# Overcoming Arbitrage Limits: Option Trading and Momentum Returns*

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**Abstract**

In this paper we find that the decline in the momentum profitability is 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, there are more barriers to short selling and the short position offers lower returns. Our results are robust to exogenous changes in short selling due to Regulation SHO and are supported by other short-leg depended anomalies.

*Keywords*: Momentum returns, stock option trading, short-sale constraints.
*JEL Classification*: G11, G12, G14, G32.

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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, where the short leg returns play a key role in its profitability.

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 20% in 1996 and rising to 74% in 2016 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 fundamental 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 (see for example Blocher and Ringgenberg, 2018). 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 confirm our hypothesis as optionability does not seem to affect the long-leg dependent group of anomalies in contrast to the short-leg dependent ones. Specifically, strategies that depend more on the short leg tend be affected by the trading activity of the options attached to the constituents of the short portfolios. To the best of our knowledge, this is the first study that associates option trading with the profitability of anomaly portfolios.

In our empirical work, we start by confirming earlier results that returns to cross-sectional momentum trading, in the U.S. equity markets over the 1972 to 2016 period, are strong and statistically significant rendering, on average, 117 basis points (bps) per month. We also show that this result is mainly driven by high momentum returns during the earlier 1972 to 1996 sub-period (149 bps per month and statistically significant) while those in a latter period from 1996 to 2016 are significantly lower (80 bps per month) and are no longer statistically significant. These results, reported in earlier work, hold for both raw and risk-adjusted returns.

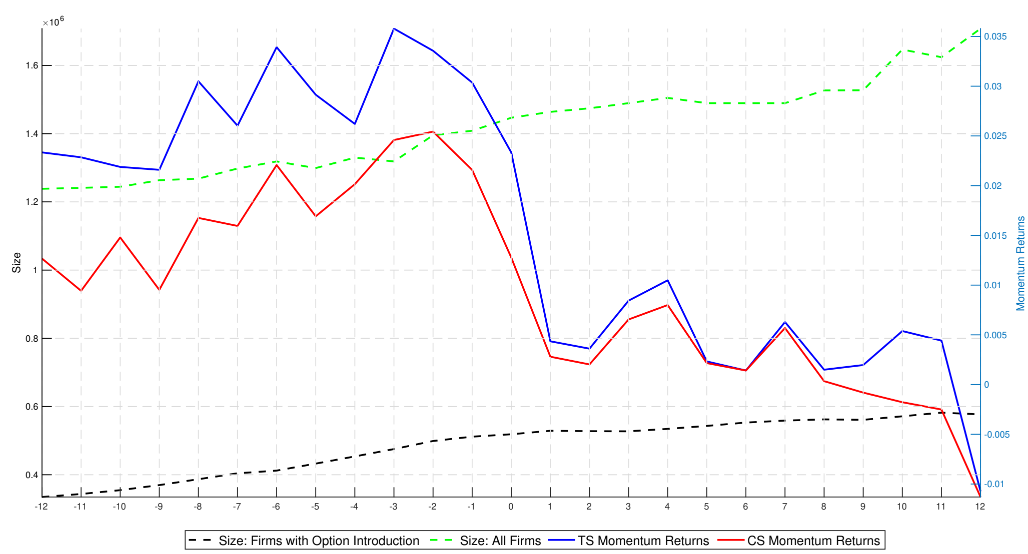
We next turn to the result that motivates our work. We partition stocks over the 1996-2016 period into those with and without traded options as our options data from Optionmetrics is available only after 1996. We are then able to construct momentum portfolios of stocks with and without options. We find that the average returns to a momentum portfolio of stocks without options is high and statistically significant (137 bps per month) while the momentum strategy is not significant for stocks with options. 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 (-35 bps per month) compared to that of the short leg for stocks with options which is positive and large (by an order of magnitude) at 33 bps per month. The returns to the winner (long leg) portfolio for both stocks with options and stocks without options are of similar size and sign. These results are robust to the presence of microcap stocks, to the construction of different optionable vs. non optionable momentum sorting strategies and to the use different definitions of stock with and without options. We also control for different dimensions of the momentum strategy and obtain similar results.

We perform an out-sample test and study earlier option introductions from 1973 to 1996. 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 particular, we find that the return of the optionable loser portfolio is positive while the corresponding return of the loser portfolio of stocks without options is negative. 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.

It is likely that our results might be driven by the fact that stocks without options are in a special category and different therefore from stocks with options. We use data from options introductions, which pre-date the availability of detailed options data from 1996. We construct an event study design around options introductions and find that option listing affects the momentum profitability for optionable stocks, which is highly significant before but not after the option introduction.

Figure 1 shows that optionability is the driving reason for the reduction in momentum returns. Similarly to Goyal and Jegadeesh (2017), we show returns of cross-sectional (CS) and time-series (TS) momentum around an option introduction for the period of June 1977 to April 2016. 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. A striking feature of this pattern is that the short interest doubles after the introduction of an option. 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 returns around the introduction of an option. 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 June 1977 to April 2016.

Our first result, using the Bai, Philippon, and Savov (2016) informativeness measure, is that information flows are higher for stocks in the loser portfolios with traded options compared to the loser portfolio of stocks without traded options. In other words, optionable loser portfolios are significantly more informative due to enhanced information flows from the option market.

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, Geczy, Musto, and Reed, 2008).[1] 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.

The most striking result of this mechanism is that when the expensiveness of the options is high, momentum 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.

Third, we find that the higher short interest indicates a large investor demand for option positions in the loser portfolios. Using option order imbalance data we find more net selling positions in the loser portfolio relative to the winner portfolio. 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.

Finally, we use the plausibly exogenous changes introduced by Regulation SHO between May 2005 and August 2007. Regulation SHO removed the short-sale price tests (removal of the

[1] The regulation change regarding the naked shorting exception in 2008 and 2013 could affect the profitability of optionable momentum returns in the future.

uptick rule) for every third stock ranked by trading volume in the Russell 3000 index. Simply put, it was easier to short pilot stocks, during this Regulation SHO period, relative to non-pilot stocks. We analyse the effect of Reg SHO change on momentum returns for stocks with and without options. Using a difference-in differences regression design we find a striking decline in the returns to the momentum strategy of -288 bps percent for stocks without options which is economically large and statistically significant while that for stocks with options is neither economically nor statistically significant. These results reinforce the role of options trading since the relaxation of short-sale constraints due to Regulation SHO directly affects portfolios of stocks without options which cannot access the options market channel in order to circumvent short sales constraints.

Taken together, our results show that the stock options market, by contributing to enhanced transactional and information efficiency, plays a role in the secular decline in momentum returns over the last two 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. Next, in Section 4, we study the variation of stock returns with and without options in loser and winner portfolios. Section 5 analyses the role of price informativeness in the momentum profitability. Section 6 shows how short sales and options trading affects the behaviour of momentum with options. Section 7 investigates the implications of our findings during the implementation of the regulation SHO. Section 8 presents a battery of tests for robustness and Section 9 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, Subrahmanyam, and Tong (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. They find that shorting is inconsequential for these strategies in terms of raw returns. However, if investors care about market-adjusted returns then in contrast to size and value, over this longer period too, half of the momentum return premium derives from the short leg.

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 also consider, following Chu, Hirshleifer, and Ma (2016), the natural experiment provided by Regulation SHO to investigate the link between the contribution of stocks with and without traded options to the decline in momentum returns. Briefly, Reg SHO, relaxed short sale constraints on a randomly selected set of stocks (termed pilot stocks) from the Russell 3000 index by removing the "uptick" rule test. Chu et al. (2016) find that the anomalies they study are weaker based on portfolios constructed with pilot stocks and that is driven by lower returns to the short leg. In related work, Haas (2016) finds, using the Reg. SHO experiment, that traders substitute for equity short sales by trading in options markets once short-sale constraints bind. Specifically, she finds that equity market trading volume falls significantly for stocks which are subject to short sale constraints and have options traded. Importantly, as we also do, she finds that up to 60% in short sale constrained stocks moves to the options market.

Finally, our work is related to Hoberg, Kumar, and Prabhala (2017) who study how competition between mutual funds reduces stock mispricing that in turn impacts the profits to momentum trading. They construct a measure of buy-side competition that includes funds that hold a stock and similar funds that compete with this set of funds but do not hold the stock. Using only large-cap stocks (NYSE/AMEX), they find that anomalous momentum returns exist only when fund competition is low. Our work, similar to Hoberg et al. (2017), studies the role of market frictions and obstacles to short sales play in returns to anomalies. Our focus however is different. We explore how the presence of the stock options market creates additional avenues for information flow and for the incorporation of negative information about stocks which contributes to attenuation in momentum profits. 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), recents 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. As a consequence, short selling has become more difficult than before. Such market interventions could, in the future, again create an environment when momentum might again be profitable.

# 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 equity market data covers the period of January 1972 to April 2016. Our option data starts from January 1996. 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: 1973 to 1996 for earlier option introductions, 1996-2013 for stock order imbalances and 2006-2016 for option order imbalances.

**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). Following the literature on momentum, we exclude financial stocks, i.e. stocks with

SIC codes between 6000 and 6900, and stocks with prices less than $5 at the end of the month. 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 total assets and earnings before interest and taxes (EBIT) for constructing the Bai et al. (2016) measure of price informativeness and to construct some of our control variables.

**Stock Options.** We merge the CRSP/COMPUSTAT stock data with options data from the OptionMetrics IvyDB US database which starts from 1996. 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). We consider a stock as an optionable stock if it has, on the last trading day of the month, at least one pair of a call and put option written on that stock with the same strike price and expiration date. We filter the OptionMetrics data (details can be found in the Online Data Appendix) following the literature as in Goyal and Saretto (2009) and Boyer and Vorkink (2014).

Table A1 in the Internet Appendix presents, the total number of listed firms with and without options for every year during our sample period 1996-2016. We note that the growth in the number of stocks with traded options is driven by new option introductions as well as the overall decrease 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, only 20% of our sample of stocks had traded options. By the end of our sample period, in 2016, this percentage has risen to 74%. We depict these changes in Figure A1. Interestingly, we find that just prior to the last financial crisis, the number of stocks with traded options exceeds those without traded options.

**Short Interest and Shorting Fees.** Our data on short interest is from the COMPUSTAT Short Interest Supplemental file. We use the mid-month data (available prior to September 2007) to obtain a longer sample. For each stock, we compute the shares held short as a proportion of the mid-month shares outstanding obtained from the daily CRSP database. As in Hanson and Sunderam (2014), we provide a proxy of shorting fees that captures the shorting interest as a function of the lending supply estimated based on the institutional ownership. In particular, the shorting fee is defined as the ratio of the aggregated short interest in an equity to its institutional ownership (e.g., the total number of shares held by institutions). We employ short interest data from Compustat in order to derive a proxy for firm-level shorting fees by estimating a ratio of the mid-month short interest in a stock to the number of shares of the stock of interest held by 13F institutions. We convert the quarterly institutional holdings to monthly observations by keeping the holdings constant within each quarter. In this way, we assume that the institutional holdings change on a quarterly bases and remain constant otherwise.[2]

**Fails to Deliver.** We obtain fails-to-deliver (FTD) data from the SEC website from 2004 to 2016.[3] 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. 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). We convert the daily FTD to monthly observations by aggregating the daily FTD during the rebalancing period.

**Stock Order Imbalances.** We obtain data to compute the stock order imbalance measures from the Trade and Quote (TAQ) monthly database. Our results using this data are for the

[2]The short interest could server as a proxy of the impact of sophisticated arbitrageurs (e.g., Hanson and Sunderam, 2014). To this end, short interest reflects the marginal share supply that is associated with positions of less sophisticated investors.

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

sub-period 1996-2013 due to the non-availability of the TAQ monthly data after December 2013. In order to classify transactions as either a buy or a sell order we use the Lee and Ready (1991) algorithm that considers the movements of the prices above or below the quote midpoint. 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 $\text{SOI}^{\text{NUM}}$, computes net trading based on the number of trades thus having a higher weight on retail trading. The second measure termed $\text{SOI}^{\text{SH}}$ computes stock order imbalances based on the total volume of shares traded and emphasizes the trading activity of institutional investors. Specifically, these measures of stock $i$ imbalances at time $t$ are defined as

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

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

where $\text{SOI}^{\text{NUM}}$ is the number of buys less number of sells as a fraction of the total trades at time $t$. $\text{SOI}^{\text{SH}}$ is the number of shares bought less number of shares sold as a fraction of the total shares traded at time $t$. Thus, a positive (negative) value of the order imbalance (e.g., $\text{SOI}^{\text{NUM}}, \text{SOI}^{\text{SH}}$) implies that investors are, on average, net buyers (net sellers) of the stocks of interest. We aggregate daily trades to obtain a monthly measure of stock imbalances per stock.

**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 data 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. 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 ones. 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 April 2016. We focus on disaggregated trades for small customers (e.g., retail traders who place option orders of less than 100 contracts each, through a broker) and firms (e.g., a market participant who places an order for her own account).

We follow Bollen and Whaley (2004) and we define option order imbalances for each stock i as:

$$\mathrm{OOI}_{i,t} = \frac{\sum_j^N abs(\Delta_{i,j,t})[(\mathrm{BC_{i,j,t}} + \mathrm{SP_{i,j,t}}) - (\mathrm{SC_{i,j,t}} + \mathrm{BP_{i,j,t}})]}{\sum_\mathrm{j}(\mathrm{BC_{i,j,t}} + \mathrm{SP_{i,j,t}} + \mathrm{SC_{i,j,t}} + \mathrm{BP_{i,j,t}})} \tag{3}$$

where OOI is the number of opening and closing trades call and put option j written on stock i at time t regardless of moneyness and expiration that provides positive exposure to the stock price (e.g., buy calls (BC) and sell puts (SP)) less the 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 opening and closing option trades at time t. In line with our monthly rebalancing strategy, we aggregate daily trades at a monthly level. In other words, a positive option order imbalance means that investors tend on average to buy (sell) call (put) options. Similarly, a negative option order imbalance shows that traders assign upward price pressure on put options and downward price pressure on call options. We focus on delta weighted order flows. This converts raw option orders into units of exposure to the underlying stock.

# 4 The role of Option Trading

We begin by examining the importance of shorting for the profits of the momentum strategy. We then show secular changes and differences in cross-sectional momentum returns, over the 1996-2016 period, for winner and loser portfolios of all listed firms and for firms with and without traded options in our sample period. We compare the differences in momentum returns for these firms using portfolio sorts and Fama and MacBeth (1973) regressions. We finally show that momentum becomes profitable again when it is more expensive to trade in the options market.

### 4.1 The Importance of Shorting for Momentum and Other Anomalies

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. Interestingly, we find that the profitability of the short-leg dependent group of asset pricing anomalies has declined in the last decades. On the other hand, we observe that the performance of long leg-dependent strategies tend to exhibit significant returns in the recent period.

We then hypothesise that strategies with higher exposure to the short leg might be more sensitive to the optionability of the stocks exhibiting less pronounced mispricing. In other words, investors that are involved in such strategies could exploit the lower transaction costs offered in the options market, if they exist, by constructing synthetic short positions or by buying puts or selling calls over these stocks. For that reason, we examine the role of shorting on the profitability of a universe of 94 anomaly-based firm level characteristics studied also by Green et al. (2017).[4] In particular, we allocate stocks into deciles based on each characteristic using NYSE breakpoints. All portfolios are value weighted. The spread portfolios are determined based on their exposure to the short and long positions. Then, we split the portfolios into optionable and non-optionable stocks as it is defined in the data section.

To this end, Figure 2 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 April 2016.[5] The strategies are sorted based on the short leg of each anomaly portfolio. Thus, the

[4]We would like to thank the authors for making their code which constructs the 94 characteristics available on their webpage. Table A6 of the Internet Appendix offers a detailed explanation of the stock characteristics.

[5]The short positions have an opposite sign so as to illustrate their contribution in the spread portfolios.

anomalies appeared on the left (right) part of Figure 2 demonstrate the most (least) negative return of the short position. The bottom graphs of Figure 2 shows the corresponding spread portfolios. We find that momentum is the most profitable strategy and more dependent on its short leg relatively to other anomaly portfolios.[6] 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.

Figure 3 shows the short (with opposite sign) and long positions of stocks with (top graph) and without (middle graph) options following the order of Figure 2. The bottom graph displays the corresponding spread portfolios. We find that the short positions of stocks with options are significantly smaller in comparison to stocks without options consistently with our conjecture regarding the effect of options trading on short positions. Overall, we find that the returns of most of the strategies that depend more on the short-leg tend to be less profitable for optionable stocks relatively to stocks without options.

### 4.2 Univariate Sorts

Once we have shown the importance of shorting for the profitability of cross-sectional momentum we analyse the performance of the strategy when options markets have grown to be easily accessible by retail investors. We start by dividing our full sample period, 1972-2016, into two sub-periods, before and after 1996, 1972-1995 and 1996-2016 as our options data from Optionmetrics is available only after 1996.[7] In the robustness section we also consider equity options introductions from 1973 to 1996 and show that our results do not depend on the choice of our sample.

We report in Table 1, the value-weighted average monthly excess returns to decile momentum portfolios using NYSE breakpoints. Hou et al. (2017) show that many anomalies are driven by microcap stocks which are overweighted when using equal-weighted portfolios with NYSE-AMEX-NASDAQ breakpoints. Fama and French (2008) show that microcaps represent only

[6] One exception is the change in forecasted EPS (chfeps) which offers a very high short position. However, the long position of this strategy is also negative.

[7] We start from 1972 to make our results comparable with other studies in the literature.

3% of the total market capitalization of the NYSE-AMEX-NASDAQ universe but account for 60% of publicly traded stocks. A potential concern with the profitability of momentum returns for stocks without options is that this could be driven by microcap stocks. To alleviate this concern, we follow Hou et al. (2017) and sort our momentum portfolios using NYSE breakpoints and value-weighted excess returns.[8] We also exclude from our sample all financial firms and stocks with prices less than 5 dollars.[9]

Specifically, these decile portfolios are formed by sorting stocks based on their cumulative returns (e.g., R(2,12)) over the last twelve months skipping the most recent month on the formation date. The momentum returns (e.g., WML) reported represent those to an investor who takes a long-short position in the winner and loser portfolios and then holds this position for one month. For each sample period we report the average excess returns as well as CAPM and Fama and French (1993) three factor model (FF3 hereafter) alphas for all the deciles and for the WML spread portfolio. Table 1 shows that the momentum strategy has high and statistically significant average returns of 117 basis points (bps) per month over the full sample period 1972-2016. The returns to this strategy continue to be high (149 bps per month) between January 1972 to December 1995 but they fall by almost 50% to 80 bps per month and are not statistically significant over the period 1996-2016. A closer look at the returns to the winner and loser portfolios shows that the decline in the profitability of the momentum strategy over the period 1996-2016 is mainly driven by the positive returns of the loser portfolios (18 bps per month).

We now focus on the period 1996-2016 and divide our stock sample into stocks that have traded options and those that do not. We consider a stock as having a traded option if it has at least one tradable pair of a call and a put option with the same strike price and expiration date during the rebalancing period (i.e. the last trading day of each month when we form our momentum portfolios). In line with Table 1, we first use the NYSE breakpoints to identify losers and winners stocks and we then partition these into stocks with and without options. Our

[8]We also perform the same analysis relaying on sorts based on the whole NYSE-AMEX-NASDAQ universe of stocks and results are similar but smaller in magnitude than using NYSE breakpoints.

[9]Our results are similar if we only include in our universe the number of stocks that account cumulatively for 90% of the total market capitalization of the NYSE-AMEX-NASDAQ.

results are qualitatively similar if we reverse these steps i.e. first partition all stocks into stocks with and without options and then use NYSE breakpoints. Our analysis considers options with different strike prices and expiration dates. We also use other definitions of stocks with options (i.e. one call and one put with one month to expiration) with qualitatively similar results.

We report in Panel A Table 2 the value-weighted monthly excess returns, CAPM and FF3 alphas for each decile and for the WML spread portfolio separately for stocks with and without options. We find that momentum returns for stocks with options are low and not statistically different from zero (69 bps per month) while for stocks without options they are higher (137 bps per month) and also statistically significant. This decline in momentum returns for stocks with options is driven by the positive payoffs of the loser portfolios (33 bps per month) compared to stocks without options (-35 bps per month) with a similar pattern for CAPM and FF3 alphas.[10] Panel B of Table 2 reports differences between optionable and nonoptionable loser (winner) portfolio returns. We find that the differences between loser stocks with and without options are striking in both economic and statistical terms while we do not observe significant differences between optionable and non-optionable winner portfolios. This finding is in line with our conjecture regarding the contribution of the optionable loser portfolios in the decline of momentum profits.

In our main analysis, we are very restrictive with the definition of optionable and non-optionable stocks (i.e. in Table 2) as we apply different filters in order to ensure tradability of the options attached to the stocks of interest.[11] In addition, we focus our attention on stocks with at least one available call and an one put option. Our current definition of stocks with and without traded options might lead to some stocks switching to and from being optionable. For that reason, in Table A3 of the Internet Appendix we report results before applying the aforementioned filters. We find that the difference in momentum returns between stocks with and without options is much more pronounced than before and this is mainly driven by the more negative returns to the loser portfolio of stocks without options (-72 bps per month).

[10]Table A2 of the Internet Appendix provides summary statistics of stocks with and without options and a detailed description is available in section A1 of the Internet Appendix.

[11]The filters are described of the section 2.2 in the Internet Appendix.

Finally, we compute the performance of the momentum strategy from 1996 to 2016 for momentum portfolios with and without options to demonstrate visually our main point. Figure 4 depicts cumulative returns to winner-loser (WML) momentum portfolios of, all stocks, stocks with and stocks without options. The grey bars indicate the growth in the individual stock options market - each bar represents the stocks with options as a percentage of all our sample stocks - over the 1996-2016 period. Figure 4 shows that momentum profits for stocks without options are much higher than those for a momentum portfolio of stocks with options as well as one of all stocks in the market. Figure 5 confirms that the difference in profitability between momentum portfolios with and without traded options as documented in Figure 4 is driven by the performance of the short-leg of the momentum strategy. Loser portfolios of stocks without options exhibit lower and more negative cumulative returns than losers with options. In contrast, winner portfolios of all firms and firms with and without options exhibit similar cumulative returns.

### 4.3 Cross-sectional Regressions

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

In Table 3 we show the results of the following cross-section regression separately for 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 $t$. $\mathbf{Z}$ represents the set of control variables. 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, stock price, percentage of institutional ownership (IOR), book-to-market, idiosyncratic volatility, reversal return and the illiquidity (ILLIQ) factor.[12]

Table 3 reports the average cross-sectional coefficients and adjusted $R^2$s 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. Interestingly, we find that our results are not affected by size which is a strong determinant of the momentum profitability.

### 4.4 Panel Regressions

We also perform an alternative specification that takes into consideration the whole universe of stocks. In this way, we guard against potential selection biases occurred from the separation between optionable and non-optionable stocks. In particular, Table 4 shows panel regressions of firm's returns on past performance, measured based on the cumulative stock return of the past 12-months (R(2,12)), an option variable ($\mathrm{I}_{Option}$) that takes a value of 1 if a stock is optionable and 0 otherwise as well as an interaction variable ($\mathrm{CumRet}_{i,t}$*$\mathrm{I}_{Option}$) of cumulative returns with the options variable. 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 panel regression coefficients, $t$-statistics with clustered standard errors, and the regression R-squares. We offer results for the whole universe of stocks as well as loser and winner stocks. The main model takes the following form:

$$\mathrm{Ret}_{i,t+1} = \delta_{0,t} + \delta_{1,i}\mathrm{CumRet}_{i,t} + \delta_{2,i}\mathrm{I}_{Option} + \delta_{3,i}\mathrm{CumRet}_{i,t}{*}\mathrm{I}_{Option} + \delta'_{4,i}\mathbf{Z}_{i,t} + \varepsilon_{i,t+1} \tag{5}$$

where $\mathrm{Ret}_{i,t+1}$ denotes the time $t+1$ stock return of firm $i$, $\mathrm{CumRet}_{i,t}$ is the cumulative stock return over the past 12-months of stock $i$ on month $t$. $\mathbf{Z}$ represents the set of control variables.

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

Our regressions consider time- and firm-fixed effects.

We find that the coefficient the cumulative returns is positive for the whole universe of stocks. However, the coefficient of the interaction effect is negative and statistically significant indicating that option trading reduces the momentum profitability due to the enhancement of information flows into loser and to lesser extend winner portfolios. We find that this result is mainly driven by loser stocks. In addition, we find that inclusion of size does not alter our results.

### 4.5 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 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), 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 across option 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.[13] This effect could be driven by limits to arbitrage or

[13] We offer a detailed description of the implied volatility spreads in the Internet Appendix.

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.

Table 5 reports results using double-sorts on R(2,12) and implied volatility spreads from 1996 to 2016 and indicate 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 highly negative and significant (-51 bps) compared to the case in where the puts are relatively cheaper (88 bps). In other words, the momentum strategy for stock with options tends to be profitable when it is more expensive to trade in the options market.

## 5 Have Optionable Losers become more Informative?

The previous section highlights the statistically and economically significant differences in the returns to momentum portfolios of stocks with and without options. These results are mainly driven by the positive returns to the loser portfolios of stocks with options compared to the negative returns for the case of loser stocks without options. In this section, we investigate whether this finding is related to differences in information flows between stocks with and without traded options.

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 high and positive returns. This is partly driven by the lower short-selling constraints of loser portfolios with options relative to the loser stocks without traded options. This 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 informative 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:

$$E_{i,t+1}/A_{i,t} = \alpha_t + b_t \log(M_{i,t}/A_{i,t}) + c_t(E_{i,t}/A_{i,t}) + d_t^s \mathbb{1}_{i,t}^s + \varepsilon_{i,t} \tag{6}$$

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.

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.[14] We define price informativeness (PI) as the product of the cross-sectional beta of market capitalization to asset ratio (e.g., $b_t$) with the cross-sectional standard deviation of $\log M_t/A_t$ within each portfolio in month $t$:

$$PI_t = b_t \times \sigma_t(\log(M_t/A_t)) \tag{7}$$

Panel A of Table 6 shows the estimates of the price informativeness measure for loser, winner and the spread (WML) portfolios for all stocks and stocks with and without options along with the associated $t$-statistics. We find that there is no significant difference between loser and

[14]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.

winner portfolios for all stocks and stocks with options. In contrast, we find that the winner portfolio of stocks without options has a higher informativeness measure (0.833) relative to the corresponding loser portfolio (0.43). We also note that the informativeness measure is higher for stocks with options compared to stocks without options.

Panel B reports differences in price informativeness between loser (winner) portfolios of stocks with and without options. We find that price informativeness is 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 0.393 and this is statistically significant. However, the difference between winner portfolios of stocks with and without option is -0.010 and not statistically significant.

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 2). It is likely that momentum returns for stocks with options tend to be insignificant because option trading enhances information flow 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 loser stocks with options compared to loser stocks without options.

Figure A2 depicts cross-sectional betas, price informativeness and marginal $R^2$ of loser and winner portfolios. We show results for momentum portfolios of all stocks and for stocks with and without options. The figures are centred around the rebalancing date and all variables are estimated over a 36-month rolling window. Of interest in these graphs is the difference between the two groups. Figure A2 shows that the coefficients, marginal $R^2$, and the price informativeness all display an upward trend for the portfolio of losers stocks with options relative to the loser portfolio without options. This contrasts to the case of winner portfolios where the difference between option and no-option portfolios is much lower. The dramatic increase in the number of stocks with options, in the recent past, shown in Figure A1 likely contributes to the small difference between stocks of all firms and stocks with options found in the last part of our sample.

# 6 Short-Sale Constraints and Option Trading Activity

We now study the link between short sales and options markets. We first focus on the short demand side, in where an investor implementing a long/short strategy can choose either stock or options to establish a short position. We start by confirming earlier studies which show that optionable stocks have higher significant short interest than stocks without traded options. To this end, short interest should be more pronounced for loser stocks with options. We then examine whether the higher short interest for the loser portfolios of stocks with traded options results from a large options traders demand for short option positions - option traders buying more puts and writing more calls for these particular stocks- as manifested in their option order imbalances. Finally, we focus on the short supply side and on the hedging motives of option market markers.

## 6.1 Short Interest and Momentum Portfolios

We first examine whether short interest is higher for stocks that have traded options relative to stocks without traded options and its relation to the loser portfolios of stocks with options. The options market provides an alternative trading avenue for investors with unfavourable 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 interest. If it is the case, we ought to see higher short interest especially in the case of loser stocks with options.

Table 7 reports monthly time-series averages of short interest of all the momentum strategy decile portfolios (both for stocks with and without options) for the period of 1996 to 2016 during the rebalancing period. We find in Panel A of Table 7 that short interest is higher for stocks with options than for stocks without options. We also find that average short interest is substantially higher for loser portfolios of stocks with options resulting in a very negative and significant WML spread.[15] In contrast, the average short interest for decile portfolios of stocks without options is smaller and the difference between the short interest of winner and loser portfolios remains negative but not significant. As Panel B in Table 7 shows, the average short interest, for the WML portfolio, is -0.004 in the case of stocks with options compared to -0.015 for stocks without options. For the period from 1973-1976 i.e. the period prior to the availability of detailed options data we find, that average short interest is low and the difference between short interest in loser and winner portfolios is positive but not significant. These untabulated results imply large volume of short interest coincided with the huge growth in stock options after 1996.

Next, we run cross-sectional Fama and MacBeth (1973) regressions of firm-level excess stocks returns over the holding period on lagged cumulative returns and short interest. We estimate:

$$\text{Ret}_{i,t+1} = \delta_{0,t} + \delta_{1,i}\text{R(2,12)}_{i,t} + \delta_{2,i}\text{Short Interest}_{i,t} + \delta'_{3,i}\mathbf{Z}_{i,t} + \varepsilon_{i,t+1} \tag{8}$$

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 $t$. $\mathbf{Z}$ represents the set of control variables. We control for a number of factors that might also affect the returns to the momentum strategy as reported in our earlier regression-based tests and indicate robust $t$-statistics.

Table 8 reports results of the above predictive regression of short interest on subsequent momentum returns. We expect that the average coefficient of the short interest is negative since low short interest likely reflects higher mispricing and therefore higher returns to momentum portfolios. For momentum portfolios of stocks with options we would expect the average coefficient to be less negative since for these stocks investors can use the alternate shorting route available

[15]We find that the high levels of short interest are more concentrated in stocks with more put option trading. Specifically, we find that short interest is substantially higher for loser stocks with high put ratios. This is in line with our conjecture regarding the effect of option trading on short interest.

in the options market. In fact, if options trading allows pessimistic investors to take effective short positions without selling short directly, this effect should be reduced for optionable stocks.

We find, in Table 8, that short interest predicts excess returns with a negative sign and this effect is more extreme for stocks without options. In particular, we find an average coefficient of short interest of -0.042 for stocks with options as opposed to an average coefficient of -0.095 for stocks without options. These results are consistent with those reported earlier in Table 3. We also provide in Table A4 of Internet Appendix cross-sectional regressions of short and medium term momentum. We find that short term and medium term momentum strategies cannot explain the cross-sectional variation of stocks with or without options indicating that R(2,12) is a strong determinant of stock prices even after controlling for other formation periods. Finally, in line with Figlewski and Webb (1993) we find that if trading in options allows for unfavourable information to enter stock prices indirectly (e.g., in loser portfolios), the negative association between high short interest and subsequent excess returns should be mitigated or eliminated for stocks with traded options. Specifically, we find that the return of loser portfolios becomes positive when short interest is high. This is in line with Hanson and Sunderam (2014) who show that the increasing number of arbitrageurs who try to exploit the momentum returns results in a weaker relationship between short interest and stock returns. Here, we show that this effect is more pronounced for loser stocks with options due to the effect of option trading activity.

### 6.2 Option Trading and Momentum Portfolios

In the previous section, we show that short interest is substantially higher for loser portfolios of stocks with options. We now study whether this higher short interest is related to a higher demand for short positions for the loser stocks in the options market. In fact, if investors with unfavourable 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. Moreover, after an options trader executes a transaction, the options market maker takes the opposite position which allow us to relate short interest with delta-hedge option order imbalances.

We report, in Table 9, the time-series monthly averages of 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.[16] Panel A offers aggregate results for all market participants. We find that option traders establish more short selling positions for loser portfolios compared to those in the winner portfolios. In particular, the average delta-hedge option order imbalances is -0.013 and significant. In contrast, the average option order imbalances for winners remains negative -0.002 but insignificant. The difference between the two (0.021) 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. We also report (Panel B) separately average option order imbalances initiated by firms and small customers. We show that these short option positions are mainly driven by orders initiated by small customers (i.e. retail investors) rather than firms.[17]

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, short interest and the set of lagged control variables used earlier. We estimate the following regression:

$$\mathrm{OOI}_{i,t+1} = \delta_{0,t} + \delta_{1,i}\mathrm{R(2,12)}_{i,t} + \delta_{2,i}\text{Short Interest}_{i,t} + \delta'_{3,i}\mathbf{Z}_{i,t} + \varepsilon_{i,t+1} \tag{9}$$

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.

[16] In unreported results, and for the period 1996-2016, we use unsigned PUT and CALL ratios and find that put (call) volume dominates in the case of loser (winner) stocks.

[17] In the Robustness section we examine the behaviour of the daily option order imbalances around the rebalancing period. In line with our reasoning, investors tend to be net sellers of options written on the loser stocks specially around the time in where the momentum strategy is rebalanced.

Table 10 reports the results of this estimation. We use aggregate trades of all participants in the market as well as separately for small customers and firms. 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 small customers and firms. We find that the cumulative return R(2,12) also positively predicts option order imbalances of small customers. However, there is no evidence of predictability for option order imbalances of firms.

In addition, we show that short interest negatively predicts the option order imbalances over the holding period. In particular, we observe a negative and statistically significant coefficient of the short interest for both firms and small customers. The coefficient for firms is much larger, in absolute value, than the coefficient of small customers as firms respond more heavily to changes in short interest by increasing their exposure in the options market.

Our previous analysis focuses on the net effect of option order imbalances which could reflect both negative and positive information. In other words, the measure considers both long and short positions. We also provide in Table A5 of the Internet Appendix cross-sectional regressions of short and long synthetic positions on cumulative returns and short interest providing similar results.

### 6.3 Shorting Fees and Fails to Deliver

We now turn to study the variation of shorting fees and fails to deliver within loser and winner portfolios as a proxy for shorting supply in the case of portfolios of stocks with and without options. The previous section shows that there is more option trading activity for loser portfolios that results in higher shorting demand. Of interest here is whether this higher shorting demand affects the stock loan market and results in higher equity 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 increase supply, but rather passes through the demand to the equity lending market. If that is the case we should expect higher 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. 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).[18] To this end, the option market can offer elastic supply of stocks for short selling. In addition, Evans et al. (2008) shows that option market makers fail to deliver when hard-to-borrow stocks are recalled and this has an effect on option prices. In this section, we test the existence of such mechanism for the momentum strategy.

Consistently with our conjecture, we find in Panel A of Table 11 that shorting fees are on average higher for stocks without options. In Panel B we find that the shorting fees of loser portfolios with options are lower than the corresponding loser portfolios of the stocks without options. In addition, there are significant differences in the shorting fees of winner and loser portfolios of stocks with options. We find in Panel C that there are more fails to deliver for optionable losers than for losers without options.[19] These findings are in line with our conjecture regarding the role of option trading for optionable loser stocks as the higher levels of shorting supply -due to option trading- render high short selling, lower shorting fees and more fails to deliver.

[18]We note that prior to 2008 option market makers, due to an exemption, could use naked short selling. Regulators removed this exemption in 2008 and in 2013 and they also prohibited a workaround that market makers were using through reverse conversions. Blocher and Ringgenberg (2018) find that these regulatory changes have increased the redundancy of option securities and caused a significant increase in equity loan fees. Following these exemptions market quality has deteriorated as price efficiency is lower and stocks are more overpriced.

[19]Fails to deliver correspond to the period of March 2004 to April 2016.

### 6.4 Stock Trading and Momentum Portfolios

We show that options traders 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. If the loser stocks with options are less overpriced we should not expect negative selling pressure 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 1996-2013 to investigate the stock trading activity of losers and winner portfolios. Panel A of Table 12 shows the average monthly stock order imbalances of the all-stock momentum portfolio while Panel B (Panel C) displays the corresponding results for stocks with (without) options. We find for the momentum portfolio with all stocks that retail investors (denoted as $\mathrm{SOI}^{\mathrm{NUM}}$) tend to be net buyers of the winner portfolios. However, for these stocks there is no significant trading activity of institutional investors (denoted by $\mathrm{SOI}^{\mathrm{SH}}$). On the other hand, we find that for both retail and institutional trading our measure is positive and highly significant for the winner portfolio of stocks with options. This implies that on average investors are net buyers of the portfolio of stocks with options that performed well in the previous period.

However, the order imbalances in the loser portfolios of stocks with options, are neither economically nor statistically significant. 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. Finally, we observe that the loser portfolio of stocks without options have on average negative order imbalances that are economically and statistically significant rendering a significant momentum return for stocks without options.

Our results, using stock order imbalance data, imply that retail investors and, to a lesser extent institutional 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 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 thanks to the role of the options market.

# 7 Causal Effect of Limits to Arbitrage and Option Trading

In this section, we investigate whether there is a causal link between the presence of options and momentum profitability using an quasi-random change in short sale constraints to stocks with and without traded options. To this end, we use Reg SHO which was a program adopted by the Securities and Exchange Commission (SEC) in July 2004. Regulation SHO removed the short-sale price tests (removal of the uptick rule) for every third stock ranked by trading volume in the Russell 3000 index. These stocks were designated as pilot stocks and this exemption ran from May 2, 2005 to August 6, 2007. Simply put, it was easier to short pilot stocks, during this Regulation SHO period, relative to non-pilot stocks. The initial sample of the pilot group comprises 986 stocks. Following the literature (see for example, Diether, Lee, and Werner, 2009) that relies on Reg SHO we use data only on NYSE and AMEX stocks.

We show, consistent with Chu et al. (2016), that during the Reg SHO momentum returns are lower but not statistically significant for the portfolio of pilot stocks (easier to short sell) relative to non-pilot stocks. Our work deviates from Chu et al. (2016) as we analyse the effect of Reg SHO change on momentum returns for stocks with and without options. Our hypothesis is that Reg SHO did not have much effect on returns to momentum portfolios of stocks with options but reduced them substantially for stocks without options. To test this, we first partition our sample of NYSE/AMEX firms into two groups: stocks with and without options. In each group, we now use the allocation into pilot and non-pilot stocks thus preserving the randomness in the Reg SHO experiment. We now end up with four sub-samples; pilot stocks with and without listed options and non-pilot stocks with and without options. Our empirical strategy is to use a difference-in-differences (DiD hereafter) approach, similar to Chu et al. (2016), preserving the random selection of the pilot and non-pilot groups and to study the differences between stocks with and without options.

We begin by confirming the random nature of the assignment of stocks to the pilot and non-pilot groups and our further two sub-categories. This is important as we would like to ensure that differences arise only from the effect of Reg SHO and there is no major difference in cumulative returns in the period prior to the announcement of Reg SHO. Table 13 reports cumulative returns for pilot and non-pilot firms before the start of the Reg SHO program. We focus on December 2003 (Panel A) which is the date before the announcement of the short selling pilot program in order to avoid any contamination due to the effects of the pilot program. We report cumulative returns for pilot and non-pilot stocks (with and without options) as well as their corresponding differences. Our results show that there are no systematic differences in the cumulative returns between the pilot and the non-pilot groups and for the groups further sub-divided into stock with and without options. Hence, if we find any differences between the pilot and non-pilot firms during the Reg SHO period we can be reasonably assured that these are not due to differences prior to the start of Reg SHO.

In order to provide the power of the DiD methodology, Chu et al. (2016) suggest showing anomaly returns during the pilot program for only non-pilot firms. By doing so, we ensure that momentum anomaly exists if there is no change in the market. This analysis also provides evidence of the underlying parallel trend assumption. Our earlier results show that the momentum anomaly is stronger for stocks without options (due to greater restrictions on short selling). If we find that momentum anomaly exists for the non-pilot group (stocks with short sale restrictions) in a smaller sample and for a shorter period, then this could support the parallel trend assumption. Our hypothesis is that the momentum anomaly exists for stocks without options but is attenuated for stocks with options. Panel B of Table 13 reports momentum returns as well as the corresponding CAPM and FF3 alphas for non-pilot firms during the pilot program.

We see that the momentum returns are highly significant for non-pilot stocks without options and insignificant for stocks with options. These results are similar to those in Table 2 (but for a smaller sample and a different time period).

Next, having confirmed that there are no differences in the cumulative returns of pilot and non-pilot stocks with and without options prior to the initiation of the pilot program, we use a difference-in-difference analysis to study any causal relation between the relaxation of short sale constraints and momentum returns. Our sample period here begins in January 1996 due to the options data availability. We estimate the following DiD regression:

$$Ret_{i,t} = \alpha_t + \beta Pilot_i * During_t + \beta_1 Pilot_i + \varepsilon_{i,t}$$

where $Ret_{i,t}$ corresponds to the monthly return of loser, winner or spread portfolios, in month $t$; $\alpha_t$ is the time-fixed effects, which are associated with the common factors that capture the variability of both pilot and non-pilot portfolios; $Pilot_i$ is a dummy variable which is equal to one if the portfolio of interest corresponds to pilot firms (e.g., the treatment group), and zero otherwise; $During_t$ is a dummy variable, which equals one if month $t$ is between June 2005 and August 2007 (i.e., during the pilot program of Regulation SHO). $During_t$ is not included in the regression because it is subsumed by the time-fixed effects (FE).

We first construct momentum portfolios for four groups separately: stocks with options (pilot group), stocks with options (non-pilot group), stock without options (pilot group) and stocks without options (non-pilot group). We construct winner, loser and WML portfolios for each of these four samples. We then examine three sets of DiD estimations to study if momentum returns are different for pilot groups compared to non-pilot groups in each set of estimations.

Table 14 presents the main results of the DiD estimation for the long leg (i.e. winner stocks), short leg (i.e. loser stocks) and the WML portfolio returns. The sample period is between January 1996 and August 2007, the portfolios are equal-weighted using only NYSE/AMEX stocks. We also use time-fixed effects in the DiD regression. Panel A of table 14 reports results for all sample stocks (i.e. both with and without options). Consistent with Chu et al. (2016), we find that momentum returns decrease for the pilot group in comparison with the non-pilot group when all stocks are used in the momentum portfolio construction. In the case of stocks with options, the decline is less pronounced. These differences are not statistically significant.

On the other hand, the striking part of our analysis is concentrated in the universe of stocks without options. Here we see that the decline in the returns to the momentum strategy is -288 bps per month which is economically large and statistically significant. We also find a decline on WML for stocks with options but it is not economically or statistically significant. Panels B and C, of table 14 report results for benchmark-adjusted returns instead of raw returns based on CAPM and Fama and French (1993) (FF3) three-factor models. We find that our results are consistent with Panel A.

Taken together, our results suggest that relaxation of short selling constraint by Reg SHO for a random group of stocks reduces the momentum profits but only for stocks without options but not for stocks with traded options. These results provide further evidence supporting our main point that the presence of the individual stocks options markets increases both information flows and reduces short sale constraints resulting in the lower mispricing of stocks in the loser portfolios (i.e. the short leg) and the attenuation of returns to momentum portfolios.

# 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 full sample period.

## 8.1 Earlier Option Listing

The previous analysis consider stocks with options starting from January 1996 due to data availability from Optionmetrics. Similar to Mayhew and Mihov (2004), we identify equity options chosen for listing on all domestic exchanges from 1973 to 1996. 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 1973.

*Panel A* of Table 15 shows average returns and the corresponding CAPM and FF3 alphas of stocks with or without options for the period of June 1977 to April 2016. Our monthly series starts from June 1977 as we have enough stocks in each of our decile portfolios from that date. 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 introduced. 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 less accesible 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 15 shows that only the differences between optionable and nonoptionable losers is statistically significant. In particular, we find that the return of the optionable loser portfolio is positive while the corresponding return of the loser portfolio of stocks without options is negative. 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 Arbitrage Activity and Option Trading

Earlier, we found that portfolios of stocks with options have a higher level of informativeness, using the Bai et al. (2016) measure, relative to portfolios of stocks without options. This implies that the existence of an options market might lead to lower mispricing and consequently lower anomaly returns. We now investigate whether arbitrage activity is different between winner and loser portfolios of stocks with and without options. Arbitrage activity is, however, difficult to measure due to a lack of data about how arbitrageurs - utilise their capital under management, short-selling, and derivatives contracts in conducting arbitrage trades. Lou and Polk (2012) suggest a measure defined as comomentum that is a good proxy for arbitrage activity especially in the case of unanchored anomaly strategies like momentum (e.g., Stein, 2009). Essentially their measure computes an average partial autocorrelation for pairs of stocks in winner and loser portfolios over the look-back period. They find, using this measure, evidence of destabilizing arbitrage activity due to the increasing growth in arbitrage capital over the last thirty years.

In related work, Liu, Lei, Bo, and Hongjun (2015) propose a stylized model of anomaly discovery with testable predictions. Relevant to our study is that their arbitrage activity, after an anomaly discovery, leads to a reduction in the correlation between extreme anomaly portfolios i.e. the long and short portfolios. They test this prediction by studying whether the correlation between deciles 1 and 10, formed from the corresponding portfolio sort, decreases after the discovery of the anomaly. They find, using a five-year rolling window to estimate the correlation, that it fluctuates between 0.6 and 0.8 in the six decades before the publication of Jegadeesh and Titman (1993). Subsequent to this the correlation drops significantly to around 0.4. They relate this to the rise in hedge fund activity which proxies for the increased flow of arbitrage capital. The predictions of this model about information revelation should also hold for the differential flow of information facilitated by the equity options market in the case of stocks with traded options relative to stocks without traded options. We therefore use, the formal test in Liu et al. (2015) to study whether correlations differ between winner and loser portfolios of CBOE-listed stocks and stocks without options. For momentum, we compute the correlation ratio as:

$$\mathrm{X}_t = \frac{\rho_t^{W,L}}{\rho_t^{5,6}} \tag{10}$$

where $\rho_t^{W,L}$ is the correlation coefficient between the monthly excess returns of the Winner and Loser momentum portfolios during a rolling five years prior to month t. This correlation is normalized by the correlation between portfolios in Decile 5 and 6: $\rho_t^{5,6}$ in order to control for potential time trend in the correlations.

We calculate the correlation coefficients using different rolling windows and report results in

Table 16. We also report the results of regressing the ratio $X_t$ on Option, a dummy variable that takes the value of 1 if the stock has an option and 0 for non-option for WML momentum portfolio of stocks with and without options. We use pooled OLS regressions with robust standard deviations. The correlation coefficient is based on 1 to 5 years rolling windows.

$$\mathrm{X}_t = \alpha + \beta \mathrm{Option}_{i,t} + \epsilon_{i,t} \tag{11}$$

where Option is a dummy variable that takes the value of 1 if the stock has an option and 0 otherwise.

Panel A of Table 16 reports the correlation coefficients for the spread portfolio of winner minus loser portfolios of all stocks, stocks with and stocks without options. We find that $\mathrm{X}_t$ is higher for WML portfolios of stocks without options (e.g 0.74 for 5 years) and lower for both stocks with options and for all stocks together (0.59 and 0.61 respectively). This suggests that, as predicted by the model, the presence of individual options trading facilitates the flow of information reducing the correlation between the extreme portfolios relative to that of stocks without traded options. Thus, the correlations are higher for companies without traded options regardless of the length of the rolling window.

Panel B of Table 16 reports the regression results. The coefficients for the option dummy are between -0.139 to -0.164 in a statistically significant fashion. This implies that the correlation ratio decreases by 0.15 for stocks with options relative to stocks without options.

## 8.3 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 average positive (negative) stock (option) 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). Figures A3 and A4 display stock and option imbalances of loser (in blue) and winner (in red) portfolios as well as a “reference” portfolio (dashed black line) that corresponds to the cross-sectional average of order imbalances of momentum portfolios (e.g., the cross-section of R(2,12) decile portfolios) at each point of time.

In particular, Figure A3 demonstrates stock order imbalances of the portfolios for a 20-day window around the rebalancing date (date 0) for the period January 1996 to December 2013. The upper left graph shows results of the whole universe of stocks in our sample while the top right (bottom) graph shows results for stocks with (without) options. We find that investors tend to be on average net buyers (sellers) of winner (loser) portfolios when considering the whole universe of equities. This pattern is mainly driven from the group of stocks without options and can partly explain the profitability of the momentum strategy for stocks without options because there is negative price pressure on the constituents of the loser portfolios that makes their returns more negative and the momentum returns positive and statistically significant.

On the other hand, investors tend to be net buyers of winner portfolios with options creating positive price pressure on the winner portfolios. However, trading activity for loser stocks with options is not significant and investors are more involved in the options market. This is in line with the fact that investors tend to be net sellers of options written on loser and winner portfolios (figure A4) as shorting is less expensive in the options market. The top right and bottom graphs of figure A4 illustrate that this pattern is mainly driven by the trading activity of retail investors. Overall, we find that retail investors tend to be net buyers of stocks with options that comprise the loser portfolio and net sellers of the options that are written of the aforementioned stocks in an attempt to alleviate short-selling constraints in the stock market.

# 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. More importantly, momentum is the most prominent and short leg-dependent strategy among the universe of 94 strategies studied by Green et al. (2017).

However, returns to cross-sectional momentum have attenuated during the last two decades 1996-2016 relative to the prior two 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 20% of all stocks traded in 1996 to 74% in 2016. 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 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 flow about variations from fundamental value especially the reduction in short sale constraints can result in reduction in 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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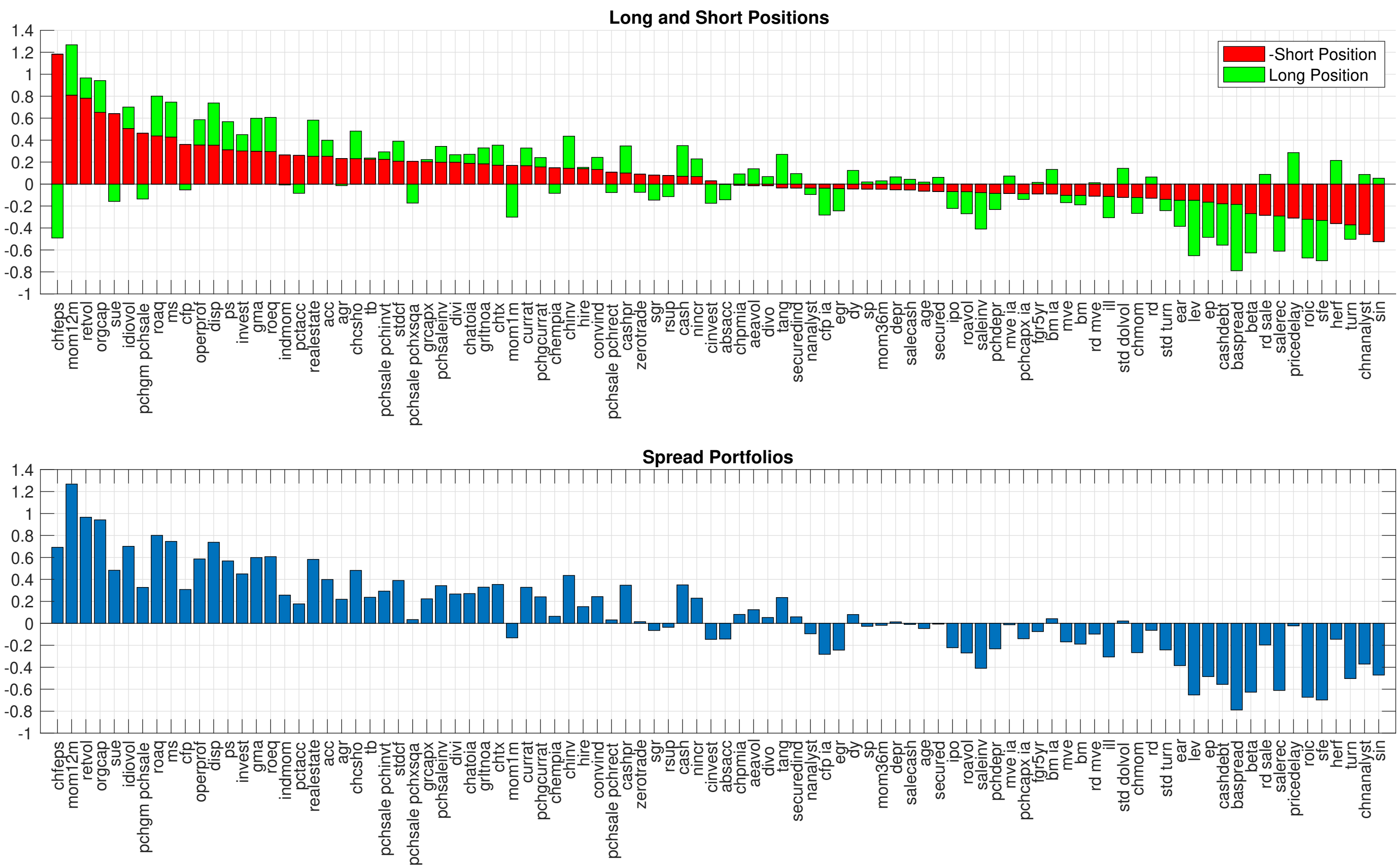
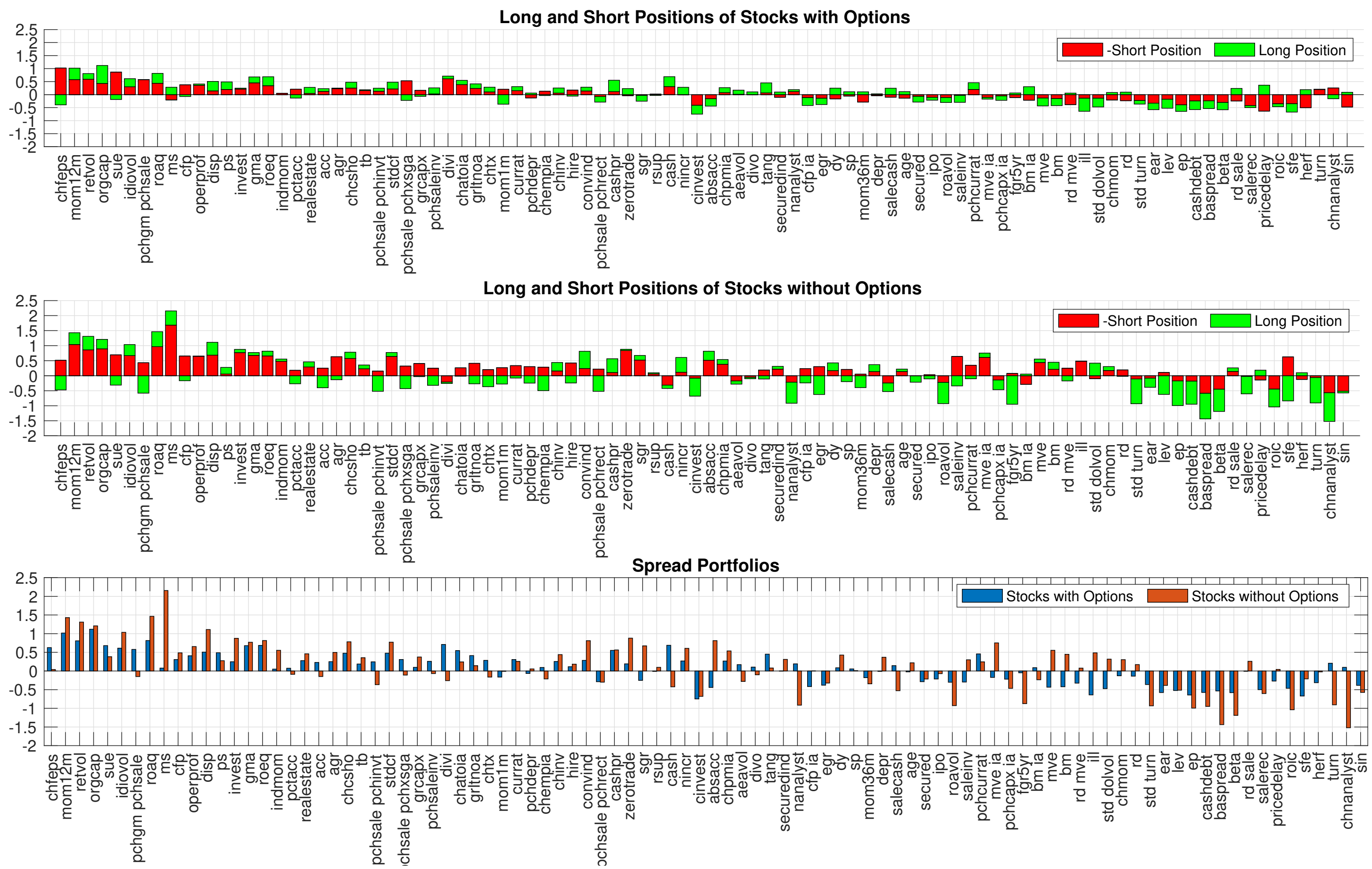
## Figure 2. Alphas of Anomaly Portfolios



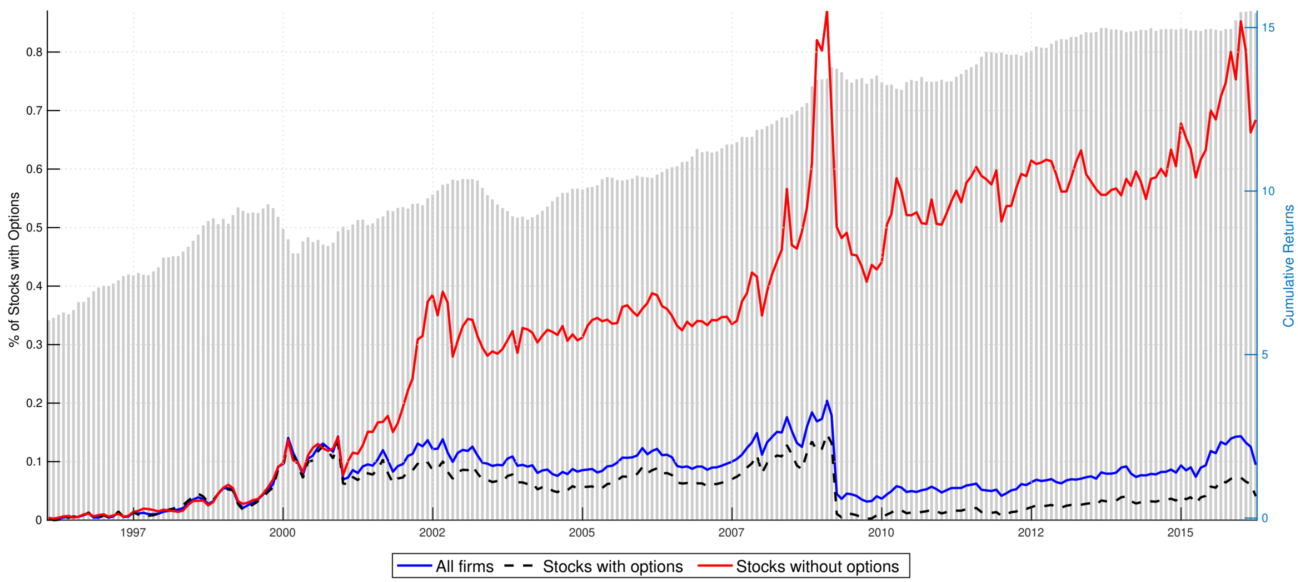

The figure displays alphas of the Fama and French (1993) 3-factor model (FF3) for long and short positions (with opposite sign) of 94 anomaly portfolios (top graph) and the corresponding spread portfolios (bottom graph). The ordering of the anomalies is based on the magnitude of the short position. The data is monthly from January 1980 - April 2016. However, a small number of anomalies start on a later date due to data availability.

**Figure 3. Alphas of Anomaly Portfolios with and without Options**



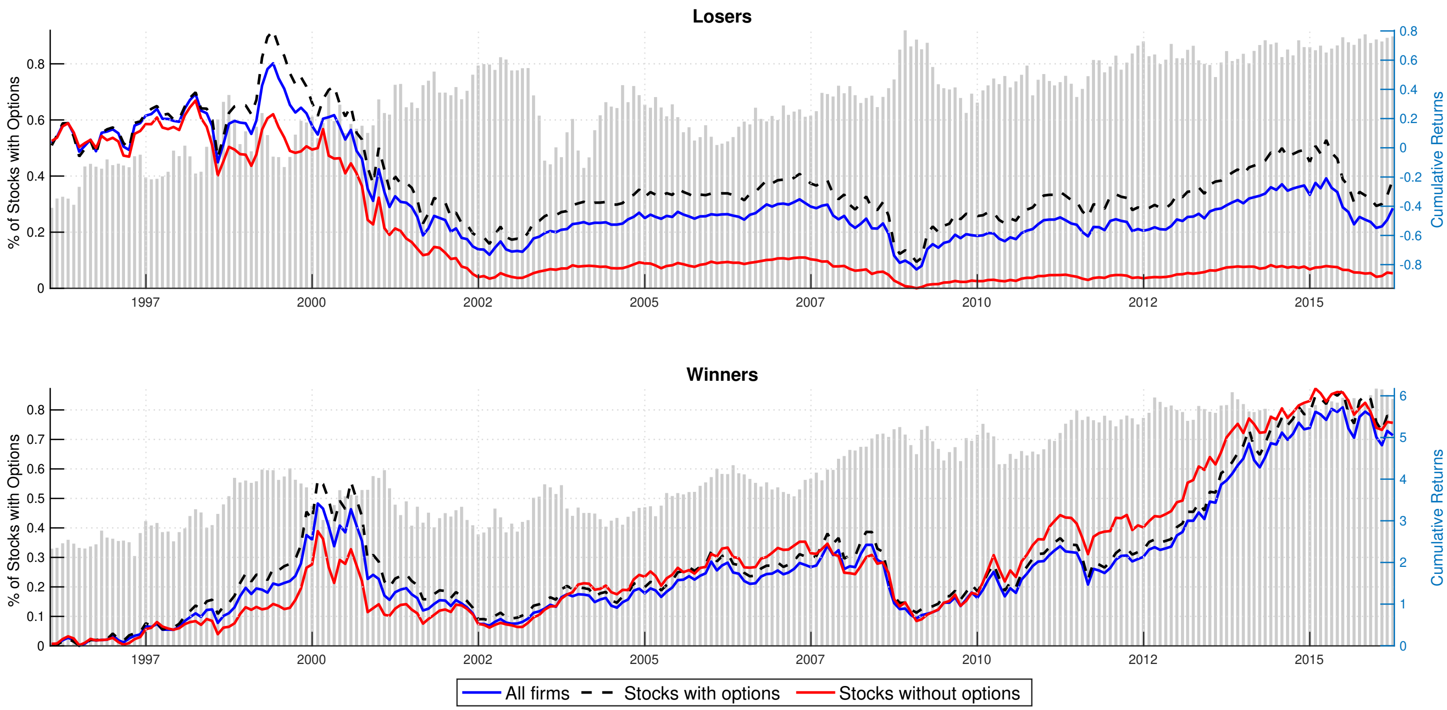

The figure displays alphas of the Fama and French (1993) 3-factor model (FF3) for long and short positions (with opposite sign) of 94 anomaly portfolios and the corresponding spread portfolios (bottom graph). We consider stocks with (top graph) and without (middle graph) options. The ordering of the anomalies is based on the magnitude of the short position using the full sample period. The data is monthly from January 1996 - April 2016.

## Figure 4. Cumulative Returns of Momentum Portfolios




The figure displays the cumulative returns of WML portfolios for all stocks, stocks with and without options. We also report in grey bars the percentage of stocks with options in our sample every month. The data is monthly from January 1996 - April 2016.

## **Figure 5.** *Cumulative Momentum Returns of Loser and Winner Portfolios*




The figure displays the cumulative returns of loser and winner portfolios for all stocks, stocks with and without options. We also report in grey bars the percentage of losers and winners stocks with options in our sample every month. The data are from a merged CRSP and OptionMetrics data set. The graphs depict monthly cumulative return series from January 1996 to April 2016.

## Table 1. Returns to Momentum Portfolios

Decile portfolios are formed every month from January 1972 to April 2016 by sorting stocks based on the previous period 12-month cumulative returns (R(2,12)) after skipping the most recent month using NYSE breakpoints. Decile 10 indicates the winner portfolio, Decile 1 denotes the loser portfolios and WML indicates the winner-minus-loser portfolio. The table reports the value weighted average excess monthly returns for each decile portfolio as well as the corresponding alphas of the CAPM and the three-factor Fama and French (1993) model (FF3). The last two rows present the differences in monthly returns and the differences in alphas between winners and losers portfolios with their associated HAC adjusted $t$-statistics ($t$-stat). Average raw and risk-adjusted returns are given in percentage terms. The samples cover January 1972 to April 2016, January 1972 to December 1995 and January 1996 to April 2016, respectively.

| Stock returns | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Jan 1972 - Apr 2016 | | | Jan 1972 - Dec 1995 | | | Jan 1996 - Apr 2016 | | |
| *Decile* | Avg Ret | CAPM Alpha | FF3 Alpha | Avg Ret | CAPM Alpha | FF3 Alpha | Avg Ret | CAPM Alpha | FF3 Alpha |
| Losers | -0.119 | -0.829 | -0.940 | -0.375 | -0.948 | -1.004 | 0.184 | -0.705 | -0.777 |
| 2 | 0.423 | -0.137 | -0.241 | 0.308 | -0.181 | -0.249 | 0.559 | -0.090 | -0.161 |
| 3 | 0.541 | 0.027 | -0.069 | 0.353 | -0.115 | -0.171 | 0.764 | 0.195 | 0.124 |
| 4 | 0.465 | -0.006 | -0.068 | 0.261 | -0.191 | -0.242 | 0.705 | 0.216 | 0.173 |
| 5 | 0.436 | -0.035 | -0.088 | 0.387 | -0.077 | -0.102 | 0.494 | 0.022 | -0.021 |
| 6 | 0.496 | 0.015 | -0.030 | 0.393 | -0.096 | -0.095 | 0.618 | 0.156 | 0.101 |
| 7 | 0.599 | 0.129 | 0.124 | 0.629 | 0.162 | 0.198 | 0.564 | 0.097 | 0.076 |
| 8 | 0.676 | 0.180 | 0.196 | 0.666 | 0.179 | 0.267 | 0.688 | 0.188 | 0.169 |
| 9 | 0.736 | 0.204 | 0.252 | 0.918 | 0.393 | 0.489 | 0.521 | -0.012 | 0.004 |
| Winners | 1.053 | 0.402 | 0.560 | 1.109 | 0.509 | 0.684 | 0.987 | 0.275 | 0.367 |
| WML | 1.172 | 1.231 | 1.500 | 1.485 | 1.458 | 1.688 | 0.804 | 0.980 | 1.145 |
| $t$-stat | 4.01 | 4.43 | 5.47 | 4.21 | 4.04 | 4.83 | 1.59 | 2.18 | 2.69 |

## Table 2. Momentum Returns for Stocks with and without Options

Decile portfolios are formed every month from January 1996 to April 2016 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 using NYSE breakpoints. Decile 10 indicates the winner portfolio, Decile 1 denotes the loser portfolios and WML indicates the winner-minus-loser portfolio. The table reports the value weighted average excess monthly returns for each decile portfolio as well as the corresponding alphas of the CAPM and the three-factor Fama and French (1993) model (FF3). 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.

Stock returns

| | Stocks with Options | | | Stocks without Options | | |
|---|---|---|---|---|---|---|
| *Decile* | Avg Ret | CAPM Alpha | FF3 Alpha | Avg Ret | CAPM Alpha | FF3 Alpha |
| Losers | 0.328 | 0.135 | 0.133 | -0.345 | -0.530 | -0.513 |
| 2 | 0.522 | 0.444 | 0.424 | 0.693 | 0.511 | 0.512 |
| 3 | 0.778 | 0.702 | 0.696 | 0.846 | 0.744 | 0.734 |
| 4 | 0.707 | 0.665 | 0.674 | 0.848 | 0.721 | 0.749 |
| 5 | 0.513 | 0.478 | 0.505 | 0.818 | 0.750 | 0.782 |
| 6 | 0.637 | 0.610 | 0.646 | 0.617 | 0.520 | 0.535 |
| 7 | 0.558 | 0.497 | 0.536 | 0.570 | 0.489 | 0.510 |
| 8 | 0.698 | 0.644 | 0.687 | 0.695 | 0.630 | 0.665 |
| 9 | 0.470 | 0.439 | 0.486 | 0.614 | 0.516 | 0.555 |
| Winners | 1.017 | 0.968 | 1.043 | 1.025 | 0.926 | 0.959 |
| WML | 0.689 | 0.833 | 0.911 | 1.370 | 1.455 | 1.472 |
| $t$-stat | 1.29 | 1.63 | 1.82 | 2.75 | 2.97 | 2.92 |

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

| | $\Delta$Losers | $\Delta$Winners |
|---|---|---|
| Avg Ret | 0.673 | -0.008 |
| $t$-stat | 2.13 | -0.03 |

## Table 3. Cross-Sectional Regressions - Stock Returns

This table presents results from Fama-MacBeth regressions of 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-squareds. 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 $t$. $\mathbf{Z}$ represents the set of control variables.

| Stock Returns | | | | |
|---|---|---|---|---|
| | *Stocks with Options* | | *Stocks without Options* | |
| | (1) | (2) | (3) | (4) |
| Intercept | 0.006 | 0.021 | 0.008 | 0.029 |
| *t-stats* | 1.65 | 1.98 | 2.08 | 3.41 |
| $\text{CumRet}_{i,t}$ | 0.003 | 0.004 | 0.005 | 0.008 |
| *t-stats* | 0.85 | 1.40 | 2.36 | 3.85 |
| *Control Variables* | | | | |
| $\text{Ln(Size)}_{i,t}$ | | 0.000 | | -0.001 |
| *t-stats* | | 0.23 | | -1.26 |
| $\text{Ln(Price)}_{i,t}$ | | -0.004 | | -0.002 |
| *t-stats* | | -2.47 | | -1.58 |
| $\text{IOR}_{i,t}$ | | 0.001 | | 0.000 |
| *t-stats* | | 0.36 | | -0.02 |
| $\text{B/M}_{i,t}$ | | 0.000 | | 0.001 |
| *t-stats* | | 0.30 | | 1.07 |
| $\text{IVOL}_{i,t}$ | | -0.202 | | -0.294 |
| *t-stats* | | -2.02 | | -3.63 |
| $\text{R(1)}_{i,t}$ | | -0.014 | | -0.021 |
| *t-stats* | | -2.38 | | -3.77 |
| $\text{ILLIQ}_{i,t}$ | | 0.570 | | -0.006 |
| *t-stats* | | 0.30 | | -0.19 |
| Adj-$R^2$ | 2.30% | 2.32% | 1.38% | 5.66% |

## Table 4. Panel Regressions

This table presents results from panel regressions of firm's returns on past performance, measured based on the cumulative stock return of the past 12-months (R(2,12)), an option variable ($I_{Option}$) that takes a value of 1 if a stock is optionable and 0 otherwise as well as an interaction variable ($CumRet_{i,t}*I_{Option}$) of cumulative returns with the options variable. 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 panel regression coefficients, $t$-statistics with clustered standard errors, and the regression R-squares. We offer results for the whole universe of stocks as well as loser and winner stocks. The main model takes the following form:

$$\mathrm{Ret}_{i,t+1} = \delta_{0,t} + \delta_{1,i}\mathrm{CumRet}_{i,t} + \delta_{2,i}\mathrm{I}_{Option} + \delta_{3,i}\mathrm{CumRet}_{i,t}*\mathrm{I}_{Option} + \delta'_{4,i}\mathbf{Z}_{i,t} + \varepsilon_{i,t+1}$$

where $\mathrm{Ret}_{i,t+1}$ denotes the time $t+1$ stock return of firm $i$, $\mathrm{CumRet}_{i,t}$ is the cumulative stock return over the past 12-months of stock $i$ on month $t$. $\mathbf{Z}$ represents the set of control variables. Our regressions consider time- and firm-fixed effects.

| Stock Returns | | | |
|---|---|---|---|
| | *All Stocks* | *Losers* | *Winners* |
| Intercept | 0.396 | 0.204 | 0.726 |
| *t-stats* | [32.75] | [4.91] | [15.20] |
| $\mathrm{CumRet}_{i,t}$ | 0.011 | -0.038 | -0.017 |
| *t-stats* | [10.94] | [-5.18] | [-4.94] |
| $\mathrm{I}_{Option}$ | -0.003 | -0.009 | -0.012 |
| *t-stats* | [-3.55] | [-2.25] | [-2.14] |
| $\mathrm{CumRet}_{i,t}*\mathrm{I}_{Option}$ | -0.005 | -0.014 | -0.001 |
| *t-stats* | [-4.31] | [-2.07] | [-0.16] |
| *Control Variables* | | | |
| $\mathrm{Ln(Size)}_{i,t}$ | -0.029 | -0.010 | -0.053 |
| *t-stats* | [-25.70] | [-2.60] | [-11.16] |
| $\mathrm{Ln(Price)}_{i,t}$ | -0.001 | -0.031 | -0.005 |
| *t-stats* | [-1.00] | [-6.57] | [-0.90] |
| $\mathrm{IOR}_{i,t}$ | 0.000 | -0.003 | -0.010 |
| *t-stats* | [-0.83] | [-0.34] | [-1.05] |
| $\mathrm{B/M}_{i,t}$ | -0.001 | 0.001 | -0.001 |
| *t-stats* | [-1.20] | [0.59] | [-0.49] |
| $\mathrm{IVOL}_{i,t}$ | -0.013 | 0.037 | 0.098 |
| *t-stats* | [-0.38] | [0.32] | [1.36] |
| $\mathrm{REV}_{i,t}$ | -0.014 | -0.079 | -0.037 |
| *t-stats* | [-6.77] | [-9.54] | [-5.49] |
| $\mathrm{ILLIQ}_{i,t}$ | -8.377 | -7.038 | 30.945 |
| *t-stats* | [-2.65] | [-0.49] | [0.99] |
| Time FE | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes |
| $R^2$ | 8.09% | 17.41% | 10.55% |

## Table 5. Double Sorts - Momentum and Option Impediments

Double-sorted quintile portfolios of momentum returns are formed every month from January 1996 to April 2016 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

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

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. 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 the WML as well as the corresponding alphas of the three-factor Fama and French (1993) model (FF3) with their associated HAC adjusted $t$-statistics ($t$-stat). Average raw and risk-adjusted returns are given in percentage terms.

| Implied Volatility Spread | | | | | |
|---|---|---|---|---|---|
| | Low Volatility Spread | 2 | 3 | 4 | High Volatility Spread |
| Loser | -0.510 | 0.577 | 0.183 | 0.578 | 0.872 |
| Winner | 0.676 | 0.654 | 1.283 | 1.214 | 1.317 |
| WML | 1.186 | 0.077 | 1.100 | 0.636 | 0.445 |
| $t$-stat | 2.06 | 0.15 | 2.12 | 1.13 | 0.99 |
| FF3 Alphas | 1.451 | 0.265 | 1.174 | 0.731 | 0.688 |
| $t$-stat | 2.88 | 0.58 | 2.33 | 1.51 | 1.63 |

## Table 6. Momentum and Price Informativeness

Decile portfolios are formed every month from January 1996 to April 2016 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 using NYSE breakpoints. 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 | Losers | Winners | WML |
|---|---|---|---|---|---|---|---|---|---|
| | *All Stocks* | | | *Stocks with Options* | | | *Stocks without Options* | | |
| PI | 0.728 | 0.838 | 0.109 | 0.823 | 0.813 | -0.010 | 0.430 | 0.833 | 0.403 |
| $t$-stat | 9.67 | 11.63 | 1.06 | 9.03 | 8.71 | -0.08 | 2.24 | 9.35 | 2.32 |

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

| | $\Delta$Losers | $\Delta$Winners |
|---|---|---|
| PI | 0.393 | -0.019 |
| $t$-stat | 3.22 | -0.19 |

## Table 7. 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 using NYSE breakpoints. 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 average of 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*). The average measures correspond to the rebalancing period (15th of each month due to data availability).

*Panel A*: All firms

| *Decile* | All stocks | Stocks with Options | Stocks without Options |
|---|---|---|---|
| Average | 0.042 | 0.054 | 0.024 |
| $t$-stat | 14.08 | 15.61 | 15.67 |

*Panel B*: Momentum Portfolios

| *Decile* | All stocks | Stocks with Options | Stocks without Options |
|---|---|---|---|
| Losers | 0.062 | 0.080 | 0.032 |
| 2 | 0.045 | 0.058 | 0.025 |
| 3 | 0.040 | 0.051 | 0.023 |
| 4 | 0.037 | 0.047 | 0.022 |
| 5 | 0.036 | 0.045 | 0.022 |
| 6 | 0.036 | 0.044 | 0.022 |
| 7 | 0.036 | 0.048 | 0.021 |
| 8 | 0.037 | 0.046 | 0.022 |
| 9 | 0.040 | 0.051 | 0.022 |
| Winners | 0.049 | 0.065 | 0.027 |
| WML | -0.012 | -0.015 | -0.004 |
| $t$-stat | -6.04 | -5.81 | -3.60 |

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

| | ΔLosers | ΔWinners |
|---|---|---|
| Short Interest | 0.048 | 0.037 |
| $t$-stat | 14.69 | 14.06 |

## Table 8. Cross-Sectional Regressions - Stock Returns and Short Interest

This table presents results from Fama-MacBeth regressions of firm's returns on past performance, measured based on the previous period 12-month cumulative returns (R(2,12)) after skipping the most recent month and short interest. 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:

$$\text{Ret}_{i,t+1} = \delta_{0,t} + \delta_{1,i}\text{R(2,12)}_{i,t} + \delta_{2,i}\text{Short Interest}_{i,t} + \delta'_{3,i}\mathbf{Z}_{i,t} + \varepsilon_{i,t+1}$$

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 $t$ and Short Interest the percentage of short interest of stock i on month t. $\mathbf{Z}$ represents the set of control variables.

| Stock Returns | | | | |
|---|---|---|---|---|
| | *Stocks with Options* | | *Stocks without Options* | |
| | (1) | (2) | (3) | (4) |
| Intercept | 0.008 | 0.023 | 0.010 | 0.019 |
| *t-stats* | 2.55 | 2.40 | 2.85 | 2.18 |
| $\text{CumRet}_{i,t}$ | 0.002 | 0.004 | 0.004 | 0.007 |
| *t-stats* | 0.56 | 1.35 | 2.03 | 3.05 |
| $\text{Short Interest}_{i,t}$ | -0.039 | -0.039 | -0.086 | -0.077 |
| *t-stats* | -3.12 | -3.68 | -3.96 | -3.92 |
| *Control Variables* | | | | |
| $\text{Ln(Size)}_{i,t}$ | | 0.000 | | 0.000 |
| *t-stats* | | -0.17 | | -0.28 |
| $\text{Ln(Price)}_{i,t}$ | | -0.003 | | -0.002 |
| *t-stats* | | -2.75 | | -1.49 |
| $\text{IOR}_{i,t}$ | | 0.001 | | 0.003 |
| *t-stats* | | 0.39 | | 1.25 |
| $\text{B/M}_{i,t}$ | | 0.002 | | 0.001 |
| *t-stats* | | 1.33 | | 2.04 |
| $\text{IVOL}_{i,t}$ | | -0.184 | | -0.247 |
| *t-stats* | | -2.03 | | -3.03 |
| $\text{R(1)}_{i,t}$ | | -0.014 | | -0.026 |
| *t-stats* | | -2.41 | | -4.60 |
| $\text{ILLIQ}_{i,t}$ | | -2.184 | | -0.073 |
| *t-stats* | | -0.96 | | -1.28 |
| Adj-$R^2$ | 2.87% | 8.40% | 1.90% | 6.28% |

## Table 9. Option Order Imbalances of Momentum Portfolios

Decile portfolios are formed every month from January 2006 to April 2016 by sorting stocks with options based on the previous period 12-month cumulative returns (R(2,12)) after skipping the most recent month using NYSE breakpoints. 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*)

$$\mathrm{OOI}_{i,t} = \frac{\sum_j^N abs(\Delta_{i,j,t})[(\mathrm{BC_{i,j,t}} + \mathrm{SP_{i,j,t}}) - (\mathrm{SC_{i,j,t}} + \mathrm{BP_{i,j,t}})]}{\sum_\mathrm{j}(\mathrm{BC_{i,j,t}} + \mathrm{SP_{i,j,t}} + \mathrm{SC_{i,j,t}} + \mathrm{BP_{i,j,t}})}$$

where OOI is the number of opening and closing option trades written on stock $i$ at time $t$ regardless of moneyness and expiration 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 opening and closing option trades at time t. Panel A reports results for option order imbalances for all trades while Panel B displays the corresponding results for firms and small customers. The measures are computed over the holding period (e.g., a month).

*Panel A*: Order Imbalances

| | Losers | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Winners | WML |
|---|---|---|---|---|---|---|---|---|---|---|---|
| OOI | -0.016 | -0.011 | -0.009 | -0.005 | -0.008 | -0.012 | -0.005 | -0.009 | -0.001 | -0.001 | 0.014 |
| $t$-stat | -4.77 | -4.84 | -3.65 | -2.59 | -3.69 | -4.29 | -2.08 | -3.13 | -0.59 | -0.82 | 3.79 |

*Panel B*: Disaggregated Order Imbalances

| | Losers | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Winners | WML |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $\mathrm{OOI}_{Firms}$ | -0.006 | 0.007 | -0.003 | -0.001 | -0.001 | -0.001 | 0.002 | -0.003 | -0.002 | -0.004 | 0.002 |
| $t$-stat | -1.11 | 1.84 | -1.15 | -0.31 | -0.16 | -0.20 | 0.64 | -0.88 | -0.74 | -1.47 | 0.28 |
| $\mathrm{OOI}_{Small\ Customers}$ | -0.018 | -0.016 | -0.014 | -0.015 | -0.016 | -0.019 | -0.012 | -0.016 | -0.002 | -0.004 | 0.014 |
| $t$-stat | -3.77 | -4.10 | -3.97 | -5.62 | -5.44 | -5.80 | -3.10 | -4.03 | -0.62 | -1.24 | 3.01 |

## Table 10. Cross-Sectional Regressions - Option 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:

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

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.

| Option Order Imbalances | | | | | | |
|---|---|---|---|---|---|---|
| | *All Market Participants* | | *Small Customers* | | *Firms* | |
| Intercept | -0.022 | 0.086 | -0.029 | 0.048 | -0.001 | 0.091 |
| *t-stats* | -8.90 | 3.59 | -6.86 | 1.51 | -0.32 | 2.51 |
| $\mathrm{CumRet}_{i,t}$ | 0.019 | 0.018 | 0.016 | 0.015 | 0.003 | 0.006 |
| *t-stats* | 4.86 | 3.25 | 3.76 | 2.70 | 0.47 | 0.79 |
| *Control Variables* | | | | | | |
| Short $\mathrm{Interest}_{i,t}$ | | -0.181 | | -0.056 | | -0.318 |
| *t-stats* | | -8.05 | | -1.89 | | -6.10 |
| $\mathrm{Ln(Size)}_{i,t}$ | | -0.006 | | -0.003 | | -0.004 |
| *t-stats* | | -4.39 | | -1.82 | | -1.75 |
| $\mathrm{Ln(Price)}_{i,t}$ | | -0.009 | | -0.010 | | -0.013 |
| *t-stats* | | -2.83 | | -2.63 | | -4.11 |
| $\mathrm{IOR}_{i,t}$ | | 0.031 | | 0.011 | | 0.054 |
| *t-stats* | | 3.57 | | 0.97 | | 3.46 |
| $\mathrm{B/M}_{i,t}$ | | -0.002 | | -0.008 | | 0.000 |
| *t-stats* | | -0.51 | | -1.94 | | -0.07 |
| $\mathrm{IVOL}_{i,t}$ | | 0.109 | | 0.342 | | -0.069 |
| *t-stats* | | 0.62 | | 1.69 | | -0.27 |
| $\mathrm{R(1)}_{i,t}$ | | -0.038 | | -0.052 | | 0.008 |
| *t-stats* | | -2.54 | | -2.90 | | 0.42 |
| $\mathrm{ILLIQ}_{i,t}$ | | -21.130 | | 36.760 | | -239.602 |
| *t-stats* | | -0.36 | | 0.50 | | -2.53 |
| Adj-$R^2$ | 0.20% | 2.14% | 0.19% | 1.95% | 0.23% | 2.42% |

## Table 11. Shorting Fees and Fails to Deliver of Momentum Portfolios

Decile portfolios are formed every month from January 1996 to April 2016 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 using NYSE breakpoints. The fees are expressed in percentage. Decile 10 indicates the winner portfolio, Decile 1 denotes the loser portfolios and WML indicates the winner-minus-loser portfolio. *Panel A* presents time-series average of short interest relative to shares owned by institutions for all firms and for momentum portfolios (*Panel B*) with and without options and their corresponding adjusted HAC $t$-statistics ($t$-stat). *Panel C* shows the average number of fails to deliver for momentum portfolios with and without options from March 2004 to April 2016 from the SEC. The average measures of fails to deliver and shorting fees correspond to the rebalancing period (15th of each month in the case of shorting fees due to data availability on short interest).

*Panel A*: Shorting Fees - All Firms

| *Decile* | All stocks | Stocks with Options | Stocks without Options |
|---|---|---|---|
| Average | 12.172 | 8.067 | 20.429 |
| $t$-stat | 10.00 | 21.86 | 6.06 |

*Panel B*: Shorting Fees - Momentum Portfolios

| *Decile* | All stocks | Stocks with Options | Stocks without Options |
|---|---|---|---|
| Losers | 16.234 | 12.889 | 25.710 |
| 2 | 9.791 | 8.869 | 12.508 |
| 3 | 13.741 | 7.337 | 26.035 |
| 4 | 14.356 | 6.743 | 30.987 |
| 5 | 10.189 | 6.473 | 16.517 |
| 6 | 12.627 | 6.234 | 26.302 |
| 7 | 6.978 | 6.286 | 9.667 |
| 8 | 7.879 | 6.538 | 13.444 |
| 9 | 9.259 | 7.194 | 14.501 |
| Winners | 17.072 | 11.339 | 21.871 |

*Panel C*: Fails to Deliver

| *Decile* | All Stocks | Stocks with Options | Stocks without Options |
|---|---|---|---|
| Losers | 98.967 | 91.406 | 7.561 |
| 2 | 55.838 | 51.829 | 4.010 |
| 3 | 44.465 | 40.370 | 4.095 |
| 4 | 34.853 | 32.063 | 2.789 |
| 5 | 30.253 | 27.531 | 2.723 |
| 6 | 29.017 | 25.866 | 3.151 |
| 7 | 27.029 | 23.807 | 3.222 |
| 8 | 34.832 | 30.415 | 4.416 |
| 9 | 38.664 | 33.598 | 5.066 |
| Winners | 101.762 | 84.571 | 17.191 |

## Table 12. Stock Order Imbalances 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)) after skipping the most recent month using NYSE breakpoints. 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 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. $SOI^{NUM}$ 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. $SOI^{SH}$ is the number of shares bought less the number of shares sold over the holding period as a fraction of the total shares traded that month. Both measures are reported in percent per month. Panel A reports results for all stocks while Panel B (Panel C) displays results for stocks with (without) options.

*Panel A*: All Stocks

| | Losers | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Winners | WML |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $SOI^{NUM}$ | -0.014 | -0.011 | -0.007 | -0.003 | -0.001 | 0.002 | 0.004 | 0.005 | 0.007 | 0.007 | 0.021 |
| $t$-stat | -2.37 | -1.76 | -1.16 | -0.61 | -0.15 | 0.35 | 0.78 | 1.23 | 1.77 | 2.26 | 5.66 |
| $SOI^{SH}$ | -0.022 | -0.017 | -0.014 | -0.009 | -0.005 | -0.004 | -0.004 | -0.003 | -0.004 | -0.008 | 0.014 |
| $t$-stat | -3.45 | -2.87 | -2.39 | -1.71 | -1.10 | -0.82 | -0.79 | -0.66 | -0.97 | -2.21 | 4.06 |

*Panel B*: Stocks with Options

| | Losers | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Winners | WML |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $SOI^{NUM}$ | 0.004 | 0.011 | 0.014 | 0.017 | 0.021 | 0.024 | 0.025 | 0.027 | 0.028 | 0.025 | 0.021 |
| $t$-stat | 0.98 | 2.63 | 3.65 | 4.26 | 5.60 | 6.20 | 7.01 | 7.54 | 8.10 | 8.39 | 5.28 |
| $SOI^{SH}$ | 0.003 | 0.015 | 0.020 | 0.023 | 0.026 | 0.026 | 0.028 | 0.027 | 0.026 | 0.017 | 0.013 |
| $t$-stat | 0.77 | 3.66 | 4.77 | 5.54 | 6.32 | 6.20 | 6.87 | 6.97 | 7.20 | 5.74 | 6.25 |

*Panel C*: Stocks without Options

| | Losers | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Winners | WML |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $SOI^{NUM}$ | -0.027 | -0.025 | -0.019 | -0.016 | -0.013 | -0.009 | -0.008 | -0.005 | -0.004 | -0.002 | 0.026 |
| $t$-stat | -4.25 | -3.72 | -2.97 | -2.32 | -2.05 | -1.55 | -1.34 | -0.97 | -0.77 | -0.43 | 7.48 |
| $SOI^{SH}$ | -0.043 | -0.042 | -0.037 | -0.031 | -0.027 | -0.024 | -0.024 | -0.023 | -0.025 | -0.024 | 0.019 |
| $t$-stat | -6.53 | -6.40 | -5.94 | -5.08 | -4.68 | -4.30 | -4.47 | -4.37 | -5.08 | -5.66 | 5.63 |

## Table 13. Momentum Profitability for Pilot and Non-Pilot Firms

This table presents returns of equal-weighted momentum portfolios (WML) of stocks sorted based on the previous period 12-month cumulative stock returns after skipping the most recent month. *Panel A* display cumulative returns (e.g., R(2,12)) for pilot and non-pilot firms when considering the whole universe of stocks or stocks with and without options for the month December 2003. *Panel B* shows raw returns as well as risk adjusted momentum returns based on CAPM and the 3-factor Fama and French (1993) model (FF3) of non-pilot firms during the pilot programme (e.g., from June 2005 to August 2007). Robust $t$-statistics are presented in squared brackets. Momentum returns are winsorized at 1 and 99 %. The data are collected from CRSP and OptionMetrics IvyDB datasets and cover NYSE and AMEX firms.

*Panel A*: Momentum Returns

| | Pilot Mean | Non-Pilot Mean | Difference | Pilot Mean | Non-Pilot Mean | Difference | Pilot Mean | Non-Pilot Mean | Difference |
|---|---|---|---|---|---|---|---|---|---|
| | | *All Stocks* | | | *Stocks with Options* | | | *Stocks without Options* | |
| R(2,12) | 0.303 | 0.306 | -0.003 | 0.288 | 0.281 | 0.007 | 0.330 | 0.350 | -0.020 |
| $t$-stat | 17.89 | 22.59 | -0.14 | 14.04 | 17.74 | 0.26 | 11.19 | 14.16 | -0.53 |

*Panel B*: Momentum Returns of Non-pilot firms during the Pilot Programme

| | Avg Ret | CAPM Alpha | FF3 Alpha | Avg Ret | CAPM Alpha | FF3 Alpha | Avg Ret | CAPM Alpha | FF3 Alpha |
|---|---|---|---|---|---|---|---|---|---|
| | | *All Stocks* | | | *Stocks with Options* | | | *Stocks without Options* | |
| WML | 1.326 | 1.413 | 1.368 | 1.298 | 1.224 | 1.228 | 1.782 | 1.974 | 1.960 |
| $t$-stat | 1.90 | 1.84 | 1.70 | 1.59 | 1.42 | 1.32 | 2.26 | 2.41 | 2.40 |

## Table 14. Difference-in-Differences Approach

This table presents results of the difference-in-differences approach for loser, winner and momentum portfolios. Specifically, our difference-in-differences test follows the specification below:

$$Ret_{i,t} = \alpha_t + \beta Pilot_i * During_t + \beta_1 Pilot_i + \varepsilon_{i,t}$$

where $Ret_{i,t}$ corresponds to the monthly return of loser, winner or spread portfolios, in month $t$; $\alpha_t$ is the time fixed effects, which capture the common factors that capture the variability of both pilot and non-pilot portfolios; $Pilot_i$ is a dummy variable which is equal to one if the portfolio of interest corresponds to pilot firms, and zero otherwise; $During_t$ is a dummy variable, which equals one if month $t$ is between June 2005 and August 2007 (i.e. during the pilot program of Regulation SHO). $During_t$ is not included in the regression because it is subsumed by the time fixed effects (FE). *Panel A* reports results for raw returns with *Panel B* (*Panel C*) display CAPM (Fama and French (1993) 3-factor model (FF3)) adjusted stock returns. All coefficients are expressed in percentage points. Robust $t$-statistics are presented in squared brackets. The data are collected from CRSP and OptionMetrics IvyDB datasets and contain monthly series from NYSE and AMEX of the period January 1996 to August 2007.

| | Winners | Losers | WML | Winners | Losers | WML | Winners | Losers | WML |
|---|---|---|---|---|---|---|---|---|---|
| ***Panel A*: Raw Returns** | | | | | | | | | |
| | *All Stocks* | | | *Stocks with Options* | | | *Stocks without Options* | | |
| Pilot*During | -0.184 | 0.666 | -0.850 | -0.182 | 0.130 | -0.312 | -0.908 | 1.971 | -2.880 |
| | [-0.50] | [1.59] | [-1.48] | [-0.45] | [0.35] | [-0.57] | [-1.30] | [2.07] | [-2.51] |
| Pilot | -0.168 | -0.005 | -0.164 | 0.371 | -0.029 | 0.400 | -0.685 | -0.269 | -0.416 |
| | [-0.73] | [-0.02] | [-0.55] | [1.48] | [-0.12] | [1.21] | [-1.80] | [-0.78] | [-0.84] |
| Constant | -5.470 | -9.410 | 3.940 | -4.355 | -8.554 | 4.198 | -8.676 | -13.267 | 4.590 |
| | [-21.62] | [-17.41] | [10.18] | [-6.53] | [-11.34] | [17.62] | [-7.10] | [-8.97] | [8.13] |
| Time FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| ***Panel B*: CAPM Adjusted Returns** | | | | | | | | | |
| | Winners | Losers | WML | Winners | Losers | WML | Winners | Losers | WML |
| | *All Stocks* | | | *Stocks with Options* | | | *Stocks without Options* | | |
| Pilot*During | -0.173 | 0.661 | -0.834 | -0.169 | 0.133 | -0.303 | -0.897 | 1.962 | -2.859 |
| | [-0.46] | [1.58] | [-1.43] | [-0.41] | [0.36] | [-0.55] | [-1.28] | [2.07] | [-2.51] |
| Pilot | -0.119 | -0.031 | -0.089 | 0.431 | -0.014 | 0.445 | -0.630 | -0.310 | -0.320 |
| | [-0.53] | [-0.15] | [-0.30] | [1.75] | [-0.06] | [1.35] | [-1.66] | [-0.90] | [-0.65] |
| Constant | -1.679 | -4.325 | 2.646 | -0.424 | -3.247 | 2.823 | -5.150 | -8.710 | 3.560 |
| | [-10.46] | [-7.05] | [4.56] | [-0.86] | [-4.58] | [8.86] | [-3.73] | [-6.39] | [6.87] |
| Time FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| ***Panel C*: FF3 Adjusted Returns** | | | | | | | | | |
| | Winners | Losers | WML | Winners | Losers | WML | Winners | Losers | WML |
| | *All Stocks* | | | *Stocks with Options* | | | *Stocks without Options* | | |
| Pilot*During | -0.248 | 0.652 | -0.900 | -0.228 | 0.119 | -0.348 | -1.017 | 1.928 | -2.945 |
| | [-0.64] | [1.57] | [-1.52] | [-0.53] | [0.32] | [-0.61] | [-1.48] | [2.03] | [-2.59] |
| Pilot | -0.059 | 0.009 | -0.068 | 0.503 | -0.045 | 0.548 | -0.567 | -0.263 | -0.304 |
| | [-0.28] | [0.05] | [-0.24] | [2.12] | [-0.19] | [1.68] | [-1.59] | [-0.77] | [-0.63] |
| Constant | 1.940 | 0.993 | 0.947 | 2.593 | 1.677 | 0.916 | -0.488 | -2.364 | 1.876 |
| | [9.54] | [1.95] | [1.45] | [8.34] | [2.12] | [1.61] | [-0.31] | [-1.58] | [3.54] |
| Time FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |

## Table 15. Momentum Returns and Option Listing

Decile portfolios are formed every month from June 1977 to April 2016 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 using NYSE breakpoints. Here, the universe of optionable stocks from the earlier period is determined by option listing. Decile 10 indicates the winner portfolio, Decile 1 denotes the loser portfolios and WML indicates the winner-minus-loser portfolio. We consider stocks with options based on option listing. *Panel A* reports the value weighted average excess monthly returns for each decile portfolio as well as the corresponding alphas of the CAPM and the three-factor Fama and French (1993) model (FF3). *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*: Stock returns

| | Stocks with Options | | | Stocks without Options | | |
|---|---|---|---|---|---|---|
| *Decile* | Avg Ret | CAPM Alpha | FF3 Alpha | Avg Ret | CAPM Alpha | FF3 Alpha |
| Losers | 0.201 | -0.661 | -0.778 | -0.316 | -1.180 | -1.253 |
| 2 | 0.704 | 0.042 | -0.057 | 0.627 | -0.066 | -0.248 |
| 3 | 0.737 | 0.151 | 0.048 | 0.689 | 0.069 | -0.067 |
| 4 | 0.589 | 0.043 | -0.005 | 0.709 | 0.111 | -0.040 |
| 5 | 0.522 | -0.026 | -0.066 | 0.730 | 0.152 | 0.010 |
| 6 | 0.643 | 0.069 | 0.040 | 0.613 | 0.032 | -0.090 |
| 7 | 0.624 | 0.062 | 0.058 | 0.651 | 0.075 | 0.007 |
| 8 | 0.766 | 0.167 | 0.180 | 0.722 | 0.140 | 0.084 |
| 9 | 0.671 | 0.023 | 0.105 | 0.790 | 0.177 | 0.125 |
| Winners | 1.018 | 0.219 | 0.412 | 1.025 | 0.213 | 0.328 |
| WML | 0.818 | 0.880 | 1.190 | 1.341 | 1.393 | 1.582 |
| $t$-stat | 2.29 | 2.63 | 3.67 | 4.26 | 4.36 | 5.40 |

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

| | $\Delta$Losers | $\Delta$Winners |
|---|---|---|
| Avg Ret | 0.517 | -0.007 |
| $t$-stat | 2.348 | -0.04 |

## Table 16. Correlation Coefficient Analysis

Decile portfolios are formed every month from January 1996 to April 2016 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. This table present average correlation coefficients and pooled OLS regression for the hedged WML portfolio. The correlation coefficient is calculated between the monthly excess returns of the Winner and Loser momentum portfolios during a rolling periods prior to month $t$. This correlation is normalised by the correlation between portfolios in Decile 5 and 6. The normalised correlation ratio can be shown as:

$$\mathrm{X}_t = \frac{\rho_t^{W,L}}{\rho_t^{5,6}}$$

where $\rho_t^{W,L}$ is the correlation coefficient between the monthly excess returns of the Winner and Loser momentum portfolios during a rolling period prior to month $t$. This correlation is normalised by the correlation between portfolios in Decile 5 and 6: $\rho_t^{5,6}$ in order to control for potential time trend in the correlations. We also estimate a pooled OLS regression to capture the effect of options on the correlation coefficient. Our dependent variable is the normalised correlation coefficient and our independent variables is a dummy which gets a value of one if the stock has an options and zero otherwise.

$$\mathrm{X}_t = \alpha + \beta \mathrm{Option}_{i,t} + \epsilon_{i,t}$$

where Option is a dummy variable that takes the value of 1 if the stock has an option and 0 for non-option stocks. Robust $t$-statistics are presented in the parenthesis. *Panel A* displays results for the average correlation coefficient for different rolling windows from 1 to 5 years while *Panel B* displays results for pooled OLS regressions. The data are collected from CRSP and Optionmetrics IvyDB datasets and contain monthly of stock returns from January 1996 to April 2016.

*Panel A:* Average Coefficient Correlations

| Rolling Window | All Stocks | Stocks with Options | Stocks without Options |
|---|---|---|---|
| 1 Year | 0.693 | 0.673 | 0.811 |
| 2 Years | 0.686 | 0.662 | 0.802 |
| 3 Years | 0.673 | 0.649 | 0.786 |
| 4 Years | 0.655 | 0.632 | 0.777 |
| 5 Years | 0.638 | 0.614 | 0.768 |

*Panel B:* Pooled OLS Regression

| | 1 Year | 2 Years | 3 Years | 4 Years | 5 Years |
|---|---|---|---|---|---|
| Option Dummy | -0.138 | -0.140 | -0.137 | -0.144 | -0.154 |
| | (-4.11) | (-6.85) | (-8.15) | (-9.95) | (-12.94) |
| Constant | 0.811 | 0.802 | 0.786 | 0.777 | 0.768 |
| | (35.71) | (67.83) | (89.87) | (121.48) | (148.46) |

*Internet Appendix to*

# "Overcoming Arbitrage Limits: Option Trading and Momentum Profitability"

by

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(Not for publication)

## Appendix A: Sort-based comparison

Even though the number of stocks with options is more than 50% in every year of our sample after 2002 it would be useful to compare the two categories along with other dimensions. We provide in Table A2 a comparison, based on eight different characteristics, of the winner and loser portfolios of our momentum strategy for stocks with and without options. Starting with stocks with options, as we move from losers to winners, the average cumulative returns R(2,12) increases significantly from -48.7% to 111.3%. The average price also shows an increasing pattern, suggesting that winners with options are likely to have higher prices. The negative and significant differences of R(1), book-to-market ratio, and illiquidity between winners and losers with options indicate that winner portfolios with options tend to have smaller average returns during the previous month, lower book-to-market ratios and lower illiquidity. Notably, size, institutional ownership and idiosyncratic volatility do not vary significantly between winners and losers with options.

On the other hand, and similar to the case of stocks with options, the average cumulative returns R(2,12) for losers and winners without options increases significantly from -43.8% to 123.5%. Moreover, winners without options have higher prices and idiosyncratic volatility than loser stocks without options. In contrast, winners without options have smaller institutional ownership, book-to-market ratios and illiquidity than losers without options. Finally, there are no differences in terms of size and short term reversals between winners and losers without options.

In view of this, it would seem reasonable to assume that the differences between stocks with and without options are not very different along a number of important dimensions.

# Appendix B: Data Description

## 2.1 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 month $t$ obtained from the **?** 3-factor model:

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_{1,i}(R_{m,d} - r_{f,d}) + \beta_{2,i}HML_d + \beta_{3,i}SMB_d + \varepsilon_{i,d}, \tag{12}$$

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$^{Stock}$): We measure liquidity for each stock as the ratio of the bid-ask spread to its mid-price during the rebalancing period (e.g last trading day of the month).

*Turnover*: We compute monthly stock turnover as the number of shares traded in a month divided by the outstanding shares at the end of the month.

*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).

*Debt-to-assets* (D/A): This ratio is computed as the ratio of the the book value in moth $t$ of total debt –which is defined as long term debt plus debt in current liabilities– over the book value of total assets.

*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 is obtained by allocating equities into portfolios based on their previous month return.

## 2.2 Filters of Options Data

We apply a number of filters in the options data in order to ensure tradability and avoid outliers (e.g., Byun and Kim, 2016; Boyer and Vorkink, 2014). We eliminate all options with any of the following characteristics: i) the underlying asset is an index (Optionmetrics "index flag" is nonzero), ii) the expiration date of the option is at the market open of the last trading day, iii) we control for options with nonstandard settlement, that is, when the number of shares to be delivered is different from 100 (i.e. a "special settlement flag" that it is different from zero), v) the bid price is equal to zero or missing (i.e. values of 998 or 999), or bid-ask spreads that are below zero or greater than \$5, vi) the delta of the option is below -1, above +1 or missing, vii) the open interest is zero or missing, viii) the option's price (i.e., the midpoint of the bid and ask prices) is below 50% of the intrinsic value or \$100 above, and ix) the implied volatility of the options is less than zero or missing. In addition, we eliminate duplicates (i.e. options with the same underlying asset, maturity date, and strike price at the rebalancing date).

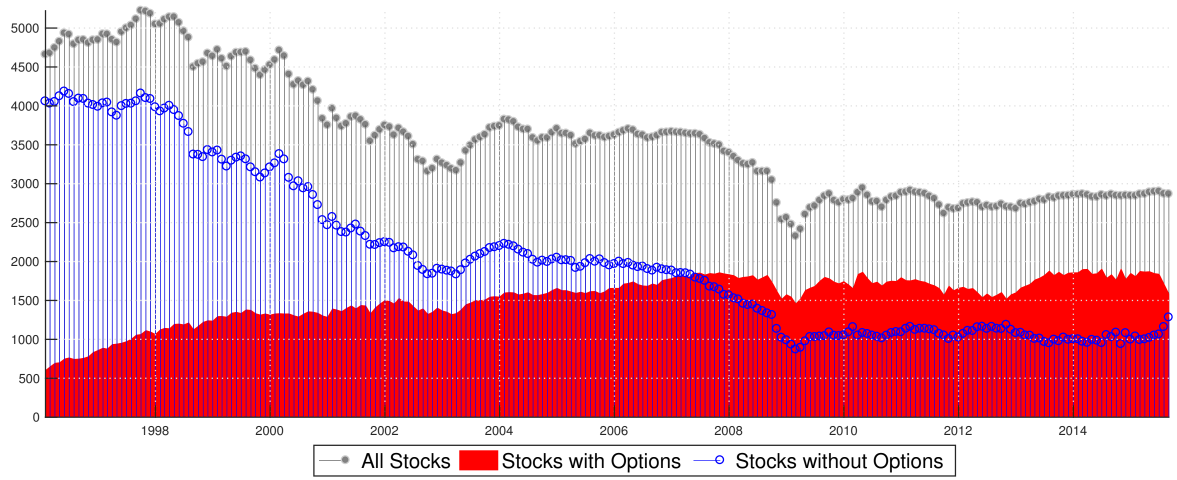
## 2.3 Implied Volatility Spread

We use the OptionMetrics IvyDB US data to measure deviations from put-call parity. We follow Amin et al. (2004) and Figlewski and Webb (1993) and compute the average difference in implied volatilities between call and put options with the same strike price and expiration date. 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

$$\mathrm{VS}_{\mathrm{i,t}} = \mathrm{IV}^{\mathrm{calls}}_{\mathrm{i,t}} - \mathrm{IV}^{\mathrm{puts}}_{\mathrm{i,t}} = \sum_{j=1}^{N_{i,t}} w^i_{j,t}(\mathrm{IV}^{\mathrm{i,call}}_{\mathrm{j,t}} - \mathrm{IV}^{\mathrm{i,put}}_{\mathrm{j,t}}) \tag{13}$$

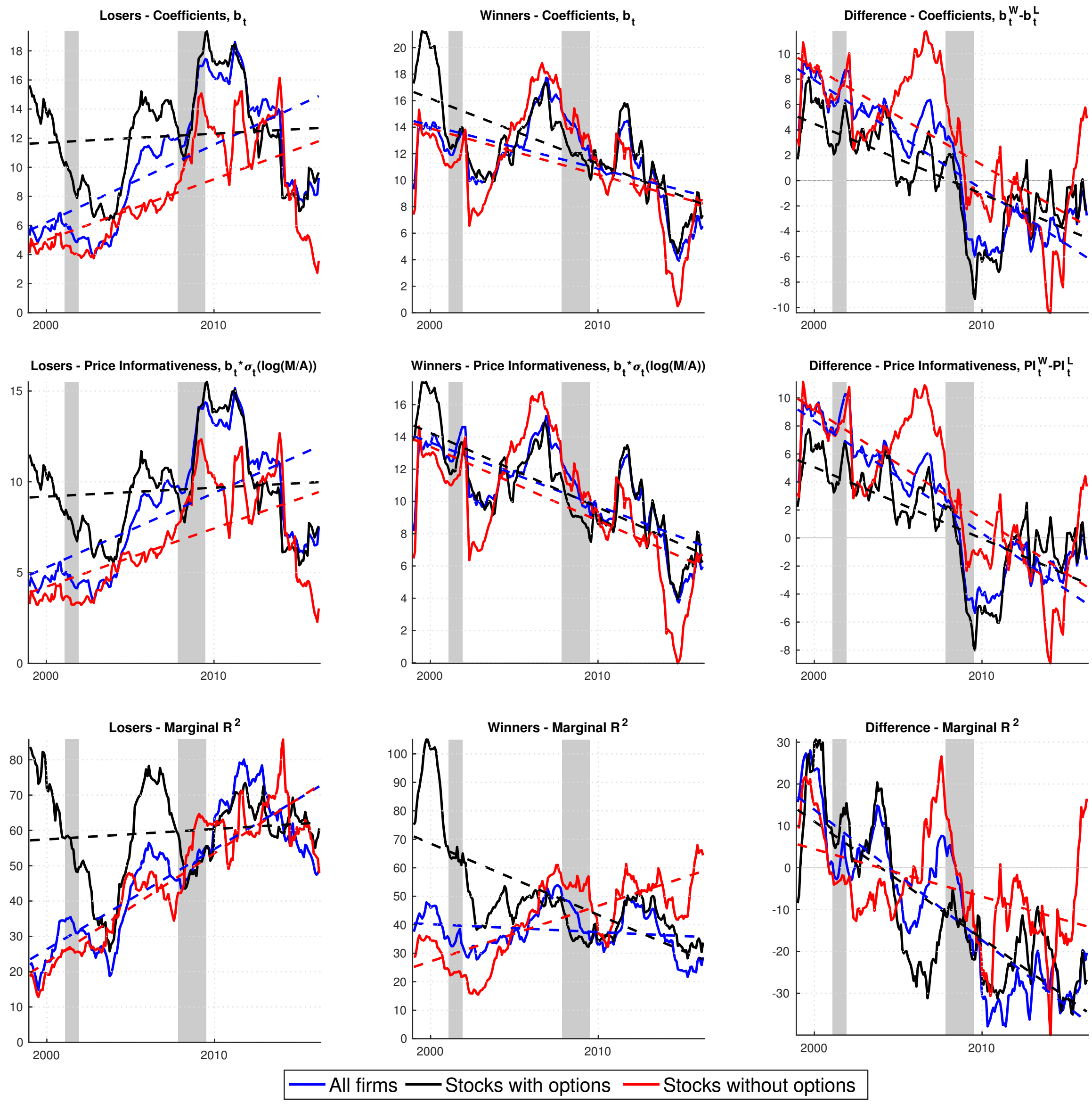
where $j$ refers to pairs of put and call options and thus indexes both strike prices and maturities, $w^i_{j,t}$ are weights, there are $N^i_t$ valid pairs of options on stock $i$ on day $t$, and $IV^i_{j,t}$ denotes the Black-Scholes (1973) implied volatility (adjusted for expected dividends and early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

**Figure A1.** ***Stocks with and without Options***



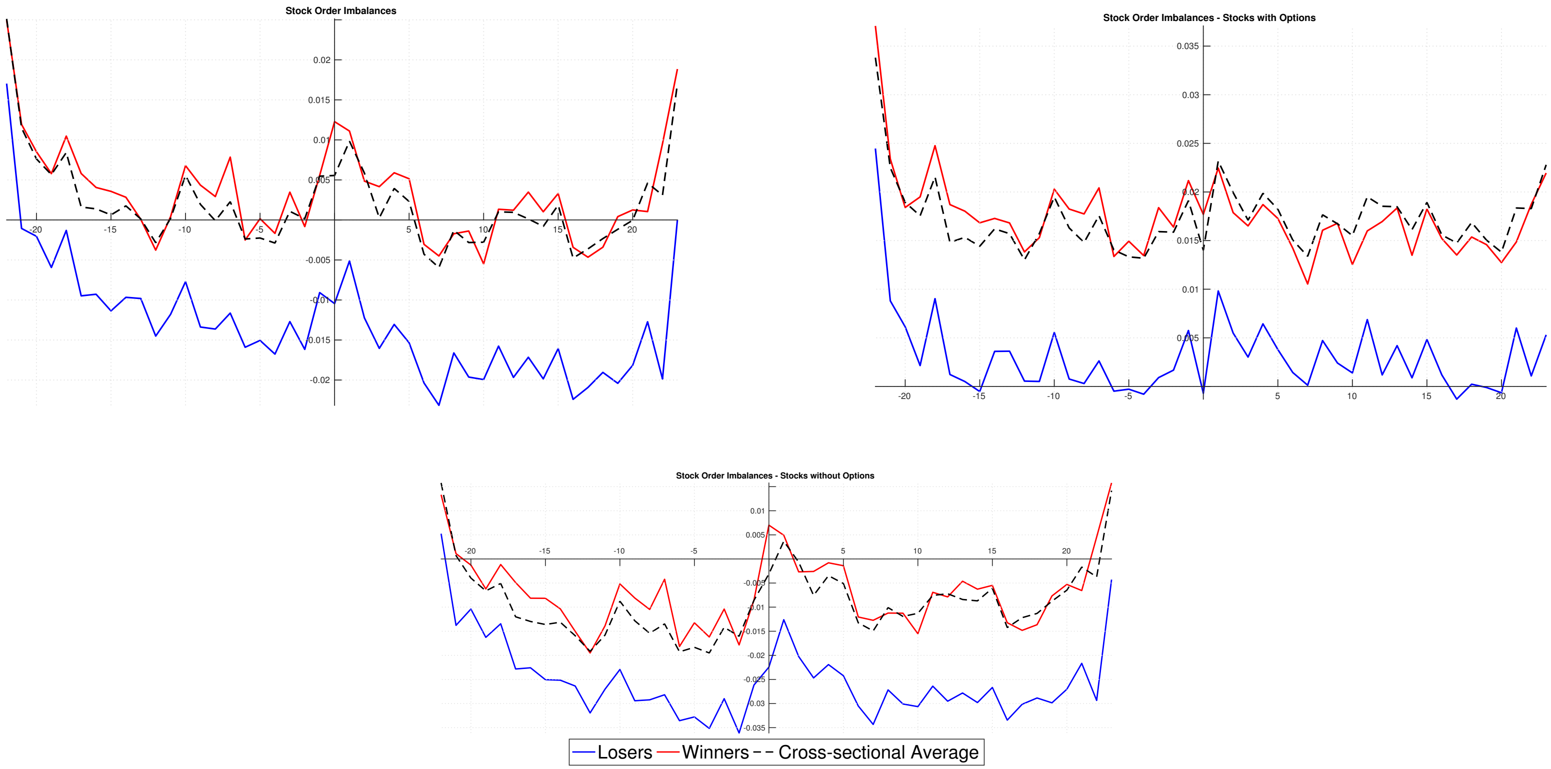

This figure displays the total number of stocks in our sample and the number of stocks *with* and *without* options. The data, are monthly series from January 1996 to April 2016, obtained from a merged CRSP and OptionMetrics dataset.

## Figure A2. Price Informativeness



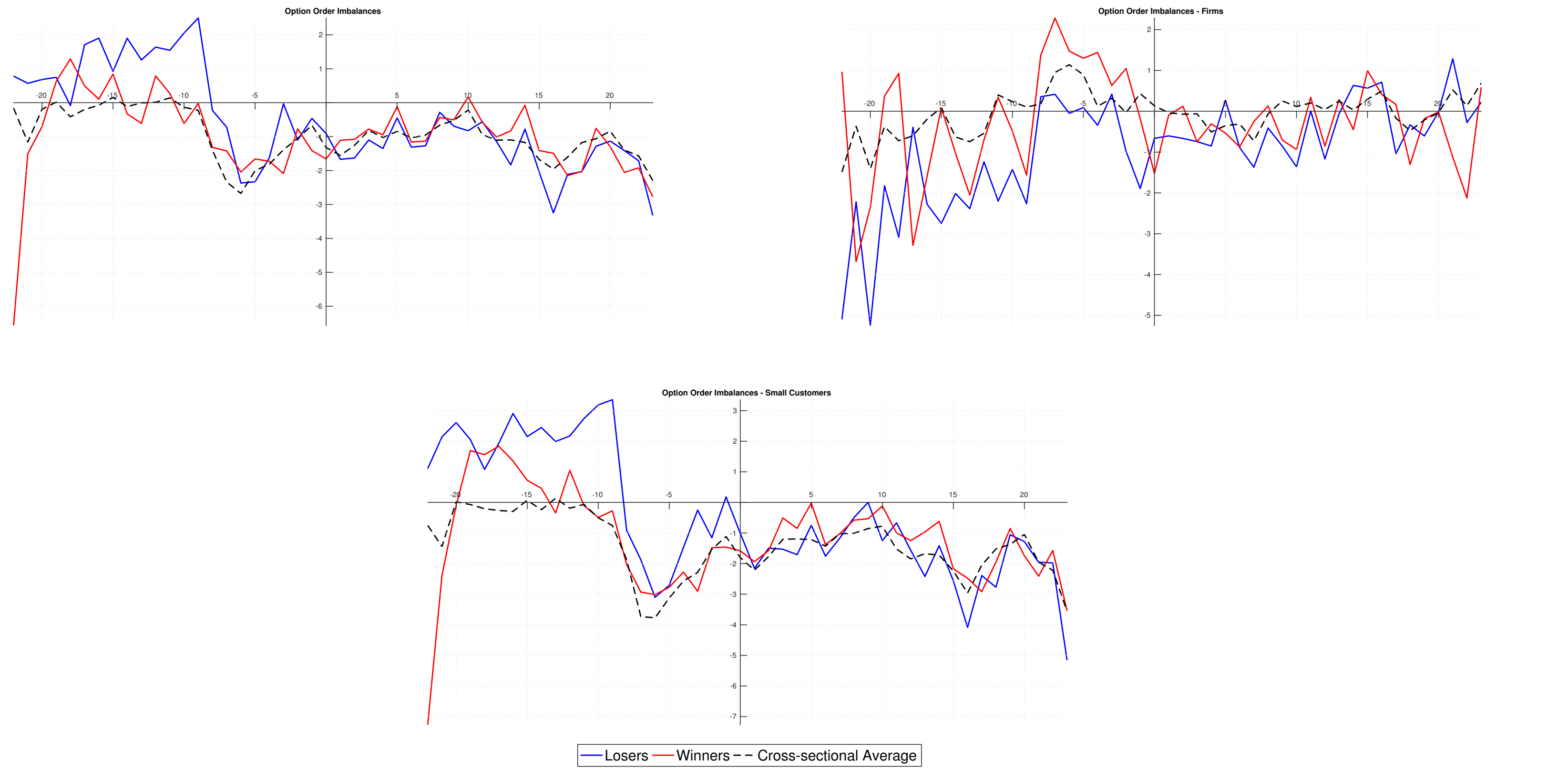

This figure displays the cross-sectional betas, the price informativeness and the marginal $R^2$ of loser and winner portfolios for all stocks and stocks with and without options. The figures are centered around the rebalancing date. All variables are estimated over a 36-month rolling window. Dashed lines correspond to linear time trend lines of each variable of the same colour. The data are collected from CRSP, COMPUSTAT and OptionMetrics and are monthly series from January 2006 to April 2016.

## Figure A3. Stock Order Imbalances



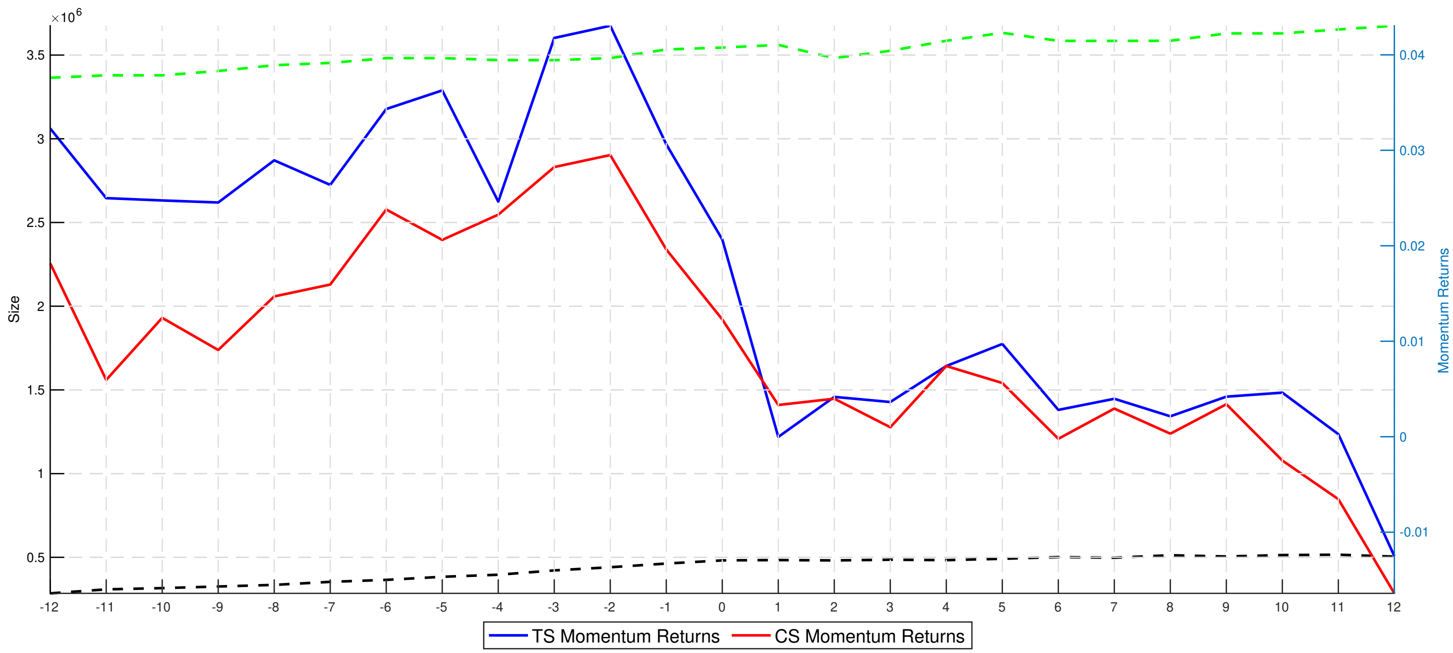

The figure displays stock order imbalances of loser and winner portfolios as well as the cross-sectional average of stock imbalances. We considers stocks of all stocks as well as stocks with and without options. The figures are centered around the rebalancing date. The data are collected from CRSP and OptionMetrics and contain monthly series from January 2006 to April 2016.

## Figure A4. Option Order Imbalances




The figure displays options order imbalances of open and close positions of loser and winner portfolios as well as the cross-sectional average of option imbalances. We considers options of all expirations. The figures are centered around the rebalancing date. The data are collected from CRSP and OptionMetrics and contain monthly series from January 2006 to April 2016.

**Figure A5.** ***Momentum Returns Around Option Listing***




The figure displays time-series and cross-sectional momentum returns around the introduction of an option. 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 February 1996 to April 2016.

## Table A1. Stocks with and without Options

This table presents the number and percentage of firms with and without options in our sample annually 1996 to 2016. A stock with an option is one for which we can find, during the last trading day of December of each year, at least a pair of a call and put with the same strike price and expiration date. The corresponding values for 2016 are based on the information during the last trading day of April due to the availability of the Optionmetrics data until the end of that month.

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 | 3712 | 726 | 0.196 | 2986 | 0.804 |
| 1997 | 4001 | 969 | 0.242 | 3032 | 0.758 |
| 1998 | 3589 | 1084 | 0.302 | 2505 | 0.698 |
| 1999 | 3387 | 1168 | 0.345 | 2219 | 0.655 |
| 2000 | 2858 | 1151 | 0.403 | 1706 | 0.597 |
| 2001 | 2781 | 1292 | 0.465 | 1489 | 0.535 |
| 2002 | 2436 | 1232 | 0.506 | 1204 | 0.494 |
| 2003 | 2833 | 1365 | 0.482 | 1468 | 0.518 |
| 2004 | 2792 | 1445 | 0.518 | 1347 | 0.482 |
| 2005 | 2747 | 1471 | 0.535 | 1276 | 0.465 |
| 2006 | 2786 | 1571 | 0.564 | 1215 | 0.436 |
| 2007 | 2576 | 1617 | 0.628 | 959 | 0.372 |
| 2008 | 1884 | 1321 | 0.701 | 563 | 0.299 |
| 2009 | 2172 | 1498 | 0.690 | 674 | 0.310 |
| 2010 | 2263 | 1534 | 0.678 | 729 | 0.322 |
| 2011 | 2116 | 1427 | 0.674 | 689 | 0.326 |
| 2012 | 2110 | 1392 | 0.660 | 718 | 0.340 |
| 2013 | 2240 | 1618 | 0.722 | 622 | 0.278 |
| 2014 | 2253 | 1559 | 0.692 | 694 | 0.308 |
| 2015 | 2254 | 1595 | 0.709 | 659 | 0.292 |
| 2016 | 2206 | 1634 | 0.741 | 572 | 0.259 |

## Table A2. Summary Statistics: Stocks with and without Options

Decile portfolios are formed every month from January 1996 to April 2016 by sorting stocks based on the previous period 12-month cumulative returns (R(2,12)) after skipping the most recent month using NYSE breakpoints. Decile 10 indicates the winner portfolio, Decile 1 denotes the loser portfolios and WML indicates the winner-minus-loser portfolio. The table presents for winners and losers portfolios of stocks with and without options the average across of various characteristics for the stocks - price, cumulative returns (R(2,12)), reversals (R(1)), illiquidity, idiosyncratic volatility (IVOL), book to market (B/M), market equity (SIZE) (in millions) and institutional ownership (IOR). The last two columns present the differences in characteristics between winners and losers portfolios with their associated HAC adjusted $t$-statistics ($t$-stat).

| Characteristics of Momentum Portfolios | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Stocks with options | | | | Stocks without options | | | |
| *Decile* | Losers | Winners | Difference | $t$-statistic | Losers | Winners | Difference | $t$-statistic |
| Size | 2.825 | 3.949 | 1.124 | 1.84 | 0.325 | 0.349 | 0.0237 | 0.62 |
| Price | 16.768 | 34.018 | 17.250 | 9.36 | 13.303 | 22.976 | 9.674 | 4.45 |
| R(2,12) | -0.484 | 0.901 | 1.386 | 29.20 | -0.454 | 0.983 | 1.437 | 33.15 |
| R(1) | 0.030 | 0.015 | -0.015 | -2.34 | 0.056 | 0.036 | -0.019 | -2.95 |
| IOR | 0.653 | 0.675 | 0.021 | 2.22 | 0.400 | 0.357 | -0.043 | -5.40 |
| B/M | 0.901 | 0.330 | -0.570 | -12.27 | 1.240 | 0.609 | -0.631 | -7.68 |
| IVOL | 0.033 | 0.032 | -0.001 | -0.86 | 0.035 | 0.039 | 0.003 | 3.06 |
| ILLIQ | 0.292 | 0.122 | -0.171 | -8.00 | 6.638 | 4.351 | -2.287 | -4.09 |

## Table A3. Momentum Returns for Stocks with and without Options

Decile portfolios are formed every month from January 1996 to April 2016 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 using NYSE breakpoints. Decile 10 indicates the winner portfolio, Decile 1 denotes the loser portfolios and WML indicates the winner-minus-loser portfolio. The table reports the value weighted average excess monthly returns for each decile portfolio as well as the corresponding alphas of the CAPM and the three-factor Fama and French (1993) model (FF3). 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. We do not impose any restriction in the tradability of the options and we define a stock as an optionable stock when a stock has listed options or not.

| Stock returns | | | | | | |
|---|---|---|---|---|---|---|
| | Stocks with Options | | | Stocks without Options | | |
| *Decile* | Avg Ret | CAPM Alpha | FF3 Alpha | Avg Ret | CAPM Alpha | FF3 Alpha |
| Losers | 0.289 | 0.104 | 0.097 | -0.719 | -0.933 | -0.935 |
| 2 | 0.564 | 0.476 | 0.464 | 0.449 | 0.245 | 0.228 |
| 3 | 0.769 | 0.693 | 0.690 | 0.638 | 0.497 | 0.472 |
| 4 | 0.730 | 0.689 | 0.703 | 0.550 | 0.412 | 0.420 |
| 5 | 0.491 | 0.459 | 0.483 | 0.706 | 0.613 | 0.659 |
| 6 | 0.615 | 0.587 | 0.621 | 0.553 | 0.423 | 0.462 |
| 7 | 0.537 | 0.477 | 0.513 | 0.730 | 0.627 | 0.645 |
| 8 | 0.683 | 0.632 | 0.674 | 0.658 | 0.533 | 0.572 |
| 9 | 0.499 | 0.467 | 0.515 | 0.567 | 0.439 | 0.468 |
| Winners | 0.967 | 0.918 | 0.992 | 1.099 | 0.985 | 1.028 |
| WML | 0.678 | 0.814 | 0.894 | 1.819 | 1.919 | 1.963 |
| | 1.29 | 1.64 | 1.83 | 3.47 | 3.66 | 3.68 |

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

| | ΔLosers | ΔWinners |
|---|---|---|
| Avg Ret | 1.009 | -0.132 |
| *t*-stat | 3.19 | -0.53 |

**Table A4. Cross-Sectional Regressions - Different Momentum Periods and Short Interest**

This table presents results from Fama-MacBeth regressions of firm's returns on past performance, measured based on the cumulative stock return of the past 12-months (R(2,12)), short-term (R(2,6)) or medium-term (R(7,12)) momentum and short interest. 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:

$$\text{Ret}_{i,t+1} = \delta_{0,t} + \delta_{1,i}\text{CumRet}_{i,t} + \delta_{2,i}\text{Short Interest}_{i,t} + \delta'_{3,i}\mathbf{Z}_{i,t} + \varepsilon_{i,t+1}$$

where $\text{Ret}_{i,t+1}$ denotes the time $t+1$ stock return of firm $i$, $\text{CumRet}_{i,t}$ is the cumulative stock return over the past 12-months (standard momentum), short-term (ST) or medium-term (MT) momentum of stock $i$ on month $t$. $\mathbf{Z}$ represents the set of control variables.

| Stock Returns | | | | | | |
|---|---|---|---|---|---|---|
| | *Stocks with Options* | | | *Stocks without Options* | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Intercept | 0.006 | 0.007 | 0.022 | 0.007 | 0.009 | 0.019 |
| *t-stats* | 1.57 | 2.27 | 2.30 | 2.12 | 2.77 | 2.18 |
| $\text{CumRet}_{i,t}$ | 0.006 | 0.002 | 0.004 | 0.005 | 0.005 | 0.005 |
| *t-stats* | 1.66 | 0.55 | 1.25 | 1.87 | 1.93 | 2.05 |
| $\text{CumRet}^{ST}_{i,t}$ | -0.005 | -0.001 | -0.001 | 0.001 | 0.000 | 0.003 |
| *t-stats* | -1.48 | -0.48 | -0.28 | 0.43 | 0.17 | 1.57 |
| $\text{CumRet}^{MT}_{i,t}$ | -0.003 | 0.001 | 0.000 | -0.002 | -0.003 | -0.001 |
| *t-stats* | -1.18 | 0.27 | 0.08 | -0.91 | -1.29 | -0.42 |
| $\text{Short Interest}_{i,t}$ | | -0.040 | -0.038 | | -0.089 | -0.079 |
| *t-stats* | | -3.19 | -3.58 | | -4.10 | -4.07 |
| *Control Variables* | | | | | | |
| $\text{Ln(Size)}_{i,t}$ | | | 0.000 | | | 0.000 |
| *t-stats* | | | -0.14 | | | -0.28 |
| $\text{Ln(Price)}_{i,t}$ | | | -0.003 | | | -0.001 |
| *t-stats* | | | -2.72 | | | -1.40 |
| $\text{IOR}_{i,t}$ | | | 0.001 | | | 0.003 |
| *t-stats* | | | 0.32 | | | 0.98 |
| $\text{B/M}_{i,t}$ | | | 0.002 | | | 0.001 |
| *t-stats* | | | 1.53 | | | 1.94 |
| $\text{IVOL}_{i,t}$ | | | -0.213 | | | -0.272 |
| *t-stats* | | | -2.44 | | | -3.41 |
| $\text{R(1)}_{i,t}$ | | | -0.014 | | | -0.025 |
| *t-stats* | | | -2.30 | | | -4.50 |
| $\text{ILLIQ}_{i,t}$ | | | -2.011 | | | -0.074 |
| *t-stats* | | | -0.89 | | | -1.30 |
| Adj-$R^2$ | 3.14% | 3.84% | 9.01% | 1.87% | 2.57% | 6.82% |

## Table A5. Cross-Sectional Regressions - Synthetic Short and Long Order Imbalances

This table presents results from Fama-MacBeth regressions of synthetic short and long 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:

$$\Upsilon_{i,t+1} = \delta_{0,t} + \delta_{1,i}\text{R}(2,12)_{i,t} + \delta_{2,i}\text{Short Interest}_{i,t} + \delta'_{3,i}\mathbf{Z}_{i,t} + \varepsilon_{i,t+1}, \Upsilon = \text{Short and Long.}$$

where $\Upsilon_{i,t+1}$ denotes the time $t+1$ synthetic short and long 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* | | *Small Customers* | | *Firms* | |
| | *Short* | *Long* | *Short* | *Long* | *Short* | *Long* |
| Intercept | 0.336 | 0.363 | 0.364 | 0.372 | 0.293 | 0.372 |
| *t-stats* | 40.92 | 38.25 | 33.85 | 31.81 | 24.31 | 31.81 |
| $\text{CumRet}_{i,t}$ | -0.003 | 0.004 | -0.004 | 0.006 | 0.001 | 0.006 |
| *t-stats* | -1.71 | 2.97 | -2.08 | 3.42 | 0.44 | 3.42 |
| *Control Variables* | | | | | | |
| $\text{Short Interest}_{i,t}$ | 0.005 | -0.100 | -0.038 | -0.087 | 0.055 | -0.087 |
| *t-stats* | 0.61 | -12.29 | -4.71 | -7.76 | 3.54 | -7.76 |
| $\text{Ln(Size)}_{i,t}$ | -0.006 | -0.007 | -0.007 | -0.008 | -0.003 | -0.008 |
| *t-stats* | -10.89 | -12.07 | -10.92 | -10.77 | -3.95 | -10.77 |
| $\text{Ln(Price)}_{i,t}$ | -0.002 | -0.007 | -0.002 | -0.006 | -0.003 | -0.006 |
| *t-stats* | -2.11 | -7.21 | -1.70 | -5.78 | -2.74 | -5.78 |
| $\text{IOR}_{i,t}$ | -0.001 | 0.016 | 0.010 | 0.011 | -0.008 | 0.011 |
| *t-stats* | -0.49 | 5.00 | 2.50 | 2.79 | -1.99 | 2.79 |
| $\text{B/M}_{i,t}$ | 0.000 | 0.001 | 0.002 | 0.000 | 0.001 | 0.000 |
| *t-stats* | 0.32 | 0.48 | 1.52 | 0.11 | 0.53 | 0.11 |
| $\text{IVOL}_{i,t}$ | -0.494 | -0.439 | -0.615 | -0.433 | -0.457 | -0.433 |
| *t-stats* | -7.44 | -6.12 | -9.49 | -5.42 | -6.31 | -5.42 |
| $\text{REV}_{i,t}$ | 0.037 | 0.009 | 0.042 | 0.007 | 0.008 | 0.007 |
| *t-stats* | 7.21 | 2.02 | 7.18 | 1.41 | 1.14 | 1.41 |
| $\text{ILLIQ}_{i,t}$ | -11.127 | -16.441 | -28.004 | -3.792 | 40.026 | -3.792 |
| *t-stats* | -0.59 | -0.97 | -1.23 | -0.19 | 1.50 | -0.19 |
| Adj-$R^2$ | 2.32% | 2.77% | 2.33% | 2.27% | 2.41% | 2.27% |

## Table A6. Anomaly Portfolios

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

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