Overcoming Arbitrage Limits: Option Trading and Momentum Returns *

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Abstract

We find that the decline in the momentum profitability is partly driven by option trading. Momentum profits arise from the short leg and therefore on barriers to short selling. We find strong evidence that the presence of stock options creates alternate avenues for short selling, augmenting the stock lending market, thus contributing to improved pricing efficiency. However, when option trading becomes expensive, the short position offers lower returns. We find that our results remain unchanged when we match the universe of stocks with and without options based on variables that determine the eligibility of a stock to be optionable indicating that firm-level characteristics cannot account for the significant differences in the profitability of the two strategies.

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1 Introduction

The existence and discovery of a large number of anomalies in equity markets has spurred research seeking to identify market frictions that lie behind these violations of market efficiency. Recent work shows that, in a number of anomalies, it is the return to the short leg in the long-short strategies that plays a key role in their profitability (e.g., Stambaugh, Yu, and Yuan, 2012; Israel and Moskowitz, 2013). We note here that returns to the short leg play, in this set of anomalies, the most prominent role in momentum profits. Other research relates attenuation in anomaly returns to more efficient pricing due to enhanced arbitrage capital flows, lower stock trading costs, greater competition between institutions and improved investor awareness after publication. We build on this work and find, in this paper, that the growth in the stock options market, a hitherto unexplored area, also contributes to the attenuation in anomaly returns by enhancing stock price informativeness and by lowering barriers to short selling. While we also study other anomalies, our main focus is on momentum – it is a violation of weak form efficiency, easy to implement, and a focus of institutional arbitrage – where here the short leg returns play a key role in its profitability.[1]

The first options on individual stocks started trading in April 1973 (e.g., Mayhew and Mihov, 2004). Since then, these have increased in number to 27% in 1996 and rising to 72% in 2018 of all listed stocks in our sample. In fact, at one stage in the recent financial crises we find that there were more stocks with traded options than without. While stock options are in theory redundant assets, in markets with frictions (e.g., Grossman, 1988), traded options reveal information about investors' future trading intentions and price volatility in a way that a dynamic option replication scheme does not. As a result, in the presence of short sale constraints, the options market provides an alternate channel of information flows about the fundamen-

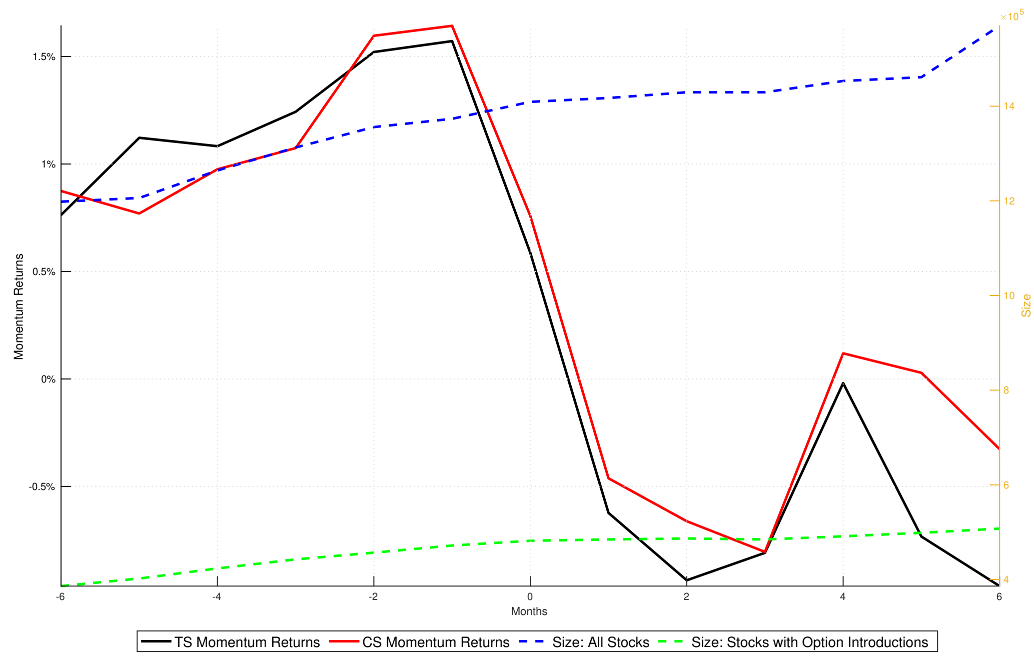
[1]For example, Filippou, Garcia-Ares, and Zapatero (2020) find that option trading has a strong effect on lottery strategies (e.g., MAX).

tal value of an underlying stock. If stocks that are difficult to short in the stock market have options traded on them, then the options market provides an additional avenue for incorporating information and reducing mispricing (e.g., Evans, Geczy, Musto, and Reed, 2008). This avenue works via options traders that buy (sell) put (call) options on these "difficult to short" stocks while the option market maker takes the opposite side of the transaction and shorts the underlying stocks to hedge the put option written or call option bought. As a result, if an investor uses options to establish a short position, this is transformed into an actual short sale by a market professional who faces lower costs and fewer constraints. This short selling by options market makers should have an effect on the short leg of a momentum strategy for stocks with listed options. Specifically, the lower mispricing of such stocks should result in reduced profits to the short leg and consequently lower profits to the Winner-Loser portfolio. Our empirical results all point towards support for this avenue.

We set the background by demonstrating that the momentum anomaly provides a good laboratory for studying the role played by the reduction in barriers to short selling due to the existence of a stock options market. We show, using alpha analysis, that momentum is a natural candidate for testing the impact of options as it is the most profitable strategy and more dependent on its short leg among the universe of 94 anomaly-based firm characteristics studied by Green, Hand, and Zhang (2017). We then use this to study the relation between momentum returns over time and the growth of the stock options market. We also consider all these cross-sectional anomaly-based firm characteristics together and create an aggregate anomaly variable which also verifies our main results with respect to the role of options in the profitability of anomaly portfolios. To the best of our knowledge, this is the first study that associates option trading with the profitability of anomaly portfolios.

It is likely that stocks without options are in a special category and different therefore from stocks with options. As a first test, we construct an event study around option introductions using data from option listings dates from Mayhew and Mihov (2004), which pre-date the availability of detailed options data from 1996 and complement this with more recent data from Optionmetrics. Figure 1 shows that optionability is the driving reason for the reduction in momentum returns. Similarly to Goyal and Jegadeesh (2017), we show abnormal returns, based on the Fama and French (1993) model, of cross-sectional (CS) and time-series (TS) momentum six months prior and after an option introduction for the period of June 1977 to December 2018. For the CS strategy, each month we go long (short) in stocks with cumulative returns higher (smaller) than the cross-sectional average. In the case of the TS strategy, each month we buy (sell) stocks with cumulative returns higher (smaller) than zero. We also plot the median size of these stocks and the set of all firms in our sample during the same period. We find that both, time-series and cross-sectional returns, decreases significantly after the introduction of an option. We also see that size increases before the introduction but there is no significant change after option listing. This exercise also serves as an out-of-sample test of our analysis as it considers a period before the starting date of our main analysis. Our results are also similar if we focus on option introductions from Optionmetrics after 1996.

Figure 1. ***Momentum Returns Around Option Listing***



The figure displays time-series and cross-sectional momentum abnormal returns around the introduction of an option based on the Fama and French (1993) model that is estimated using a 36-month estimation window. The dashed lines show the median of the size of the stocks with options as well as the median size of all firms. The graph depicts results for the period of July 1977 to December 2018.

We evaluate the performance of momentum portfolios when considering the whole universe of stocks over the 1996-2018 period. Consistently with the literature (e.g., Chordia, Subrahmanyam, and Tong, 2014; McLean and Pontiff, 2016) we observe that momentum returns have decreased significantly during the recent period. Then, we partition stocks into those with and without options as our options data from Optionmetrics is available only after 1996 and arguably is the period when options were widely available to retail investors. We are then able to construct momentum portfolios of optionable and non-optionable stocks. We show that the momentum strategy is more profitable for portfolios of stocks without options mainly due to the more negative returns of their loser portfolios.

The universe of stocks with options could be different, in nature, from stocks without options exhibiting significant differences in size, liquidity and other relevant firm-level characteristics (e.g., Pástor and Stambaugh, 2003; Israel and Moskowitz, 2013; Chordia et al., 2014; Bali and Murray, 2019) and this might explain the differences in profitability between momentum portfolios with and without options. In order to guard against this issue, we match optionable and non-optionable stocks based on variables that determine the eligibility of a stock to be optionable – which is a non-parametric way of controlling for these characteristics – and then we allocate the matched firms into portfolios based on their previous 12-month cumulative returns. Our main results are based on stocks that are matched based on market capitalization, trading volume and industry but they are robust when we match firms based on size, trading volume and volatility as well as other relevant firm-level characteristics such as institutional ownership and by using a parametric approach instead. We find that the remarkable difference in the profitability between stocks with and without options remains as momentum portfolios with options exhibit very low excess returns per month that are not statistically different from zero while the universe of matched stocks without options offer a very positive and statistically significant return. The difference in the profitability arises from the statistically and economically significant difference in the return of the loser portfolios.

In particular, we find that the average returns to a momentum portfolio of matched stocks without options is high and statistically significant (348 bps per month) while the momentum strategy is not significant for stocks with options (59 bps per month). This result is driven, both for stocks with and without options, by the change in returns to the short (losers) leg of the strategy. For stocks without options, the return to the short leg is highly negative (-221 bps per month) compared to that of the short leg for stocks with options which is not different from 0 at 16 bps per month. The returns to the winner (long leg) portfolio is bigger for stocks without options but the difference between the two is not statistically significant. Interestingly, we find that the differences between optionable and non-optionable stocks is driven by the differences in the loser portfolios in a statistically significant manner. We also control for different dimensions of the profitability of the momentum strategy and obtain similar results.

Our next set of results show, using the Hou and Moskowitz (2005) and Bai, Philippon, and Savov (2016) information measures, that loser portfolios of stocks with traded options, have a higher "informativeness" measure relative to loser portfolio of stocks without traded options. This suggests that stocks with options are more efficiently priced relative to stocks without options. This results in the observed lower returns to the momentum trading strategy for stocks with options.

Next we show, building on early work by Figlewski and Webb (1993), that in the case of momentum there is an increase in options trading to establish short positions which results in higher shorting demand. We also find that options are shifting effective lendable supply up, meaning that shorting of these stocks is higher and the corresponding shorting fees are lower. For example, option market makers (prior to 2008 and 2013) could alleviate short selling constraints by paying lower loan fees due to naked short selling (e.g., Evans et al., 2008). In this way, the option market was offering elastic supply of stocks for short selling. In addition, Evans et al. (2008) find that option market makers fail to deliver when hard-to-borrow stocks are recalled and this has an effect on option prices. Similarly, we find that optionable loser portfolios demonstrate more fails to deliver, consistently with the previous finding.

In addition, our work contributes to a large literature which shows that proxies for short selling and short sale constraints predict the cross section of stock returns. Specifically, we know that many anomaly profits are earned mostly from the short leg, and this fact has been connected before with the cost of shorting ((e.g., Drechsler and Drechsler, 2016)). Their paper provides a theory on why hard-to-short stocks earn a risk premium; arbitrageurs must be compensated for the risk they bear in shorting overpriced stocks. In particular, they study the relationship between short fees and the returns of eight large cross-sectional pricing anomalies (including momentum) and find that anomaly returns depend on short fees. In fact, the anomalies only survive for stocks with high fees. They focus on the whole universe of stocks without distinguishing between optionable and non-optionable stocks. We replicate their main results and find that when shorting fees are high, momentum is only significant in the case of stocks without options. This is related to our main conjecture about the presence of short sale constraints which impede these stocks from incorporating information and reduce mispricing quickly. This finding is also related to Muravyev, Pearson, and Pollet (2019) who found that for the subset of stocks with options the risk of borrowing stocks does not create a substantial risk premium reflected in option prices.

Next, we also find that the higher shorting activity for loser stocks with options indicates a large investor demand for option positions in these portfolios. Using option order imbalance data we find more net selling positions in the loser portfolio relative to the winner portfolio. In particular, we show that when stocks are hard to borrow, the delta hedging by options market makers typically involves shorting stock. This evidence supports the notion of information revelation from the options market for stocks in the short leg of the momentum strategy. In addition, we find that cumulative returns also predict the sign of these option order imbalances. This high option trading volume might be at odds with conventional estimates of large costs of taking option positions. Recent work by Muravyev and Pearson (2020) using proprietary data about options prices find that option trading costs are much lower than previously thought.

The most striking result of this mechanism is that when the expensiveness of the options is high, momentum for the subset of stocks with options is highly significant indicating that investors are less involved in the options market. In other words, the options market provides less supply of stock for short selling resulting in more pronounced short selling constraints. We use the difference between call and put implied volatilities as a measure of option expensiveness. Muravyev, Pearson, and Pollet (2020) show that the implied volatility spread predicts underlying stock returns because it proxies for the expected cost of borrowing stock.

Additionally, we perform several robustness tests and verify that our main results hold. In particular, we consider earlier –to our default starting point 1996– option introductions to rule out that the disappearance of momentum returns for stocks with options written on them is not due to some other factor associated with our starting date. In other tests we consider different matching procedures, as well as alternative measures of price informativeness. Finally, we examine whether momentum crashes could partly explain our results.

Taken together, our results show that the stock options market, by contributing to enhanced transactions and information efficiency, plays a role in the secular decline in momentum returns over the last decades.

The rest of the paper proceeds as follows. We begin with a review of related research in Section 2 and then describe in Section 3 the data we use. Section 4 analyses the role of option trading in anomaly profits. Next, in Section 5, we discuss our main empirical results. Section 6 examines the role of option trading and option impediments in the momentum profitability. Section 7 presents a battery of tests for robustness and Section 8 concludes.

2 Prior Related Research

Over the last few decades, academic researchers have reported hundreds of cross-sectional anomalies (see for example, Harvey, Liu, and Zhu, 2016). However, Hou, Xue, and Zhang (2017) find that few anomalies survive if multiple hypotheses testing is accounted for. Apart from the statistical issues involved in tests for anomalies, there is also research on economic factors that affect anomaly profits. These include the impact of increased liquidity and lower stock trading costs (Chordia et al. (2014)), the growth of institutional ownership growth (Nagel (2005)), increased arbitrage capital flows (Hanson and Sunderam (2014)) and awareness amongst investors following an anomaly discovery (McLean and Pontiff (2016)).

Other work, for example, Stambaugh et al. (2012) study, over the 1965-2008 period, the drivers of returns to the long and short legs of eleven prominent stock market anomalies. In an efficient market, mispricing would not exist as arbitrageurs drive prices towards fundamental value. In real world markets, there are significant barriers to short sales; arising from regulatory interventions like the uptick rule and frictions in the stock lending market or lack of arbitrage capital (Shleifer and Vishny, 1997). Stambaugh et al. (2012) find that in many, but not all anomalies, it is the mispricing of stocks in the short leg that is not corrected due to short sales constraints. Specifically, they find that the short leg plays a dominant role in the determination of profits to momentum trading. In related work, Israel and Moskowitz (2013) study, over a much longer period (from 1926 to 2011) the sources of profit to size, value and momentum strategies and find that the short position of momentum accounts for almost fifty percent of the profitability of the strategy.

Clearly, the ability to short sell is related to the frictions and to the supply and demand of stocks in the stock lending market. An additional channel for short sale is created when there is an option trading on a stock thus augmenting that via the equity lending market. This works in two ways. First, bearish investors (or those implementing a long/short arbitrage) can now choose to use either the stock or the options markets to establish her short position. Sorescu (2000); Danielsen and Sorescu (2001); Battalio and Schultz (2011) find that options ease short sale constraints by expanding supply for short positions. The second arises from the hedging motives of options market makers. If an investor chooses options, the option market maker (OMM) borrows and shorts the underlying stock to hedge the put option written (or call option bought). This could result in increasing the supply or in a pass through for short demand. For example, if short sellers buy put options but the market maker writing that option hedges by shorting the stocks and borrowing in the lending market, then the option market does not increase supply, but rather passes through the demand to the equity lending market. Evidence for this is reported by Battalio and Schultz (2011); Grundy, Lim, and Verwijmeren (2012).

In contrast, Evans et al. (2008) find that options market makers (OMM) fail to deliver when expensive-to-borrow stocks are recalled and this failure passes through to options prices as violations of put-call parity. This was possible before 2008, as OMM had an exception whereby they were not required to locate and borrow stocks, and effectively could naked short sell as a hedge. These failures to deliver expand the supply of expensive-to-borrow stocks by capping loan prices and mitigate equity overpricing. This situation continues even after the OMM exception was revoked by the SEC. Specifically, Stratmann and Welborn (2013) show that this change in rules was not fully effective and conclude that the options market still provided an alternative to the securities lending market when borrowing constraints existed. In fact, the SEC prohibited a workaround using "reverse conversions" as short sales in 2013.

We note that our results do not imply that momentum returns might again be as profitable as in the 1980-1990s if markets and institutions create an environment where mispricing occurs and persists. In fact, according to Blocher and Ringgenberg (2018), recent change in the option market maker exception from borrowing shares when short selling has likely increased equity loan fees resulting in more expensive option trading and a decline in informational efficiency for stocks with options while stocks without options are immune to such changes. In contrast, Muravyev et al. (2019) find that located and close-out requirements do not create a large stock borrowing premium but find a significant increase in the risk premium during the financial crisis and for stocks affected by the short sale ban in 2008. They suggest that the borrowing fee risk for individual stocks is diversifiable and the options market is enough competitive to distribute this risk effectively even after the naked short selling ban.

3 Data

We use a number of different datasets for equity and options market data and not all are available over our full sample period. Our main equity market data covers the period of January 1996 to December 2018. We also study specific sub-periods, again dictated by data availability, where we look for supportive evidence of information flows between the stock and the options markets. These sub-periods are: 1975-1996 for early option introductions, 2006-2016 for option order imbalances and 2007-2018 for equity lending data.

Equities. We use daily and monthly stock returns of all ordinary common shares (i.e. CRSP shares codes 10 and 11) listed in the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ markets from the Center for Research in Security Prices (CRSP). We also obtain the number of shares outstanding, bid and ask prices and volume for calculating other variables like market capitalization and illiquidity. We use the COMPUSTAT/CRSP merged database for annual and quarterly accounting information which we require for computing some of our control variables. Details about the construction of these variables can be found in the Internet Appendix.

Stock Options. We merge the CRSP stock data with options data from the OptionMetrics IvyDB US database which starts from 1996.[2] We divide our sample into portfolios of stocks with and without options during the last trading day of each month (i.e. the day when we rebalance our momentum portfolios). A stock is considered optionable if it appears in OptionMetrics data the last trading day of month t. Alternatively, we consider stocks as optionable if their options found on the last trading day of month t are tradable. Details about the filters we apply to the options data can be found in a later section of the paper.

[2]We merge the two datasets using the Linking Suite provided by WRDS.

Short Demand and Supply. Our measures of short demand and supply are collected from a new comprehensive dataset from Markit Data Explorer (DXL) spanning the period from January 2007 to December 2018. The demand measure is based on the daily total shares borrowed from DXL lenders and the supply measure reflects the daily total lendable inventory that is available from DXL lenders. We express these measures as a percentage of shares outstanding. We obtain the Daily Cost of Borrowing Score (DCBS), which is the relative cost of borrowing for each stock, taking values from 1 to 10 representing low and high costs respectively. We report the simple average fee (SAF), which measures the buy-side cost to borrow.[3] We also compute short interest which is from the COMPUSTAT Short Interest Supplemental file. We use the mid-month data (available prior to September 2007) to obtain a longer sample. This sample starts from January 2003 because firms traded in NASDAQ are not available before that date. For each stock, we compute the shares held short as a proportion of the mid-month shares outstanding obtained from the daily CRSP database.

Stock Order Imbalances. We directly obtain data about stock order imbalances from the WRDS Intrady Indicator Database (IID). This database contains daily stock market indicators obtained from the Trade and Quote (TAQ) data. Specifically, we focus on the millisecond intraday indicators available from 2003 until the end of our sample period in December 2018 and extract two measures of order imbalances based on total number of trades and total trade volume. In order to classify transactions as either a buy or a sell order, they use the Lee and Ready (1991) algorithm that considers the movements of the prices above or below the quote midpoint. We extend this data to 1996 by computing the stock order imbalance measures from the Trade and Quote (TAQ) monthly database by using the same trade classification algorithm. Results are similar if we only focus on the millisecond intraday indicators for the subperiod

[3] For stock loan fees, we interpolate the missing observations of average lending fees following Blocher and Whaley (2016).

2003-2018 or if we compute stock order imbalances from the monthly TAQ database which is available until 2013.

The trade-level classifications are aggregated to obtain monthly trade imbalances keeping in line with our monthly rebalancing strategy. Chordia, Goyal, and Jegadeesh (2016) find that this aggregation also alleviates concerns about the accuracy of the trade-level classifications using the Lee and Ready (1991) algorithm. Following Chordia, Roll, and Subrahmanyam (2005) and Chordia et al. (2016), we use two measures of order imbalances. The first, called $\mathrm{SOI}^{\mathrm{NUM}}$, computes net trading based on the number of trades. The second measure termed $\mathrm{SOI}^{\mathrm{VOL}}$ computes stock order imbalances based on the total trade volume. Specifically, these measures of stock i imbalances at time t are defined as

$$\mathrm{SOI}_{\mathrm{i,t}}^{\mathrm{NUM}} = \frac{\mathrm{BO}_{\mathrm{i,t}}^{\mathrm{NUM}} - \mathrm{SO}_{\mathrm{i,t}}^{\mathrm{NUM}}}{\sum_{\mathrm{i,t}}(\mathrm{BO}_{\mathrm{i,t}}^{\mathrm{NUM}} + \mathrm{SO}_{\mathrm{i,t}}^{\mathrm{NUM}})} \tag{1}$$

$$\mathrm{SOI}_{\mathrm{i,t}}^{\mathrm{VOL}} = \frac{\mathrm{BO}_{\mathrm{i,t}}^{\mathrm{VOL}} - \mathrm{SO}_{\mathrm{i,t}}^{\mathrm{VOL}}}{\sum_{\mathrm{i,t}}(\mathrm{BO}_{\mathrm{i,t}}^{\mathrm{VOL}} + \mathrm{SO}_{\mathrm{i,t}}^{\mathrm{VOL}})} \tag{2}$$

where $\mathrm{SOI}^{\mathrm{NUM}}$ is the number of buys less number of sells as a fraction of the total number of trades at time t. $\mathrm{SOI}^{\mathrm{VOL}}$ is the number of buy trade volume less sell trade volume as a fraction of the total volume traded at time t. Thus, a positive (negative) value of the order imbalance (e.g., $\mathrm{SOI}^{\mathrm{NUM}}, \mathrm{SOI}^{\mathrm{VOL}}$) implies that investors are, on average, net buyers (net sellers) of the stocks of interest.[4]

Option Order Imbalances. We obtain data on Option Order Imbalances using signed option trading volume from the International Security Exchange (ISE) Open/Close Trade Profile database. This dataset has daily buy and sell volume trades and prices for each option traded at the ISE but it is only available for a part of our sample period from 2006-2016. We merge these

[4]We merge the CRSP and TAQ datasets using the Linking Suite provided by WRDS.

data with OptionMetrics in order to obtain the delta of each option. For this shorter sub-period, we extract data on the direction of each trade and on whether the trades open new positions or close existing positions. Trades reported in the ISE Open/Close database represents more than 30% of the total trading volume in individual equity options during our sample spanning January 2006 to December 2016. Following Pan and Poteshman (2006); Ge, Lin, and Pearson (2016) we only consider opening trades as they are generally more informative than closing trades. As in Muravyev (2016), we focus on disaggregated trades for customers in order to identify which trade side is taken by option market-makers.[5]

We define delta-hedged option order imbalances for each stock i as:

$$\mathrm{OOI}_{i,t} = \frac{\sum_j^N abs(\Delta_{i,j,t})[(\mathrm{BC}_{i,j,t} + \mathrm{SP}_{i,j,t}) - (\mathrm{SC}_{i,j,t} + \mathrm{BP}_{i,j,t})]}{\mathrm{Num\_shares\_outstanding}_t} \tag{3}$$

where OOI is calculated as the difference between the number of option buy and sell transactions of call and put options j written on stock i at time t, regardless of expiration, as a fraction of the total number of shares outstanding at time t. We focus on delta weighted order flows. This converts raw option orders into units of exposure to the underlying stock. OOI are reported as basis points. In particular, the options order imbalance reflects the option buy (sell) orders of calls (puts) by non- market-makers over the total number of shares outstanding. In other words, this variant of option imbalances reflects the dominance of buy (sell) call (put) trades as opposed to sell (buy) call (put) trading. In this way, we capture the demand for synthetic positions. This implies that market markers are shorting the stock if the order imbalances are *positive*. In line with our monthly rebalancing strategy, we aggregate daily trades at a monthly level.

[5]According to the ISE, the universe of customers comprises retail investors as well as investment banks such as Morgan Stanley and Goldman Sachs who enter trades on behalf of large customers or hedge funds. In addition, firms represents investment banks who place orders using their own accounts or on behalf of an another broker dealer who is not a member of the exchange.

4 The role of Option Trading

4.1 Growth in Traded Options and Listed Stocks

We now report on the link between the equity options market and the total number of listed firms. The decision to list equity options for a particular equity is entirely at the discretion of the exchanges themselves. Options exchanges have put specific requirements in place before a company´s stock can be listed for option contracts. Individual companies have no say on whether or not options on their shares trade on an options exchange. According to CBEO, a firm should meet the following criteria before an option introduction: i) it must be listed on the NYSE, AMEX or NASDAQ, ii) the closing price of a stock should be higher or equal to a minimum threshold price the last three calendar months,[6] iii) the firms should exhibit a minimum of 7 million shares and 2,000 shareholders. These are the current criteria but CBOE has been changing them overtime.

Figure 2 and Table A1 describe the evolution of the listed firms and the stock options market over our sample period 1996-2018. We note that the growth in the proportion of stocks with traded options is driven both by new option introductions and a decrease in the number of listed stocks over this period (as documented in Doidge, Karolyi, and Stulz (2017); Kahle and Stulz (2017)). In 1996, at the start of our sample period based on Optionmetrics data, only 27% of sample stocks had traded options but by 2018, this rose to 72%. Interestingly, we note that the number of stocks with traded options exceeds those without traded options just prior to the 2008 financial crisis.

[6] Hu (2018) shows that the minimum price requirement was set to $7.5 until the end of 2002 and it decreased to $3 after that date.

4.2 The Importance of Shorting for Momentum and Other Anomalies

The next step in our empirical strategy is to understand the role of both short and long legs in the momentum strategy and the contribution of the growth in traded options in the decline of momentum profits. Our main conjecture is that in markets with frictions, such as short sale constraints, the options market enhances information flows as investors are able to trade options on these difficult to short stocks while the market maker turns around and delta hedges such trades by shorting the underlying stock and reducing overpricing. It might be the case that anomalies that depend more on the short leg of the trade tend to be more affected by option trading. Thus, studying the whole universe of short leg-dependent asset pricing anomalies would be one way of testing the role of option trading in alleviating short sale constraints.

As discussed earlier, Stambaugh et al. (2012) and Israel and Moskowitz (2013) highlight the importance of the short leg in the momentum strategy. We supplement this finding by investigating the relative importance of the short leg in momentum trading compared to other anomalies for our sample period. We use a set of 94 anomaly-based firm characteristics used in Green et al. (2017).[7] Each of the anomaly variables has been reported to predict the cross-section of stock returns. Similar to Israel and Moskowitz (2013), we examine the returns to these firm-level characteristics and the contribution to profits from the long and short sides.

To create the anomaly portfolios, stocks are sorted each month on each of the anomaly characteristics. We define the extreme deciles as the long and short side of each anomaly strategy. Due to data availability per anomaly portfolio, we also sort some of the anomaly characteristics into quintiles and terciles portfolios. The universe of the Green et al. (2017) characteristics includes 7 indicator variables (e.g. the IPO characteristic-based anomaly which equals to 1 if first year available on CRSP monthly file). We exclude these variables from our

[7]We thank the authors for their code, available on their webpage, that constructs the 94 characteristics available on their webpage. Table A9 of the Internet Appendix offers a detailed description.

analysis because there is only one long or short side. All portfolios are value weighted. The spread portfolios are determined based on their exposure to the short and long positions.

Figure 3 offers alphas of the Fama and French (1993) three factor model for the short (red bars) and long (green bars) legs of these strategies from January 1980 to December 2018.[8] The strategies are sorted based on the short leg of each anomaly portfolio.[9] Thus, the anomalies appeared on the left (right) part of Figure 3 demonstrate the most (least) negative alpha of the short position. The bottom graph of Figure 3 shows the corresponding spread portfolios. We find that momentum is the most profitable strategy and together with return volatility the most dependent on its short leg relatively to other anomaly portfolios. For this reason, together with its long history among both academics and practitioners, it serves as a natural candidate for testing the role of option trading on its profitability. In a later section, we build a strategy that takes into consideration all the 87 anomalies together and verify our main results with respect to the role of options in the reduction of anomaly profits.

4.3 Momentum Returns and Optionability

We now report, in Table 1, average excess monthly returns for each momentum decile portfolio for all stocks and separately for stocks with and without options. Our sample consists all US-based common stocks that trade on the NYSE, AMEX, or NASDAQ and covers the 1996-2018 period for which Optionmetrics is available. A stock is considered optionable if, on the last trading day of month t, it appears in Optionmetrics options data. In the Table, Decile 10 indicates the winner portfolio, Decile 1 denotes the loser portfolios and WML indicates the winner-minus-loser portfolio. The momentum returns (e.g., WML) reported are those obtained by an investor who takes a long-short position in the winner and loser portfolios and then holds this position for one month. We also report the corresponding alphas of the CAPM,

[8]The short positions have an opposite sign so as to illustrate their contribution in the spread portfolios.
[9]The short leg is determined based on the sign of the Fama and French (1993) alpha of the extreme portfolios.

the three-factor Fama and French (1993) model (FF3) and the five-factor Fama and French (2015) model (FF5). The Table shows clearly that the WML return for all stocks (137 bps) is driven by the higher return for stocks without options (252 bps). Panel B also indicates that the difference in returns between loser portfolios of stocks with and without options are significantly different (-105 bps) compared to those of winner portfolios of stocks with and without options (-3 bps). This is an indication that option trading can partly explain the decline in momentum profits.

One could argue that optionable stocks differ from non-optionable stocks in many different ways. On the other hand, option listing occurs endogenously as a result of decisions made by exchanges and regulators. In order to guard against these issues, we match stocks with and without options in a non parametric setting based on variables that determine the eligibility of a stock to be optionable. Specifically, Mayhew and Mihov (2004) examine stock characteristics that determine option listing. The authors find that stock exchanges are more likely to list options on stocks that exhibit more pronounced trading volume, volatility and market capitalization. Despite the fact that option listing decisions of stock exchanges change over time –with the tendency to relax their criteria– those three factors are the main determinants of option listing. For that reason, in our matching procedure we match (without replacement) the universe of stocks with options with the group of stocks without options based on trading volume, market capitalisation, and industry.[10] This way, we identify a non optionable stock that meets the criteria for option listing. This implies that the two set of stocks are comparable in term of eligibility for option listing.

We compare stocks with and without options by using one-to-one matching. In particular,

[10]We do not include stock volatility in our matching criteria because a triple-matching procedure would limit the number of available stocks in the treatment and control groups. In addition, we show in Table 2 that after matching based on size, volume and industry the differences in volatility between the two groups are not economically significant. We further verify this in the Internet Appendix where we show results for matched firm based on size, trading volume, industry and volatility as well as other relevant firm-level characteristics and find similar results.

at the end of each month we match each optionable stock with a non-optionable stock imposing that the later has higher market capitalisation, higher average trading volume during the previous month and belong to a different industry based on the 48 Fama French industries classification. This way we ensure that size, trading volume and industry are not the drivers of the difference in the anomaly profits we found between stocks with and without options.

In order to investigate this issue further, we report in Panel A of Table 2 time-series averages of median firm-level characteristics examining the relative importance of various factors influencing the exchanges´ decision of which options to list. In particular, we present time-series averages of median market capitalization, price, volume, and volatility. Price is the price of the stock at the end of the month. Volume is the average number of daily shares of the stock traded in the previous month, recorded in millions of shares. Volatility is the standard deviation of the daily log returns during the same month. Panel A of Table 2 demonstrates that there are substantial differences between the sample of optionable and non-optionable stocks. In the average month, there are more non-optionable stocks than optionable ones, the median market capitalization for optionable stocks is 1,187 compared to only 0.074 in the case stocks without options, and the share volume of optionable stocks is, in median, 0.463, in contrast to 0.023 in the case of non-optionable stocks. The price of the median optionable stock is $23.49 as opposed to $8.46 for stocks without options.[11] The time-series average of the median volatility of an optionable stock is smaller than that of non-optionable stocks. The results clearly demonstrates that optionable stocks tend to be larger and more liquid than non-optionable stocks.

Panel B of Table 2 shows time-series averages of the median characteristics of the matched treated and non-treated firms based on size, trading volume and industry. We find that stocks

[11]Recall that one of the criteria that is set from CBOE for a stock to be optionable is to have a closing price that is greater than a threshold for a majority of trading over a particular time period (e.g., three months). Hu (2018) shows that the minimum price requirement was set to $7.5 until the end of 2002 and it decreased to $3 after that date.

without options now exhibit characteristics that meet the criteria for option listing as they have higher size, volume, volatility and price compared to the group of stocks with options. All the differences are statistically and economically significant. The differences in volatility are not economically significant. We also report the number of resulted firms after matching. Our matching criteria reduces our sample of optionable and non-optionable stocks to 461 firms per category.

5 Empirical Results

In this section we focus on the universe of matched firms based on trading volume, market capitalisation and industry. In particular, we show secular changes and differences in cross-sectional momentum returns, over the 1996-2018 period, for winner and loser portfolios of our sample of matched firms with and without traded options. We compare the differences in momentum returns for these firms using portfolio sorts and Fama and MacBeth (1973) regressions. We also examine the role of information flows as well as shorting supply and demand for the constituents of loser and winner portfolios.

5.1 Univariate Sorts

Table 3 reports the value-weighted average monthly excess returns to decile momentum portfolios for the matched stocks with and without options. To do this, we allocate stocks into deciles based on their cumulative returns using the whole sample of matched stocks. Then, we label as optionable losers (winners) the stocks with options within the loser (winner) portfolios. We then repeat this exercise for stocks without options. By doing this we avoid distorting the breakpoints for the momentum portfolios. We find that momentum returns for stocks with options are low and not statistically different from zero (59 bps per month) while for stocks without options they are higher (348 bps per month) and also statistically significant. This decline in momentum returns for stocks with options is mainly driven by the positive payoffs of the loser portfolios (16 bps bps per month) compared to stocks without options (-221 bps per month) with a similar pattern for CAPM, FF3 and FF5 alphas.

This finding is in line with our conjecture regarding the contribution of the optionable loser portfolios to the decline of momentum profits. In contrast, although it is true that returns to winners portfolios of stocks with options are smaller than winners of stocks without options this difference is small and not statistically significant. Until now we have defined an stock as optionable if it appears in Optionmetrics data during the last trading day of month t. Table A2 in the Internet Appendix reports results when we define a stock as optionable if its options found on the last trading day of month t are "tradable". We define the filters we apply to the option data in a later section. We verify our main results with respect to the role of options in the decline of momentum profits due to the reduction of the profitability of the loser portfolios with options.

Finally, Table A3 in the Internet Appendix shows results based on stocks that are matched based on market capitalization, trading volume, industry and volatility (Panel A) while Panel B considers optionable and non-optionable stocks matched based on market capitalization, trading volume and institutional ownership as optionable stocks tend to be held by institutional investors. We show that our conclusions are unchanged when we examine portfolios constructed using other relevant firm-level characteristics.

5.2 Cross-sectional Regressions

In addition to our portfolio level sorts, we run Fama and MacBeth (1973) cross-sectional regression which allows us to control for additional factors that might drive the profitability of momentum and to incorporate information that is omitted in portfolio sorts.

In Table 4, we show the results of the following cross-section regression separately for matched stocks with and without options:

$$\text{Ret}_{i,t+1} = \delta_{0,t} + \delta_{1,i}\text{R(2,12)}_{i,t} + \delta'_{2,i}\mathbf{Z}_{i,t} + \varepsilon_{i,t+1} \tag{4}$$

where $\text{Ret}_{i,t+1}$ denotes the time $t+1$ stock return of firm i, $\text{R(2,12)}_{i,t}$ is the 12-month cumulative stock return (after skipping the most recent month) of stock i on month t. $\mathbf{Z}_{i,t}$ represents the set of control variables of firm i on month t. Our set of control variables included in $\mathbf{Z}$ are similar to those used in the prior literature (e.g., Novy-Marx, 2012; Bali, Cakici, and Whitelaw, 2011). Specifically, we control for size (Ln(Size)), stock price (Ln(Price)), percentage of institutional ownership (IOR), book-to-market (B/M), idiosyncratic volatility (IVOL), reversal return (R(1)) and the illiquidity (ILLIQ) factor.[12]

Table 4 reports the average cross-sectional coefficients and adjusted R^2s of the regression above. We find that cumulative returns (R(2,12)) have strong and positive cross-sectional predictive power for stocks without options. In contrast, these returns do not exhibit cross-sectional predictive power for stocks with options. Our results are robust to controlling for stock characteristics that might potentially matter for stocks with and without options.

5.3 Information Flows

We now investigate what drives the lower returns to the short leg that has a dominant effect on the overall strategy. Clearly, there is an easing in short sales constraints that as previous theoretical studies show could be due to increased information flows to the stock lending market. In fact, the returns to the short leg will attenuate if stocks are less mispriced due to improved information flows. We follow Hou and Moskowitz (2005) and compute the price

[12] Appendix A of the Internet Appendix provides a detailed description of the control variables.

delay of the constituents of momentum portfolios of stocks with and without options. In particular, at the end of each month, we run a regression of each stock's i weekly returns on contemporaneous and four-week lagged returns on the market portfolio over the prior year. The estimation uses the following form:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \sum_{n=1}^{4} \delta_i^{(-n)} R_{m,t-n} + \varepsilon_{i,t}, \tag{5}$$

where $R_{i,t}$ represents the return on stock i and $R_{m,t}$ denotes the CRSP value-weighted market index in week t. An immediate response of the stock to market news would imply that the $\beta_{i,t}$ coefficient is statistically different from zero while the $\delta_i^{(-n)}$ coefficients remain insignificant. On the other hand, a delayed response of the stock to market news would be reflected in non zero $\delta_i^{(-n)}$ coefficients. Thus, this specification captures the time it takes for a stock to respond to market-wide news assuming that expecting returns remain unchanged over weekly horizons.

As pointed by Hou and Moskowitz (2005), due to the volatility of weekly individual stock returns, the coefficients from the previous regression are estimated imprecisely. To mitigate an errors-in-variable problem, we sort firms into our momentum portfolios and compute delay measures for each of the momentum portfolios instead. In fact, we compute, at the end of each month and for each of the momentum portfolios, a measure of price delay defined as the part of the variation of individual stock returns at time t that are explained by lagged market returns. The measure resembles an F-test as it is one minus the ratio of the R^2 from a restricted version of model 5 where all $\delta_i^{(-n)}$s are set to zero over the R^2 of the full specification (i.e. unrestricted) model:

$$D1 = 1 - \frac{R^2_{\delta_i^{(-n)}=0, \forall n \in [1,4]}}{R^2}. \tag{6}$$

Thus, a higher value of $D1$ implies that lagged market returns explain a higher fraction of the variation of individual stock returns, and hence the greater the delay of the stock to respond to market-wide news. In other words, these stocks are less informative as it takes more time to incorporate the new information.

Panel A of Table 5 shows time-series averages of the median price delay measure to decile momentum portfolios and the spread (WML) portfolio for stocks with and without options that are matched based on trading volume, industry and size. We find that the economic and statistically differences between loser and winner portfolios for stocks with options is small (-0.027 with a t-stat of -1.99). In contrast, we find that the winner portfolio of stocks without options has a *lower* price delay measure (0.122) relative to the corresponding loser portfolio (0.212) and this difference is high (-0.090) and highly significant (-6.75).

Panel B reports differences in price delay between loser (winner) portfolios of stocks with and without options. We find that price delay is much lower for loser stocks with options than for loser stocks without options. This suggests that the presence of option trading enhances information flows for loser stocks with options relative to loser stocks without options. Specifically, we find that the difference between the price delay of loser portfolios of the two groups is 0.082 and this is statistically significant compared to the case of winner portfolios in where the difference is small and insignificant.

Our results imply that the significant differences in price informativeness between loser and winner portfolios could partially explain the differences in the payoffs of momentum strategies of stocks without options (e.g., as documented in Table 3). It is likely that momentum returns for stocks with options tend to be insignificant because option trading enhances information flows about future movements of the underlying asset. In other words, the mispricing of stocks with options is relatively short-lived as increased information flow pushes their prices towards their fundamental value. This finding is consistent with Figlewski and Webb (1993) who report that options trading allows for a less costly way of short-selling stocks with options compared to stocks without options.

5.4 Supply and Demand of Stocks for Short Sale

We first examine whether short demand is higher for stocks that have traded options relative to stocks without traded options and its relation to the loser portfolios of optionable stocks. If stocks that are difficult to short in the stock market have options traded on them, then the options market provides an alternative trading avenue for investors with unfavorable information about a stock by allowing them to sell the stock indirectly. When stocks are hard to borrow, the delta hedging by option market makers typically involves shorting the stocks. Thus, an investor's purchase of a put option would result in a short sale of the underlying stock by the market maker resulting in an increase in the level of short demand. If it is the case, we ought to see higher short demand especially in the case of loser stocks with options.

Table 6 reports monthly time-series averages of median short demand of all the momentum strategy decile portfolios (both for stocks with and without options) for the period of 2007 to 2018 during the rebalancing period (e.g., the entire month prior to the holding period).[13] Following Beneish, Lee, and Nichols (2015), we proxy for short demand with the Markit Data Explorer (DXL) daily measure of the total shares borrowed from DXL lenders. We express this measure as a percentage of shares outstanding.

We find in Panel A of Table 6 that short demand is substantially higher for loser portfolios of stocks with options resulting in a very negative and significant WML spread. In contrast, the average short interest for decile portfolios of stocks without options is smaller and the difference between the short demand of winner and loser portfolios remains negative but less economically significant. Panel B in Table 6 shows that the differences in short demand be-

[13]Results are similar when we calculate short demand based on the last trading day of each month.

tween loser stocks with and without options is -0.015 and statistically significant verifying the higher levels of short demand for loser stocks with options.[14]

We now turn to study the variation of shorting supply within loser and winner portfolios. Following Beneish et al. (2015), we proxy supply with the DXL daily total lendable inventory available from DXL lenders. As before, we express this measure as a percentage of shares outstanding and it is also computed during the rebalancing period. We find in Panel A of Table 6 that the shorting supply of loser portfolios with options is *higher* than the corresponding shorting supply for loser portfolios without options. In addition, we show in Panel B that the difference in shorting supply between stocks with and without options is also statistically significant.

We also study the behavior of utilization which is defined as the ratio of shares supplied to shared demanded. In fact, utilization captures the percentage of lendable shares that are actually on loan. We find in Panel A of Table 6 that utilization is on average higher for stocks with options in comparison to stocks without options. Utilization of loser portfolios with options is also *higher* than the utilization for loser portfolios of stocks without options although the difference is not statistically significant.

Beneish et al. (2015) find that, for the whole universe of stocks, utilization is a reasonable measure of borrowing and that the costs of borrowing are largely driven by the level of supply. Of interest here is whether this similar utilization between the two groups of stocks affects the stock loan market and results in similar loan fees for the loser stocks with options. If short sellers buy put options, for instance, but the market maker writing that option hedges by shorting the stocks and borrowing in the lending market, then the option market does not

[14] We also find similar results using the short interest ratio (e.g., the ratio of shares shorted from COMPUSTAT divided by shares outstanding) in Table A4 of the Internet Appendix. However, SIR is a good proxy of short demand when supply is unconstrained. In the case of binding constraints the SIR cannot capture the variation of short-sellers demand as it becomes an equilibrium outcome of demand, supply and borrowing costs (e.g., Beneish et al., 2015).

increase supply, but rather passes through the demand to the equity lending market. If that is the case we should expect similar fees for loser stocks with options. In contrast, if option markets acts as an additional supply, option trading should also shift the effective lending supply resulting in higher short selling, lower shorting fees and cheaper options. In fact, the equity options market provides a supplemental supply of shares for short sellers ("shadow supply").

Stock Loan Fees Table 7 reports time-series averages of median stocks loan fees for stocks with and without options. Lending fees are the interpolated lending fees and they are expressed in basis points (e.g., Blocher and Ringgenberg, 2018). Panel A of Table 7 presents time-series averages of median shorting fees for momentum portfolios. The last two rows present the differences in shorting fees between winners and losers portfolios with associated HAC adjusted t-statistics (t-stat). Panel B shows differences in lending fees for loser and winner portfolios of the two groups of stocks.

In line with the previous reasoning, we find that despite the similar utilization ratios for stocks with options this is not translated into similar stock loan fees for these stocks with respect to stocks without options. We find in Panel A of Table 7 that stock loan fees are particularly high for loser stocks in comparison to winner stocks. The time-series average of the median lending fees exceed 100bps for both groups indicating that they belong to the category of hard-to-borrow stocks (e.g., Blocher and Ringgenberg, 2018). When comparing optionable with non-optionable stocks we find that loan fees are much lower for stocks with options due to higher supply of lendable shares. We find in Panel B that differences in the loan fees is more than 192bps and statistically significant. It is important to note that these loser stocks with and without options are of similar size and trading volume and belong to the same momentum portfolio.

The underlying mechanism of such effect is related to the ability of the options market maker to alleviate short selling constraints and pay lower loan fees by naked short selling (e.g., Evans et al., 2008). This effect more pronounced for hard-to-borrow stocks that tend to be loser stocks. To this end, the option market maker can offer elastic supply of stocks for short selling.

We now analyse the effect of stock loan fees and utilisation in the performance of our momentum portfolios of stocks with and without options. A large literature shows that proxies for short selling and short sale constraints predict the cross section of stock returns. One possible explanation is that the returns to short positions reflect compensation for particular risks associated with holding short positions. In fact, Drechsler and Drechsler (2016) suggest that short-sellers have concentrated portfolios and that the abnormal returns to stocks with high stock borrowing fees reflect the compensation that short sellers require for bearing the idiosyncratic risk of undiversified short positions. They focus on the whole universe of stocks without distinguishing between stocks with and without options. In contrast, Muravyev et al. (2019) find that for the subset of stock with options the risk of borrowing stocks does not create a substantial risk premium reflected in option prices and claim that the borrowing fee risk for individual stocks is largely diversifiable and the options market is sufficiently competitive and is typically well-capitalized enough to distribute this risk effectively. They also find that the change in the option market exception from borrowing shares when short selling does not have an effect on a increased risk premium reflected in option prices.

We reconcile these two apparent contradictory results by considering separately stocks with and without options. Our conjecture is that this predictability is restricted to the case of stocks without options due to the presence of short sale constraints which impedes these stocks from incorporating information and reducing mispricing quickly. Table 8 presents results using double sorts on momentum (R(2,12)) and shorting fees and utilisation from 1996 to

2018. As in our previous portfolio sorts, we allocate stocks into quintiles based on their cumulative returns and shorting fees (utilisation). By doing this we avoid distorting the breakpoints and we ensure that all portfolios for stocks with and without options are comparable as they have similar values of shorting fees (utilisation) and cumulative returns. We find in Panel A of Table 8 that momentum is only significant when fees for stocks without options are high. In contrast, momentum for stocks with options is not significant even when shorting fees are high. The same happens when we compute double sorts based on utilisation which is another proxy for shorting fees (Panel B).

5.4.1 Fails-To-Deliver

As stated in Evans et al. (2008), a failure-to-deliver is a form of zero-rebate equity loan from the buyer to the seller who fails to deliver. Since failures to deliver primarily happen among hard-to-borrow stocks, this behaviour has the effect of alleviating supply constraints right as they are most likely to bind. Therefore, we should expect much more fails to deliver in the case of loser stocks with options which will reflect this increased supply with respect to loser portfolios of non-optionable stocks. Figure 4 examines the behaviour of fails to deliver around the rebalancing period for loser and winner portfolios of stocks with and without options. In particular, the right panel of Figure 4 plots the Outstanding fails-to-deliver ratio (OFR), defined for each day t as the number of outstanding failed positions reported on day $t + 3$ scaled by the total number of shares outstanding of the firm on day t for a 20-day window around the rebalancing date for the period of March 2004 to December 2018. On the other hand, the left panel plots the number of stocks that failed to deliver during the same period.[15]

Figure 4 shows that both, the fails to deliver ratio and the number of firms with fails to deliver are much more pronounced for loser stocks with options. In contrast, the differences

[15] We offer a detailed description of the data in the Internet Appendix.

between winners portfolios of stocks with and without options are low. Recall that the winners stocks with and without options are not considered hard to borrow as their fees are quite low. Table A5 in the Internet Appendix shows similar results for the time-series average of the OFR measure and the average number of firms with fails to deliver over the holding period for stocks with and without options.

6 Option Trading and Momentum Portfolios

In this section, we examine trading patterns in the options market that are associated with our findings. We also relate these patterns with stock trading of winner and loser stocks. In addition, we investigate the role of option trading frictions in the profitability of the momentum strategy.

We apply a number of filters in the options data in order to ensure tradability and avoid outliers (e.g., Muravyev, Pearson, and Pollet, 2018; Muravyev et al., 2019). In particular, we focus on call-put pair observations with particular characteristics. Specifically, we keep options with put moneyness K/S less than or equal to 1.1. We only consider options with between 15 and 90 days remaining to expiration. We also keep options in where the sum of the call and put bid-ask spreads divided by the stock price is less than or equal to 5%. In addition, open interest of the options is positive, the absolute delta is between 0.01 and 0.99, implied volatility is between 0.03 and 2, the bid is greater than 0.1 and the bid is less than the ask. As pointed out by Muravyev et al. (2018, 2019), the requirements that the dividend yield be less than or equal to 5% and the put moneyness K/S be less than or equal to 1.1 are included to filter out calls and puts, respectively, for which early exercise is important. The other filters eliminate options with wide bid-ask spreads, low liquidity, or unreasonable prices. Our results remain similar if any of these restrictions is dropped or relaxed.

6.1 Option Order Imbalances

In the previous section, we show that short demand is substantially higher for loser portfolios of stocks with options. In fact, if investors with unfavorable information buy puts and write calls when they would like to short the underlying stock, we should see this reflected in higher trading activity of these particular options for the loser stocks compared to the other momentum portfolios. To this end, we compute delta-hedge option order imbalances (OOI) for call and put options written on the constituents of our loser and winner momentum portfolios. In other words, after an options trader executes a transaction, the options market maker takes the opposite position which allow us to relate short demand with delta-hedge option order imbalances.

We report, in Table 9, the time-series monthly averages of median option order imbalances during the holding period for options in our loser and winner portfolios. Our option imbalance data is only available for the period 2006-2016 i.e. it is not available from 1996 which is the start date for our other results. We find that option traders establish more net selling positions for loser portfolios compared to those in the winner portfolios. In particular, the average delta-hedge option order imbalances for losers is -0.007. In contrast, the average option order imbalances for winners is 0.021. The difference between the winners and losers (0.028) is economically and statistically significant. Intuitively, we find that option traders tend on average to buy (sell) more put (call) options for the loser portfolios and buy (sell) call (put) options for the winners. We also show that our previous finding is mainly driven by orders placed by customers. Thus, options market makers are buying calls and writing puts, and will delta-hedge the resulting exposure to stock price changes by shorting the stock.[16] Similarly, Muravyev et al. (2019) show that when stocks are hard to borrow, the delta hedging by options market

[16] In the Robustness section we examine the behaviour of the daily option order imbalances around the rebalancing period separately for puts and calls. In line with our reasoning, investors tend to buy puts and sell calls on the loser stocks specially around the time in where the momentum strategy is rebalanced.

makers typically involves shorting stock. They show, using the same signed option data from ISE, that options market makers' positions in calls and puts vary substantially with utilization. This is in line with our results as we show before that losers stocks have high utilisation ratios.

We now study whether this effect is robust to controlling for other determinants of the momentum strategy using Fama and MacBeth (1973) regressions of option order imbalances on lagged cumulative stock returns and the set of lagged control variables used earlier. We estimate the following regression:

$$\mathrm{OOI}_{i,t+1} = \delta_{0,t} + \delta_{1,i}\mathrm{R(2,12)}_{i,t} + {\delta'}_{3,i}\mathbf{Z}_{i,t} + \varepsilon_{i,t+1} \tag{7}$$

where $\mathrm{OOI}_{i,t+1}$ denotes the time $t+1$ option order imbalances of options written on stock i, $\mathrm{R(2,12)}_{i,t}$ is the 12-month cumulative stock return (after skipping the most recent month) of stock i on month t. $\mathbf{Z}$ represents the set of control variables.

Table A6 reports the results of this estimation. We use aggregate trades of all participants in the market as well as customers trades. We report the point estimates of coefficients and HAC standard errors. We see that, using all aggregate trades, cumulative returns (e.g., R(2,12)) positively predict the cross-sectional variation of option order imbalances. This positive slope of the option order imbalances is robust to different determinants of the momentum strategy. This finding is in line with our earlier findings regarding the role of option trading in the momentum strategy. Next, we explore the source of this predictability by using order imbalances of customers. We find that the cumulative return also positively predicts option order imbalances of customers.

6.2 Stock Trading and Momentum Portfolios

As we show in the previous sections, options traders tend to buy (sell) put (call) options on the loser stocks while the option market maker covers positions by shorting the stock. As a result, such stocks, despite possible constraints to short sale in the stock market, have improved information flows and are likely to be less mispriced as options market makers short sell these stocks thereby conveying information to the stock market and reducing overpricing. We now investigate whether this reduced overpricing could be supported by trading activity based on stock order imbalances (e.g., Chordia and Subrahmanyam, 2004). If the loser stocks with options are less overpriced we should not expect significant negative trading activity over these stocks during the holding period compared to loser stocks without options.

To this end, we now use high frequency data on order flows from buyers and sellers for the period 1996-2018 to investigate the stock trading activity of losers and winner portfolios. Panel A of Table 10 shows time-series averages of median stock order imbalances for momentum portfolios of stocks with and without options. We find that both order imbalances based on trades (denoted as $\mathrm{SOI}^{\mathrm{NUM}}$) and total trade volume (denoted by $\mathrm{SOI}^{\mathrm{VOL}}$) indicate that investors tend to be net buyers of the winner portfolios and net sellers of loser portfolios.

Panel A shows that the order imbalances in the loser portfolios of stocks with options, are much less negative than the corresponding stock imbalances of loser stocks without options in a statistically significant manner (Panel C). This finding may indicate the willingness of investors to replicate the short leg of the momentum strategy in the options market, consistently with our previous findings. Our results, using stock order imbalance data, imply that investors tend to be net buyers of winner portfolios with options and net sellers of loser portfolios without options. It is likely that this could be due to short sale constraints being binding in the case of stocks without options which results in overpricing. The subsequent selling of such stocks is seen in the very negative stock order imbalances of loser stocks without options. However, this effect is not present in the loser portfolio of stocks with options because the options market has improved their information flows and the loser stocks with options are likely to be less mispriced because of the role of the options market. In untabulated results, we confirm that the predictability found in Table 8 for stocks without options in the case of high stock fees is accompanied by a large negative selling pressure of the loser stocks without options.

6.3 Option Expensiveness

Our results suggest that the options market plays a role in attenuating the returns to the momentum strategy by reducing the effect of constraints on short sales. These findings depend on the ability of the investors to buy (sell) puts (calls) for loser stocks with options and also short sales by the option market maker to cover her option positions by shorting the underlying stock. We should then expect that momentum becomes more profitable when it is more expensive or difficult to trade in the options market. This would restrict investors from using the options market when faced with barriers to short sale. Thus, the option market makers would not turn to the stock market to hedge away the underlying stock exposure thereby reducing the mispricing of the loser stocks with options.

In a frictionless market the implied volatilities of call and put options must be equal for given maturities. Intuitively, high call implied volatilities related to put implied volatilities suggest that calls are expensive relative to puts, and high put implied volatilities relative to call implied volatilities suggest the opposite. In line with Amin, Coval, and Seyhun (2004) and Cremers and Weinbaum (2010), we define the difference between call and put implied volatilities (e.g., price pressure) as the implied volatility spread. The implied volatility spread is estimated as the average difference in implied volatilities between call and put options pairs within each portfolio for a given strike price and maturity. In other words, a low implied volatility spread (e.g., Implied volatility of Calls$-$Implied Volatility of Puts< 0) indicates that put option prices exceed the price implied by call option prices or put-call parities.[17] This effect could be driven by limits to arbitrage or the behaviour of irrational investors that drive stock prices away from their fundamental values (e.g., Ofek, Richardson, and Whitelaw, 2004; Bali and Hovakimian, 2009). Given that the implied volatilities are estimated in a non-model-free setting, we cannot associate the volatility spreads with potential arbitrage opportunities. We rather associate positive or negative option volatility spreads with price pressure in the options market.

In fact, the volatility spread has been found to predict stock returns. This predictability is often interpreted as evidence that demand pressure in the options market due to informed trading alters options prices and implied volatilities but is only slowly reflected in stock prices; as a result, information in options prices predicts stock returns. In contrast, Muravyev et al. (2020) show that the implied volatility spread predict underying stock returns because they proxy for the expected cost of borrowing stock. Their hypothesis is that the costs of borrowing and short selling stock are reflected in options prices, and the option-implied stock borrowing fee can be computed from the prices of put-call pairs.

Table 11 reports results using double-sorts on R(2,12) and implied volatility spreads from 1996 to 2018. For each stock i and each month t, we define the volatility spread as the difference between the implied volatilites of calls and on the last trading day of month t. The results that we report use equal weights.[18] We find that momentum portfolios with options tend to be economically and statistically significant when the implied volatility spread is low (i.e. when the implied volatility of puts is higher than the implied volatility of call options) as put options become relatively more expensive. This is affecting the returns of the loser stocks which becomes negative and significant (-94 bps) compared to the case in where the puts are relatively cheaper (47 bps). It is also similar in the case of winner portfolios where their returns

[17]We offer a detailed description of the implied volatility spreads in the Internet Appendix.
[18]Results are similar if we weigh implied volatilities by open interest.

increase from 32 bps when puts are relatively more expensive to 112 bps when call options gets relatively more expensive. In other words, the momentum strategy for stocks with options tends to be profitable when it is more expensive to trade in the options market or when the option-implied stock borrowing fee is high as shown in Muravyev et al. (2020).

6.4 Early Exercises of Options

Our previous analysis shows that loser stocks exhibit higher short-selling constraints and there is higher demand for the attached options. Thus, we conjecture that options written on loser portfolios are more likely to be exercised earlier. This is in line with Jensen and Pedersen (2016) who find that early exercises of options might be rational as they are more pronounced for stocks with higher short-sales costs and larger option transactions costs.

We calculate the fraction of options that are exercised before expiration. Our dataset contains actual exercise patterns based on a data that is originally from Options Clearing Corporation (OCC).[19] The data include the number of contracts that are exercised per option on a daily basis. There are three main categories of market participants comprising customers of brokers, market makers, and firm proprietary traders. Our sample starts from July 2001 until June 2014.[20]

Following Jensen and Pedersen (2016), we define the options that are exercised earlier (EX) as the ratio of open interest on the close of the day before.

$$EX_t^i = \frac{\#\text{exercised options}_t^i}{\max\{OI_{t-1}^i, \#\text{exercised options}_t^i\}} \tag{8}$$

where EX takes values between zero and one by construction as we obtain the maximum

[19] We thank Robert E. Whaley for making the data available. Barraclough and Whaley (2012) provide a detailed description of the data.

[20] The data are missing for the months of November 2001, January and July 2002, and January 2006.

value in the denominator. We focus on options written on stocks that do not pay dividends. We also eliminate observations of option that expire at maturity. We merge these data with OptionMetrics.

Figure 5 shows the percentage of early exercises of options attached to loser (top graph) and winner (bottom graph) portfolios. The figure reports an event study around the rebalancing period of the percentage of early exercises for Firms, Market Markers and Customers. Indeed, we find that in Figure 5 there is a higher percentage of early exercises for loser than winner portfolios in a statistically significant manner. In particular, Table A7 of the Internet Appendix shows early exercises of momentum portfolios for Firms, Market Makers and Customers. In line with our conjecture, we find that overall options attached to loser portfolios show higher levels of early exercises and this is driven by option market makers.

7 Other Anomalies

In this section, examine the importance of option availability for the profitability of other anomalies. To this end, we consider portfolios of stocks with and without options based on 94 characteristics that are detailed in Green et al. (2017). We build a strategy that incorporates the information of all the aforementioned characteristics and evaluate the performance of this strategy for the match stocks with and without options.

Net Portfolios. We consider in Table 12 a net portfolio in the spirit of Engelberg, McLean, and Pontiff (2018) after we match the universe of stocks with and without options based on trading volume, industry and size. Specifically, we allocate stocks into portfolios every month based on different characteristics and we compute the total number of times that the stock appears in the long and short portfolios. Recall that we form the long and short portfolios by placing stocks into deciles based on monthly ranking of each anomaly variable and we count the number of times that stocks are present in the two extreme portfolios. Each stock belongs to the long and short portfolio based on the alphas of the Fama and French (1993) model in Figure 3.

Then, we compute the net measure which is defined as the number of long-side and short-side anomaly portfolios that the observations belong to for each stock-month observation (Net=Long-Short).[21]. Thus, the lowest portfolio comprises of the most overvalued firms and the highest portfolios correspond to the most undervalued firms. In fact, in the case of the the lowest net portfolio the average stock is in -19 portfolios and the highest net is in 9 portfolios.

Panel A of Table 12 shows average returns of decile portfolios sorted based on the Net variable. Consistently with our previous findings, we show that a portfolio that buys the most undervalued stocks and sells the more overvalued stocks tend to offer very positive and highly significant returns for stocks without options even after accounting for CAPM, FF3 and FF5 factors. On the other hard, we observe a reduction in the profitability of stocks with options in terms of economic and statistical significance as these stocks tend to be less mispriced due to the presence of equity options. In particular, we find that stock without options have twice as much higher returns and alphas in comparison to stocks with options. Panel B shows that this finding is driven by the short leg of the strategy.

We also calculate the portfolio turnover of the NET portfolios so as to examine the contribution of each firm-level characteristic to the NET portfolio. Figure 6 shows the frequency of characteristics in low and high Net portfolios. Almost all the characteristics contribute significantly to the long and short positions of the strategy. In particular, nincr which is defined as the number of earnings increases, nanalayst which is the number of analyst covering the stock, age which is the number of years in compustat coverage and herf which is based on industry sales concentration contributes the most to the short position of the Net strategy. In

[21]We eliminate the characteristics that are dummy variables from our analysis because there is only one long or short side.

contrast, the dividend to price (dy) and the two financial statement scores (ds and ms) matters more for the long leng of the net portfolio.

8 Tests for Robustness

We now describe the results of alternate tests that confirm and support our main results. In some of these tests we use data for longer periods than our main sample period.

8.1 Option Introductions

In this section, we evaluate the performance of momentum portfolios using stocks with option introductions. Similar to Mayhew and Mihov (2004), we identify equity options chosen for listing on all domestic exchanges from 1977 to 1996.[22] The CBOE provides information about listing and delisting dates on all domestic markets for this period. Combining the listing and delisting information, we construct, at each point in time, a new sample with the set of all stocks with options trading from 1977.

Panel A of Table 13 shows average returns of momentum portfolios based on an option introduction. We have focus on matched firms based on size, trading volume and industry. We report average returns and the corresponding alphas of stocks with or without options for the period of June 1977 to December 2018. The novelty of our approach is that we consider an optionable stock for the earlier period based on its option listing date. If an option is delisted, we consider the corresponding stock as non optionable after the period of delisting and until a new option is again introduced on that particular stock. In addition, this exercise serves as an out- of-sample test of our analysis as we expand the data period of optionable stocks to the first years in where options where introduced for the first time and they were less accessible

[22] Our data start from 1973 but we report results from 1977 due to limited data availability on options before that date.

to retail investors. Interestingly, we find that momentum is significant for stocks with and without options for the whole period but there is a deterioration of the momentum profits of optionable stocks as the growth of options increases overtime.

In addition, Panel B of Table 13 shows that only the differences between optionable and nonoptionable losers is statistically significant. In particular, we find that the return of the optionable loser portfolios is less negative than the corresponding return of the loser portfolio of stocks without options. This pattern has a strong effect on the performance of the momentum strategy as the appreciation of optionable losers lead to a momentum portfolio which generates almost half of the return that we observe in the momentum portfolios of nonoptionable stocks.

8.2 Propensity Score Matching

We also follow a parametric approach in order to match the control with the treatment group. Specifically, we apply propensity score matching and estimate a logit regression model where the dependent variable is the log-odds ratio that a stock will be eligible for option listing and the independent variables capture different criteria that a firm should satisfy in order to have a available option (e.g., Mayhew and Mihov, 2004). In particular, we consider as independent variables the average daily trading volume over the 250 trading days prior to the 15th of the month, the annualized standard deviation of log returns over the same period, the ratio of the 30-day to 250-day average trading volume and the same ratio for volatility and the market capitalization of the firm. We finally match stocks with and without options by using the Greedy matching method with a caliper width of 0.10.[23] Similar to our previous results, our objective is to compare optioned stocks with those eligible for option listing but not yet selected.

Panel A of Table 14 displays average excess returns for each momentum decile portfolio

[23]Our results are similar if we use a different caliper width or if we consider other matching methods like the nearest neighbor or the optimal matching.

for stocks with and without options that are matched based on the propensity score matching procedure. We find that our results are similar with those obtained from the non parametric matching indicating that our findings are robust to the method being used and the controls employed in order to matched the universe of stocks with and without options. Panel B shows that are our findings are driven by the short leg of the strategy.

8.3 Momentum Crashes

Here we examine whether momentum crashes could partly explain our results. To this end, we eliminate the months with momentum crashes from our sample before allocating stocks with and without options into portfolios based on their 12-month cumulative returns after skipping the most recent month. Following Daniel and Moskowitz (2016), we eliminate January 2001, October 2001, November 2001, November 2002, March 2009, April 2009 and August 2009.

Panel A of Table 9 shows average excess returns for decile momentum portfolios of stocks with and without options. Despite the significant average excess returns of the momentum strategy for stocks with options –which was anticipated as we eliminated the worst performing months of the momentum strategy– arguably the higher levels of mispricing for stocks without options is depicted in the magnitude of the average returns and corresponding alphas of the momentum portfolios of nonoptionable stocks that are more than twice as much the average returns of the optionable momentum strategy. In Panel B, we find that this finding is still driven by the short leg of the strategy.

8.4 Informativeness of Stocks with Options

Here, we construct an alternative measure of price informativeness. Specifically, Bai et al. (2016) propose a measure of price informativeness of stocks that captures future cash flow movements. This measure captures the rate at which public market information is incorporated into a stock price. Bai et al. (2016) find that relative to firms without options, those with options have higher price informativeness that also increases with option turnover. They suggest that options markets facilitate the incorporation of information that leads to improvements in pricing efficiency by providing traders with the ability to hedge, leverage and a low-cost way to sell short. In our data, we find that the momentum strategy is less profitable for stocks with options due to loser portfolios having higher returns. This is partly driven by the lower short-selling constraints of loser portfolios with options relative to the loser stocks without traded options. It implies that investors may have more information about future movements of the underlying asset due to option trading as also reported by Figlewski and Webb (1993). If information is incorporated quickly into the prices of stocks with options as a result of the reduction of short sale constraints, we should expect an increase of the price informativeness measure for loser stock with options relatively to loser stocks without options.

We test this hypothesis by using the price informativeness measure (PI) of Bai et al. (2016) and extending its use to study the differences between the loser and winner portfolios for stocks with and without options. We do this by estimating the following cross-sectional regression:

$$E_{i,t+1}/A_{i,t} = \alpha_t + b_t \log(M_{i,t}/A_{i,t}) + c_t(E_{i,t}/A_{i,t}) + d_t^s \mathbb{1}_{i,t}^s + \varepsilon_{i,t} \tag{9}$$

where M denotes the market capitalization of stock i, A denotes its total assets, E represents the earnings before interest and taxes (EBIT), and $\mathbb{1}^s$ is an indicator variable of the sector (s) based on one-digit SIC codes.[24]

We run cross-sectional regressions considering the constituents of loser and winner portfolios for each month of our data period with a horizon of one month.[25] We define price informativeness (PI) as the product of the cross-sectional beta of market capitalization to asset

[24]The data is based on the quarterly file from COMPUSTAT. Our results are similar for annual data.

[25]We focus on monthly regressions in order to link our results with the holding period of the momentum strategy while Bai et al. (2016) use an annual horizon in their study.

ratio (e.g., b_t) with the cross-sectional standard deviation of $\log M_t/A_t$ within each portfolio in month t:

$$PI_t = b_t \times \sigma_t(\log(M_t/A_t)) \tag{10}$$

Panel A of Table A8 shows the estimates of the price informativeness measure for loser, winner and the spread (WML) portfolios for stocks with and without options along with the associated t-statistics. We find that there is no significant difference between loser and winner portfolios for stocks with options. In contrast, we find that the winner portfolio of stocks without options has a higher informativeness measure (0.000) relative to the corresponding loser portfolio (-0.024).

Panel B reports differences in price informativeness between loser (winner) portfolios of stocks with and without options. We find that price informativeness is much higher for loser stocks with options than for loser stocks without options. This suggests that the presence of option trading enhances information flows for loser stocks with options relative to loser stocks without options. Specifically, we find that the difference between the informativeness of loser portfolios of the two groups is -0.014 and this is statistically significant. However, the difference between winner portfolios of stocks with and without option is 0.003 and not statistically significant.

8.5 Time-variation of Stock and Option Order Imbalances

Here, we examine the performance of stock and option order imbalances around the rebalancing period in an attempt to observe whether the behaviour of order imbalances of loser and winner portfolios can be attributed to specific time periods around the rebalancing date (the last trading day of the month where we rebalance our momentum portfolios). Figure 7 displays stock imbalances of loser (left panel) and winner (right panel) portfolios of stocks with (dashed black line) and without options (red line) at each point of time. Figure 8 shows option imbalances of loser (top panel) and winner (bottom panel) portfolios at each point of time.

Stock Order Imbalances. In particular, Figure 7 demonstrates stock order imbalances of the portfolios for a 20-day window around the rebalancing date (date 0) for the period of January 1996 to December 2018. The top figures show results for our first measure of stock order imbalances ($\mathrm{SOI}^{\mathrm{NUM}}$), which computes net trading based on the number of trades and the bottom figures display order imbalances that are based on our second measure ($\mathrm{SOI}^{\mathrm{VOL}}$), which computes stock order imbalances based on the total volume of shares traded. We find that investors tend to be on average net buyers (sellers) of winner (loser) portfolios. This pattern is more pronounced for the group of stocks without options and can partly explain the profitability of the momentum strategy for stocks without options because there is more negative price pressure on the constituents of the loser portfolios that makes their returns more negative and the momentum returns positive and statistically significant. Interestingly, the stock imbalances of winner portfolios are close to zero, on average, indicating the importance of the trading in the loser portfolio for the momentum strategy.

Option Order Imbalances. We also find that investors tend to be net sellers of options written on loser portfolios (top panel of Figure 8) as shorting is less expensive in the options market. Interestingly, a large amount of the selling pressure for losers occur around the rebalancing period. This mainly results from investors selling calls starting more than 10 days before the rebalancing date and buying puts from five days before the last day of the month. There is also selling pressure around the 15th of the month in where options expire. On the other hand, we find that investors tend to be net buyers of options of stocks that belong in winner portfolios.

9 Conclusions

Cross-sectional momentum is arguably one of the most well-known stock market anomalies. An investor who buys stocks that have performed well over the past 12 months ("winners") and shorts stocks that have performed poorly ("losers") earns a high and significant return over the next one to six months. While some trading strategies are less profitable once they have been discovered, momentum has remained surprisingly lucrative ever since first documented by Jegadeesh and Titman (1993). Momentum is also pervasive - it is present not only for stocks, but also bonds, commodities, exchange rates and other asset classes.

However, returns to cross-sectional momentum have attenuated during the last two decades 1996-2018 relative to the prior decades. Several studies have explored the economic forces that might be behind the fall in profitability of what is a violation of weak-form market efficiency. Clearly, it is possible that the market has become more efficient and that lower mispricing has reduced trading profits. This change is attributed to increased flows of arbitrage capital, greater liquidity and lower transactions costs in the stock market and increased investor awareness about anomalies like momentum.

This period also coincides with a significant growth in the number of stocks with options from about 27% of all stocks traded in 1996 to 72% in 2018. We find that the presence of the stock options market enhances information flows about stocks and reduce short sale constraints. Both of these factors contribute to the decline in momentum profits which mainly arise from the reduced profits in the loser or short leg of stocks with options. This is particularly relevant for anomalies like momentum in where the short leg plays a key role in its profitability.

Our results show that a combination of a variety of economic forces that improve information flows about variations from fundamental value especially the reduction in short sale constraints can result in a reduction of profits from anomalies. While this seems to hold for momentum and other short-leg dependent anomalies over the period we study, if conditions in the market change it is not possible to dismiss that their profits may rise again in the U.S. stock market. This may be the case of the recent change in the option market maker exception from borrowing shares when short selling. Indeed this is seen in the revival (e.g., Gandhi and Lustig, 2015) of the size anomaly.

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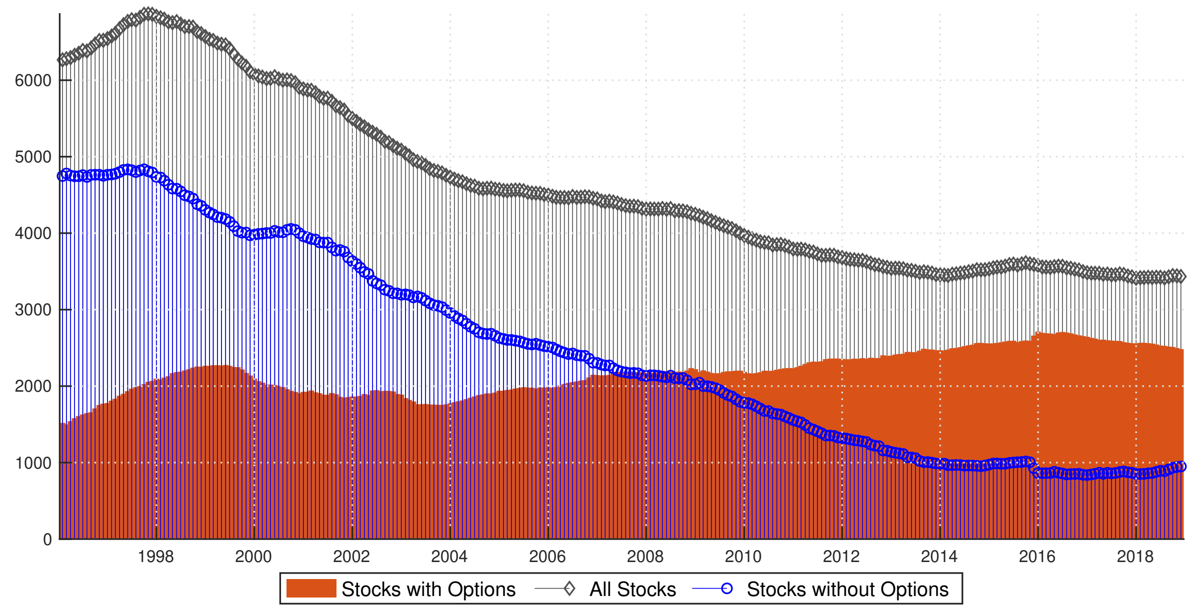
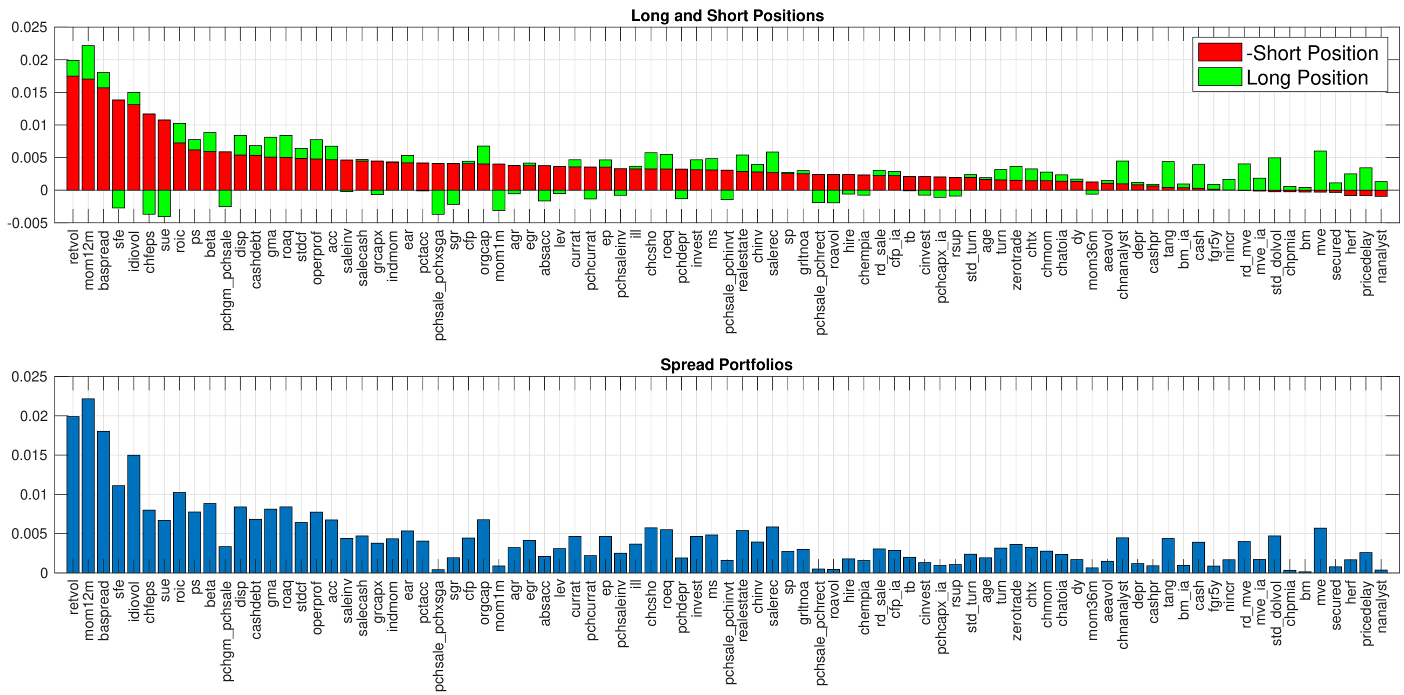
Figure 2. ***Stocks with and without Options***



This figure displays the total number of stocks in our sample and the number of stocks *with* and *without* options based on option availability in Optionmetrics. The data, are monthly series from January 1996 to December 2018, obtained from a merged CRSP and OptionMetrics dataset.

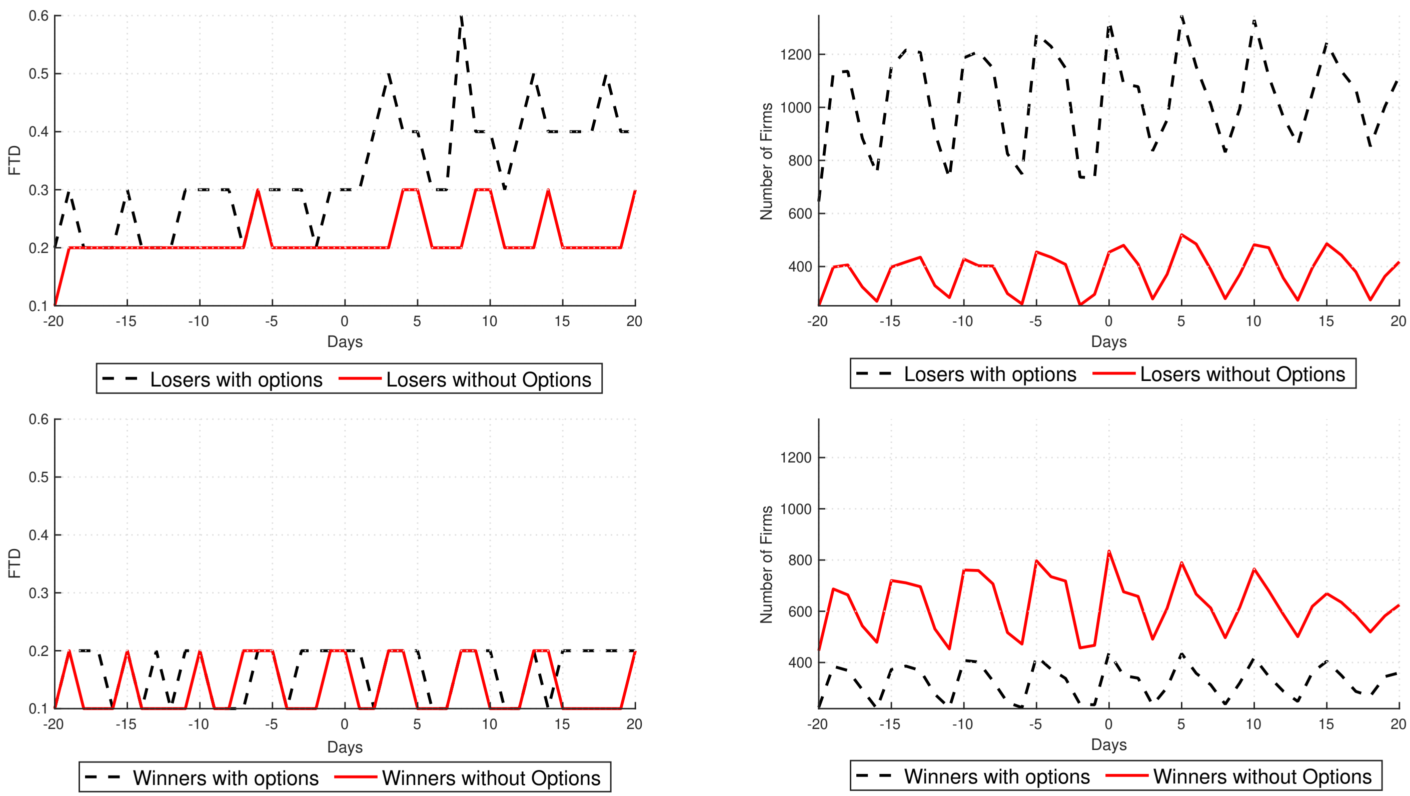
54

Figure 3. Alphas of Anomaly Portfolios



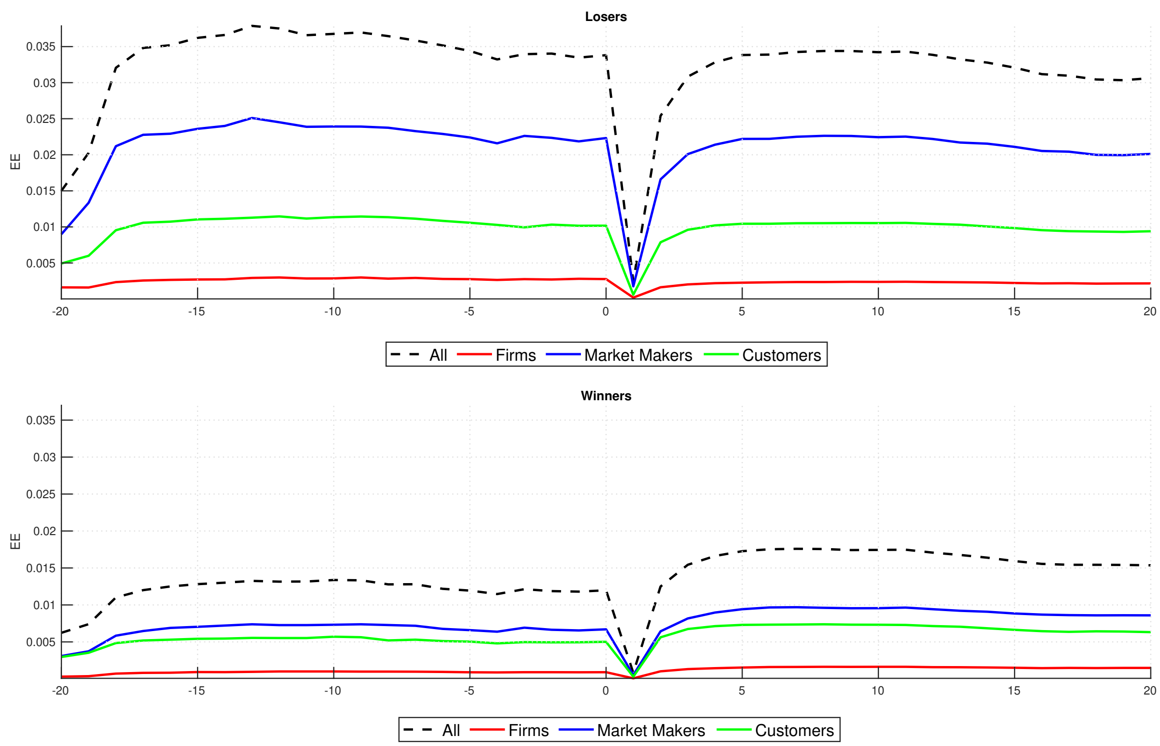
The figure displays alphas of the Fama and French (1993) 3-factor model (FF3) for long and short positions of 87 anomaly portfolios and the corresponding spread portfolios (bottom graph). The ordering of the anomalies is based on the magnitude of the short leg position. The data is monthly from January 1980 - December 2018.

Figure 4. Fails-to-Deliver within Loser and Winners



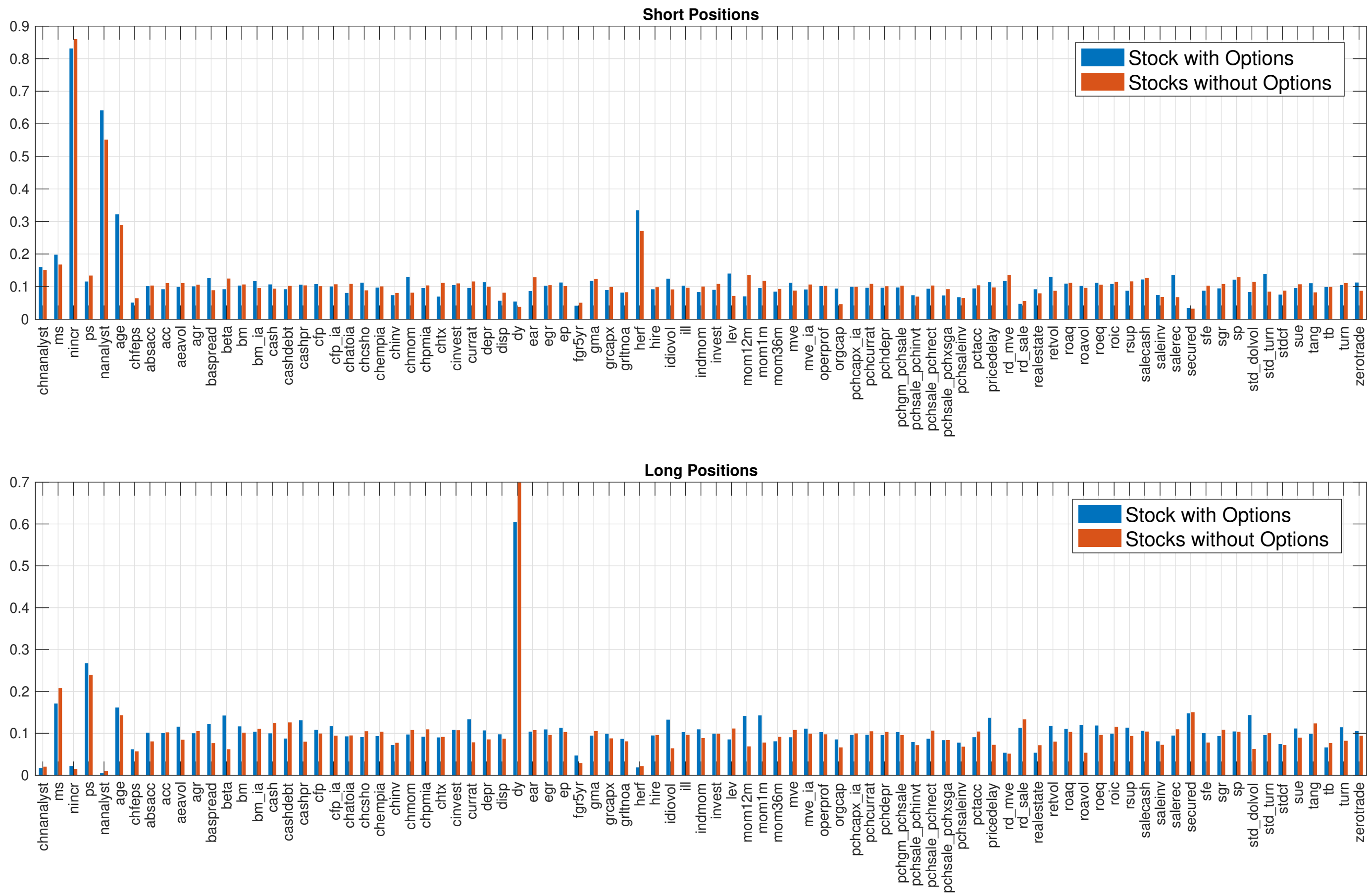
The figure displays daily average fails-to-deliver (FTD) for loser stocks with and without options around the rebalancing period (last trading day of each month). The right graphs show the number of firms. The data is collected from the SEC, Optionmetrics and CRSP and contains monthly series from March 2004 to December 2018.

Figure 5. Early Exercise of Options within Loser and Winners



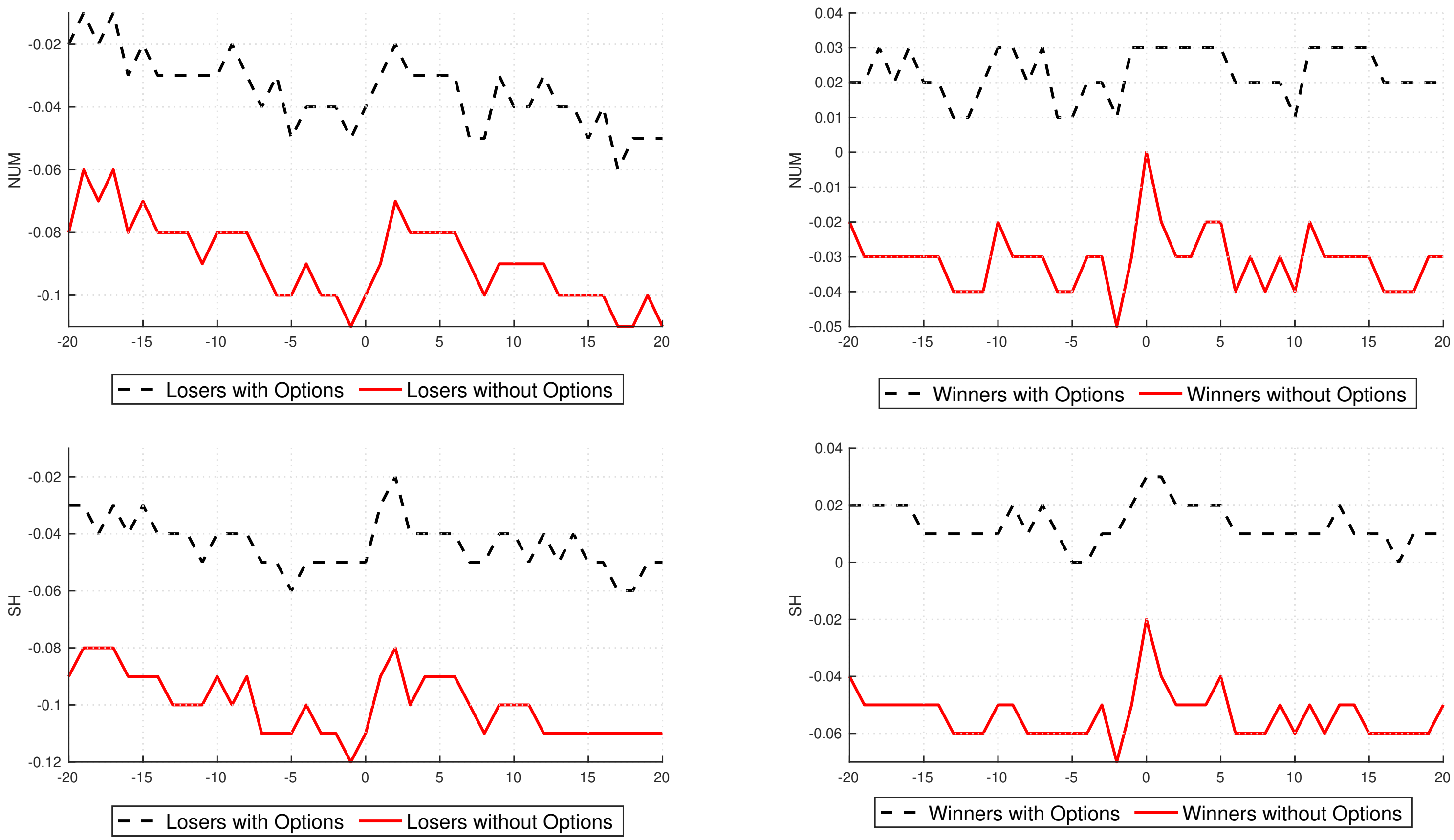
The figure displays daily median percentage of early exercises of options for loser and winner stocks around the rebalancing period. The data is collected from the Options Clearing Corporation (OCC), Optionmetrics and CRSP and contains monthly from July 2001 until June 2014.

Figure 6. Turnover of the NET Portfolio



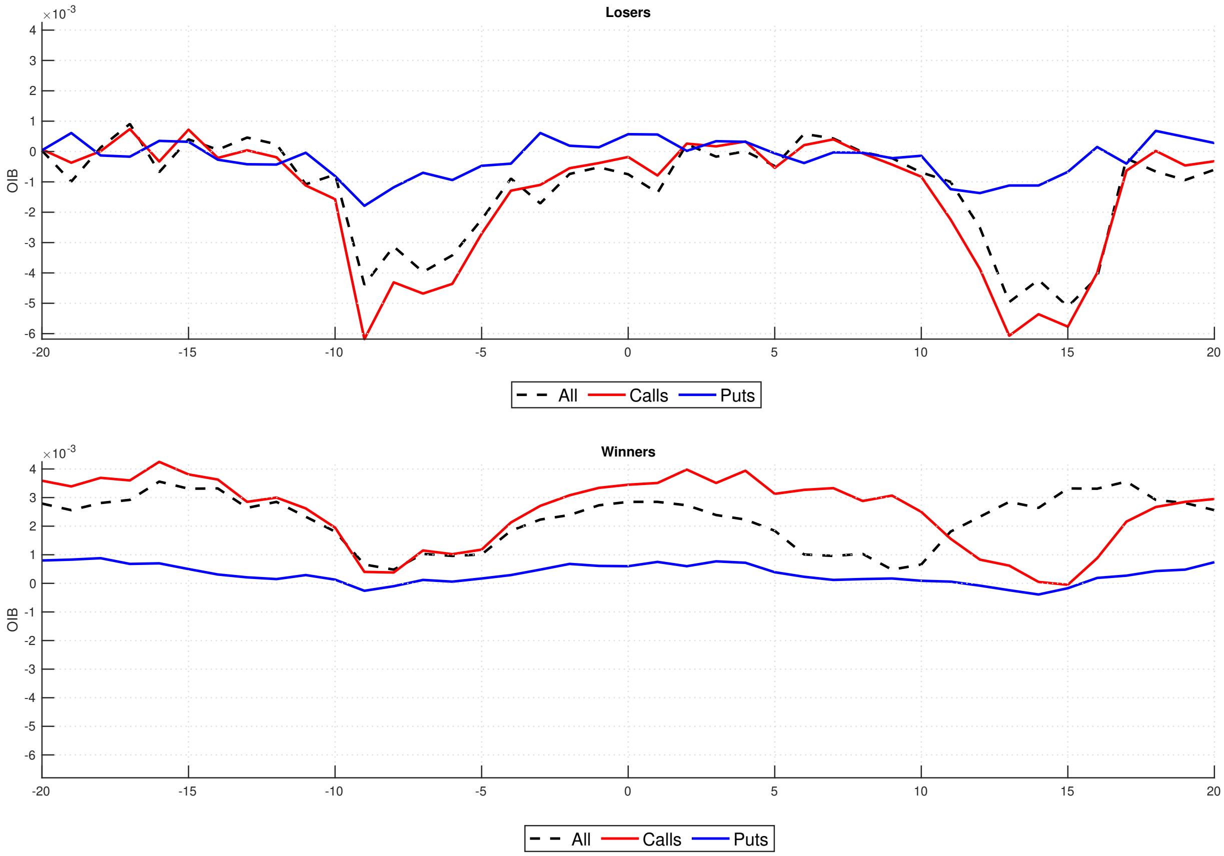
The figure displays the frequency of stock characteristics (in percentage) that are included in low and high net portfolios with and without options. The data is monthly from January 1996 until December 2018.

Figure 7. Stock Order Imbalances



The figure displays stock order imbalances of loser and winner portfolios. We considers stocks of all stocks as well as stocks with and without options. The figures are centered around the rebalancing date. The data are collected from from the WRDS Intrady Indicator Database (IID), CRSP and OptionMetrics and contain monthly series from January 1996 to December 2018.

Figure 8. Option Order Imbalances



The figure displays options order imbalances of open positions of loser and winner portfolios for all options and separately for call and put options. The option order imbalances are expressed in basis points. The figures are centered around the rebalancing date. The data are collected from the International Security Exchange (ISE) Open/Close Trade Profile database, CRSP and OptionMetrics and contain monthly series from January 2006 to December 2016.

Table 1. Momentum Returns and Option Availability: All firms

Decile portfolios are formed every month from January 1996 to December 2018 for all stocks as well as for stocks with and without options by sorting stocks based on the previous period 12-month cumulative returns (R(2,12)) after skipping the most recent month. Decile 10 indicates the winner portfolio, Decile 1 denotes the loser portfolios and WML indicates the winner-minus-loser portfolio. Panel A reports the value weighted average excess monthly returns for each decile portfolio as well as the corresponding alphas of the CAPM, the three-factor Fama and French (1993) model (FF3) and the five-factor Fama and French (2015) model (FF5) based on option availability In Optionmetrics during the last trading day of each month. The last two rows present the differences in monthly returns and the differences in alphas between winners and losers portfolios with associated HAC adjusted t-statistics (t-stat). Panel B shows differences between loser (winner) portfolios of stocks with and without options based on option listing. T All returns are in percentages.

Panel A: Stock returns

	All Stocks				Stocks with Options				Stocks without Options			
Decile	Avg Ret	CAPM Alpha	FF3 Alpha	FF5 Alpha	Avg Ret	CAPM Alpha	FF3 Alpha	FF5 Alpha	Avg Ret	CAPM Alpha	FF3 Alpha	FF5 Alpha
Losers	-0.226	-1.405	-1.451	-0.722	-0.105	-1.306	-1.349	-0.603	-1.153	-2.213	-2.303	-1.679
2	0.221	-0.700	-0.767	-0.467	0.216	-0.718	-0.780	-0.475	0.418	-0.360	-0.495	-0.303
3	0.266	-0.484	-0.552	-0.436	0.243	-0.514	-0.578	-0.461	0.515	-0.180	-0.336	-0.307
4	0.567	-0.063	-0.126	-0.118	0.560	-0.077	-0.136	-0.132	0.905	0.351	0.209	0.253
5	0.620	0.019	-0.025	-0.093	0.630	0.020	-0.022	-0.094	0.626	0.170	0.057	0.010
6	0.501	-0.016	-0.067	-0.133	0.491	-0.035	-0.081	-0.149	0.759	0.336	0.209	0.193
7	0.650	0.176	0.134	-0.024	0.641	0.161	0.124	-0.036	0.763	0.337	0.243	0.174
8	0.692	0.178	0.158	0.009	0.673	0.152	0.136	-0.016	0.998	0.549	0.453	0.375
9	0.578	0.036	0.050	-0.057	0.542	-0.001	0.018	-0.079	1.013	0.504	0.426	0.244
Winners	1.142	0.423	0.484	0.606	1.128	0.402	0.468	0.605	1.099	0.447	0.436	0.466
WML	1.367	1.828	1.934	1.328	1.233	1.708	1.817	1.208	2.252	2.661	2.739	2.145
t-stat	1.99	3.19	3.32	1.85	1.78	2.91	3.03	1.64	3.41	4.90	5.25	3.32

Panel B: Differences between optionable and non optionable Loser and Winner stocks

	ΔLosers	ΔWinners
Avg Ret	-1.048	-0.029
t-stat	-2.50	-0.10
CAPM Alpha	-0.907	0.045
t-stat	-1.99	0.17
FF3 Alpha	-0.955	-0.032
t-stat	-2.30	-0.13
FF5 Alpha	-1.076	-0.139
t-stat	-2.22	-0.63

Table 2. Summary Statistics: Stocks with and without Options

This table present time-series averages of median characteristics for all stocks and for matched firms with and without options. Panel A reports results for the whole universe of firms and Panel B shows results for stocks with and without options that are matched based on trading volume, industry and size. The data are monthly from January 1996 to December 2018. The table presents the following time series median average characteristics for the stocks: trading volume (in millions), size (in millions), price and volatility. The last two columns present the differences in characteristics between stocks with and without options with their associated HAC adjusted t-statistics (t-stat).

Panel A: All firms

	Stocks with Options	Stocks without Options	Difference	t-statistic
Number of Firms	2,187	2,460		
Size	1.187	0.074	-1.113	-31.97
Volume	0.463	0.023	-0.440	-20.03
Volatility	0.025	0.030	0.057	12.78
Price	23.482	8.464	-15.018	-42.07

Panel B: Matched firms based on Trading Volume and Size

	Stocks with Options	Stocks without Options	Difference	t-statistic
Number of Firms	461	461		
Size	0.243	0.274	0.031	17.79
Volume	0.115	0.125	0.010	18.89
Volatility	0.029	0.030	0.001	2.88
Price	10.638	13.118	2.480	11.02

Table 3. Momentum Returns and Option Availability: Matching based on Trading Volume, Industry and Size

Decile portfolios are formed every month from January 1996 to December 2018 for stocks with and without options based on option availability in Optionmetrics during the last trading day of each month, and matched based on trading volume, industry and market capitalization by sorting the whole sample of matched stocks based on the previous period 12-month cumulative returns (R(2,12)) after skipping the most recent month. Decile 10 indicates the winner portfolio, Decile 1 denotes the loser portfolios and WML indicates the winner-minus-loser portfolio. Panel A reports the value weighted average excess monthly returns as well as the corresponding alphas of the CAPM, the three-factor Fama and French (1993) model (FF3) and the five-factor Fama and French (2015) model (FF5). Panel B shows differences between loser (winner) portfolios of stocks with and without options. The last two rows present the differences in monthly returns and the differences in alphas between winners and losers portfolios with associated HAC adjusted t-statistics (t-stat). All returns are in percentages.

Panel A: Matched firms based on Trading Volume, Industry and Size

	Stocks with Options				Stocks without Options			
Decile	Avg Ret	CAPM Alpha	FF3 Alpha	FF5 Alpha	Avg Ret	CAPM Alpha	FF3 Alpha	FF5 Alpha
Losers	0.161	-0.979	-1.101	-0.445	-2.211	-3.341	-3.421	-2.999
2	0.102	-0.832	-0.977	-0.530	0.562	-0.412	-0.597	-0.274
3	0.277	-0.514	-0.647	-0.535	0.774	-0.024	-0.199	-0.195
4	0.985	0.326	0.205	0.099	0.591	-0.101	-0.268	-0.342
5	0.882	0.226	0.085	-0.030	0.855	0.267	0.134	0.138
6	1.142	0.594	0.499	0.365	0.753	0.263	0.145	0.106
7	1.055	0.464	0.349	0.350	0.819	0.372	0.285	0.251
8	1.042	0.454	0.365	0.286	1.219	0.687	0.594	0.465
9	0.743	0.078	0.026	0.111	1.053	0.503	0.460	0.295
Winners	0.746	-0.012	-0.003	0.107	1.273	0.541	0.573	0.673
WML	0.585	0.967	1.098	0.552	3.484	3.882	3.995	3.672
t-stat	0.82	1.58	1.81	0.80	5.20	6.32	7.06	5.08

Panel B: Differences between optionable and non optionable Loser and Winner stocks

	ΔLosers	ΔWinners
Avg Ret	-2.372	0.527
t-stat	-3.82	1.19
CAPM Alpha	-2.362	0.553
t-stat	-3.99	1.29
FF3 Alpha	-2.320	0.576
t-stat	-4.01	1.38
FF5 Alpha	-2.554	0.566
t-stat	-3.87	1.20

Table 4. Cross-Sectional Regressions

This table presents results from Fama-MacBeth regressions of matched firm's returns on past performance, measured based on the previous 12-month cumulative returns (R(2,12)) skipping the most recent month. We also use several control variables; log size (Ln(Size)), log stock price (Ln(Price)), institutional ownership (IOR), book-to-market (B/M), idiosyncratic volatility (IVOL), reversals (R(1)) and illiquidity (ILLIQ) used in prior research. The table reports the time-series averages of the cross-sectional regression coefficients, their HAC adjusted t-statistics, and the R-squared. The main model takes the following form:

$$\text{Ret}_{i,t+1} = \delta_{0,t} + \delta_{1,i}\text{R(2,12)}_{i,t} + \delta'_{2,i}\mathbf{Z}_{i,t} + \varepsilon_{i,t+1}$$

where $\text{Ret}_{i,t+1}$ denotes the time $t+1$ stock return of firm i, $\text{R(2,12)}_{i,t}$ is the 12-month cumulative stock return (after skipping the most recent month) of stock i on month t. **Z** represents the set of control variables.

Stock Returns				
	Stocks with Options		*Stocks without Options*	
	(1)	(2)	(3)	(4)
Intercept	0.004	0.014	0.006	0.057
t-stats	1.04	1.06	1.47	4.32
$\text{CumRet}_{i,t}$	0.001	0.003	0.006	0.006
t-stats	0.22	0.89	2.31	3.06
Control Variables				
$\text{Ln(Size)}_{i,t}$		0.001		-0.002
t-stats		1.23		-2.51
$\text{Ln(Price)}_{i,t}$		-0.007		-0.005
t-stats		-3.16		-2.93
$\text{ILLIQ}_{i,t}$		0.010		0.002
t-stats		0.89		0.17
$\text{R(1)}_{i,t}$		-0.030		0.002
t-stats		-4.37		0.32
$\text{B/M}_{i,t}$		0.003		0.001
t-stats		2.22		0.73
$\text{IOR}_{i,t}$		0.001		0.005
t-stats		0.2		1.49
$\text{IVOL}_{i,t}$		-0.247		-0.331
t-stats		-2.71		-4.62
Adj-R^2	1.63%	9.00%	1.46%	9.91%

Table 5. Momentum Portfolios and Price Delay

Decile portfolios are formed every month from January 1996 to December 2018 by sorting matched stocks with and without options based on the previous 12-month cumulative returns (R(2,12)) after skipping the most recent month. Decile 10 indicates the winner portfolio, Decile 1 denotes the loser portfolios and WML indicates the Winner-minus-Loser portfolio. Stocks with and without options are matched based on size. This table presents results, for the momentum portfolios, of the time series average of the median price delay ($D1$) following Hou and Moskowitz (2005). In particular, at the end of each month, and for each momentum portfolio we run a regression of each stock's i weekly returns on contemporaneous and four-week lagged returns on the market portfolio over the prior year. The model takes the form below:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \sum_{n=1}^{4} \delta_i^{(-n)} R_{m,t-n} + \varepsilon_{i,t},$$

where $R_{i,t}$ represents the return on stock i and $R_{m,t}$ denotes the CRSP value-weighted market index in week t. At the end of each month, we compute a measure of price delay using the aforementioned coefficients. The measure resembles an F-test as it is one minus the ratio of the R^2 from a restricted version of model 5 where all $\delta_i^{(-n)}$s are set to zero over the R^2 of the full specification (i.e. unrestricted) model:

$$D1 = 1 - \frac{R^2_{\delta_i^{(-n)}=0, \forall n \in [1,4]}}{R^2}.$$

Panel A shows time-series averages of median price delay for each of the momentum portfolios for stocks with and without options. Panel B shows the price delay difference between loser (winner) portfolios of stocks with and without options.

Panel A: Matched firms based on Trading Volume, Industry and Size

Decile	Stocks with Options	Stocks without Options
Losers	0.130	0.212
2	0.094	0.146
3	0.077	0.117
4	0.065	0.092
5	0.054	0.076
6	0.054	0.069
7	0.050	0.066
8	0.052	0.076
9	0.059	0.080
Winners	0.103	0.122
WML	-0.027	-0.090
t-stat	-1.99	-6.75

Panel B: Differences in Price Delay of Stocks with and without Options

	ΔLosers	ΔWinners
Price Delay	0.082	0.019
t-stat	8.85	1.63

Table 6. Demand and Supply of Shorting for Momentum Portfolios

Decile portfolios are formed every month from January 2007 to December 2018 by sorting all stocks and stocks with and without options based on the previous period 12-month cumulative returns (R(2,12)) after skipping the most recent month. Decile 10 indicates the winner portfolio, Decile 1 denotes the loser portfolios and WML indicates the winner-minus-loser portfolio. This table presents time-series averages of median supply, demand and utilization. Panel A presents time-series average of median demand,supply and utilization for momentum portfolios. The last two rows present the differences in supply, demand and utilization between winners and losers portfolios with associated HAC adjusted t-statistics (t-stat). Panel B shows differences in supply, demand and utilization for loser and winner portfolios of the two groups of stocks.

Panel A: Matched firms based on Trading Volume, Industry and Size

	Stocks with Options			*Stocks without Options*		
	Demand	Supply	Utilisation	Demand	Supply	Utilisation
Losers	0.037	0.094	0.482	0.022	0.067	0.441
2	0.027	0.126	0.235	0.019	0.091	0.261
3	0.026	0.156	0.162	0.019	0.114	0.184
4	0.024	0.182	0.125	0.018	0.129	0.147
5	0.023	0.194	0.116	0.018	0.146	0.119
6	0.023	0.204	0.109	0.018	0.156	0.111
7	0.022	0.206	0.105	0.018	0.160	0.103
8	0.022	0.200	0.109	0.017	0.148	0.105
9	0.022	0.187	0.113	0.016	0.136	0.106
Winners	0.023	0.147	0.152	0.014	0.105	0.141
WML	-0.014	0.053	-0.329	-0.008	0.038	-0.299
t-stat	-7.14	8.30	-10.05	-5.67	8.58	-6.53

Panel B: Differences in Demand and Supply of Stocks with and without Options

	ΔLosers	ΔWinners
Demand	-0.015	-0.009
t-stat	-10.44	-6.49
Supply	-0.027	-0.042
t-stat	-10.19	-9.19
Utilisation	-0.041	-0.011
t-stat	-1.04	-0.90

Table 7. Shorting Fees of Momentum Portfolios

Decile portfolios are formed every month from January 2007 to December 2018 by sorting size and price matched stocks with and without options based on the previous period 12-month cumulative returns (R(2,12)) after skipping the most recent month. Decile 10 indicates the winner portfolio, Decile 1 denotes the loser portfolios and WML indicates the winner-minus-loser portfolio. Lending fees are the interpolated lending fees and they are expressed in basis points. Panel A presents time-series average of median shorting fees for momentum portfolios. The last two rows present the differences in shorting fees between winners and losers portfolios with associated HAC adjusted t-statistics (t-stat). Panel B shows differences in fees for loser and winner portfolios of the two groups of stocks.

Panel A: Matched firms based on Trading Volume, Industry and Size

Decile	Stocks with Options	Stocks without Options
Losers (in bps)	242.793	435.181
2 (in bps)	78.297	165.955
3 (in bps)	46.986	74.553
4 (in bps)	34.665	49.771
5 (in bps)	30.675	39.212
6 (in bps)	29.711	33.712
7 (in bps)	29.008	31.683
8 (in bps)	29.503	35.071
9 (in bps)	30.180	37.565
Winners (in bps)	42.657	65.610
WML	-200.136	-369.571
t-stat	-6.03	-3.52

Panel B: Differences in Shorting Fees of Stocks with and without Options

	ΔLosers	ΔWinners
Average (in bps)	192.39	22.95
t-stat	2.02	2.69

Table 8. Double Sorts: Momentum Returns and Shorting Fees

Double-sorted quintile portfolios of momentum returns are formed every month from January 1996 to December 2018 for the matched stocks with and without options by sorting stocks based on the previous period 12-month cumulative returns (R(2,12)) after controlling for shorting fees and utilization. We first sort the stocks into quintiles using shorting fees (utilisationn), then within each quintile, we short stocks into quintile portfolios based on on the previous period 12-month cumulative returns (R(2,12)) after skipping the most recent month so that WML contains the winner-minus-loser portfolio for each level of shorting fees (utilisation). The table reports the value weighted average excess monthly returns for each of the double-sorted portfolios and as well as for the WML with their associated HAC adjusted t-statistics (t-stat). Average raw returns are given in percentage terms.

Panel A: Shorting Fees and Momentum Returns

	Stocks with Options			Stocks without Options		
	Low Fees	2	High Fees	Low Fees	2	High Fees
Loser	0.910	0.583	-0.141	1.045	0.852	-4.502
2	1.275	0.813	1.195	0.695	0.796	-0.134
3	1.002	1.391	1.299	0.522	0.965	0.296
4	1.246	1.087	0.350	1.291	0.896	1.155
5	0.558	0.280	0.125	0.934	1.278	0.363
WML	-0.352	-0.303	0.265	-0.110	0.426	4.866
t-stat	-0.41	-0.40	0.21	-0.18	0.51	3.34

Panel B: Utilization and Momentum Returns

	Stocks with Options			Stocks without Options		
	Low Utilization	2	High Utilization	Low Utilization	2	High Utilization
Loser	1.846	1.396	-0.699	1.206	0.476	-3.740
2	1.650	1.111	0.606	1.576	0.775	0.502
3	1.382	1.225	0.710	0.954	0.941	0.690
4	1.259	0.786	0.801	1.316	0.539	0.830
5	1.335	-0.116	0.439	1.370	0.654	0.921
WML	-0.511	-1.512	1.138	0.164	0.178	4.661
t-stat	-0.65	-1.66	1.22	0.22	0.24	3.05

Table 9. Option Order Imbalances of Momentum Portfolios

Decile portfolios are formed every month from January 2006 to December 2016 by sorting stocks with options based on the previous period 12-month cumulative returns (R(2,12)) after skipping the most recent month. Decile 10 indicates the winner portfolio, Decile 1 denotes the loser portfolios and WML indicates the winner-minus-loser portfolio. This table presents time-series averages of option order imbalances and their corresponding adjusted HAC t-statistics (t-stat) of each of the decile portfolios as well the spread portfolios that buy best performing stocks (i.e., *winners*) while selling stock with poor past performances (i.e., *losers*)

$$\mathrm{OOI}_{i,t} = \frac{\sum_j^N abs(\Delta_{i,j,t})[(\mathrm{BC}_{i,j,t} + \mathrm{SP}_{i,j,t}) - (\mathrm{SC}_{i,j,t} + \mathrm{BP}_{i,j,t})]}{\mathrm{Num\_shares\_outstanding}_t}$$

where OOI is the number of opening option trades written on stock i at time t that provides positive exposure to the stock price (e.g., buy calls (BC) and sell puts (SP)) less number of option trades that provides negative exposure to the stock price (sell calls (SC) and buy puts (BP)) as a fraction of the total number of shares outstanding at time t. We report time-series averages of median order imbalances for all market participants and for customers only. The measures are computed over the holding period (e.g., a month).

Momentum Portfolios		
$Decile$	OOI	$\mathrm{OOI}_{Customers}$
Losers	-0.007	-0.009
2	-0.006	-0.009
3	-0.006	-0.008
4	-0.007	-0.009
5	-0.006	-0.008
6	-0.006	-0.008
7	-0.005	-0.006
8	-0.003	-0.005
9	0.003	0.003
Winners	0.021	0.018
WML	0.028	0.026
t-stat	2.74	2.53

Table 10. Stock Order Imbalances of Momentum Portfolios

Decile portfolios are formed every month from January 1996 to December 2018 by sorting all stocks and stocks with and without options based on the previous period 12-month cumulative returns (R(2,12)) after skipping the most recent month. Decile 10 indicates the winner portfolio, Decile 1 denotes the loser portfolios and WML indicates the winner-minus-loser portfolio. This table presents time-series averages of median stock order imbalances and the adjusted HAC t-statistics (t-stat) of each of the decile portfolios as well the spread portfolios that buy the Winners-Loser portfolio. $\mathrm{SOI}^{\mathrm{NUM}}$ is the number of buys less number of sells over the holding period (e.g., a month) as a fraction of the total trades in that month. $\mathrm{SOI}^{\mathrm{VOL}}$ s the number of buy trade volume less sell trade volume as a fraction of the total volume traded over the holding period as a fraction of the total volume traded that month. Both measures are reported in percent per month. Panel A reports results for all momentum portfolios while Panel B displays results for the differences in stock imbalances for loser and winner portfolios of stocks with and withot options

Panel A: Momentum Portfolios

	Stocks with Options		*Stocks without Options*	
	$\mathrm{SOI}^{\mathrm{NUM}}$	$\mathrm{SOI}^{\mathrm{VOL}}$	$\mathrm{SOI}^{\mathrm{NUM}}$	$\mathrm{SOI}^{\mathrm{VOL}}$
Losers	-0.006	-0.016	-0.053	-0.082
2	0.001	-0.001	-0.057	-0.077
3	0.005	0.005	-0.053	-0.071
4	0.009	0.012	-0.047	-0.065
5	0.013	0.015	-0.040	-0.056
6	0.016	0.017	-0.029	-0.047
7	0.018	0.019	-0.023	-0.039
8	0.020	0.019	-0.016	-0.034
9	0.020	0.017	-0.011	-0.029
Winners	0.017	0.011	-0.009	-0.028
WML	0.023	0.027	0.044	0.054
t-stat	5.09	6.87	9.80	16.57

Panel B: Differences in Stock Imbalances of Stocks with and without Options

	ΔLosers	ΔWinners
$\mathrm{SOI}^{\mathrm{NUM}}$	-0.047	-0.026
t-stat	-9.70	-5.87
$\mathrm{SOI}^{\mathrm{VOL}}$	-0.066	-0.039
t-stat	-18.07	-9.60

Table 11. Double Sorts: Momentum and Option Impediments

Double-sorted quintile portfolios of momentum returns are formed every month from January 1996 to December 2018 for stocks with options in our sample by sorting stocks based on the previous period 12-month cumulative returns (R(2,12)) after controlling for the implied volatility spread. We refer to the difference between call and put implied volatilities as the volatility spread. In fact, for every day t and every stock i with put and call options data on day t, we compute the volatility spread (VS) as

$$\mathrm{VS_{i,t}} = \mathrm{IV_{i,t}^{calls}} - \mathrm{IV_{i,t}^{puts}}$$

where $IV_{j,t}^{i}$ denotes the Black-Scholes (1973) implied volatility (adjusted for expected dividends and early exercise). The results that we report use equal weights. We first sort the stocks into quintiles using the volatility spread, then within each quintile, we short stocks into quintile portfolios based on on the previous period 12-month cumulative returns (R(2,12)) after skipping the most recent month so that WML contains the winner-minus-loser portfolio for different levels of the volatility spread. The table reports the value weighted average excess monthly returns for each of the double-sorted portfolios and as well as for the WML with their associated HAC adjusted t-statistics (t-stat). Average raw returns are given in percentage terms.

	Implied Volatility Spread				
	Low PIV-CIV	2	3	4	High PIV-CIV
Loser	-0.944	0.367	0.538	0.387	0.471
2	0.047	0.156	0.788	0.811	1.193
3	0.418	0.442	0.496	0.693	1.113
4	0.306	0.439	0.729	0.851	1.030
5	0.316	1.125	0.799	1.086	1.124
WML	1.260	0.758	0.261	0.699	0.653
t-stat	2.56	1.473	0.552	1.673	1.188

Table 12. Net Trading and Option Trading: Matching based on Trading Volume, Industry and Size

Decile portfolios are formed every month from January 1996 to December 2018 for matched stocks with and without options. We allocate stocks into portfolios every month based on different characteristics and we compute the total number of times that the stock appears in long or short portfolios. Then, we compute the net measure which is defined as Net=long-short for each stock-month observation. Panel A reports the value weighted average excess monthly returns of stocks that are matched based on size, trading volume and industry for each decile portfolio as well as the corresponding alphas of the CAPM, the three-factor Fama and French (1993) model (FF3) and the five-factor Fama and French (2015) model (FF5) based on option trading during the rebalancing date. Panel B shows differences between low and high Net portfolios of stocks with and without options. The last two rows present the differences in monthly returns and the differences in alphas between winners and losers portfolios with associated HAC adjusted t-statistics (t-stat). All returns are in percentages.

Panel A: Matched firms based on Trading Volume, Industry and Size

	Stocks with Options				Stocks without Options			
Decile	Avg Ret	CAPM Alpha	FF3 Alpha	FF5 Alpha	Avg Ret	CAPM Alpha	FF3 Alpha	FF5 Alpha
Low NET	-0.503	-1.810	-1.839	-1.103	-3.403	-4.475	-4.380	-3.612
2	-0.337	-1.279	-1.302	-0.762	-0.027	-1.056	-1.078	-0.274
3	0.774	-0.027	-0.109	0.033	0.774	0.133	0.064	0.299
4	0.925	0.349	0.265	0.177	1.032	0.534	0.428	0.260
High NET	1.152	0.691	0.608	0.469	1.119	0.787	0.734	0.417
WML	1.655	2.501	2.447	1.571	4.522	5.262	5.113	4.029
t-stat	2.05	3.58	3.46	1.90	4.12	5.23	5.21	4.13

Panel B: Differences between optionable and non optionable stocks

	ΔLow Net	ΔHigh Net
Avg Ret	-2.900	-0.033
t-stat	-2.77	-0.11
CAPM Alpha	-2.665	0.096
t-stat	-2.49	0.33
FF3 Alpha	-2.541	0.125
t-stat	-2.36	0.41
FF5 Alpha	-2.509	-0.052
t-stat	-2.10	-0.17

Table 13. Momentum Returns and Option Introductions: Matching based on Trading Volume, Industry and Size

Decile portfolios are formed every month from July 1977 to December 2018 for matched stocks with and without options by sorting stocks based on the previous period 12-month cumulative returns (R(2,12)) after skipping the most recent month. An stock is considered optionable after option listing. Decile 10 indicates the winner portfolio, Decile 1 denotes the loser portfolios and WML indicates the winner-minus-loser portfolio. Panel A reports the value weighted average excess monthly returns of stocks that are matched based on size, trading volume and industry for each decile portfolio as well as the corresponding alphas of the CAPM, the three-factor Fama and French (1993) model (FF3) and the five-factor Fama and French (2015) model (FF5) based on option trading during the rebalancing date. Panel B shows differences between loser (winner) portfolios of stocks with and without options based on option listing. The last two rows present the differences in monthly returns and the differences in alphas between winners and losers portfolios with associated HAC adjusted t-statistics (t-stat). All returns are in percentages.

Panel A: Matched firms based on Trading Volume, Volatility and Size

	Stocks with Options				Stocks without Options			
Decile	Avg Ret	CAPM Alpha	FF3 Alpha	FF5 Alpha	Avg Ret	CAPM Alpha	FF3 Alpha	FF5 Alpha
Losers	0.130	-0.877	-1.031	-0.427	-1.515	-2.481	-2.568	-2.055
2	0.057	-0.820	-0.989	-0.612	0.613	-0.221	-0.444	-0.057
3	0.543	-0.231	-0.372	-0.230	0.524	-0.195	-0.409	-0.244
4	0.800	0.110	-0.013	-0.064	0.620	-0.048	-0.245	-0.220
5	0.881	0.190	0.053	-0.016	0.681	0.085	-0.062	-0.045
6	0.993	0.369	0.281	0.155	0.672	0.118	-0.004	-0.057
7	0.906	0.244	0.146	0.105	0.648	0.124	0.008	-0.064
8	1.054	0.380	0.313	0.195	0.996	0.397	0.302	0.209
9	0.845	0.101	0.100	0.104	1.125	0.492	0.486	0.378
Winners	1.037	0.199	0.286	0.317	1.114	0.338	0.454	0.594
WML	0.907	1.077	1.318	0.744	2.629	2.819	3.022	2.649
t-stat	2.04	2.68	3.55	1.53	5.94	5.99	6.94	4.81

Panel B: Differences between optionable and non optionable Loser and Winner stocks

	ΔLosers	ΔWinners
Avg Ret	-1.644	0.077
t-stat	-4.00	0.27
CAPM Alpha	-1.604	0.139
t-stat	-3.98	0.51
FF3 Alpha	-1.537	0.168
t-stat	-3.97	0.56
FF5 Alpha	-1.628	0.277
t-stat	-3.71	0.77

Table 14. Momentum Returns and Option Availability: Propensity Score Matching

Decile portfolios are formed every month from January 1996 to December 2018 for stocks with and without options based on option availability in Optionmetrics during the last trading day of each month, and matched using propensity score matching. In particular, we estimate a logit regression model where the dependent variable is the log-odds ratio that a stock will be eligible for option listing and the independentvariables the average daily trading volume over the 250 trading days prior to the 15th of themonth, the annualized standard deviation of log returns over the same period, the ratio of the30-day to 250-day average trading volume and the same ratio for volatility and the market cap-italization of the firm. We match stocks with and without options by using the Greed matching method with a caliper width of 0.10. Decile 10 indicates the winner portfolio, Decile 1 denotes the loser portfolios and WML indicates the winner-minus-loser portfolio. Panel A reports the value weighted average excess monthly returns for each decile portfolio as well as the corresponding alphas of the CAPM, the three-factor Fama and French (1993) model (FF3) and the five-factor Fama and French (2015) model (FF5) based on option trading during the rebalancing date. Panel B shows differences between loser (winner) portfolios of stocks with and without options. The last two rows present the differences in monthly returns and the differences in alphas between winners and losers portfolios with associated HAC adjusted t-statistics (t-stat). All returns are in percentages.

Panel A: Matched firms based on Trading Volume, Volatility and Size

	Stocks with Options				Stocks without Options			
Decile	Avg Ret	CAPM Alpha	FF3 Alpha	FF5 Alpha	Avg Ret	CAPM Alpha	FF3 Alpha	FF5 Alpha
Losers	0.511	-0.672	-0.791	-0.084	-1.404	-2.510	-2.570	-1.931
2	0.351	-0.566	-0.706	-0.482	0.307	-0.531	-0.636	-0.293
3	0.375	-0.467	-0.582	-0.443	0.855	0.105	-0.058	-0.082
4	0.786	0.056	-0.058	-0.067	0.658	0.043	-0.071	0.105
5	0.610	-0.050	-0.147	-0.264	0.608	0.114	0.015	0.002
6	0.806	0.205	0.096	-0.066	0.869	0.377	0.287	0.330
7	0.864	0.302	0.214	0.119	0.841	0.429	0.331	0.352
8	0.761	0.202	0.134	0.005	0.840	0.380	0.292	0.169
9	0.590	0.000	-0.042	-0.145	1.064	0.519	0.464	0.386
Winners	0.885	0.171	0.172	0.223	0.751	0.089	0.101	0.154
WML	0.374	0.842	0.962	0.307	2.155	2.599	2.671	2.085
t-stat	0.49	1.31	1.50	0.43	3.02	4.28	4.59	2.94

Panel B: Differences between optionable and non optionable Loser and Winner stocks

	ΔLosers	ΔWinners
Avg Ret	-1.915	-0.134
t-stat	-4.56	-0.53
CAPM Alpha	-1.838	-0.082
t-stat	-4.03	-0.29
FF3 Alpha	-1.779	-0.070
t-stat	-3.93	-0.25
FF5 Alpha	-1.847	-0.069
t-stat	-3.63	-0.27

Table 15. Momentum Returns and Option Availability: Momentum Crashes

Decile portfolios are formed every month from January 1996 to December 2018 for stocks with and without options based on option availability in Optionmetrics during the last trading day of each month, and matched based on trading volume, industry and market capitalization by sorting the whole sample of matched stocks based on the previous period 12-month cumulative returns (R(2,12)) after skipping the most recent month. Following Daniel and Moskowitz (2016) we eliminate the months with momentum crashes: January 2001,October 2001, November 2001, November 2002, March 2009, April 2009 and August 2009. Decile 10 indicates the winner portfolio, Decile 1 denotes the loser portfolios and WML indicates the winner-minus-loser portfolio. Panel A reports the value weighted average excess monthly returns as well as the corresponding alphas of the CAPM, the three-factor Fama and French (1993) model (FF3) and the five-factor Fama and French (2015) model (FF5). Panel B shows differences between loser (winner) portfolios of stocks with and without options. The last two rows present the differences in monthly returns and the differences in alphas between winners and losers portfolios with associated HAC adjusted t-statistics (t-stat). All returns are in percentages.

Panel A: Matched firms based on Trading Volume, Volatility and Size

	Stocks with Options				Stocks without Options			
Decile	Avg Ret	CAPM Alpha	FF3 Alpha	FF5 Alpha	Avg Ret	CAPM Alpha	FF3 Alpha	FF5 Alpha
Losers	-0.840	-1.613	-1.657	-1.102	-3.051	-3.852	-3.892	-3.626
2	-0.663	-1.302	-1.386	-1.033	-0.182	-0.847	-0.962	-0.712
3	-0.195	-0.763	-0.868	-0.818	0.348	-0.232	-0.371	-0.356
4	0.589	0.118	0.032	-0.137	0.239	-0.260	-0.396	-0.483
5	0.649	0.159	0.047	-0.111	0.617	0.184	0.077	0.062
6	0.992	0.578	0.502	0.355	0.410	0.062	-0.035	-0.196
7	0.900	0.449	0.361	0.366	0.737	0.392	0.319	0.259
8	0.959	0.507	0.440	0.399	1.110	0.702	0.628	0.515
9	0.677	0.158	0.140	0.275	1.017	0.583	0.566	0.421
Winners	0.729	0.124	0.158	0.350	1.244	0.663	0.746	0.915
WML	1.569	1.737	1.815	1.452	4.296	4.515	4.638	4.541
t-stat	2.80	3.24	3.17	2.44	6.02	6.83	7.46	6.35

Panel B: Differences between optionable and non optionable Loser and Winner stocks

	ΔLosers	ΔWinners
Avg Ret	-2.211	0.515
t-stat	-3.90	1.14
CAPM Alpha	-2.239	0.539
t-stat	-4.00	1.23
FF3 Alpha	-2.235	0.588
t-stat	-4.05	1.36
FF5 Alpha	-2.525	0.565
t-stat	-3.62	1.13

Internet Appendix to

“Overcoming Arbitrage Limits: Option Trading and Momentum Returns”

(Not for publication)

Appendix A: Data Description

1.1 Control Variables Construction

Idiosyncratic Volatility (IVOL): We estimate the monthly idiosyncratic volatility of each stock at month t as the standard deviation of daily residuals in the previous 3 months obtained from the Fama and French (1993) 3-factor model:

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_{1,i}(R_{m,d} - r_{f,d}) + \beta_{2,i}HML_d + \beta_{3,i}SMB_d + \varepsilon_{i,d}, \tag{11}$$

where $R_{i,d}$ is the stock return i on day d, $R_{m,d}$ is the market return and $r_{f,d}$ is the risk-free rate. In addition, HML and SMB represent the zero-cost portfolios that are related to the high-minus-low book-to-market and the small-minus-big size factors. Thus, we define the idiosyncratic volatility (IVOL) of stock i in month t as the standard deviation of the daily residuals obtained from the model above: $IVOL_{i,t} = \sqrt{var(\varepsilon_{i,d})}$.

Stock Illiquidity (ILLIQ^{Stock}): Following Amihud (2002), we measure illiquidity as the monthly average of the daily ratio of each stock absolute return to its dollar volume.

Size: Firm size is defined as the market value of equity (that is stock price times shares outstanding at the end of the previous month)

Book-to-market (B/M): Following Fama and French (1992), we compute a firm's book to market ratio at the end of each month (book values are lagged 6 months while we consider the most recent market values in order to obtain the ratios).

Institutional Ownership (IOR): Institutional ownership is computed as the percentage of shares outstanding reported by 13F institutions at the end of each month. Institutional holdings are reported on a quarterly basis. We assume that the holdings remain constant during the quarter in order to compute our monthly measure.

Short-term reversals (REV): As in Jegadeesh (1990) and Lehmann (1990), the short term reversal refers to the previous month return.

1.2 Fails-To-Deliver

We obtain fails-to-deliver (FTD) data from the SEC website from March 2004 to December 2018.[26] The value of total fails-to-deliver shares represent the aggregate net balance of shares that failed to be delivered as of a particular settlement date. Similarly to measures of "relative short interest", we normalize the data by the number of shares outstanding (Fotak, Raman, and Yadav, 2014). If the aggregate net balance of shares that failed to be delivered is less than 10,000 as of a particular settlement date prior to September 16, 2008, then no record will be present in the file for that date even if there are fails in that security. To ensure comparability since September 2008 we also exclude observations with less than 10,000 shares after that date. The FTD data from the SEC represent the open interest of failed-to-deliver trades that occurred up to three days prior. For each day t, we look at the number of outstanding FTDs on day $t+3$, as we are interested in investigating the impact of FTD changes on the market on the day on which the transaction actually occurs (day t), rather than on the day on which the resulting failures are disclosed (day $t+3$). In the absence of reported data, we record the number of FTDs as zero.

1.3 Implied Volatility Spread

We use the OptionMetrics IvyDB US data to measure deviations from put-call parity. We follow Amin et al. (2004) and Cremers and Weinbaum (2010) and compute the average difference in implied volatilities between call and put options pairs with the same strike price and expiration date. We refer to the difference between call and put implied volatilities as the volatility spread.

[26] https://www.sec.gov/data/foiadocsfailsdatahtm

In fact, for every day t and every stock i with put and call options data on day t, we compute the volatility spread (VS) as

$$\mathrm{VS_{i,t}} = \mathrm{IV_{i,t}^{calls}} - \mathrm{IV_{i,t}^{puts}} = \sum_{j=1}^{N_{i,t}} w_{j,t}^{i} (\mathrm{IV_{j,t}^{i,call}} - \mathrm{IV_{j,t}^{i,put}}) \tag{12}$$

where j refers to pairs of put and call options and thus indexes both strike prices and maturities, $w_{j,t}^{i}$ are weights, there are N_t^i valid pairs of options on stock i on day t, and $IV_{j,t}^{i}$ denotes the Black-Scholes (1973) implied volatility (adjusted for expected dividends and early exercise). The results that we report use equal weights.

Table A1. Stocks with and without Options

This table presents the number and percentage of firms with and without options in our sample annually from 1996 to 2018. In this table we define a stock as optionable if it appears in Optionmetrics data the last trading of each year.

Stocks with and without Options

Year	Total Number of Stocks	Number of Stocks with Options	% Stocks with Options	Number of Stocks without Options	% Stocks without Options
1996	6521	1771	0.272	4750	0.728
1997	6861	2068	0.301	4793	0.699
1998	6609	2253	0.341	4356	0.659
1999	6111	2139	0.350	3972	0.650
2000	5906	1906	0.323	4000	0.677
2001	5538	1856	0.335	3682	0.665
2002	5110	1897	0.371	3213	0.629
2003	4756	1762	0.370	2994	0.630
2004	4574	1916	0.419	2658	0.581
2005	4504	1981	0.440	2523	0.560
2006	4455	2149	0.482	2306	0.518
2007	4322	2180	0.504	2142	0.496
2008	4259	2236	0.525	2023	0.475
2009	3998	2203	0.551	1795	0.449
2010	3820	2237	0.586	1583	0.414
2011	3688	2360	0.640	1328	0.360
2012	3552	2396	0.675	1156	0.325
2013	3458	2470	0.714	988	0.286
2014	3521	2560	0.727	961	0.273
2015	3588	2661	0.742	927	0.258
2016	3496	2655	0.759	841	0.241
2017	3428	2561	0.747	867	0.253
2018	3433	2484	0.724	949	0.276

Table A2. Momentum Returns and Option Tradability: Matching based on Trading Volume, Industry and Size

Decile portfolios are formed every month from January 1996 to December 2018 for stocks with and without options based on option tradability in Optionmetrics during the last trading day of each month and matched based on trading volume, industry and market capitalization by sorting the whole sample of matched stocks based on the previous period 12-month cumulative returns (R(2,12)) after skipping the most recent month. Decile 10 indicates the winner portfolio, Decile 1 denotes the loser portfolios and WML indicates the winner-minus-loser portfolio. Panel A reports the value weighted average excess monthly returns as well as the corresponding alphas of the CAPM, the three-factor Fama and French (1993) model (FF3) and the five-factor Fama and French (2015) model (FF5). Panel B shows differences between loser (winner) portfolios of stocks with and without options. The last two rows present the differences in monthly returns and the differences in alphas between winners and losers portfolios with associated HAC adjusted t-statistics (t-stat). All returns are in percentages.

Panel A: Matched firms based on Trading Volume, Industry and Size

	Stocks with Options				Stocks without Options			
Decile	Avg Ret	CAPM Alpha	FF3 Alpha	FF5 Alpha	Avg Ret	CAPM Alpha	FF3 Alpha	FF5 Alpha
Losers	-0.047	-1.203	-1.344	-0.800	-1.454	-2.640	-2.704	-2.029
2	0.271	-0.579	-0.718	-0.472	0.363	-0.653	-0.851	-0.460
3	0.663	-0.124	-0.289	-0.133	0.665	-0.162	-0.359	-0.488
4	0.801	0.133	-0.006	-0.141	0.863	0.177	0.010	0.038
5	0.556	-0.050	-0.221	-0.280	0.878	0.273	0.124	0.054
6	1.178	0.617	0.508	0.438	0.908	0.413	0.300	0.296
7	0.718	0.164	0.039	-0.187	0.687	0.191	0.101	0.094
8	1.000	0.422	0.351	0.225	1.226	0.680	0.588	0.429
9	0.712	0.081	0.022	0.009	0.756	0.161	0.102	-0.010
Winners	0.988	0.206	0.182	0.292	1.345	0.582	0.610	0.651
WML	1.034	1.409	1.526	1.092	2.799	3.221	3.314	2.680
t-stat	1.39	2.27	2.47	1.55	3.54	4.59	4.84	3.11

Panel B: Differences between optionable and non optionable Loser and Winner stocks

	ΔLosers	ΔWinners
Avg Ret	-1.407	0.357
t-stat	-2.76	0.83
CAPM Alpha	-1.437	0.376
t-stat	-3.01	0.85
FF3 Alpha	-1.360	0.428
t-stat	-2.81	0.98
FF5 Alpha	-1.229	0.359
t-stat	-2.56	0.61

Table A3. Momentum Returns and Option Availability: Alternative Matches

Decile portfolios are formed every month from January 1996 to December 2018 for all stocks as well as for stocks with and without options by sorting stocks based on the previous period 12-month cumulative returns (R(2,12)) after skipping the most recent month. Decile 10 indicates the winner portfolio, Decile 1 denotes the loser portfolios and WML indicates the winner-minus-loser portfolio. Panel A (Panel B) reports the value weighted average excess monthly returns of stocks that are matched based on trading volume, industry, size and volatility (institutional ownership) for each decile portfolio as well as the corresponding alphas of the CAPM, the three-factor Fama and French (1993) model (FF3) and the five-factor Fama and French (2015) model (FF5) based on option trading during the rebalancing date. The last two rows show the differences in monthly returns and the differences in alphas between winners and losers portfolios with associated HAC adjusted t-statistics (t-stat). Panel C shows differences between loser (winner) portfolios of stocks with and without options. All returns are in percentages.

Panel A: Matched firms based on Trading Volume, Industry, Size and Stock Volatility

	Stocks with Options				Stocks without Options			
Decile	Avg Ret	CAPM Alpha	FF3 Alpha	FF5 Alpha	Avg Ret	CAPM Alpha	FF3 Alpha	FF5 Alpha
Losers	-0.131	-1.290	-1.423	-0.752	-2.380	-3.551	-3.662	-3.170
2	0.562	-0.327	-0.459	-0.223	0.208	-0.763	-0.971	-0.652
3	0.431	-0.350	-0.493	-0.339	0.730	-0.120	-0.319	-0.389
4	1.026	0.334	0.170	0.040	0.691	-0.008	-0.184	-0.252
5	0.362	-0.264	-0.429	-0.475	0.888	0.284	0.135	0.189
6	0.878	0.349	0.200	0.101	0.736	0.218	0.103	0.031
7	0.865	0.310	0.195	0.046	0.818	0.336	0.240	0.257
8	0.900	0.321	0.251	0.134	1.160	0.613	0.520	0.371
9	0.581	-0.077	-0.136	-0.212	0.954	0.337	0.285	0.111
Winners	1.144	0.365	0.348	0.457	1.291	0.542	0.576	0.629
WML	1.275	1.655	1.771	1.209	3.671	4.093	4.238	3.799
t-stat	1.66	2.48	2.64	1.54	5.16	6.36	7.25	5.30

Panel B: Matched firms based on Trading Volume, Industry, Size and Institutional Ownership

	Stocks with Options				Stocks without Options			
Decile	Avg Ret	CAPM Alpha	FF3 Alpha	FF5 Alpha	Avg Ret	CAPM Alpha	FF3 Alpha	FF5 Alpha
Losers	0.462	-0.582	-0.679	-0.200	-2.481	-3.566	-3.690	-3.415
2	0.348	-0.530	-0.599	-0.363	0.991	-0.022	-0.225	0.097
3	0.973	0.188	0.076	0.186	1.129	0.400	0.237	0.050
4	0.691	0.063	-0.061	-0.142	1.037	0.418	0.252	0.292
5	1.030	0.433	0.302	0.187	0.913	0.363	0.251	0.165
6	1.047	0.498	0.359	0.235	0.986	0.510	0.381	0.238
7	0.969	0.433	0.308	0.228	0.889	0.460	0.383	0.395
8	1.033	0.407	0.317	0.235	1.116	0.632	0.533	0.301
9	0.831	0.248	0.168	0.135	1.108	0.597	0.545	0.326
Winners	1.510	0.767	0.756	0.733	1.426	0.785	0.810	0.880
WML	1.048	1.349	1.435	0.933	3.907	4.350	4.500	4.295
t-stat	1.61	2.37	2.56	1.45	4.29	5.22	5.54	4.81

Panel C: Differences between optionable and non optionable Loser and Winner stocks

	ΔLosers$_{PanelA}$	ΔWinners$_{PanelA}$	ΔLosers$_{PanelB}$	ΔWinners$_{PanelB}$
Avg Ret	-2.250	0.147	-24	0.382
t-stat	-3.99	0.32	-2.14	0.81

Table A4. Short Interest of Momentum Portfolios

Decile portfolios are formed every month from January 1996 to December 2013 by sorting all stocks and stocks with and without options based on the previous period 12-month cumulative returns (R(2,12)) skipping the most recent month. Decile 10 indicates the winner portfolio, Decile 1 denotes the loser portfolios and WML indicates the Winner-minus-Loser portfolio. We have matched stocks with and without options based on size, trading volume and industry. This table presents time-series average of median short interest and their corresponding adjusted HAC t-statistics (t-stat) of each of the decile portfolios as well the spread portfolios that buy best performing stocks (i.e., *winners*) while selling stock with poor past performances (i.e., *losers*). Panel A shows results for momentum portfolios of stocks with and without options. Panel B shows the corresponding differences between the two groups for loser and winner portfolios. The measures correspond to the rebalancing period (15th of each month due to data availability).

Panel A: Matched firms based on Trading Volume, Industry and Size

Decile	Stocks with Options	Stocks without Options
Losers	0.040	0.021
2	0.032	0.021
3	0.030	0.020
4	0.028	0.020
5	0.027	0.019
6	0.026	0.020
7	0.026	0.020
8	0.027	0.019
9	0.028	0.019
Winners	0.034	0.020
WML	-0.007	-0.001
t-stat	-2.84	-0.36

Panel B: Differences in Short Interest of Stocks with and without Options

	ΔLosers	ΔWinners
Short Interest	-0.020	-0.014
t-stat	-8.37	-8.53

Table A5. Fails to Deliver of Momentum Portfolios

Decile portfolios are formed every month from March 2004 to December 2018 by sorting all stocks and stocks with and without options based on the previous period 12-month cumulative returns (R(2,12)) after skipping the most recent month. Decile 10 indicates the winner portfolio, Decile 1 denotes the loser portfolios and WML indicates the winner-minus-loser portfolio. This table presents time-series averages of fails to deliver and the adjusted HAC t-statistics (t-stat) of each of the decile portfolios as well the spread portfolios that buy the Winners-Loser portfolio. OFR is the number of outstanding failed positions reported on day t+3 scaled over the holding period (e.g., a month) as a fraction of the total number of shares outstanding of the firm during that month. FAILS is the number of stocks that failed to deliver over the holding period. Panel A shows results for momentum portfolios of stocks with and without options. Panel B shows the corresponding differences between the two groups for loser and winner portfolios.

Panel A: Matched firms based on Trading Volume, Industry and Size

	Stocks with Options		*Stocks without Options*	
	OFR	FAILS	OFR	FAILS
Losers	0.017	20.798	0.011	8.747
2	0.007	15.438	0.005	9.511
3	0.004	13.348	0.003	9.674
4	0.004	10.815	0.003	10.101
5	0.003	10.275	0.002	9.466
6	0.003	10.017	0.002	9.669
7	0.003	9.865	0.002	10.079
8	0.003	10.174	0.003	10.854
9	0.004	9.663	0.003	12.629
Winners	0.007	9.371	0.007	16.876
WML	-0.009	-11.427	-0.004	8.129
t-stat	-4.11	-10.72	-3.25	6.71

Panel B: Differences in Fails to Deliver of Stocks with and without Options

	ΔLosers	ΔWinners
OFR	-0.006	-0.001
t-stat	-2.41	-0.70
FAILS	-12.051	7.506
t-stat	-6.90	10.85

Table A6. Cross-Sectional Regressions: Option Order Imbalances

This table presents results from Fama-MacBeth regressions of options order imbalances on past performance, measured based on the previous period 12-month cumulative returns (R(2,12)) after skipping the most recent month. We also take into consideration a number of control variables including log size (Ln(Size)), log stock price (Ln(Price)), institutional ownership (IOR), book-to-market (B/M), idiosyncratic volatility (IVOL), reversals (R(1)) and illiquidity (ILLIQ). The table reports the time-series averages of the cross-sectional regression coefficients, their associated HAC adjusted t-statistics, and the regression R-squares. The main model takes the following form:

$$\text{OOI}_{i,t+1} = \delta_{0,t} + \delta_{1,i}\text{R(2,12)}_{i,t} + \delta'_{2,i}\mathbf{Z}_{i,t} + \varepsilon_{i,t+1}$$

where $\text{OOI}_{i,t+1}$ denotes the time $t+1$ option order imbalances of options written on stock i, $\text{R(2,12)}_{i,t}$ is the 12-month cumulative stock return (after skipping the most recent month) of stock i on month t. $\mathbf{Z}$ represents the set of control variables.

Option Order Imbalances				
	All Market Participants		*Customers*	
Intercept	-0.001	-0.323	-0.006	-0.311
$t\text{-}stats$	-0.07	-4.46	-0.73	-4.32
$\text{CumRet}_{i,t}$	0.118	0.106	0.118	0.107
$t\text{-}stats$	3.08	3.22	3.06	3.21
Control Variables				
$\text{Ln(Size)}_{i,t}$		0.014		0.014
$t\text{-}stats$		3.39		3.64
$\text{Ln(Price)}_{i,t}$		0.026		0.024
$t\text{-}stats$		1.60		1.56
$\text{ILLIQ}_{i,t}$		1.048		1.596
$t\text{-}stats$		1.48		2.26
$\text{R(1)}_{i,t}$		0.160		0.168
$t\text{-}stats$		1.68		1.72
$\text{B/M}_{i,t}$		-0.007		-0.008
$t\text{-}stats$		-0.87		-1.01
$\text{IOR}_{i,t}$		-0.052		-0.059
$t\text{-}stats$		-2.48		-2.98
$\text{IVOL}_{i,t}$		3.440		3.057
$t\text{-}stats$		3.43		3.08
Adj-R^2	1.16%	3.99%	1.16%	3.98%

Table A7. Early Exercise of Options of Momentum Portfolios

Decile portfolios are formed every month from July 2001 until June 2014 by sorting stocks with options based on the previous period 12-month cumulative returns (R(2,12)) after skipping the most recent month. Decile 10 indicates the winner portfolio, Decile 1 denotes the loser portfolios and WML indicates the winner-minus-loser portfolio. This table presents time-series averages of early exercises of options and their corresponding adjusted HAC t-statistics (t-stat) of each of the decile portfolios as well the spread portfolios that buy best performing stocks (i.e., *winners*) while selling stock with poor past performances (i.e., *losers*). The table reports results for All participants together with Firms, Market Makers and Customers. The data is collected from the Options Clearing Corporation (OCC), Optionmetrics and CRSP and contains monthly from July 2001 until June 2014.

Momentum Portfolios

Decile	All	Firms	Market Makers	Customers
Losers	3.176%	0.220%	2.087%	0.976%
2	2.308%	0.197%	1.495%	0.714%
3	1.879%	0.184%	1.198%	0.593%
4	1.572%	0.162%	0.971%	0.522%
5	1.424%	0.151%	0.865%	0.493%
6	1.302%	0.135%	0.784%	0.462%
7	1.235%	0.129%	0.723%	0.456%
8	1.222%	0.124%	0.704%	0.468%
9	1.307%	0.130%	0.735%	0.521%
Winners	1.510%	0.134%	0.806%	0.657%
WML	-1.666%	-0.086%	-1.280%	-0.319%
t-stat	-7.33	-5.80	-6.86	-6.44

Table A8. Momentum and Price Informativeness

Decile portfolios are formed every month from January 1996 to December 2018 by sorting all stocks and stocks with and without options based on the previous 12-month cumulative returns (R(2,12)) after skipping the most recent month. Decile 10 indicates the winner portfolio, Decile 1 denotes the loser portfolios and WML indicates the Winner-minus-Loser portfolio. This table presents results, for the winner and loser portfolios, of the time series average of price informativeness (PI) based on the measure in Bai et al. (2016). Specifically, the price informativeness measure is estimated using the following cross-sectional regression:

$$E_{i,t+1}/A_{i,t} = \alpha_t + b_t \log(M_{i,t}/A_{i,t}) + c_t(E_{i,t}/A_{i,t}) + d_t^s \mathbb{1}_{i,t}^s + \varepsilon_{i,t}$$

where M denotes the market capitalization, A the total asset, E represents the earnings before interest and taxes (EBIT), and $\mathbb{1}^s$ is an indicator variable of the sector (s) based on one-digit SIC codes. We run separate cross-sectional regressions for the constituents of each portfolio for each month of our data period with a one month horizon. We define price informativeness as the product of the cross-sectional beta of market cap to assets (e.g., b_t) with the cross-sectional standard deviation of $\log M_t/A_t$ in month t. Panel A displays time-series average of Price Informativeness of Loser and Winner portfolios for all stocks, and for stocks with and without options. Panel B shows the difference between loser (winner) portfolios of stocks with and without options.

Panel A: Price Informativeness

	Losers	Winners	WML	Losers	Winners	WML
	Stocks with Options			*Stocks without Options*		
PI	-0.010	-0.002	0.008	-0.024	0.000	0.024
t-stat	-4.09	-0.55	1.10	-5.11	0.03	3.03

Panel B: Differences in PI of Stocks with and without Options

	ΔLosers	ΔWinners
PI	-0.014	0.003
t-stat	-3.26	0.16

Table A9. Anomaly Portfolios

This table presents the set of 94 characteristics offered in Green et al. (2017). We provide the variable names and their explanations. We have excluded the 7 indicator variables.

Characteristics			
Names	Description	Names	Description
absacc	Absolute accruals	operprof	Operating profitability
acc	Working capital accruals	orgcap	Organizational capital
aeavol	Abnormal earning announcement volume	pchcapxia	Industry adjusted % change in capital expenditures
age	Number of years in compustat coverage	pchdepr	% change in depreciation
agr	Asset growth	pchgcurrat	% change in current ratio
baspread	Bid-ask spread	pchgmpchsale	% change in gross margin - % change in sales
beta	Beta	pchsalepchinvt	% change in sales - % change in inventory
bm	Book-to-market	pchsalepchrect	% change in sales - % change in A/R
bmia	Industry-adjusted book-to-market	pchsalepchxsqa	% change in sales - % change in SG&A
cash	Cash holdings	pchsaleinv	% change sales-to-inventory
cashdebt	Cash flow to debt	pctacc	Percent accruals
cashpr	Cash productivity	pricedelay	Price delay
cfp	Cash flow to price ratio	ps	Financial statements score
cfpia	Industry-adjusted cash flow to price ratio	rd	R&D increase
chatoia	Industry-adjusted change in asset turnover	rdmve	R&D to market capitalization
chcsho	Change in share outstanding	rdsale	R&D to sales
chempia	Industry-adjusted change in employees	realestate	Real estate holdings
chfeps	Change in forecasted EPS	retvol	Return volatility
chinv	Change in inventory	roaq	Return on assets
chmom	Change in 6-month momentum	roavol	Earnings volatility
chnanalyst	Change in number of analysts	roeq	Return on equity
chpmia	Industry-adjusted change in profit margin	roic	Return on invested capital
chtx	Change in tax expense	rsup	Revenue surprise
cinvest	Corporate investment	salecash	Sales to cash
convind	Convertible debt indicator	saleinv	Sales to inventory
currat	Current ratio	salerec	Sales to receivables
depr	Depreciation / PP&E	secured	Secured debt
disp	Dispersion in forecasted EPS	securedind	Secured debt indicator
divi	Dividend initiation	sfe	Scaled earnings forecast
divo	Dividend omission	sgr	Sales growth
dy	Dividend to price	sin	Sin stocks
ear	Earnings announcement return	sp	Sales to price
egr	Growth in common shareholder equity	stddolvol	Volatility of liquidity (dollar trading volume)
ep	Earnings to price	stdturn	Volatility of liquidity (share turnover)
fgr5yr	Forecasted growth in 5-year EPS	stdcf	Cash flow volatility
gma	gross profitability	sue	Unexpected quarterly earnings
grcapx	Growth in capital expenditures	tang	Debt capacity/firm tangibility
grltnoa	Growth in long term net operating assets	tb	Tax income to book income
herf	Industry sales concentration	turn	Share turnover
hire	Employee growth rate	zerotrade	Zero trading days
idiovol	Idiosyncratic return volatility		
ill	illiquidity		
indmom	industry momentum		
invest	Capital expenditures and inventory		
ipo	New equity issue		
lev	Leverage		
mom12m	12-month momentum		
mom1m	1-month momentum		
mom36m	36-month momentum		
ms	Financial statement score		
mve	Size		
mveia	Industry-adjusted size		
nanalyst	Number of analysts covering stock		
nincr	Number of earnings increases		