a decrease of volume, respectively, with the absolute value of short-side *ANT*. Combined together, the volume increases in early years with the stock demand and decreases with the stock supply. Observing the same asymmetry in both the long-side and short-side portfolios implies that when buying and selling stocks, arbitrageurs employ different trading strategies that differ according to their execution time horizon. This phenomenon becomes insignificant in the more recent years.

3.6 Robustness Tests and Alternative Explanations

The regressions in Table 8 check the robustness of the results while verifying that the effect is not driven by other well-known phenomena. The first test considers the turn-of-the-month (TM) effect (Ariel, 1987). As previously explained, the post-discovery effect differs from the TM effect in several respects, including the existence of the negative effect in the short-side portfolio, its emergence only after the anomalies are published, and the existence of the volume effect. Nevertheless, the first test in Table 8 confirms that the post-discovery effect is not affected by the TM effect. The test is identical to the first test in Table 4 with an additional interaction variable between the TM dummy variable and *ANT*. The post-discovery effect coefficients are identical to those in Table 4, implying that the TM effect has no impact on the anomaly effect. TM is also not related to anomalies in general as its interaction with *ANT* is not significant.

The second test adds the interaction variable between a dummy variable for Mondays and *ANT* to control for the weekend effect (French, 1980). This test is important because according to Birru (2018), long–short anomaly returns are strongly related to the day of the week. The post-discovery effect coefficients are, again, not affected by the interaction variable with Mondays, indicating that the effect is robust to weekend returns. Unreported tests that control for other days of the week lead to similar conclusions. The interaction variable in the third test between a dummy variable for the first ten days of January and *ANT* controls for the turn-of-the-year effect (Rozeff and Kinney, 1976). The identical post-discovery effect coefficients indicate that the effect is robust to turn-of-the-year returns as well.

Finally, *ANT* assigns equal weight to each anomaly portfolio. To verify that the results do not depend on this procedure, in the last test in Table 8, the original *ANT* is replaced with a three-level variable, one for $ANT > 0$, minus one for $ANT < 0$, and zero otherwise. This procedure also smooths out potential errors in individual anomalies portfolios. The $E\text{-}PostpANT \times D1$ and $L\text{-}PostpANT \times D1$ coefficients of 6.07 and 4.04, respectively, are significantly positive (t = 5.15 and 3.27) in comparison to 5.13 and 1.82 (t = 5.17 and 3.22) in the first test in Table 4. Thus, the significance of the first-day effect is negligibly affected when merging all anomalies portfolios into a single three-level variable.

4. The Loss from Slow Trading

The evidence in the previous sections shows a significant shift of returns on post-discovery anomalies to the beginning of the month. Prior to 1993, this effect was accompanied by a corresponding change in the volume of trade. The main implication to arbitrageurs from this phenomenon is that they should strive to update their portfolios before the increase in returns. However, the evidence also displays unusual trading activity on the second day of the month. To show how important the effect is to arbitrageurs in practice, in this section, we estimate the potential loss from being slow in updating anomalies portfolios. The analysis is not intended to estimate the average loss of a representative arbitrager but rather to estimate the value of the first-day effect relative to other days to determine the importance of early trading. The difference in loss between pre- and post-discovery anomalies also confirms that the effect is directly linked to anomalies arbitrage capital. This is because the general characteristics of anomalies are expected to affect all anomalies before and after they are discovered, whereas the impact of arbitrage capital can start only after the anomalies are discovered.

To estimate the loss from a delay in trading, we first define an investment strategy based on *API*. As previously explained, *API* is calculated from 71 anomalies in a way that is similar to how Engelberg, McLean, and Pontiff (2018) calculate their aggregate index. The *API* long-side portfolio strategy holds stocks with positive *API* at a weight that is proportional to stock *API* values. For instance, the weight of a stock with an *API* value of three is three times larger than the weight of a stock with an *API* value of one. This procedure assigns equal weight to each anomaly portfolio. The short-side portfolio is constructed the same way from stocks with negative values of *API*. The total return on the *API* strategy is the return on the long-side portfolio minus the return on the short-side portfolio.

To calculate the percentage loss, we compare the value of $1 invested in the *API* strategy with and without a delay at the beginning of each month in updating the portfolio. To illustrate this, suppose that the *API* value of a stock in January is equal to four and is changed to six in February. Then the one-day delayed *API* is equal to four on the first trading day of February and six during the rest of the month. The *API* value in case of a two-day delay is four in the first two trading days of February and six thereafter. The actual percentage loss is calculated as $Loss = (Vn - V) / V$, where V is the value of the portfolio that is updated at the beginning of the month and Vn is the value of the portfolio that is updated at a delay of $n = 1$ or 2 trading days.

Note that during the delay period, the portfolio includes the previous month's equities without updating them. Therefore, the actual loss on anomalies from a delay is limited to the outdated portion of the portfolio. Assuming a simple naive model, the average loss on this outdated portion is the mean return on anomalies. Thus, according to the null hypothesis, the loss is proportional to the outdated portion of the portfolio, *OP*, and the duration of the delay. For pre-discovery anomalies, the loss is thus expected to be proportional to $OP \times n / 21$, where $n / 21$ is the monthly ratio between the delayed and total number of trading days. According to the alternative hypothesis, if the discovery of anomaly shifts returns to the beginning of the month, the loss on post-discovery anomalies is expected to be substantially higher.

Panel A of Figure 2 plots the percentage loss from delays of one and two days in updating anomalies portfolios. The figure presents the loss separately for pre-discovery (dashed), post-discovery pre-publication (dotted), and post-publication (solid) anomalies. According to the arbitrage capital explanation, the expected loss caused by a shift of returns to the beginning of the month starts only after the anomalies are discovered. Each figure also plots the loss estimated from the naive model. This loss is based on a hypothetical portfolio in which all daily returns on *API* are uniformly reduced by a factor of $(1 - OP \times n / 21)$. As explained above, *OP* is the average portion of outdated anomalies portfolios, and $n = 1$ or 2 trading days of delay.

The losses from one- and two-day delays on pre-discovery anomalies (in dashed graphs) are mainly positive, indicating profits, with minimum values of −3.3% and −3.5% at the end of the sample period, respectively. These values are similar in magnitude to the loss of −1.8% predicted from the naive model. The dotted graphs, which plot the losses for the interim case of post-discovery pre-publication anomalies, are negative and decline during the early years. The end-of-period values of −2.1% and −3.9% are also similar in magnitude to the loss of −2.42% predicted from the naive model. In a sharp contrast to the pre-discovery graphs, the solid graphs, which plot the losses for post-publication anomalies, decline during most of the sample period. The losses drop to −12.3% and −15.6% by the end of the sample period or more than fifteen times the loss of −0.8% predicted from a naive model.

Panel B compares the post-publication loss from a one-day delay in the general case versus the losses in case of market and momentum anomalies. The loss calculations in all cases start from 1984 so that they can be compared despite the presence of post-publication momentum anomalies only after 1983. Consistent with the regression results in the previous section, the losses are substantially larger in the case of market and momentum anomalies. The post-publication graphs decline during most of the sample period with end-of-sample values of −10.63%, −13.77%, and −29.69 for all, market, and momentum anomalies respectively. These values are more than twelve, thirteen, and nine times larger than the losses predicted from naive models of −0.85, −1.03%, and −3.01%, respectively.

According to Figure 2, the sign of the impact of a delay in updating anomalies portfolios is opposite for pre- and post-discovery anomalies. While the loss on pre-discovery anomalies is close to zero or positive, implying profits, it is negative and large in absolute terms in case of post-discovery anomalies. The negative tendency is further strengthened after publication. The loss from a delay of one day in updating the post-publication portfolio is accumulated to 12.3% of the portfolio value (10.6% from 1984). The loss is as high as 15.4% (13.8% from 1984) and 29.7% in case of market and momentum anomalies. Those losses are several times larger than those predicted from a naive model that assumes losses proportional to the length of the delay and the outdated portion of the portfolio. This confirms that after the anomalies are discovered, a large portion of their profits is realized at the beginning of the month, mainly on the first day. As a result, missing out on only one day each month in updating the portfolio accumulates a loss of more than 12%, which increases to almost 30% in case of momentum anomalies.

5. Conclusion

This study shows how arbitrage capital reshapes out-of-sample returns on anomalies portfolios. Studying 71 cross-section anomalies, we show that after the anomalies are published, a strong and persistent return effect occurs at the beginning of each month, opposite the general tendency of returns on anomalies to decay. As a result, a large portion of profits on anomalies are realized at the beginning of the month, mainly on the first day. The first-day return on anomalies accounts for more than 12% of the portfolio value on average as well as 15.4% and 29.7% in case of market and momentum anomalies, respectively. The effect is not related to calendar phenomena, such as the TM and weekend effects. It is persistent over time, across different types of anomalies, in long-side and short-side portfolios, and in the bought and sold stocks of both portfolios. Prior to 1994, the effect was accompanied by a significant volume effect, in which the first-day volume increases with the stock demand and decreases with the stock supply.

Observing the long-lasting trading activity of arbitrageurs in out-of-sample returns indicates that arbitrageurs find anomalies to be profitable in the long run. This strongly supports the argument for the mispricing component in anomalies and the idea of arbitrage price pressure. Nevertheless, the results also indicate that unless one can trade an anomaly at the end of the month closing price, profitability substantially deteriorates with any real-time trading delay. This decline is in addition to the direct impact of transaction costs reported in other studies. Consequently, arbitragers should strive to execute their transactions as early as possible because the loss implied from any delay is substantially larger than the time of the delay relative to the investment horizon.

This study suggests avenues for future research. First, it would be interesting to study the returns on post-discovery anomalies after accounting for the intraday prices that arbitrageurs face in real time. In the same vein, whether arbitrageurs can benefit from premature trading at the end of the previous month despite not having all the market information on that day is worth studying. These and other topics are left for future research.

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Table 1. Descriptive Statistics for Anomalies Indices

The table provides descriptive statistics for an anomalies portfolios net trading (*ANT*) index and an anomalies portfolios index (*API*). Each month, stocks are sorted on 71 cross-section anomalies. The list of 71 cross-sectional anomalies is given in Appendix A. The extreme quintiles are then used to establish the long-side and short-side portfolios of each anomaly. *ANT* is the sum of changes in long-side minus changes in short-side anomalies portfolios that the firm-month observation belongs to. *API* is the number of long-side minus short-side anomalies portfolios that the firm belongs to. The sample period spans from January 1973 through December 2018.

Variable	Observations ($\times 10^3$)	Mean	Standard deviation	Min.	Max.	Percentile 5th	25th	Median	75th	95th
ANT Long	29,535	0.12	2.41	−20	32	−3	−1	0	1	4
ANT Short	29,535	0.13	2.57	−26	36	−3	−1	0	1	4
ANT (Long minus Short)	29,535	−0.01	3.28	−34	39	−5	−2	0	2	5
API Long	29,535	11.09	4.58	0	36	4	8	11	14	19
API Short	29,535	11.08	5.90	0	44	3	7	10	15	22
API (Long minus Short)	29,535	0.01	7.34	−38	31	−13	−4	1	5	11

Table 2. Patterns in Returns after Anomaly Discovery

This table reports the results of the regression in Equation (1). We regress the daily returns on the anomalies portfolios net trading (*ANT*) index, post-discovery *ANT* (*PostANT*), the dummy variables for the first two trading days of the month (*D1* and *D2*), the interactions between *ANT* and *PostANT* with the days variables, and the control variables (coefficients unreported). The control variables include lagged values for each of the past ten days for stock returns, squared returns, and trading volume. *ANT* is the sum of changes in long-side minus changes in short-side anomalies portfolios that the firm-month observation belongs to. The list of 71 cross-sectional anomalies used to construct *ANT* is given in Appendix A. *PostANT* is calculated the same way as *ANT*, with anomalies limited to the post-discovery period, which starts one month after the anomaly publication's original sample. The anomalies portfolios index (*API*) in the last test controls for the returns on anomalies. It is the sum of long-side minus short-side anomalies portfolios that the firm-month observation belongs to. Post-discovery *API* (*PostAPI*) is calculated the same way as *API*, with anomalies limited to the post-discovery period. The sample period is from 1973 to 2018. The slope coefficients in the table are multiplied by 10^4. The standard errors are clustered on time and firm. The *T*-statistics are in parentheses. One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

PostANT × *D1*	2.56	2.42	1.57	1.53	1.57
	(5.05)***	(5.19)***	(3.39)***	(3.30)***	(3.37)***
PostANT × *D2*	0.93	0.88	0.66	0.63	0.66
	(2.40)**	(2.69)***	(1.93)*	(1.83)*	(1.92)*
ANT × *D1*	−1.26	−1.24	−0.71	−0.68	−0.70
	(−4.32)***	(−4.91)***	(−2.86)***	(−2.77)***	(−2.84)***
ANT × *D2*	−0.65	−0.61	−0.45	−0.43	−0.45
	(−2.38)**	(−2.89)***	(−2.07)**	(−1.98)**	(−2.05)**
PostANT	−0.23	−0.22	−0.31	−0.20	−0.19
	(−2.81)***	(−2.95)***	(−4.02)***	(−2.66)***	(−2.34)**
ANT	0.21	0.21	0.28	0.17	0.01
	(4.39)***	(5.19)***	(6.69)***	(4.18)***	(0.28)
D1	9.20	219.77	240.60	241.07	239.30
	(1.98)**	(1.62)	(1.72)*	(1.73)*	(1.72)*
D2	11.40	81.79	89.00	89.09	88.68
	(2.64)***	(1.21)	(1.31)	(1.31)	(1.30)
PostAPI					−0.17
					(−2.69)***
API					0.48
					(11.09)***
Lagged control variables	−	−	+	+	+
Time FE	−	+	+	+	+
Firm FE	−	−	−	+	−

Table 3. Post-Discovery Effect Characteristics

This table reports the results of regressions similar to those in Table 2 with separate post-discovery anomalies portfolios net trading (*ANT*) indices for pre-publication anomalies (*PrepANT*) and post-publication anomalies (*PostpANT*). The daily returns are regressed on *ANT*, the two post-discovery *ANT* indices (*PrepANT* and *PostpANT*), a dummy variable for the first trading day of the month (*D1*), the interactions between the *ANT* versions and *D1*, the anomalies portfolios index (*API*) and post-discovery *API* (*PostAPI*), and the control variables (coefficients unreported). The regressions include the daily fixed effects and lagged control variables for each of the past ten days for stock returns, squared returns, and trading volume. *ANT* is the sum of changes in long-side minus changes in short-side anomalies portfolios that the firm-month observation belongs to. We also consider long-side and short-side *ANT* portfolios separately as well as separate buy (positive long-side *ANT* and negative short-side *ANT*) and sell (negative long-side *ANT* and positive short-side *ANT*) indices. The post-discovery indices (*PrepANT* and *PostpANT*) are calculated the same way as *ANT*, with anomalies limited to the two post-discovery periods. The post-discovery pre-publication period starts one month after the anomaly publication's original sample and ends in December of the anomaly's publication year. The post-discovery post-publication period starts immediately afterward, in January of the subsequent year. *API* controls for the returns on anomalies. It is the sum of long-side minus short-side anomalies portfolios that the firm-month observation belongs to. *PrepAPI* and *PostpAPI* are calculated the same way, with anomalies limited to the two post-discovery periods. The sample period is from 1973 to 2018. The slope coefficients in the table are multiplied by 10^4. The standard errors are clustered on time and firm. The *T*-statistics are in parentheses. One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

	ANT	**Long-Side *ANT***			**Short-Side *ANT***		
			> 0 (Buy)	**< 0 (Sell)**		**< 0 (Buy)**	**> 0 (Sell)**
PrepANT × *D1*	−0.08	−0.42	−0.16	−1.38	0.04	0.81	-0.21
	(−0.15)	(−0.66)	(−0.15)	(−1.37)	(0.06)	(0.60)	(-0.16)
PostpANT × *D1*	1.98	2.12	2.88	2.35	−1.92	−2.85	-2.01
	(3.56)***	(3.31)***	(3.43)***	(2.51)**	(−3.17)***	(−2.47)**	(-2.79)***
ANT × *D1*	−0.63	−0.67	−1.11	−0.25	0.65	1.40	0.39
	(−2.63)***	(−2.28)**	(−2.89)***	(−0.53)	(2.10)**	(3.35)***	(0.97)
PrepANT	−0.15	−0.04	0.32	−0.37	0.29	0.20	0.46
	(−1.29)	(−0.26)	(1.49)	(−1.61)	(1.65)	(0.76)	(1.88)*
PostpANT	−0.16	−0.16	−0.31	−0.05	0.13	0.18	0.14
	(−1.81)	(−1.45)	(−2.28)*	(−0.28)	(1.28)	(0.97)	(1.06)
ANT	−0.01	0.02	0.10	−0.13	0.01	0.09	0.00
	(−0.24)	(0.43)	(1.48)	(−1.44)	(0.29)	(1.08)	(0.04)
D1	159.32	159.48	160.03	159.24	159.74	160.68	159.78
	(1.46)	(1.46)	(1.47)	(1.46)	(1.46)	(1.47)	(1.46)
PrepAPI	−0.11	−0.23	−0.28	−0.22	0.05	0.09	0.04
	(−0.98)	(−1.55)	(−1.92)	(−1.56)	(0.27)	(0.49)	(0.20)
PostpAPI	−0.19	−0.28	−0.27	−0.29	0.29	0.30	0.30
	(−2.64)***	(−3.28)***	(−3.22)***	(−3.50)***	(3.03)***	(3.10)***	(3.09)***
API	0.48	0.52	0.51	0.52	−0.52	−0.52	-0.52
	(11.20)***	(11.97)***	(12.35)***	(12.27)***	(−7.67)***	(−7.80)***	(-7.64)***
Control variables	Past 10 days stock returns, squared returns, and trading volume						

Table 4. Time Change of the Post-Discovery Effect

This table reports the results of regressions similar to those in Table 3 with separate post-discovery anomalies portfolios net trading (*ANT*) indices for the early period (1973–1993) and late period (1994–2018). The daily returns are regressed on *ANT*, early and late post-publication *ANT* (*E-PostpANT* and *L-PostpANT*), the dummy variables for the first two trading days of the month (*D1* and *D2*), the interactions between the *ANT* versions and *D1* and *D2*, the anomalies portfolios index (*API*) and post-publication *API* (*PostpAPI*), and the control variables (coefficients unreported). The regressions include daily fixed effects and lagged control variables for each of the past ten days for stock returns, squared returns, and trading volume. *ANT* is the sum of changes in long-side minus changes in short-side anomalies portfolios that the firm-month observation belongs to. We also consider long-side and short-side *ANT* portfolios separately as well as separate buy (positive long-side *ANT* and negative short-side *ANT*) and sell (negative long-side *ANT* and positive short-side *ANT*) indices. The post-discovery post-publication *ANT* indices (*E-PostpANT* and *L-PostpANT*) are calculated the same way, with the anomalies limited to the post-publication period. *API* controls for the returns on anomalies. It is the sum of long-side minus short-side anomalies portfolios that the firm-month observation belongs to. *PostpAPI* is calculated the same way, with the anomalies limited to the post-publication period. The slope coefficients in the table are multiplied by 10^4. The standard errors are clustered on time and firm. The *T*-statistics are in parentheses. One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

	ANT	**Long-Side *ANT***			**Short-Side *ANT***		
			> 0 (Buy)	**< 0 (Sell)**		**< 0 (Buy)**	**> 0 (Sell)**
E-PostpANT × *D1*	5.13	6.50	10.02	4.46	−5.58	−5.56	−7.17
	(5.17)***	(4.63)***	(4.27)***	(2.46)**	(−4.57)***	(−3.79)***	(−3.38)***
L-PostpANT × *D1*	1.82	2.00	2.64	2.30	−1.83	−2.82	−1.86
	(3.22)***	(3.16)***	(3.17)***	(2.41)**	(−2.98)***	(−2.36)**	(−2.57)***
E-PostpANT × *D2*	2.48	2.50	6.06	−0.65	−3.42	−3.73	−4.18
	(2.38)**	(1.67)*	(2.62)***	(−0.35)	(−2.78)***	(−2.14)**	(−2.37)**
L-PostpANT × *D2*	0.42	0.02	0.80	−1.06	−0.89	−0.90	−1.20
	(1.06)	(0.05)	(1.24)	(−1.50)	(−1.89)*	(−1.03)	(−1.88)*
ANT ×*D1*	−0.65	−0.80	−1.27	−0.43	0.68	1.52	0.39
	(−2.87)***	(−2.90)***	(−3.31)***	(−0.95)	(2.38)**	(3.90)***	(0.95)
ANT ×*D2*	−0.32	−0.44	−1.05	0.10	0.25	0.31	0.27
	(−1.55)	(−2.10)**	(−3.41)***	(0.26)	(0.95)	(0.88)	(0.67)
E-PostpANT	0.33	0.43	0.06	0.94	−0.24	−0.07	−0.47
	(1.72)*	(1.70)*	(0.16)	(2.45)**	(−0.92)	(−0.17)	(−1.21)
L-PostpANT	−0.19	−0.18	−0.40	−0.01	0.16	0.22	0.20
	(−2.04)**	(−1.63)	(−2.81)***	(−0.08)	(1.46)	(1.11)	(1.43)
ANT	−0.02	0.03	0.19	−0.18	0.05	0.10	0.05
	(−0.50)	(0.62)	(2.75)***	(−2.12)**	(1.06)	(1.25)	(0.70)
D1	239.13	239.63	240.24	239.40	240.00	89.18	240.37
	(1.71)*	(1.72)*	(1.72)*	(1.72)*	(1.72)*	(1.31)	(1.72)*
D2	88.62	88.92	89.66	88.76	89.00	241.11	89.26
	(1.30)	(1.31)	(1.32)	(1.30)	(1.31)	(1.73)*	(1.31)
PostpAPI	−0.18	−0.26	−0.24	−0.26	0.29	0.29	0.29
	(−2.54)**	(−3.02)***	(−2.92)***	(−3.20)** *	(3.00)***	(3.04)***	(3.05)***
API	0.46	0.48	0.47	0.49	−0.51	−0.50	−0.51
	(10.68)***	(11.83)***	(12.01)***	(12.05)***	(−7.94)***	(−7.97)***	(−7.93)***
Control variables	Past 10 days stock returns, squared returns, and trading volume						

Table 5. Post-Discovery Effect and Anomaly Type

This table reports the results of regressions similar to those in Table 4 with a separate anomaly portfolio index (*ANT*) depending on the types of anomalies. The daily returns are regressed on one of the *ANT* indices, early-period (1973–1993) and late-period (1994–2018) post-publication *ANT* (*E-PostpANT* and *L-PostpANT*), the dummy variables for the first two trading days of the month (*D1* and *D2*), the interactions between the *ANT* versions and *D1* and *D2*, the specific type of anomalies portfolios index (*API*) and post-discovery *API* (*PostAPI*), and the control variables (coefficients unreported). The regressions include daily fixed effects and lagged control variables for each of the past ten days for stock returns, squared returns, and trading volume. The type of anomaly is given in Appendix A. Market, fundamental, and valuation anomalies are based on data from the market, financial statements, and ratios between the financial statements and market variables, respectively. Momentum anomalies are market anomalies based on monthly past returns. Quarterly and earnings anomalies are fundamental anomalies based on quarterly financial statements and earnings and profitability variables, respectively. To create the *ANT* versions, we sum up the changes in the long side minus changes in the short side of the specific types of anomalies portfolios that the firm-month observation belongs to. The post-publication *ANT* indices (*E-PostpANT* and *L-PostpANT*) are calculated the same way, with the anomalies limited to the post-publication period. *API* controls for the returns on the relevant types of anomalies. It is the sum of the long side minus the short side of the specific types of anomalies portfolios that the firm-month observation belongs to. *PostpAPI* is calculated the same way, with the anomalies limited to the post-publication period. The slope coefficients in the table are multiplied by 10^4. The standard errors are clustered on time and firm. The *T*-statistics are in parentheses. One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

	Market		**Fundamental**			**Valuation**
	All	**Momentum**	**All**	**Quarterly**	**Earnings**	
E-PostpANT × D1	6.80	9.51	0.14	−1.42	−0.94	−0.27
	(5.60)***	(5.73)***	(0.12)	(−0.97)	(−0.66)	(−0.03)
L-PostpANT × D1	2.47	3.10	1.54	3.43	3.57	−2.37
	(2.91)***	(2.79)***	(3.17)***	(4.39)***	(4.69)***	(−1.69)*
E-PostpANT × D2	3.01	4.32	0.44	0.49	0.20	6.35
	(2.50)**	(2.48)**	(0.29)	(0.30)	(0.13)	(1.33)
L-PostpANT × D2	0.33	0.63	0.43	0.78	0.32	1.82
	(0.59)	(0.68)	(0.95)	(1.12)	(0.50)	(1.29)
ANT × D1	−1.54	−1.00	−0.01	0.56	0.29	3.14
	(−4.44)***	(−2.27)**	(−0.05)	(1.52)	(0.89)	(2.70)***
ANT × D2	−0.51	−0.50	−0.06	0.28	0.47	−0.81
	(−1.74)*	(−1.06)	(−0.25)	(0.76)	(1.36)	(−0.74)
E-PostpANT	−0.01	−0.10	1.97	1.07	1.59	−1.69
	(−0.03)	(−0.28)	(7.00)***	(3.30)***	(5.22)***	(−1.08)
L-PostpANT	−0.15	−0.09	−0.06	−0.36	−0.29	−0.43
	(−1.01)	(−0.39)	(−0.61)	(−2.01)**	(−1.80)*	(−1.59)
ANT	−0.22	−0.24	0.02	0.07	0.30	0.17
	(−3.12)***	(−2.04)**	(0.50)	(0.79)	(3.71)***	(0.86)
D1	238.11	239.97	241.14	242.00	241.26	240.10
	(1.71)*	(1.72)*	(1.73)*	(1.73)*	(1.73)*	(1.72)*
D2	88.31	89.19	89.53	89.85	89.64	89.16
	(1.30)	(1.31)	(1.31)	(1.32)	(1.32)	(1.31)
PostpAPI	−0.26	−0.78	−0.23	0.03	0.14	−0.54
	(−1.98)**	(−3.48)***	(−2.86)***	(0.14)	(1.15)	(−2.08)**
API	0.67	1.46	0.48	1.33	0.37	0.82
	(6.42)***	(9.55)***	(11.22)***	(13.19)***	(5.87)***	(6.00)***
Control variables	Past 10 days stock returns, squared returns, and trading volume					

Table 6. Limits to Arbitrage and Post-Discovery Effect

This table reports the results of regressions similar to those in Table 4 with an additional dummy variable for high costs of arbitrage (*HCA*). The daily returns are regressed on an anomaly portfolio index (*ANT*), early-period (1973–1993) and late-period (1994–2018) post-discovery post-publication *ANT* (*E-PostpANT* and *L-PostpANT*), a dummy variable for first trading day of the month (*D1*), the interactions between *ANT* and *D1* as well as among *ANT, D1*, and *HCA*, the anomalies portfolios index (*API*) and post-discovery *API* (*PostAPI*), and the control variables (coefficients unreported). The regressions include daily fixed effects and lagged control variables for each of the past ten days for stock returns, squared returns, and trading volume. *HCA* equals one if a stock belongs to an extreme quintile of one of the variables used to estimate *HCA* (illiquidity, idiosyncratic volatility, bid–ask spread, turnover, and size) and zero otherwise. *ANT* is the sum of changes in long-side minus changes in short-side anomalies portfolios that the firm-month observation belongs to. The post-publication *ANT* indices (*E-PostpANT* and *L-PostpANT*) are calculated the same way, with the anomalies limited to the post-publication period. *API* controls for the returns on anomalies. It is the sum of long-side minus short-side anomalies portfolios that the firm-month observation belongs to. *PostpAPI* is calculated the same way, with the anomalies limited to the post-publication period. The slope coefficients in the table are multiplied by 10^4. The standard errors are clustered on time and firm. The *T*-statistics are in parentheses. One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

	Illiquidity	**Turnover**	**Idiosyncratic Volatility**	**Size**	**Spread**
E-PostpANT × *D1*	3.23	4.22	3.59	4.09	3.52
	(3.04)***	(4.00)***	(3.67)***	(4.15)***	(3.73)***
L-PostpANT × *D1*	1.80	1.83	1.85	1.80	1.70
	(2.94)***	(2.97)***	(3.84)***	(2.95)***	(2.89)***
E-PostpANT × *D1* × *HCA*	7.82	4.67	4.91	3.70	5.85
	(3.98)***	(2.66)***	(2.50)**	(2.05)**	(3.26)***
L-PostpANT × *D1* × *HCA*	0.03	–0.15	–0.21	0.00	0.38
	(0.05)	(–0.24)	(–0.32)	(–0.00)	(0.80)
ANT × *D1*	–0.64	–0.64	–0.63	–0.63	–0.64
	(–2.82)***	(–2.81)***	(–2.78)***	(–2.81)***	(–2.81)***
E-PostpANT	0.45	0.45	0.45	0.45	0.45
	(2.39)**	(2.39)**	(2.39)**	(2.39)**	(2.39)**
L-PostpANT	–0.17	–0.17	–0.17	–0.17	–0.17
	(–1.88)*	(–1.88)*	(–1.88)*	(–1.88)*	(–1.87)*
ANT	–0.04	–0.04	–0.04	–0.04	–0.04
	(–0.93)	(–0.93)	(–0.93)	(–0.93)	(–0.93)
D1	158.93	159.01	159.11	159.13	159.03
	(1.46)	(1.46)	(1.46)	(1.46)	(1.46)
PostpAPI	–0.18	–0.18	–0.18	–0.18	–0.18
	(–2.54)**	(–2.54)**	(–2.54)**	(–2.54)**	(–2.55)**
API	0.46	0.46	0.46	0.46	0.46
	(10.69)***	(10.69)***	(10.69)***	(10.69)***	(10.69)***
Control variables	Past 10 days stock returns, squared returns, and trading volume				

Table 7. Patterns in Volume Following Anomaly Discovery

This table reports the results of regressions similar to those in Equation (1), with dollar volume as a dependent variable. Daily dollar volumes are regressed on *ANT*, early and late post-publication *ANT* (*E-PostpANT* and *L-PostpANT*), the dummy variables for the first two trading days of the month (*D1* and *D2*), the interactions between the *ANT* versions and *D1* and *D2*, and the control variables (coefficients unreported). The regressions include daily fixed effects and lagged control variables for each of the past ten days for stock returns, squared returns, and trading volume. The daily dollar volume is the product of the daily number of traded shares (in millions) and the stock's closing price. *ANT* is the sum of changes in long-side minus changes in short-side anomalies portfolios that the firm-month observation belongs to. We also consider long-side and short-side *ANT* portfolios separately as well as separate buy (positive long-side *ANT* and negative short-side *ANT*) and sell (negative long-side *ANT* and positive short-side *ANT*) indices. The post-publication *ANT* indices (*E-PostpANT* and *L-PostpANT*) are calculated the same way, with the anomalies limited to the post-publication period. The standard errors are clustered on time and firm. The *T*-statistics are in parentheses. One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

	ANT	**Long-Side *ANT***			**Short-Side *ANT***		
			> 0 (Buy)	**< 0 (Sell)**		**< 0 (Buy)**	**> 0 (Sell)**
E-PostpANT × *D1*	0.25	0.38	0.51	0.34	−0.21	−0.16	−0.33
	(5.97)***	(5.65)***	(5.51)***	(4.20)***	(−4.06)***	(−2.53)**	(−4.34)***
L-PostpANT × *D1*	0.10	0.14	0.23	0.09	−0.08	−0.11	−0.10
	(1.24)	(1.24)	(1.74)*	(0.42)	(−0.72)	(−0.67)	(−0.62)
E-PostpANT × *D2*	0.22	0.31	0.38	0.30	−0.22	−0.16	−0.33
	(5.44)***	(4.51)***	(4.47)***	(3.35)***	(−3.91)***	(−2.39)**	(−4.18)***
L-PostpANT × *D2*	0.09	0.15	0.16	0.23	−0.04	−0.15	0.03
	(1.03)	(1.30)	(1.20)	(0.97)	(−0.34)	(−0.93)	(0.19)
ANT × *D1*	−0.03	−0.08	−0.10	−0.08	0.00	0.02	−0.01
	(−1.39)	(−2.50)***	(−2.75)***	(−1.23)	(0.09)	(0.32)	(−0.24)
ANT × *D2*	−0.06	−0.08	−0.08	−0.14	0.04	0.06	0.03
	(−2.11)**	(−2.32)**	(−2.14)**	(−1.69)*	(1.19)	(1.13)	(0.73)
E-PostpANT	0.06	0.13	−0.40	0.64	−0.04	−0.21	−0.01
	(4.34)***	(4.70)***	(−4.66)***	(7.26)***	(−1.94)*	(−4.02)***	(−0.19)
L-PostpANT	−0.01	−0.24	−1.13	0.77	−0.21	0.81	−1.03
	(−0.17)	(−3.90)***	(−6.87)***	(2.77)***	(−4.37)***	(4.10)***	(−5.33)***
ANT	−0.04	−0.08	0.07	−0.29	0.00	0.43	−0.16
	(−2.93)***	(−3.56)***	(2.36)**	(−5.08)***	(−0.17)	(9.82)***	(−4.92)***
D1	3.77	3.83	3.78	3.73	3.75	3.88	3.79
	(1.03)	(1.05)	(1.03)	(1.02)	(1.03)	(1.23)	(1.04)
D2	3.81	3.84	3.82	3.69	3.79	3.78	3.79
	(1.21)	(1.22)	(1.22)	(1.17)	(1.21)	(1.03)	(1.21)
Control variables	Past 10 days stock returns, squared returns, and trading volume						

Table 8. Robustness Tests

This table reports the results of regressions similar to those in Table 4. The daily returns are regressed on *ANT*, early and late post-publication *ANT* (*E-PostpANT* and *L-PostpANT*), the dummy variables for first two trading days of the month (*D1* and *D2*), the interactions between the *ANT* versions and *D1* and *D2*, the anomalies portfolios index (*API*) and post-discovery *API* (*PostAPI*), and the control variables (coefficients unreported). The regressions include daily fixed effects and lagged control variables for each of the past ten days for stock returns, squared returns, and trading volume. The first test includes an additional interaction variable between *ANT* and the turn-of-the-month effect dummy variable (*DV*), which equals one in the last two and first three days of the month and zero otherwise. The next two tests include an additional interaction variable between *ANT* and a dummy variable (*DV*) for Mondays and first ten days of January, respectively. In the last test, the *ANT* indices (*ANT*, *E-PostpANT* and *L-PostpANT*) equal one for positive *ANT*, minus one for negative *ANT*, and zero otherwise. The slope coefficients in the table are multiplied by 10^4. The standard errors are clustered on time and firm. The *T*-statistics are in parentheses. One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

	Turn-of-the-Month	**Weekend Effect**	**Turn-of-the-Year**	**Three-level *ANT***
E-PostpANT ×	5.13	5.13	5.13	6.07
	(5.17)***	(5.17)***	(5.17)***	(5.15)***
L-PostpANT ×	1.82	1.82	1.82	4.04
	(3.22)***	(3.22)***	(3.22)***	(3.27)***
E-PostpANT ×	2.48	2.48	2.48	2.34
	(2.38)**	(2.38)**	(2.38)**	(1.93)*
L-PostpANT ×	0.42	0.42	0.42	0.28
	(1.06)	(1.06)	(1.06)	(0.32)
ANT × *DV*	−0.05	0.23	0.15	
	(−0.58)	(3.17)***	(0.35)	
ANT × *D1*	−0.61	−0.69	−0.65	−1.69
	(−2.58)***	(−3.06)***	(−2.89)***	(−3.00)***
ANT × *D2*	−0.28	−0.31	−0.32	−0.60
	(−1.29)	(−1.49)	(−1.60)	(−1.19)
E-PostpANT	0.33	0.33	0.33	0.62
	(1.72)*	(1.72)*	(1.72)	(2.61)***
L-PostpANT	−0.19	−0.19	−0.19	−0.13
	(−2.04)**	(−2.04)**	(−2.05)**	(−1.57)
ANT	−0.01	−0.06	−0.02	−0.28
	(−0.31)	(−1.51)	(−0.54)	(−2.81)***
D1	239.13	239.13	239.12	239.01
	(1.71)*	(1.71)*	(1.71)	(1.71)*
D2	88.62	88.62	88.62	88.61
	(1.30)	(1.30)	(1.30)	(1.30)
PostpAPI	−0.18	−0.18	−0.18	−0.18
	(−2.54)**	(−2.54)**	(−2.54)**	(−2.58)***
API	0.46	0.46	0.46	0.46
	(10.68)***	(10.68)***	(10.68)***	(10.88)***
Control variables	Past 10 days stock returns, squared returns, and trading volume			

Figure 1. Changes in Monthly First Day Returns after Anomaly Discovery

The figure compares mean returns on anomalies portfolios. We use 71 cross-section anomalies to construct an anomalies portfolios net trading (*ANT*) index. Each month, stocks are sorted on each anomaly, and the extreme quintiles are then used to establish the long-side and short-side portfolios of each anomaly. *ANT* is the sum of changes in long-side minus changes in short-side anomalies portfolios that the firm-month observation belongs to. *ANT* is calculated for pre-discovery anomalies and separately for post-discovery pre-publication and post-publication anomalies. The figure on the left-hand (right-hand) side plots the results for positive (negative) *ANT*, implying a net increase (decrease) in anomalies portfolios that the firm-month observation belongs to. Mean returns are calculated for the first day and otherwise and separately for stocks wherein their holdings are unchanged (*ANT* = 0). Annual returns are obtained by multiplying daily returns by a factor of 252 (no compounding). The post-discovery pre-publication period starts one month after the anomaly publication's original sample and ends in December of the anomaly's publication year. The post-publication period starts immediately afterward. The list of anomalies is given in Appendix A. The sample period is from 1973 to 2018.

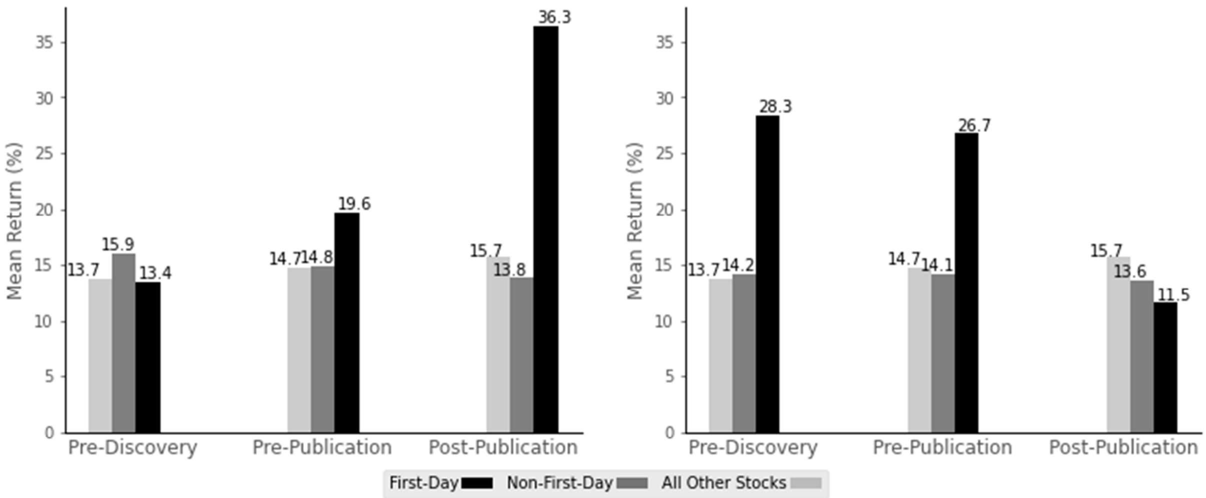
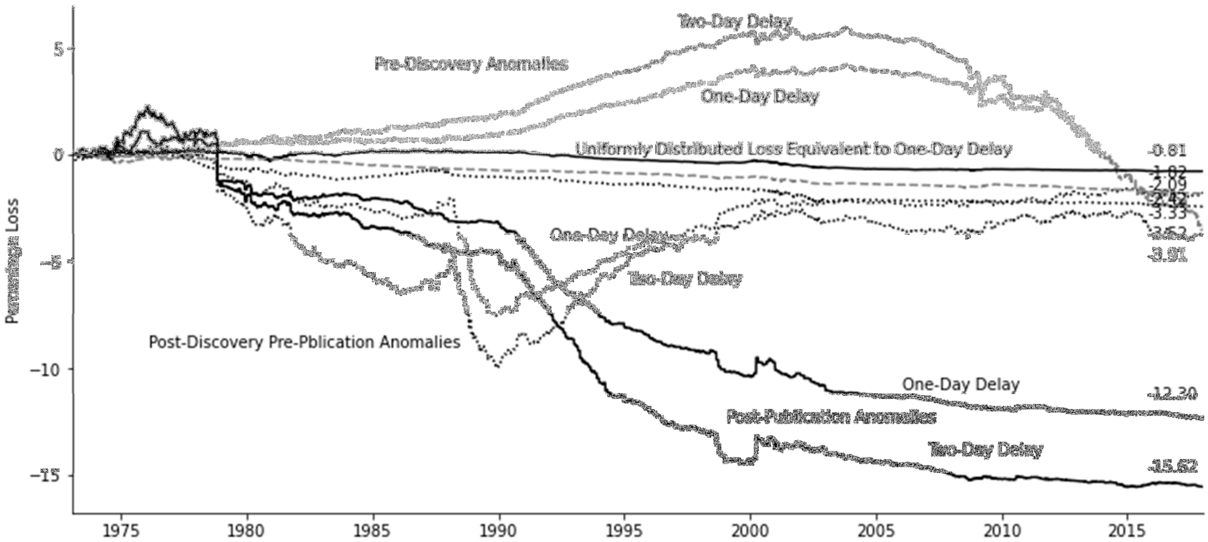


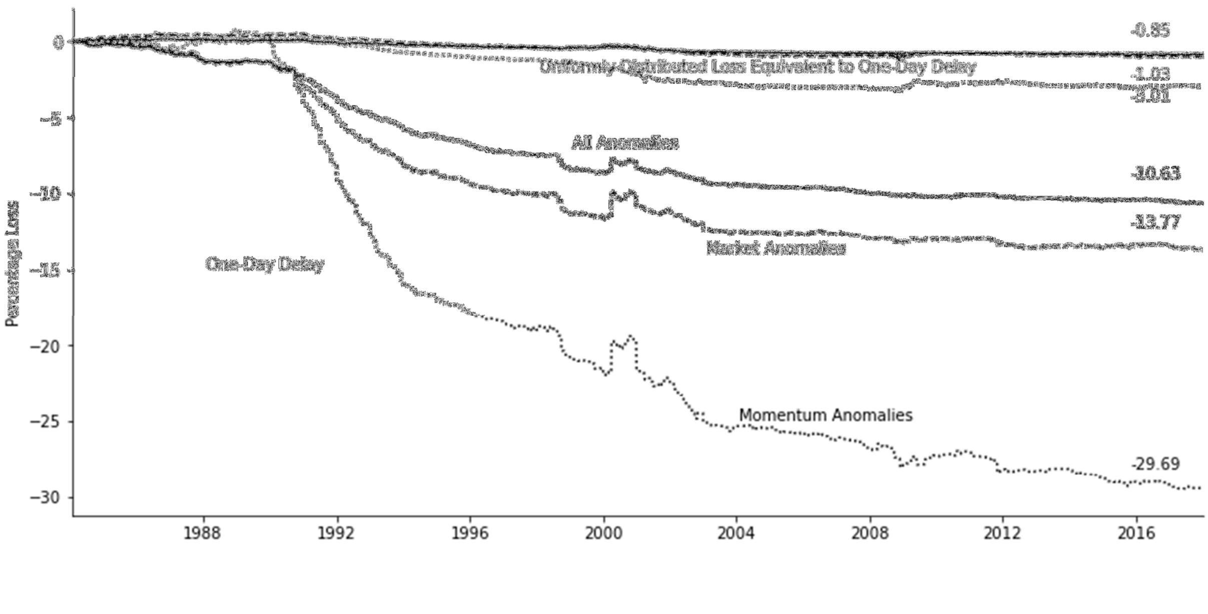
Figure 2. The Loss from Slow Trading of Anomalies

Panel A plots the percentage loss from a delay of one and two days in updating anomalies portfolios at the beginning of each month. The long-side investment strategy is holding stocks with positive anomalies portfolios indices (*API*) at a weight that is proportional to the *API* values. The short-side portfolio is constructed in the same way from stocks with negative values of *API*. The total return on the *API* strategy is the return on the long-side portfolio minus the return on the short-side portfolio. The loss is calculated as $Loss = (Vn - V) / V$, where V is the value of the portfolio that is updated each month at the beginning of the month and Vn is the value of the portfolio that is updated in a delay of $n = 1$ or 2 trading days. The loss in the figure is calculated separately for the pre-discovery (dashed), post-discovery pre-publication (dotted), and post-publication anomalies (solid). The uniformly distributed loss assumes that all daily returns are reduced by a factor equivalent to missing out one day every month of average return on the outdated portion of the portfolio. Panel B compares the loss from a one-day delay on all anomalies, market anomalies, and momentum anomalies.

Panel A. All Anomalies



Panel B. One-Day Delay



Appendix A. List of Anomalies

This table describes 71 anomalies used in constructing an anomalies net trading (*ANT*) index. The second column classifies the anomaly types (M = market, of which m = momentum; F = fundamental, of which q = quarterly data; e = earnings; and V = valuation). The third column reports the publication bibliography (author/s, journal, and year of publication). The fourth column reports the original publication's sample period. The fifth column reports whether quarterly or annual financial statements are used. The last column describes the construction of the anomaly predictor. Unless otherwise noted, all the data was collected from the CRSP and Compustat databases.

Anomaly	Type	Author(s) (Publication)	Sample Period	F-S	Construction
52-Week High	M	George and Hwang (JF 2004)	1963-2001		Current price / highest price during the last 52 weeks.
Accruals	F	Sloan (AR 1996)	1962-1991	A	((ΔCA – ΔCash) – (ΔCL – ΔSTD – ΔTP) – Dep) / ((assets$_t$ + assets$_{t-1}$) / 2); ΔCA = change in current assets; ΔCash = change in cash and cash equivalents; ΔCL = change in current liabilities; ΔSTD = change in debt included in current liabilities; ΔTP = change in income taxes payable; and Dep = depreciation and amortization expense.
Advertising / Market Value of Equity	V	Chan, Lakonishok, and Sougiannis (2001)	1975-1996	A	Advertising expenses / market value of equity.
Amihud's Measure (Illiquidity)	M	Amihud (JFM 2002)	1964-1997		Annual average of Amihud's daily illiquidity measure, (|return| / volume) × 10^6.
Asset Growth	F	Cooper, Gulen, and Schill (JF 2008)	1968-2003	A	Previous fiscal year's annual proportional change in assets per split-adjusted share.
Asset Turnover	F	Soliman (AR 2008)	1984-2002	A	Sales$_t$ / ((NOA$_t$ + NOA$_{t-1}$) / 2); Net Operating Assets (NOA) = receivables + total inventory + other current assets + PP&E + intangibles – payables – other current liabilities – other liabilities.
Beta	M	Fama and MacBeth (JPE 1973)	1969-1973		Beta with respect to the CRSP value-weighted return index. Estimated from daily returns over the past 60 months.
Bid–Ask Spread	M	Amihud and Mendelsohn (JFE 1986)	1961-1980		Spread from Shane Corwin's "Monthly High–Low Spread Estimates 1926-2013" / stock's month-end price.
Book Equity / Market Value of Equity	V	Fama and French (JF 1992)	1963-1990	A	Book equity / market value of equity. Book equity is the stockholders' book equity, plus balance sheet deferred taxes and investment tax credit, minus book value of preferred stock.
Cash Flow / Market Value of Equity	V	Lakonishok, Shleifer, and Vishny (JF 1994)	1968-1990	A	(Net income + depreciation and amortization) / market value of equity.
Change in Asset	F	Soliman (AR	1984-	A	Asset turnover$_t$ – Asset turnover$_{t-1}$. Asset turnover

Anomaly	Type	Author(s) (Publication)	Sample Period	F-S	Construction
Turnover		2008)	2002		is defined above.
Change in Profit Margin	F	Soliman (AR 2008)	1984-2002	A	Profit margin$_t$ – Profit margin$_{t-1}$. Profit margin is defined below.
Change in Recommendation	V	Jegadeesh, Kim, Kriche, and Lee (JF 2004)	1985-1998		(Recommendation upgrades – recommendation downgrades) / outstanding recommendations. Recommendation data is from I/B/E/S Recommendations Summary file.
Earnings Acceleration	Feq	He and Narayanamoorthy (JAE 2020)	2015-2020	Q	Difference in the difference between current and previous year's quarterly EPS in percentage terms and the corresponding previous quarter's difference.
Earnings Surprise	Feq	Foster, Olsen, and Shevlin (AR 1984)	1974-1981	Q	(quarterly EPS$_t$ – quarterly EPS$_{t-4}$) / standard deviation of quarterly EPS changes over the preceding eight quarters.
Enterprise Component of Book / Price	V	Penman, Richardson, and Tuna (JAR 2007)	1961-2001	A	EBP = (book value of equity +ND) / (ND + market value of eqtuity); ND = cash – long-term debt – debt in current liabilities – preferred stock – preferred dividends in arrears + preferred treasury stock.
Enterprise Multiple	V	Loughran and Wellman (JFQA 2011)	1963-2009	A	Enterprise value / operating cash flow. Enterprise value = market value of equity + long-term debt + debt in current liabilities + preferred stock – cash and short-term equivalents.
Firm Age	F	Barry and Brown (JFE 1984)	1931-1982		The number of months that a firm has been listed in CRSP database.
Firm Age-Momentum	Mm	Zhang (JF 2006)	1983-2001		Buy-and-hold returns from t – 6 through t – 1. Firms are then sorted on age, and only firms in the bottom age quintile are included.
Gross Profitability	Fe	Novy–Marx (JFE 2013)	1962-2010	A	(Revenue – cost of goods sold) / lagged total assets.
Change in Inventory	Fq	Thomas and Zhang (RAS 2002)	1970-1997	Q	(Quarterly inventory$_t$ – quarterly inventory$_{t-4}$) / annual lagged total assets.
Growth in LTNOA	F	Fairfield, Whisenant, and Yohn (AR 2003)	1964-1993	A	(ΔNOA – accruals) / total assets. NOA = accounts receivable + inventories + other current assets + net PP&E + intangibles + other long-term assets – (accounts payable + other current liabilities + other long-term liabilities). Accruals are defined above.
F–Score	Fe	Piotroski (AR 2000)	1976-1996	A	Index for value firms within the top quintile of book-to-market stocks. The index is based on the sum of the following dummy variables: one if net income > zero; one if cash flow from operations > zero; otherwise; one if return on assets (net income / assets) increased during the previous year; one if cash flow from operations > net income; long-term debt / total assets decreased during the previous year; one if current assets / current liabilities increased during the previous year; one if the firm did not issue common shares; one if EBIT / revenues increased during the previous year; and one if revenues / assets increased during the previous year.
Fundamental Mispricing	V	Bartram and Grinblatt (JFE	1987-2012	Q	Difference between firm's actual value and median fair value predicted from 28 of the most common

Anomaly	Type	Author(s) (Publication)	Sample Period	F-S	Construction
Characteristic		2018)			firm-level accounting variables.
G–score	Fe	Mohanram (RAS 2005)	1978-2001	A	Index for growth firms within the bottom quintile of book-to-market stocks. The index is ranging from zero to eight based on the sum of the following variables: one if net income / assets > industry (two-digit SIC code) median; one if cash flow / assets > industry-median; one if cash flow from operations > net income; one if net income variability < median firm in the same industry; one if revenue variability is less that median firm in the same industry; one if capital expenditures / assets > industry median; one if research and development expenditures / assets > industry median; and one if advertising expenditures / assets > industry median.
Idiosyncratic Risk	M	Ang et al. (JF 2006)	1986-2000		The standard deviation of the residual from a firm-level regression of daily stock returns on the daily innovations of the Fama-French three-factor model over a 60-month rolling window.
Information Discreteness and Momentum	Mm	Da, Gurun and Warachka (RFS 2014)	1976-2007		Buy-and-hold returns from $t-12$ to $t-2$ multiplied by ID. ID = Sign(PRET) × [%neg – %pos], where %pos and %neg are the percentage of days with positive and negative returns over the past 12 months after skipping the most recent month, and where PRET is defined as a firm's cumulative return over the same period.
Investment	F	Titman, Wei, and Xie (JFQA 2004)	1973-1996	A	(CAPEX / revenues) / average of (CAPEX / revenues) in the last three years.
Investment-to-Assets	F	Chen, Novy–Marx, and Zhang (2011)	1972-2010	A	(Change in gross PP&E + change in inventories) / lagged total assets.
Lagged Momentum	Mm	Novy-Marx (JFE 2012)	1926-2010		Buy-and-hold returns from $t-13$ through $t-8$.
Leverage	F	Bhandari (JF 1988)	1946-1981	A	Log (long-term debt / market value of equity).
Leverage Component of Book / Price	V	Penman, Richardson, and Tuna (JAR 2007)	1961-2002	A	BPEBP = BP – EBP; EBP is defined above; BP = (book value of equity + preferred treasury stock – preferred dividends in arrears) / market value of equity.
Long-Term Reversal	Mm	Debondt and Thaler (JF 1985)	1926-1982		Buy and hold returns from $t-60$ to $t-13$.
M/B and Accruals	F	Bartov and Kim (RQFA 2004)	1980-1998	A	Equal to one if both bottom book-to-market and top accruals quintiles; minus one if both top book-to-market and bottom accrual quintiles, and zero otherwise. book-to-market and accruals are defined above.
Max	M	Bali, Cakici, and Whitelaw (JF 2011)	1962-2005		Maximum daily return over the past month.
Momentum	Mm	Jegadeesh and Titman (JF 1993)	1964-1989		Buy-and-hold returns from $t-6$ to $t-1$.
Momentum and LT Reversal	Mm	Chan and Kot (JOIM 2006)	1965-2001		Equal to one if both momentum top quintile and long-term reversal bottom quintile, minus one if

Anomaly	Type	Author(s) (Publication)	Sample Period	F-S	Construction
					both momentum bottom quintile and long-term reversal top quintile, and zero otherwise. Momentum and long-term reversal are defined above.
Momentum-Reversal	Mm	Jegadeesh and Titman (JF 1993)	1964-1989		Buy and hold returns from $t-18$ to $t-13$.
Momentum-Volume	Mm	Lee and Swaminathan (JF 2000)	1965-1995		Buy-and-hold returns from $t-6$ through $t-1$. We limit the sample to stocks in the top quintile of average monthly trading volume measured over the past six months.
Net Operating Assets	F	Hirshleifer et al. (JAE 2004)	1964-2002	A	(Operating assets − operating liabilities) / lagged total assets. Operating assets = total assets − cash and short term investments. Operating liabilities = total assets − debt included in current liabilities − long term debt − minority interests − preferred stocks − common equity.
Net Working Capital Changes	F	Soliman (AR 2008)	1984-2002	A	Change in net working capital / total assets. Net working capital = total current assets − cash and cash equivalents − (total current liabilities − debt in current liabilities).
Noncurrent Operating Assets Changes	F	Soliman (AR 2008)	1984-2002	A	Change in noncurrent operating assets / total assets. Noncurrent operating assets = total assets − current assets and investment and advances − (total liabilities − current liabilities and long-term debt).
Operating Leverage	F	Novy-Marx (ROF 2010)	1963-2008	A	(SG&A + cost of goods sold) / total assets.
Organization Capital	V	Eisfeldt and Papanikolaou (JF 2013)	1970-2008	A	Organization Capital (OC) = (zero for missing SG&A; 4 × SG&A in the first year with non-missing SG&A; 0.85 × OC_{t-1} + $SG\&A_t$ thereafter) / total assets.
O–Score	F	Dichev (JF 1998)	1981-1995	A	O–Score = −1.32 − 0.407 × log(total assets / GNP price-level index) + 6.03 × (total liabilities / total assets) − 1.43 × (working capital / total assets) + 0.076 × (current liabilities / current assets) − 1.72 × (if total liabilities > total assets, else zero) − 2.37 × (net income / total assets) − 1.83 × (funds from operations / total liabilities) + 0.285 × (1 if net loss for the last two years, else zero) − 0.521 × (net income_t − net income_{t-1}) / ($\lvert\text{net income}_t\rvert$ + $\lvert\text{net income}_{t-1}\rvert$).
Percent Operating Accrual	F	Hafzalla, Lundholm, and Van Winkle (AR 2011)	1989-2008	A	(Net income − cash flow from Operations) / ǀnet incomeǀ.
Percent Total Accrual	F	Hafzalla, Lundholm, and Van Winkle (AR 2011)	1989-2008	A	Net income − ((−sale of common and preferred stock + purchase of common and preferred stock + total dividends + cash flow from operations + cash flow from financing + cash flow from investment) / ǀnet incomeǀ).
Profit Margin	Fe	Soliman (AR 2008)	1984-2002	A	EBIT / revenues.
Profitability	Fe	Balakrishnan, Bartov, and Faurel	1976-2005	A	(Income before extraordinary items − dividends on preferred + income statement deferred taxes) /

Anomaly	Type	Author(s) (Publication)	Sample Period	F-S	Construction
		(JAE 2010)			book value of equity.
R&D / Market Value of Equity	V	Chan, Lakonishok, and Sougiannis (2001)	1975-1995	A	R&D expenses / market value of equity.
Return-on-Assets	Fe	Cooper et al. (JF 2008)	1963-2003	A	Income before extraordinary items / lagged total assets.
Return-on-Equity	Feq	Haugen and Baker (JFE 1996)	1979-1993	Q	Quarterly income before extraordinary items / quarterly lagged book equity.
Recency Ratio	M	Bhootra and Hur (2013)	1965-2008		Unit minus the percentage of the year elapsed since the price was maximal in the last 52 weeks.
Revenue Surprises	Feq	Jegadeesh and Livnat (JAE 2006)	1987-2003	Q	(Quarterly revenue$_t$ − quarterly revenue$_{t-4}$) / standard deviation of quarterly revenue changes over the preceding eight quarters.
Sales / Price	V	Barbee, Mukherji, and Raines (FAJ 1996)	1979-1991	A	Total revenues / stock price.
Seasonality	M	Heston and Sadka (JFE 2008)	1965-2002		Average monthly return in the same month over the last 20 years.
Share Issuance (1-Year)	F	Pontiff and Woodgate (JF 2008)	1970-2003		Annual change in the logarithm of split-adjusted shares outstanding.
Share Issuance (5-Year)	F	Daniel and Titman (JF 2006)	1968-2003		Five-year change in the logarithm of split-adjusted shares outstanding.
Share Volume	M	Datair, Naik, and Radcliffe (JFM 1998)	1962-1991		Average number of shares traded over the previous three months / shares outstanding.
Short-Term Reversal	Mm	Jegadeesh (1990)	1934-1987		Last month return.
Size	M	Banz (JFE 1981)	1926-1975		Log of end-of-month price times shares outstanding (in thousands).
Sustainable Growth	F	Lockwood and Prombutr (JFR 2010)	1964-2007	A	Annual change in book value of equity.
Tax	Fe	Lev and Nissim (AR 2004)	1973-2000	A	Income tax / net income. Income tax = tax / k, where k = 0.48 for 1973-1978, 0.46 for 1979-1986, 0.40 for 1987, 0.34 for 1988-1992, and 0.35 from 1993.
Total XFIN	F	Bradshaw, Richardson, and Sloan (JAE 2006)	1971-2000	A	(Sale of common and preferred stock − cash dividends − purchase of common and preferred stock + sale of long-term debt − purchase of long-term debt) / total assets
Turnover	M	Haugen and Baker (JFE 1996)	1979-1993		Monthly trading shares / shares outstanding.
Volume / Market Value of Equity	M	Haugen and Baker (JFE 1996)	1979-1993		Monthly average dollar trading volume over the past 12 months / shares outstanding.
Volume Trend	M	Haugen and Baker (JFE 1996)	1979-1993		Five-year trend in monthly trading volume / average trading volume during the same five-year period.
Volume Variance	M	Chordia, Subranhmanyam, and Anshuman (JFE 2001)	1966-1995		Standard deviation of monthly trading volume over the last 36 months.

Anomaly	Type	Author(s) (Publication)	Sample Period	F-S	Construction
Xmax	M	Li and Yu (JFE 2012)	2009-2012		Current price / all-time maximum price.
ΔSales−ΔInventory	Fe	Abarbanell and Bushee (AR 1998)	1974-1988	A	ΔSales = Sales at time t minus the average value of sales from $t-1$ and $t-2$, all scaled by the average value of sales from $t-1$ and $t-2$. ΔInventory is computed the same with total inventories.
ΔSales−ΔSG&A	Fe	Abarbanell and Bushee (AR 1998)	1974-1988	A	ΔSales = Sales at time t minus the average value of sales from $t-1$ and $t-2$, all scaled by the average value of sales from $t-1$ and $t-2$. ΔSG&A is computed the same.