# Out of Sync: Dispersed Short Selling and the Correction of Mispricing[*]

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How synchronized are short sellers? We examine a unique dataset on the distribution of profits across a stock's short sellers and find evidence of substantial dispersion in the initiation of their positions. Consistent with this dispersion reflecting "synchronization risk," i.e., uncertainty among short sellers about when others will short sell (Abreu and Brunnermeier, 2002, 2003), more dispersed short selling signals (i) greater stock overpricing; and (ii) longer delays in overpricing correction. These effects are prevalent even among stocks facing low short-selling costs or other explicit constraints. Overall, our findings provide novel cross-sectional evidence of synchronization problems among short sellers and their pricing implications.

*Keywords*: Short Selling, Limits to Arbitrage, Synchronization Risk

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# 1 Introduction

A recent and growing literature uncovers the role of financial frictions facing arbitrageurs in explaining asset mispricing. However, mispricing, and in particular overpricing, has been substantial in situations of low or no frictions.[1] Why can overpricing persist in these cases? In this paper, we take on this question to the observed cross-section by investigating whether coordination problems among short sellers explain differences across stocks in the level and persistence of overpricing.

The notion that coordination problems among arbitrageurs might limit arbitrage originates from Abreu and Brunnermeier (2002, 2003). They propose a model of dispersed opinions where the aggregate resources of all arbitrageurs are sufficient to correct asset mispricing, yet the correction takes place only with a delay. The dispersion of opinions creates uncertainty among the arbitrageurs about the timing decisions of other rational arbitrageurs. Crucially, it results in a synchronization problem that renders arbitrageurs temporarily unable to coordinate their strategies and eliminate the mispricing.

To shed light on the empirical validity of this argument, we look into synchronization problems within a prototypical group of arbitrageurs, namely short sellers. For approximately 4,000 U.S. stocks, our data contain previously unavailable information on the distribution of the mark-to-market profits of all short positions in a stock at daily frequency. For each stock, we use the dispersion in these profits as a proxy for lack of synchronization, or "desynchronization," in short selling. Our approach is based on the observation that, whereas all short positions in the stock experience the same daily return, observed differences in cumulated returns across them must map back to differences in when they were established. Thus, dispersed mark-to-market profits reflect a desynchronization in short sellers' trades.

We first provide support for the use of short sellers' profit dispersion as a valid empirical proxy for disagreement-related "desynchronization" in their positions. The asset pricing implications of the synchronization-risk argument rely on the premise that coordination issues among arbitrageurs are driven by differences in their opinions ("disagreement") rather than by non-fundamental reasons such as differences in hedging motives. In line with this premise, we find that our proxy is positively associated in the cross-section with standard variables capturing disagreement around a stock such as

[1] See, e.g., Lamont and Stein (2004).

turnover, dispersion in analysts' forecasts and bid-ask spreads. These relations remain strong after controlling for differences in hedging needs across a stock's traders and other stock characteristics such as return volatility. Our proxy for desynchronization also drops after the release of negative public news about a firm or analyst downgrades, consistent with the theory's implication that "synchronizing events" should facilitate the coordination of arbitrageurs.

Using this proxy, we next examine whether stocks with more desynchronized short selling are more overpriced, in line with the insight of Abreu and Brunnermeier (2003). Following the standard approach in the literature, we first associate overpricing with inferior future abnormal returns, i.e. lower alphas relative to a standard factor pricing model. Sorting stocks by short sellers' desynchronization, we document a decreasing pattern in future abnormal returns and a statistically significant spread between high- and low-desynchronization portfolios of $-7.6\%$ per annum. This result holds strongly in double-sorted portfolios that first condition on short interest or other well-known cross-sectional determinants of returns. Consistent with the theory that synchronization problems are more prevalent in firms with a poorer information environment, the desynchronization effect on returns almost doubles among stocks subject to greater differences in beliefs or information asymmetries. We confirm these results using Fama-MacBeth regressions that simultaneously control for stock characteristics and equity lending market conditions. As an alternative proxy for overpricing, we adopt the relative mispricing score ($MISP$) of Stambaugh, Yu, and Yuan (2015). In further support for the synchronization-risk hypothesis, we find that stocks in the top tercile of our desynchronization proxy are 16% more likely than stocks in the bottom tercile to become overpriced in the next month.

We differentiate our results from other mechanisms that have been shown in prior studies to limit arbitrage activity and affect stock mispricing. First, in presence of disagreement between the traders in a stock, Miller (1977) conjectures that short-selling constraints can induce overpricing by curtailing the activity of the pessimists. Empirically, his hypothesis implies a negative relation between disagreement and future abnormal returns *only* among stocks with *both* tight short-sale constraints and high dispersion in opinions (Boehme, Danielsen, and Sorescu, 2006). In contrast, the positive relation between desynchronization and overpricing that we document holds strongly even for stocks for which either or both of these conditions are not met. Second, the failure of short sellers to correct overpricing could respond to the risks associated with sentiment-driven traders exacerbating overpricing (De Long et al., 1990, and Shleifer and Vishny, 1997). Against this possibility, we find a strong negative impact of desynchronization on risk-adjusted returns in both high- and low-sentiment periods. Third, following D'Avolio (2002), the dispersion of opinions about a stock could be positively associated with uncertainty about future shorting fees, in which case our results could just mirror the effect of fee volatility ("short-selling risk") on future returns documented by Engelberg, Reed, and Ringgenberg (2018). By contrast, the desynchronization effect prevails across different levels of short-selling risk and, importantly, generates economically significant return spreads among stocks displaying either low or high fee volatility. Fourth, synchronization problems might just arise among stocks that are more costly to arbitrage, in which case our results could reflect the effect of arbitrage asymmetries and idiosyncratic volatility on mispricing highlighted by Stambaugh, Yu, and Yuan (2015). Against this possibility, the effect of desynchronization on overpricing is robust to controlling for idiosyncratic volatility and is present when we orthogonalize our desynchronization proxy with respect to idiosyncratic volatility. Moreover, the high-minus-low desynchronization portfolios generate negative spreads also in stocks with low idiosyncratic volatility, which are arguably less costly to arbitrage.

We find evidence that short-selling desynchronization affects also the *duration* of overpricing. Abreu and Brunnermeier (2002) note that, in deciding when to short an overpriced asset, short sellers trade off the benefits of selling early and secure the profits of the eventual correction versus the costs of holding the position for too long. In these conditions, they delay acting on their information to correct a given level of overpricing, with the delay increasing with their desynchronization. To quantify this delay empirically, we first count the number of consecutive months over which a stock remains relatively overpriced according to the mispricing score $MISP$. An advantage of this approach is that it focuses on relatively long-lived overpricing events around which there is arguably more uncertainty and thus room for desynchronization among traders. Consistent with the theory, desynchronization is strongly positively associated to the duration of overpricing in the cross-section, and remains so after controlling for the level of overpricing, shorting fees, short interest, and various stock characteristics. The effect is economically meaningful, as a one standard deviation increase in the desynchronization proxy requires 16 additional days for the overpricing to disappear.

In a second approach, we document delayed mispricing correction also among the shorter-lived failures of the put-call parity no-arbitrage relation in the stock option market (Ofek, Richardson, and Whitelaw, 2004; Engelberg, Reed, and Ringgenberg, 2018). For each stock, we compare observed prices with their synthetic counterparts as implied by this parity. Accounting for transaction costs in the options market, we associate stock overpricing with a positive difference between the observed and synthetic prices. Following this approach, we find that the duration of put-call parity-related overpricing is positively associated with our desynchronization proxy, with a one standard deviation increase in desynchronization requiring 1.4 additional days, or a 16% increase relative to the mean, for the overpricing to disappear. Taken jointly, our evidence around short- and longer-lived mispricing events offers strong additional support to the synchronization-risk hypothesis.

Lastly, we subject our findings to a number of additional tests. First, we find that, as expected from the theory, the delay in price correction is greater among stocks with fewer synchronizing news events. Second, we show that the effect of short sellers' desynchronization on the extent and duration of stock overpricing does not depend on the specific desynchronization proxy that we adopt. Finally, consistent with desynchronization among short sellers affecting overpricing but not *underpricing* we find, in placebo tests, no relation between our desynchronization proxy and the delay with which stock underpricing is corrected.

Our paper contributes to two main strands of the literature. First, it contributes to the growing literature on limits to arbitrage. Several seminal theoretical studies identify frictions that can limit arbitrage activity and hinder the correction of mispricing in financial markets. These include noise trader risk (De Long et al., 1990), outflow risk (Shleifer and Vishny, 1997), search and monetary costs (Diamond and Verrecchia, 1987, and Duffie, Garleanu, and Pedersen, 2002), capital constraints (Gromb and Vayanos, 2002, Brunnermeier and Pedersen, 2009, Garleau and Pedersen, 2011), and fee-volatility risk (D'Avolio, 2002). While extensive empirical evidence supports the relevance of these limits to arbitrage, the impact of synchronization risk has been documented to a much lesser extent.[2] Indeed, the existing studies examining synchronization risk are confined to specific episodes

[2]See Jones and Lamont (2002), Nagel (2005), Saffi and Sigurdsson (2011), and Prado, Saffi, and Sturgess (2016) for evidence on the role of short-selling constraints related to lending supply and shorting costs, Kolasinksi, Reed, and Ringgenberg (2013) and Chague et al. (2017) for search costs, Liu and Mello (2011) and Giannetti and Kahraman (2018) for outflow risk, Duan, Hu, and McLean (2010) for arbitrage risk, Engelberg, Reed, and Ringgenberg (2018) for fee-volatility risk, and Gargano, Sotes-Paladino, and Verwijmeren (2019) for margin constraints.

of severe overpricing, as reflected in the emergence and burst of bubbles (Brunnermeier and Nagel, 2004; Temin and Voth, 2004). The implications of synchronization risk are further reaching, though. Following Abreu and Brunnermeier (2002), it could affect not only specific assets and market times, but also the whole cross-section of stocks during normal times. Due to the lack of a stock-level proxy for coordination problems, the impact of this type of risk on the cross-section has remained unexplored. To our best knowledge, we are the first to propose a daily measure of desynchronization among arbitrageurs based on short-selling data to directly examine the prevalence and asset pricing implications of synchronization risk within a large cross-section of stocks. Ljungqvist and Qian (2016) offer an opposing view on the effective impact of limits to arbitrage, according to which short sellers in the subset of stocks with the tightest short-selling constraints can circumvent these restrictions by disclosing their positions ("short and disclose"). By doing so, they induce the long shareholders to sell and precipitate a price correction. Complementing their findings, our results indicate that for the majority of the stocks in the cross section, for which the short-and-disclose strategy is not prevalent, synchronization risk can be an economically relevant limit to arbitrage.[3]

Second, our work contributes to the recent literature that highlights differences across short sellers and their market implications. Consistent with short sellers being capable of identifying overpricing, several papers have shown that short-selling measures anticipate future stock return declines in the cross-section.[4] A common feature of this literature is that short sellers are implicitly regarded as a relatively homogeneous group of traders with presumably similar information. However, Boehmer, Jones, and Zhang (2008) document different trading abilities among short sellers, with institutional nonprogram short sales being the most informative. Comerton-Forde, Jones, and Putnins (2016) show that short sellers are heterogeneous in their trading style, with short sellers providing liquidity being

[3]In this sense, our findings can be seen as related to the more prevalent "short-and-mum" strategy of shorting and waiting for the stock price to fall, for which desynchronization problems are more likely. Indeed, the short-and-disclose strategy has been documented on a small subset of firms in the cross section (e.g., the sample of Ljungqvist and Qian (2016) is composed of 124 stocks), consistent with the potential unprofitability of this strategy in presence of noise trading (Kovbasyuk and Pagano, 2020). Importantly, the tight constraints on these stocks imply little scope for short-selling desynchronization.

[4]The forecasting power of short selling in the cross-section has been documented using intraday (e.g., Aitken et al., 1998), daily (e.g., Boehmer, Jones, and Zhang, 2008, Diether, Lee, and Werner, 2009) and monthly (e.g., Desai et al., 2002, Asquith, Pathak, and Ritter, 2005, Cohen, Diether, and Malloy, 2007, Saffi and Sigurdsson, 2011) short-selling activity. Rapach, Ringgenberg, and Zhou (2016) exploit monthly data over a 42-year period to show that short interest is also a strong predictor of stock returns on the aggregate market. More recently, Wang, Xuemin, and Zheng (2019) show that shorting flows remain a significant predictor of negative future stock returns during the 2010-2015 period, when daily short-sale volume data are published in real time.

different from those demanding it. A contribution of our paper is to document a previously unexplored type of heterogeneity, as captured by the dispersion in the timing of positions, among short sellers. We provide evidence that this heterogeneity can reflect their inability to synchronize their trades to correct overvaluation.

The rest of the paper is organized as follows. In Section 2 we introduce the conceptual framework and hypotheses. In Section 3 we describe our dataset and our proxy for desynchronization among short sellers, and present summary statistics. In Section 4 we relate short sellers' desynchronization to firms' information environment. In Sections 5 and 6 we examine the relation between short sellers' desynchronization and, respectively, the level and duration of stock overpricing. We present additional results and robustness analyses in Section 7, and our conclusions in Section 8.

## 2 Hypotheses Development

Our main goal is to relate the degree of synchronization across the short sellers of a stock to the level and duration of the stock's overpricing, and is motivated by the theoretical work of Abreu and Brunnermeier (2002, 2003). In particular, Abreu and Brunnermeier (2003) introduce a model of dispersed opinions where arbitrageurs become sequentially aware of a common overpricing opportunity and a critical mass of the arbitrageurs is needed to correct it. In presence of growing overpricing, arbitrageurs who short the asset too early forgo much of the profits of shorting it at an even higher price just before the correction. Arbitrageurs who delay their shorting decisions too long miss exploiting the opportunity altogether. The dispersion of opinions creates uncertainty among the arbitrageurs about the timing decisions of other rational arbitrageurs. Crucially, it results in a "synchronization problem" that renders arbitrageurs temporarily unable to coordinate their selling strategies and correct the overpricing even when they have the collective ability, i.e., the aggregate capital, to do it. This motivates our first hypothesis:

**Hypothesis 1:** *Stocks with less synchronized short selling are more overpriced even if they are relatively easy to short.*

Besides the *level* of overvaluation, synchronization problems can affect the *duration* of overpricing.

Abreu and Brunnermeier (2002) note that arbitrageurs not only face uncertainty about when other arbitrageurs will start exploiting a common arbitrage opportunity, but also incur holding costs when exploiting it. This is especially the case for short sellers, who have to pay lending fees and tie up capital in margin accounts. In deciding when to short an overpriced asset, short sellers then trade off the benefits of selling early to secure the profits of the eventual correction versus the costs of holding the short position for too long. In this setting, short sellers delay acting on their information and, keeping the size of holding costs fixed, take longer to correct a given level of overpricing the less synchronized they are. This implication motivates our second hypothesis:

**Hypothesis 2:** *For a given level of overpricing and keeping holding costs fixed, less synchronized short selling is associated with longer delays in the correction of overpricing.*

Hypotheses 1 and 2 guide our empirical analysis in the remainder of the paper. We note that the extent of both desynchronization in short sellers' trades and mispricing (duration) are endogenously determined, in equilibrium, in these models. Accordingly, our tests do not aim to establish causality but the extent to which these variables are associated, following these hypotheses, in the cross-section of stocks.

# 3 Data and Desynchronization Proxy

For our empirical tests we extract a measure of short-selling desynchronization from a novel dataset on the mark-to-market profits of the short positions in a stock. We combine these data with equity lending data, as well with other firm and stock characteristics.

## 3.1 Short-Selling Datasets

Our source of short-selling data is IHS Markit, from which we obtain two datasets. The first, the Securities Finance Buyside Analytics Datafeed (MSF), contains information on stock borrowing and lending activity. Since U.S. equity short sellers need to borrow the stocks they sell, this information has been used extensively in the literature to infer short-selling activity (for recent references see, e.g., Engelberg, Reed, and Ringgenberg, 2018; Boehmer et al., 2020a; Muravyev, Pearson, and Pollet, 2021).[5] The second dataset is novel and complements MSF with information on the profits of short sellers on their open short positions. Since the equity lending market is over-the-counter (OTC), IHS Markit collects the information for both datasets at the transactions level directly from a variety of participants. These include prime brokers, custodians, asset managers and hedge funds, who together account for about 90% of the securities lending market in developed countries. We focus on the U.S. market, for which IHS Markit databases cover a broad cross-section of 4,000 stocks for a total of approximately 5.7 million stock-day observations over the period spanned between January 2011 and December 2017.

From the profits database we observe, for each stock $i$ and day $t$, the distribution of gross-of-fees mark-to-market (cumulated) returns being experienced by the short sellers of $i$ from the start date of their transactions until $t$. Short sellers can keep their positions open over a given time span by renewing shorter-term stock loans, possibly from different lenders. To account for this, IHS Markit defines the start date of a short position as the initiation date for new transactions and the original start date for renewing transactions.[6] Returns on short positions are tabulated over 19 bins, $bin_{i,t}^{\lfloor n \rfloor}$ ($n = 1, \ldots, 19$), representing the fraction of shares on loan for stock $i$ whose cumulated returns fall in the $n$th return interval, with left and right boundaries '$\lfloor$' and '$\rfloor$', at time $t$. The first 10 intervals ($n = 1, \ldots, 10$) contain the fraction of shares on loan experiencing losses in the $(-\infty, -100\%]$, $(-100\%, -75\%]$, $(-75\%, -50\%]$, $(-50\%, -40\%]$, $(-40\%, -30\%]$, $(-30\%, -20\%]$, $(-20\%, -15\%]$, $(-15\%, -10\%]$, $(-10\%, -5\%]$, and $(-5\%, 0\%]$ ranges. The remaining 9 positive-return intervals ($n = 11, \ldots, 19$) are defined analogously (e.g., $(0\%, 5\%], (5\%, 10\%], \ldots, (75\%, 100\%]$). Existing data allows researchers to observe only the aggregate level of short interest. Thus, our data contribute disaggregated information on the mark-to-market profits experienced by different subsets of short sellers to existing aggregate data.[7]

Figure 1 displays an instance of the data for Tesla as of September 11, 2015. The top panel high-

[5] Earlier references using IHS Markit data are Saffi and Sigurdsson (2011), Beneish, Lee, and Nichols (2015), Prado (2015) and Aggarwal, Saffi, and Sturgess (2016).

[6] To determine the date on which the initial short was placed with the broker, IHS Markit uses $T - 3$ from the stock lending start date assuming a 3-day settlement, unless the stock is experiencing relatively high borrowing costs, in which case they use same-day pricing assuming high demand to short the stock.

[7] Previously available equity lending information is consolidated across all short positions in the stock. To assess differences across the short positions in a stock, Jank and Smajlbegovic (2017) and Boehmer, Duong, and Huzar (2018) examine mandatory disclosures of large short positions in Europe and Japan, respectively, while von Beschwitz, Lunghi, and Schmidt (2017) and Choi et al. (2017) study hedge fund trades.

lights a wide dispersion in the profits that the short sellers of Tesla were experiencing at that point in time. Losing positions (54.1% of the outstanding short interest) were experiencing cumulative returns in the range of -40% to 0%, while winning positions (45.9% of the short interest) were accumulating gains between 0% and 15%. The high volatility of the stock price since July 2015 shown in the bottom panel suggests a high uncertainty about Tesla around the time. In Section 4, we assess the strength of the cross-sectional relationship between this type of profit dispersion, as a proxy for short-selling desynchronization, and the uncertainty surrounding a stock.

### 3.2 Auxiliary Data Sources

We use the stock's CUSIP identifier in our short-selling profits database to merge it with an array of standard datasets. We obtain stock market prices and other stock characteristics from CRSP and compute various financial accounting ratios using information from COMPUSTAT. We calculate the dispersion in stock analysts' forecasts from the I/B/E/S database. We obtain corporate news from RavenPack News Analytics database. Finally, we source options data from the Option Metrics database. We drop stocks with market capitalization below $10 million or prices below $1. In our subsequent analysis, we describe the variables that we create from these datasets in more detail.

### 3.3 Measuring Desynchronization in Short Selling

In Abreu and Brunnermeier (2002, 2003), the synchronization problems in arbitrageurs' trades follow from a disagreement about the stock's prospects. The models are agnostic about whether such (unobservable) disagreement stems from fundamental differences in the arbitrageurs' beliefs (e.g., different interpretations of a common signal) or in their information sets (e.g., information asymmetries), as long as it ultimately translates into a temporal miscoordination, or "desynchronization," in their decisions. It is this desynchronization within a group of prototypical arbitrageurs, namely equity short sellers, that we aim to capture in this study.

Existing short interest data in a stock are *consolidated* across all of its short positions, so measuring short-selling desynchronization from these data is challenging, if not impossible. To overcome this problem, we take advantage of the particular level of disaggregation across the short positions in the stock, in terms of their mark-to-market cumulated returns, that our short-selling profits dataset offers. Specifically, we note that since all the positions that remain open throughout a day experience the same daily return, differences in their cumulated returns must map back to differences in prices, hence in the timing, at which they were initiated.[8] This observation suggests using the *dispersion* in the cumulated returns of a stock's short positions as a proxy for the degree of desynchronization in its short selling.

For each stock $i$ and date $t$, the short-selling profits data contain the fraction of shares shorted within each return interval (the variable $bin_{i,t}^{\lfloor n \rfloor}$ defined in Section 3.1). A natural measure of dispersion in these returns, hence of desynchronization in short selling, is the *lack of concentration* in the associated distribution:

$$Desync_{i,t} = 1 - \sum_{n=1}^{19} \left( bin_{i,t}^{\lfloor n \rfloor} \right)^2. \tag{1}$$

The *Desync* measure defined in Equation (1) subtracts from one the Herfindahl-Hirschman index (a commonly used measure of concentration) of the return bins. Higher values of *Desync* are associated with greater desynchronization in short sellers' trades. *Desync* is bounded below by zero, when all of the stock's shorted shares experience a common level of profits, and above by 0.947, when the cumulated returns of the stock's shorted shares are uniformly distributed across all bins.[9]

Clearly, measuring lack of concentration is not the only way to assess the dispersion of a distribution. In particular, in Section 7 we examine an alternative dispersion measure, *Desync_SD*, based on the estimated standard deviation of the cumulated returns on the short positions in a stock.

**Desynchronization and Return Volatility.** The desynchronization in a stock's short selling should be closely related to the volatility in the stock's returns. On the one hand, stocks with more uncertain prospects should exhibit *both* higher disagreement among their short sellers, hence desynchronization in their positions, *and*—following Harris and Raviv (1993)—greater return volatility. Because this desynchronization is of the fundamental (information-related) type underlying the

[8] Of course, the converse is not true: outstanding short positions in a stock with different durations will experience the same cumulated return as long as the prices prevailing at the different initiation times are identical.

[9] This corresponds to the scenario where all bins contain the same fraction of shares (1/19) and *Desync* is equal to $1 - 19(1/19)^2 = 0.947$.

synchronization-risk theory, a desirable attribute of *Desync* is that it is positively associated with returns volatility. On the other hand, the dispersion in short-selling profits upon which *Desync* is based can mechanically increase with the volatility of the stock's returns even if the fundamental desynchronization across the short positions does not change.[10]

To exclude a (mechanical) effect driven by return volatility, we explicitly control for return volatility in all of our subsequent analyses. In addition, we confirm that our main results hold when we repeat our analysis replacing *Desync* by an orthogonalized version with respect to return volatility (see Section 5.3.4).

### 3.4 Summary Statistics

Table 1 displays summary statistics for *Desync* (Panel A), stock and firm fundamental variables (Panel B), equity lending market characteristics (Panel C), and pairwise correlations (Panel D). For each variable, we present the time-series averages of the daily cross-sectional summary statistics.

If the short sellers of a stock acted on their information at similar points in time we would expect the initiations of their positions to be highly synchronized and the stock's *Desync*, consequently, to be low. The summary statistics in Panel A indicate, on the contrary, that for the typical stock in our sample *Desync* is high (its mean and median are, respectively, 0.63 and 0.68) and significantly above zero (the 5th and 25th percentiles of its distribution are, respectively, 0.23 and 0.55).

Panel B shows summary statistics at the stock and firm levels. The average (median) market capitalization of a firm in our sample is \$6,847 (\$1,377) million. The average (median) monthly stock return is 1.08% (0.43%), consistent with a positive and sizable risk premium during the period. We display also summary statistics for the different proxies of the information environment surrounding a firm that we examine in Section 4; namely, stock return volatility, bid-ask spread, turnover and analysts' forecast dispersion.

Panel C displays summary statistics for our equity lending variables. In line with previous studies (e.g. D'Avolio, 2002), the mean fraction of shares available for lending is 21.6% of the total market capitalization, the mean short interest is 3.9%, and the mean borrowing fee is 1.24% per annum.[11]

[10] To see this, note that keeping the dispersion in the initiations of their positions constant, the profit dispersion of a stock's short sellers will generally increase with the stock's return volatility.

[11] As is standard in the literature (see, e.g., Boehmer et al., 2020a), we approximate total open short positions in a

Finally, Panel D reports the correlation matrix for the main variables in our subsequent analysis. *Desync* presents a fairly low correlation (in absolute value) with all variables, suggesting that it contains information not already reflected in any of the other variables. It is positively correlated with *Short Interest* and, to a lesser extent, with *Idio Vol* and *Turnover*. It is negatively correlated with firm size, and exhibits close to zero correlation with the other variables considered. The pairwise correlations across variables other than *Desync* in our sample are largely as expected.[12] Since the summary statistics for stock, firm and equity lending market characteristics displayed in Panels B and C are also consistent with prior studies, we conclude that our sample of stocks is comparable with those examined in the related literature.

# 4 Short Sellers' Desynchronization in the Cross-Section of Stocks

Our hypotheses do not depend on the specific source of disagreement driving desynchronization. However, the empirical validity of *Desync* as a proxy for disagreement-driven synchronization problems depends on the extent to which it reflects information-related, as opposed to non-fundamental, discrepancies across short positions.

We follow two approaches to link *Desync* to information-related discrepancies. In Section 4.1, we test the strength of the cross-sectional relationship between *Desync* and a set of information- and noninformation-related variables. In Section 4.2, we examine whether *Desync* falls after "synchronizing events" that facilitate the coordination among short sellers.

## 4.1 Desynchronization and Firms' Information Environment

In principle, the dispersion in timing decisions underlying *Desync* can reflect fundamental reasons such as a disagreement about the stock's degree of overvaluation, or non-fundamental reasons such as the hedging of options or relative-value (e.g., convertible arbitrage) positions on the stock (Battalio and Schultz, 2011; Brown et al., 2012; Berkman, McKenzie, and Verwijmeren, 2017).

stock, or "short interest," by the number of shares of the stock borrowed in the lending market. To avoid conditioning on an unobservable variable, we follow Richardson, Saffi, and Sigurdsson (2017) in using the shares borrowed on date $t$ to estimate the short interest at $t$ that we use in our subsequent regression and portfolio analyses.

[12] For instance, bid-ask spreads and idiosyncratic volatility are negatively correlated with size, while borrowing fees are positively correlated with short interest but negatively correlated with the supply of lendable shares.

To assess the explanatory power of its fundamental and non-fundamental drivers, we regress *Desync* on a set of proxies for the information environment surrounding a stock while simultaneously controlling for non-fundamental sources of dispersion in the timing of short sales. More precisely, we run the following panel regression:

$$Desync_{i,t} = \alpha_i + \tau_t + \beta' \boldsymbol{x_{i,t}} + \epsilon_{i,t},$$

where $\alpha_i$ and $\tau_t$ are stock- and time-fixed effects, and $x_{i,t}$ represents the set of regressors, split into two groups.

The first group consists of fundamental drivers. Given that the theory is agnostic about whether the disagreement driving desynchronization stems from differences in the arbitrageurs' beliefs or in information asymmetries, we include both sets of proxies for the firm's information environment. Our proxies for *difference in beliefs* are Turnover and Dispersion in analysts' forecast. Shalen (1993), Harris and Raviv (1993) and Kandel and Pearson (1995) introduce theoretical models in which differences in the way that traders interpret common information generate a positive relation between belief dispersion and stock turnover. The use of dispersion in forecasts across a stock's analysts follows Diether, Malloy, and Scherbina (2002), who propose using this measure as a proxy for differences in beliefs about a stock. Our proxies for *information asymmetry*, are Bid-ask spread and Firm size. Glosten and Milgrom (1985) and Easley and O'Hara (1986), among others, argue theoretically that market makers should set wider bid-ask spreads when they expect higher levels of information asymmetry. The choice of size follows the simple intuition, used by prior studies (e.g., Chae, 2005; Zhang, 2006), that more information is available for larger firms.

The second group aims to control for non-fundamental sources of short-selling desynchronization. These include Total open interest of options on the stock, Amount of convertible debt, Short interest, Supply, and Borrowing (Shorting) fee. Options hedging and the implementation of convertible arbitrage strategies could require shorting a stocks (Battalio and Schultz, 2011; Brown et al., 2012; Berkman, McKenzie, and Verwijmeren, 2017) despite having no fundamental view on its overpricing. More option hedging or convertible arbitrage activities could then affect *Desync* for reasons unrelated to disagreement. Similarly, lower supply or demand of lendable shares, as well as higher borrowing fees, could mechanically reduce *Desync* by limiting the number of traders able or willing to take short positions. To assess the strength of the relationship between return volatility and *Desync* following our argument in Section 3.3, we include idiosyncratic volatility as an additional control within this group.

Table 2 reports our regression results. Column (1) includes the proxies for difference in beliefs among the stock market participants, while column (2) includes the proxies for information asymmetry, as the only explanatory variables. Column (3) includes both types of proxies. Finally, column (4) presents results for the model in column (3) augmented with the full set of controls. To facilitate the comparison across coefficients, we standardize regressors to have zero mean and unit variance. Across models, standard errors are double-clustered in the stock and time dimension.

The results broadly support the validity of *Desync* as a proxy for information-driven desynchronization. First, *Desync* is strongly positively associated with both proxies for difference in beliefs, namely Turnover and Analysts' Forecast Dispersion, in models (1) and (3). Second, *Desync* is higher for smallcaps and for stocks with larger bid-ask spreads in models (2) and (3), highlighting a strong and positive relation with the degree of information asymmetry surrounding a stock. The adjusted R-squared of 38% in models (1) and (2) indicates that the set of proxies for difference in beliefs and information asymmetry explain a similar fraction of the variation of *Desync*. With the exception of Turnover, these relations preserve their sign and significance, indicating that *Desync* remains significantly related to proxies for disagreement in short selling, when we account for all controls in model (4).[13] The adjusted R-squared is less than 40% in all cases, implying that a substantial fraction of the information conveyed by *Desync* about short-selling desynchronization is not already contained in existing proxies.

### 4.2 *Desync* Around Synchronizing Events

Abreu and Brunnermeier (2003) consider the possibility that unanticipated "synchronizing events" facilitate the coordination of arbitrageurs and accelerate the correction of mispricing. Synchronizing

[13]The change in sign for turnover in model (4) likely responds to the inclusion of idiosyncratic volatility, another theoretically (Shalen, 1993 and Harris and Raviv, 1993) and empirically (Boehme, Danielsen, and Sorescu, 2006) motivated proxy for dispersion of opinions. As Panel D of Table 1 shows, idiosyncratic volatility and turnover are closely related in our sample.

events include news and, more generally, any public signal that can help reduce the disagreement underlying the arbitrageurs' lack of coordination. The observation suggests assessing the empirical validity of *Desync* as a proxy for desynchronization by examining whether it falls following such events.

We consider two types of synchronizing events. The first is the release of negative public news concerning a firm.[14] News events represent not only an intuitive coordination device, but have been related to the short selling in a stock (Engelberg, Reed, and Ringgenberg, 2012). The second type of events is analyst downgrades of a firm's stock,[15] which extensive evidence identifies as an important trading signal for short sellers (Christophe, Ferri, and Hsieh, 2010; Boehmer et al., 2020b). We employ the following first-difference specification for our analysis:

$$Desync_{i,t} = \alpha_i + \beta Post_{i,t} + \epsilon_{i,t},$$

where $\alpha_i$ is a stock fixed-effect, and $Post_{i,t}$ is a dummy variable equal to 1 (0) during the fifty days following (preceding) the information event. The coefficient of interest, $\beta$, captures the change in *Desync* across the two periods.

The results, displayed in Table 3, further support the validity of *Desync* as proxy for short-selling desynchronization. Following both analysts' downgrades (column (1)) and the release of negative news (column (2)), *Desync* drops significantly relative to the days preceding the event.

Finally, we examine the behavior of *Desync* around the release of reports by activist short sellers. Ljungqvist and Qian (2016) document a "short-and-disclose" strategy according to which arbitrageurs in overpriced but hard-to-short stocks publicly reveal their information to induce the target's shareholders to sell and accelerate the price correction. Despite potentially inducing synchronized selling among *long* investors, the strategy should have little impact, precisely because of the existence of tight shorting constraints, on the coordination among the stock's *short* sellers. Accordingly, *Desync* should not exhibit systematically different behavior before and after this type of events. The insignif-

[14] Using data from RavenPack, we identify a news event as the release of negative news about a firm (i.e., news with a sentiment score lower than 50). To ensure we include only news relevant enough to facilitate coordination among short sellers, we consider only news with a relevance score larger than 80.

[15] Using data from I/B/E/S, we identify analyst downgrade events with days when the average recommendation among analysts drops to either "sell" or "strong sell".

icant coefficient of *Post* in the last column of Table 3 corroborates that this is indeed the case in our sample.[16]

Summing up, we conclude that the evidence in this subsection, along with our results in the previous one, support the use of *Desync* to test the hypotheses in Section 2 on the relation between short-selling desynchronization and mispricing.

# 5 Short Sellers' Desynchronization and Stock Overpricing

Following Hypothesis 1, in this Section we investigate the relation between short sellers' desynchronization and the extent of overpricing in the cross-section of stocks. We adopt two measures of overpricing. In Section 5.1, we follow the standard approach of associating overpricing with negative future abnormal returns. In Section 5.2, we proxy for overpricing using the composite-rank mispricing measure proposed by Stambaugh, Yu, and Yuan (2015). In Section 5.3 we assess the merits of explanations other than synchronization problems to account for our findings.

## 5.1 Future returns

Overpriced stocks should subsequently exhibit inferior average benchmark-adjusted performance, as measured by their abnormal returns relative to a standard pricing model. This reasoning motivates the predominant approach in the literature of associating overpricing with subsequent returns.[17] To preview the relationship between *Desync* and future returns in our sample, in Figure 2 we plot the means of *Desync* across 100 equally sized bins against their next-month Fama-French-Carhart factor-adjusted returns.

Consistent with Hypothesis 1, a well-defined negative pattern is evident. While stocks in the bottom tercile of *Desync* earn positive abnormal returns, stocks in the top decile earn abnormal returns of less than -0.5% per month. The result is an annualized spread of around -9.0% between the top and bottom deciles of *Desync*. In the next two subsections we analyze, using calendar portfolios

[16] We thank Antonis Kartapanis for generously facilitating these data to us. See Kartapanis (2020) for a detailed description of the data.

[17] A prominent example of this approach is Baker and Wurgler (2006). On the basis that mispricing is hard to identify directly, they look for systematic patterns of mispricing correction via stocks' subsequent returns.

and multivariate regressions, the economic and statistical significance of this relation and its robustness to controlling for the influence of other variables.

### 5.1.1 Portfolio Analysis

To assess the link between short sellers' desynchronization and stock overpricing without imposing a parametric relationship, we first examine single portfolio sorts. On each day $t$, we allocate stocks into five groups determined by the quintiles of *Desync*. Intuition suggests, and inspection of Table 2 confirms, that the uncertainty potentially creating synchronization problems is higher among smaller firms. In this case, while value weighting the stocks in each group makes the results comparable with other studies, it also tends to conceal the underlying patterns. We thus compute both the equal-weighted (EW) and value-weighted (VW) monthly average returns to each buy-and-hold portfolio for a 21-day holding period. We repeat this portfolio sorting approach each day, giving rise to a series of five portfolios of 21-day overlapping returns at any given point in time. We regress the returns to these portfolios on the four Fama-French-Carhart factors, and use Newey and West (1987) standard errors to correct for autocorrelation, with a number of lags equal to the length of the holding period. Panels A.1 and B.1 of Table 4 present the resulting EW and VW alphas, respectively, of the portfolios corresponding to each *Desync* group.

The results confirm the negative relation between *Desync* and future alpha anticipated by Figure 2. Panels A.1 and B.1 evidence a strong decreasing pattern moving from the first (Q1) to the fifth (Q5) quintile. While the low-*Desync* portfolio generates a monthly EW alpha of 0.17% (significant at the 1% level) in Panel A.1, the high-*Desync* portfolio generates a negative EW alpha of -0.46% (also significant a the 1% level). As a result, the hedge portfolio long in high-*Desync* stocks and short in low-*Desync* stocks generates a statistically and economically significant EW alpha of -0.63% per month (-7.56% per annum). The effect is present and highly statistically significant in Panel B.1 (a VW alpha of -4.32% per annum), even if its economic magnitude falls as expected from the above-mentioned negative relation between *Desync* and firm size.

To control for other cross-sectional effects, Table 4 also presents conditional double portfolio sorts. Each day $t$, we first allocate stocks into five groups based on different firm and stock characteristics.

These include size, market to book, past six-month returns, and short interest, to verify that the effect of *Desync* on returns is not driven by the size, market-to-book, or momentum effects (Fama and French, 1992; Jegadeesh and Titman, 1993), or by the documented predictive power of short interest (Reed, 2013), in the cross-section. The other two characteristics we consider, bid-ask spread and turnover, proxy for the general disagreement around the stock which, to the extent it translates into more desynchronized short selling, should result in greater stock overpricing. Within each of these groupings, we further allocate stocks into five sub-groups (from low to high) conditional on *Desync* for a total of twenty-five portfolios. We then compute the EW (Panel A.2) and VW (Panel B.2) alphas for the hedge portfolio long in high-*Desync* and short in low-*Desync* stocks for each quintile of the first sorting variable.

The results add strong support for Hypothesis 1. In the first three rows of Panels A.2 and B.2, the positive relation between *Desync* and overpricing is pervasive across size, market-to-book, momentum and short interest groupings, indicating that the effect of short sellers' desynchronization on returns is not subsumed by other well-known cross-sectional determinants. The effect is stronger among smallcaps, consistent with our above observation that *Desync* tends to be larger among firms with smaller capitalization, as well as among value stocks and past losers. Within these categories, the monthly EW and VW alphas on the long-short *Desync* portfolios (-1.33% and -1.09% for small stocks, -1.26% and -0.74% for value stocks, and -1.04% and -0.86%) double those reported in Panels A.1 and B.1, respectively.

Remarkably, *Desync* generates a negative alpha not only among heavily shorted stocks, as found in prior studies, but also among mildly and lightly shorted stocks. Conditioning on *low* levels of short interest, alpha is -0.32% per month in column Q1-Q5 of Panel A.2 (significant at the 1% level), and -0.41% per month in column Q10-Q6 of Panel B.2 (significant at the 5% level). This suggests, as expected from synchronization risk limiting arbitrage, that the effect of *Desync* on returns is unrelated to the superior ability of short sellers—as reflected by heavy short selling—to identify overpricing.

In further support for Hypothesis 1, overpricing is greatest for the types of stocks for which we expect greater uncertainty about other short sellers' trades, hence greater synchronization risk. The high-minus-low *Desync* portfolio generates negative alphas in the bottom two rows of Panels A.2

and B.2, corresponding to the proxies for the information environment of the firm. These alphas are particularly large (in absolute value) and significant among stocks with higher information asymmetry or difference in beliefs, as reflected by larger values of bid-ask spread and turnover, respectively. The EW (VW) monthly alphas on the hedge portfolio Q25-Q21 of stocks with high bid-ask spreads and turnover are, respectively, -1.32% and -0.97% (-0.67% and -0.60%) in Panel A.2 (B.2), significant at the 1% (5%) level or higher.

### 5.1.2 Fama-MacBeth Regressions

To control for multiple covariates, in Table 5 we examine the relation between desynchronization and overvaluation within a multivariate regression framework. Specifically, we run daily Fama-MacBeth return regressions of the form:

$$adj\_ret_{i,t+21} = \alpha + \beta_1 \times Desync_{i.t} + \theta' \boldsymbol{x_{i,t}} + \epsilon_{i,t+21}, \tag{2}$$

where $adj\_ret_{i,t+21}$ is the factor-adjusted future return of stock $i$ cumulated over one month (21 days), $Desync_{i.t}$ is our short sellers' desynchronization measure for stock $i$ at time $t$, and $\boldsymbol{x_{i,t}}$ is a vector of control variables, as described below. We compute factor-adjusted returns following the approach in Boehmer et al. (2020a), according to which the betas for each of the $k$ factors in the model (where $rf$ is the riskfree rate of return)

$$E(r_{i,t}) - rf_t = \beta_i^{(1)} E(F_{1,t}) + ... + \beta_i^{(k)} E(F_{k,t})$$

are computed quarterly using daily data from the previous quarter, with the requirement that there are at least 21 non-missing daily observations. We calculate abnormal returns as the difference between the raw returns and the model-implied returns for the corresponding period, using the estimated betas for the previous quarter:

$$ar_{i,t} = r_{i,t} - \Big( rf_t + \hat{\beta}^{(1)}_{i,q(t)-1} F_{1,t} + ... + \hat{\beta}^{(k)}_{i,q(t)-1} F_{k,t} \Big).$$

Our set of controls follows from previous studies, and comprises the conditioning variables in the double-sorted portfolios of section 5.1.1, along with the stock returns cumulated over the previous month ($Ret_{1M}$), the active quantity of shares available to be borrowed expressed as a percentage of shares outstanding ($Supply$), borrowing fees ($Fee$), as well as the variance of borrowing fees over the previous month ($VarianceFee$) as a proxy for short-selling risk (Engelberg, Reed, and Ringgenberg, 2018). We adjust standard errors using the Newey and West (1987) methodology to correct for autocorrelation, with a number of lags equal to the length of the holding period.

According to Hypothesis 1, the sign of $\beta_1$ in Equation 2 should be negative, consistent with greater desynchronization leading to lower future abnormal returns as a result of more severe overpricing. In line with this hypothesis, $Desync$ appears with a negative and significant (at the 1% level) coefficient across all specifications, with values ranging from a minimum of -0.74 (column 3) to a maximum of -0.53 (column 2). These coefficients imply that, holding other determinants constant, one standard deviation increase in $Desync$ leads to annualized adjusted stock returns of between -1.20% and -1.68% in the following month. As expected, and in line with previous literature, short interest is a bearish signal in our sample. In the first and second specifications (where short interest is significant at the 1% level), a one standard deviation increase in short interest is followed (holding all else constant) by annualized adjusted returns of between -2.21% and -3.04% in the next month. However, the coefficient on short interest becomes statistically insignificant in the specification that controls for shorting fees (column 3), suggesting that fees subsume short interest for predicting future returns.[18] Taken jointly, the results imply that $Desync$ is a robust negative predictor of future abnormal returns in the cross-section, with similar economic significance as short interest.

### 5.2 Relative Mispricing

Stambaugh, Yu, and Yuan (2015) propose a mispricing proxy, $MISP$, for the difference between a stock's observed price and the price that would otherwise prevail in the absence of arbitrage risk and other arbitrage impediments. $MISP$ is constructed by averaging the stock's rankings across 11 anomalies, where a higher average rank proxies for a greater degree of relative overpricing, and is

[18] This result is consistent with the role of lending fees in predicting returns in the cross-section as documented by Jones and Lamont (2002), D'Avolio (2002) and Engelberg, Reed, and Ringgenberg (2018).

available at monthly frequency from July 1965 until December 2016.[19] To determine the empirical relevance of synchronization risk as an arbitrage impediment, we next test whether short sellers' desynchronization and overpricing are positively associated in the cross-section.

We convert $MISP$ into a categorical variable and employ a logit specification to model the probability that in month $m$ stock $i$ becomes overpriced, which we associate with the event that the stock rises to the top tercile of the $MISP$ distribution.[20] More formally, we estimate the following model:

$$p_{i,m} = Pr\left(y_{i,m} = 1 | \boldsymbol{x}_{i,m-1}\right) = \frac{\exp\left(\boldsymbol{x}'_{i,m-1}\boldsymbol{\beta}\right)}{1 + \exp\left(\boldsymbol{x}'_{i,m-1}\boldsymbol{\beta}\right)}, \tag{3}$$

where $\mathbf{x}_{i,m-1}$ contains $Desync$, a constant, and the same set of controls of Equation (2). Table 6 presents the results for two specifications, where the first has $Desync$ as the sole regressor and the second includes all controls. The table reports also the marginal effects of $Desync$ to facilitate the interpretation of economic magnitudes.

Consistent with our analysis of future returns, the desynchronization in the stock's short selling is strongly positively associated with its relative overpricing. $Desync$ enters with a positive and statistically significant coefficient (at the one percent level) in both specifications, implying that greater desynchronization among the stock's short sellers raises the likelihood that the stock rises to the top tercile of $MISP$ in the following month. The estimates in the first column indicate an economically relevant effect, whereby a stock that moves from the bottom (0.56) to the top tercile (0.91) of $Desync$ increases the likelihood of becoming overpriced by 16% $(= (0.91 - 0.56) \times 0.48)$.

### 5.3 Alternative explanations

In principle, the positive relation between $Desync$ and overpricing that we document could respond to limits of arbitrage unrelated to synchronization risk. To address this possibility, in this section we examine the extent to which Miller (1977)'s Hypothesis, noise-trader risk (De Long et al., 1990), short-selling risk (Engelberg, Reed, and Ringgenberg, 2018), or arbitrage asymmetries and idiosyncratic

[19] We thank the authors for making these data available from Robert F. Stambaugh's website. See the Appendix in Stambaugh, Yu, and Yuan (2015) for a description of the anomalies used to construct the score.

[20] Our logit specification follows from the fact that $MISP$ is discrete and bounded between 0 and 100, thus it is not well-suited for inclusion as dependent variable in a linear regression.

volatility (Stambaugh, Yu, and Yuan, 2015), relate to our findings.

#### 5.3.1 Miller's Hypothesis

Miller (1977) hypothesizes that, in the presence of disagreement among the traders in a stock, short-selling constraints can induce overpricing by curtailing the activity of the pessimists. This raises the concern that, to the extent that *Desync* captures the broader dispersion of opinions around a stock considered by Miller, our results just mirror the empirical confirmation of his hypothesis found by prior studies (e.g., Boehme, Danielsen, and Sorescu, 2006; Berkman et al., 2009).

While related, the Miller's and desynchronization channels on overpricing can be disentangled empirically via their contrasting implications for stocks with low or no short-selling constraints. Miller's hypothesis implies a negative relation between disagreement and future abnormal returns *only* among stocks with short-sale constraints. This is a main observation of Boehme, Danielsen, and Sorescu (2006), who find that portfolios of firms with *either* dispersed opinions *or* short-selling constraints, but not *both* of them, experience no apparent overvaluation. In contrast, the effect of *Desync* on mispricing in Abreu and Brunnermeier (2002) should be present *also* in easy-to-short stocks as reflected in our Hypothesis 1, even if likely to be stronger among stocks with tighter short-selling constraints.

To show that this is the case, in Table 7 we repeat the double-sorted portfolio analysis of Table 4 using either *Fee* or *Supply* as the first conditioning characteristic. Each of these variables has been shown by prior research (see Geczy, Musto, and Reed, 2002 and Saffi and Sigurdsson, 2011) to capture the severity of the short-selling constraints in a stock. If our findings purely reflected Miller's Hypothesis, *Desync*-sorted portfolios should generate negative returns only on high-*Fee* or low-*Supply* stocks. On the contrary, *Desync* generates statistically significant risk-adjusted spreads of between -3.6% and -5.4% per year also on the stocks with the lowest shorting fees and the highest supply of lendable shares.

We further corroborate that the effect of *Desync* on mispricing works through a different channel (i.e., desynchronization among shorts) by documenting it in tripled-sorted portfolios that control for *both* short-selling constraints *and* dispersion of opinions simultaneously. If the short-selling desynchronization effect is driven by Miller's Hypothesis, then the spread between high- and low-*Desync* stocks should not be meaningfully different from zero. The results in Table A.3 offer clear evidence that this is not the case. The high-minus-low *Desync* portfolio yields significantly negative (and no significantly positive) and sizable abnormal returns across several dispersion in beliefs and short-selling constraints levels. These are particularly striking among stocks with little dispersion in beliefs, low short-selling constraints, or both. Given that the triple sort keeps fixed both of the characteristics resulting in stock overvaluation according to Miller, the negative *Desync* spread across these stocks provides strong indication of a different effect at play.

#### 5.3.2 Noise-Trader Risk

Short sellers could delay attacking the overpricing in a stock not only because they face uncertainty about the information of other short sellers (synchronization risk), but also because they risk that noise traders move prices against their positions (De Long et al., 1990, and Shleifer and Vishny, 1997). Empirically, several sentiment-based variables have been used to proxy for the excess optimism of noise traders about a stock (Baker and Wurgler, 2007). If *Desync* is simply capturing the overpricing induced by over-optimistic noise traders, the high-minus-low *Desync* portfolio of Section 5.1.1 should generate no alpha once we condition on sentiment. Moreover, conditioning on *Desync* should lead to no significant spread among larger and low-idiosyncratic volatility stocks, for which arbitrage risk, hence the effect of noise-trader risk on prices, should be smaller (Baker and Wurgler, 2006). We confirm that these predictions do not hold in our analysis. First, using two different proxies for sentiment (Baker and Wurgler, 2006, and Jiang et al., 2019) in Table 7, we find a strong negative impact of *Desync* on risk-adjusted returns across both high- and low-sentiment periods. Second, we find that the effect is present even among large-cap in Table 4 and low-idiosyncratic volatility stocks (see below). Both results highlight the importance of considering additional factors to noise-trader risk to understand our findings.

#### 5.3.3 Short-selling Risk

Short-selling fees can be highly volatile and curtail short sellers' profits. Engelberg, Reed, and Ringgenberg (2018) find support for a "short-selling risk" channel on stock returns according to which, following the prediction of D'Avolio (2002), uncertainty about future fees might deter short sellers from attacking mispricing. The uncertainty behind synchronization problems originates from an information channel, i.e., the sequential arrival of information about a common mispricing opportunity. However, D'Avolio (2002) finds that shorting costs, while generally low, increase in the dispersion of opinions about a stock. Thus, it could be the case that the desynchronization in short selling captured by *Desync* is highly correlated with short-selling risk, and that our results are driven by the effect of the latter on stock prices. Our estimates of regression Eqs. (2) and (3) already indicate that this is not the case, as *Desync* preserves its significance when controlling for the variance of fees (short-selling risk). If short-selling risk subsumed our results, *Desync* should further fail to generate a negative spread once we condition on the stocks' fee volatility. The results reported in the third row of Table 7 indicate otherwise: *Desync* predicts negative spreads across all short-selling risk quintiles in both equal- and value-weighted portfolios.

#### 5.3.4 Arbitrage Asymmetries and Idiosyncratic Volatility

Baker and Wurgler (2006) argue that stocks with high idiosyncratic volatility are riskier to arbitrage. Because they are also harder to value, these stocks potentially create greater dispersion of opinions and synchronization risk among their traders. The possibility then arises that what we are capturing is the effect of arbitrage asymmetries and idiosyncratic volatility on overpricing, as proposed by Stambaugh, Yu, and Yuan (2015). If this is the case, the relation between *Desync* and overpricing should be weak or nonexistent once we control for idiosyncratic volatility in our tests. The results in the fourth row of Table 7 rule out this possibility. The high-minus-low *Desync* conditional portfolios generate significant spreads across different idiosyncratic volatility quintiles. In particular, the desynchronization effect is strong and significant on stocks with low (bottom two quintiles) idiosyncratic volatility, for which arbitrage asymmetries should be less pronounced. Moreover, in our regression analyses of sections 5.1 and 5.2 the effect of *Desync* on overpricing is robust to controlling for idiosyncratic volatility—which, as expected, turns up highly statistically significant.

To further clarify the relation between our results and idiosyncratic volatility, in Table A.1 we re-estimate Equations 2 and 3 replacing *Desync* with its orthogonalized version relative to $Idio\ Vol$ (i.e., the residuals from a regression of $Desync$ on $Idio\ Vol$). The first two columns refer to Fama-MacBeth regressions including adjusted returns as dependent variable, and either excluding or including $Idio\ Vol$ in the controls. The last two columns refer to logit regressions modeling the probability of a stock becoming relatively overpriced, where the columns differ depending on whether we exclude or include $Idio\ Vol$. Compared to their corresponding results in the last columns of Tables 5 and 6, the coefficients on the orthogonalized $Desync$ variable are slightly smaller (in absolute value) but still strongly statistically significant.

Altogether, our results in this section support the role of synchronization risk among short sellers, consistent with Hypothesis 1, as a distinctive and economically relevant driver of overpricing in the cross-section of stocks.

# 6 Short Sellers' Desynchronization and Overpricing Duration

In this section we analyze whether, following Hypothesis 2, short-sellers' desynchronization *delays* the arbitrage activity in a stock and its price correction. We focus on two types of overpricing events. The first follows our approach in Section 5.2 and identifies overpricing with high values of the relative mispricing score, $MISP$. The second follows Ofek, Richardson, and Whitelaw (2004) in identifying overpricing events from failures of the put-call parity no-arbitrage relation in the stock option market. An advantage of the first approach is that it focuses on relatively longer-lived overpricing events around which there is arguably more uncertainty and thus room for desynchronization among traders. An advantage of the second approach is that violations of put-call parity offer an objective—albeit shorter lived— measure of mispricing (Engelberg, Reed, and Ringgenberg, 2018).

## 6.1 Relative Mispricing Correction

We use a two-step approach to quantify the duration of the stock overpricing captured by $MISP$. For each stock $i$, we identify overpricing events as the months $t$ in which the stock's $MISP$ rises to the top tercile of the cross-sectional distribution of $MISP$. We then compute the length of each of these events as the number of months elapsed before $MISP$ drops back below the top tercile. Using this delay measure, we examine the relation between $Desync$ and $Delay$ within the following regression:

$$Delay_{i,t} = \alpha_i + \tau_t + \beta \times Desync_{i.t} + \boldsymbol{\gamma}' \boldsymbol{x_{i,t}} + \epsilon_{i,t}, \tag{4}$$

where $\alpha_i$ and $\tau_t$ denote firm and time fixed-effects, and $\boldsymbol{x_{i,t}}$ denotes a vector of controls.

We consider two groups of controls. Our first group follows directly from the analysis of Abreu and Brunnermeier (2002). Their model explains the delay in price correction for a *given* level of mispricing. To account for the initial size of the stock overpricing, we thus include the relative mispricing score $R$ $(= MISP)$ at the start of the event among our controls. Arbitrageurs' holding costs are a main ingredient in the model, and an exogenous parameter that they keep fixed throughout the analysis. In particular, they consider shorting fees to be the most important holding cost among short sellers. Accordingly, we also include a stock's borrowing fees, $Fee$, among our first group of controls. Similarly, the number of arbitrageurs is kept constant in their analysis. To isolate the effect of synchronization risk on $Delay$ from the effect of the short sellers' aggregate position in the stock, we thus include short interest, $SI$, within this first set of controls.

Our second group of controls comprises relevant stock characteristics. To account for the fact that the mispricing of more illiquid stocks could be harder to arbitrage, we include $Stock\ Bid - Ask$, the percentage bid-ask spread in the stock market. The other two controls we consider, $Size$ and $Market\ to\ Book$, are standard.

We report our estimates in Table 8 across three specifications.[21] Following hypothesis 2, we expect the sign of $\beta$ in (4) to be positive, consistent with poorer synchronization among short sellers being associated with greater delays in the correction of a stock's price ($Delay$). In line with this prior, we find a positive and statistically significant coefficient $\beta$ across all specifications. $\beta$ equals 3.35, 2.89 and 3.71 (all statistically significant at the 5% level), respectively, in the specifications with no additional controls, with the first set of controls, and with both sets of controls. The size of this coefficient indicates that the relationship between $Desync$ and $Delay$ is economically meaningful. In particular, the full model implies that a one standard deviation increase (0.145) in $Desync$ requires 16 additional

[21] We cluster standard errors in the time dimension to control for the cross-sectional dependency in relative overpricing events induced by their clustering on certain months. Clustering also in the firm dimension has virtually no impact on standard errors due to the lack of time-series dependence in these events.

days for the score to drop below the top tercile.[22] Intuitively, we also find that overpricing events tend to last longer when the initial overpricing ($R$) is higher.

### 6.2 Violations of Put-call parity

To identify violations of put-call parity we compare a stock's observed price to the synthetic price implied by this no-arbitrage relationship in the stock option market.[23] We account for transaction costs in the options market by computing an upper bound for the synthetic price using the ask price for calls and the bid price for puts. We associate stock overpricing with a positive difference between the stock's observed price and the synthetic price upper bound. Using the number of consecutive days over which this difference remains positive as our measure of the *delay* in price correction ($Delay$), we re-estimate Equation (4) and report our estimates in Table 9 across six specifications that differ depending on the controls included.

We consider several option characteristics as additional controls to the ones described in Section 6.1.[24] These include $Option\ Bid - Ask$, the percentage bid-ask spread averaged across the call and put options on the stock, and $Option\ Volume$, the (log) option volume averaged across the stock's calls and puts. These variables account for the fact that violations of put-call parity might be harder to arbitrage if the corresponding options are illiquid. Other relevant option characteristics are $Option\ Maturity$, the number of days until maturity; $Option\ Moneyness$, the moneyness of the option; $Option\ Open\ Interest$, the (log) open interest averaged across the stock's calls and puts; and $Option\ Implied\ Volatility$, the implied volatility of calls. We restrict our attention to put-call parity violation that last at least two days to avoid apparent one-day violations that are the result of misreporting. Table A.2 in the Appendix presents summary statistics for our dependent variable ($Delay_{i,t}$) and the options in our sample.[25]

[22] This calculation is based on the assumption of 30 days per month.

[23] Battalio and Schultz (2006) show that most of the violations of put-call parity during the Internet bubble are due to the asynchronicity between the option and underlying stock price quotes in the OptionMetrics database. However, our sample is not affected by this problem since, starting from 2008, OptionMetrics has reportedly corrected it.

[24] For the analysis in this section, the initial overpricing $R$ corresponds to the size of the stock overpricing on the first day of the parity violation, and is measured as the log of the ratio between the closing stock price and the put-call parity-implied synthetic stock price.

[25] Following Ofek, Richardson, and Whitelaw (2004), (i) we exclude stocks paying dividends and we require that both the put and call have positive open interest; (ii) we focus on the option pairs that are at-the-money ($-10\% < ln(Price/Strike) < 10\%$) and have intermediate maturity (between 91 and 182 days). When there are multiple option

The results are strikingly consistent with those of Table 8. *Desync* shows up with a positive and highly statistically significant (at the 1% level) coefficient of 14.38 in the first specification. This coefficient drops to 9.38 (significant at the 5% level) when we include the first set of controls in columns (2). Nevertheless, it remains positive and significant (at the 5% level) when we also include either stock or option controls (columns 3 to 5), or the full set of controls (column 6). The estimates remain consistent with economic intuition and with prior studies, as violations tend to last longer when initial overpricing $R$ or the holding costs of short sellers $Fee$ are higher. The effect of *Desync* on the duration of put-call parity-related overpricing is economically relevant. The coefficient estimate in the full model, 8.63, implies that a one standard deviation increase in *Desync* requires 1.38 additional days for the put-call parity violation to close. This corresponds to a 15.5% increase relative to the mean of *Delay*. By comparison, a one standard deviation increase in Fee—a key determinant of put-call parity violations according to Ofek, Richardson, and Whitelaw (2004)—is associated with an increase in *Delay* of 1.25 days (13.6% relative to the mean of *Delay*).

In sum, the evidence around the short- and longer-lived mispricing events that we examine in this subsection and the previous one support the role of synchronization risk as a first-order limit to arbitrage among short sellers.

# 7 Additional Results and Robustness

In this section we investigate the role of negative news releases as synchronizing events (see Section 3) that speed up the correction of mispricing. We then show that our results do not hinge on the specific measure of dispersion in short seller's profits that we employ. Finally, we provide additional support for the limiting role of short-selling desynchronization on the correction of mispricing using a placebo test of the relation between *Desync* and the duration of *underpricing* events.

pairs per stock on a given day that match the relevant maturity and moneyness criteria, we restrict our attention to the option pairs that are closest to the middle of the range. This provides us with a maximum of one option pair per stock per date. We also apply the filters described in the Appendix of Ofek, Richardson, and Whitelaw (2004).

### 7.1 Synchronizing Events and Synchronization Risk

If desynchronization in short selling is a main force behind the duration of stock overpricing, we should further find that the correction of a given overpricing should take longer among stocks with fewer synchronizing news releases. Indeed, the existence of news events surrounding a firm facilitates synchronization and accelerates the correction of mispricing in Abreu and Brunnermeier (2003). To examine this prediction, we use the number of negative news releases related to the firm over the previous month ($News$) as a proxy for the number of synchronizing news that facilitate a stock sell out. We then repeat the analysis in Section 6 but using the following specification:

$$\begin{aligned} Delay_{i,t} =& \alpha_i + \tau_t + \beta_0 \times Desync_{i.t} + \beta_1 \times DummyNews_{i,t} \\ &+ \beta_2 \times Desync_{i.t} \times DummyNews_{i,t} + \boldsymbol{\gamma}'\boldsymbol{x_{i,t}} + \epsilon_{i,t}, \end{aligned} \tag{5}$$

where $DummyNews_{i,t}$ is a dummy variable that equals one for stocks in the highest News decile in a particular day and zero otherwise.[26] The rest of the variables and controls are as in Section 6. According to the synchronization-risk argument, we expect $\beta_2 < 0$.

Consistent with this implication, in non-tabulated results we find an estimate for $\beta_2$ in (5) of $-15.47$ with a t-statistic of $-2.45$ (statistically significant at the 5% level) when measuring $Delay$ based on $MISP$. Given an estimate of 9.10 for $\beta_0$ in the same regression (t-statistic of 2.45), the results imply that negative news releases surrounding the firm act as a synchronizing event that effectively speeds up the correction of mispricing. We find similar results when measuring $Delay$ from violations of put-call parity, where our estimates for $\beta_2$ and $\beta_0$ are $-15.91$ and 9.63, respectively, with t-statistics of $-1.74$ and 2.26 (statistically significant at the 10% and 5% levels).

### 7.2 Alternative Measure of Short-Selling Profit Dispersion

Our results do not hinge on the specific measure of dispersion in short seller's profits that we employ. In Table 10, we reproduce the analysis of Tables 4–6 and 8–9 using the standard deviation of short sellers' cumulated returns as our measure of profit dispersion. More precisely, for each stock and day

[26] On average, stocks outside of the top 10% decile of News have very few or no negative news releases over the previous month in our sample.

we compute the (bin-)weighted sum of the squared distance of each bin's midpoint from the mean. The square root of the resulting value, $Desync\_SD$, is our alternative measure of short-selling profit dispersion:

$$
\begin{aligned}
Desync\_SD_{i,t} &= \sqrt{\sum_{n=1}^{N} bin_{i,t}^{(n)} \times \left(PnL_{i,t} - \frac{\lfloor n+n \rfloor}{2}\right)^2} \\
&= \sqrt{bin_{i,t}^{(-100,-75]} \times \left(PnL_{i,t} + 87.5\right)^2 + \ldots + bin_{i,t}^{(75,100]} \left(PnL_{i,t} - 87.5\right)^2},
\end{aligned}
\tag{6}
$$

where $PnL_{i,t}$ is the mean of the distribution:

$$
\begin{aligned}
PnL_{i,t} &= \sum_{n=1}^{N} bin_{i,t}^{\lfloor n \rfloor} \times \frac{\lfloor n+n \rfloor}{2} \\
&= bin_{i,t}^{(-100,-75]} \times (-87.5) + bin_{i,t}^{(-75,-50]} \times (-62.5) + \ldots + bin_{i,t}^{(50,75]} \times 62.5 + bin_{i,t}^{(75,100]} \times 87.5.
\end{aligned}
$$

Panel A shows that, in line with our results in Section 5, both single and double portfolio sorts produce negative abnormal spreads between high- and low-$Desync\_SD$ groups.[27] Panel B shows that $Desync\_SD$ is also negatively related to 21-day ahead factor-adjusted returns and positively related to the likelihood that the stock rises to the top tercile of $MISP$. In line with our findings in Section 6, Panel C shows that higher $Desync\_SD$ leads to longer delays in the correction of stock overpricing.

### 7.3 Placebo Test

Desynchronization in short selling should play no role in the correction of *underpricing*, which requires traders to establish long positions instead. To test whether this is indeed the case, we apply our analysis of Section 6 to the duration of *underpricing* events. In the analysis of relative mispricing as captured by the $MISP$ measure of Stambaugh, Yu, and Yuan (2015), we identify the start of an underpricing event with the month in which $MISP$ falls in the bottom tercile of the cross-sectional distribution of $MISP$. In the analysis of put-call parity violations, we associate stock underpricing with a negative difference between the stock's observed price and the synthetic price lower bound.[28] Our estimates,

[27] As in Table 4, the double-sorted portfolio analysis first conditions, alternatively, on size, market to book, short interest, bid-ask spread, or turnover.

[28] We account for transaction costs in the options market using the ask price for calls and the bid price for puts.

reported in Table 11, show that in contrast to our findings of Section 6, there is no relation between *Desync* and the delay in the correction of underpricing as gauged by either measure. The results confirm the importance of short selling-related synchronization problems in driving overpricing (and not underpricing) across stocks.

# 8 Conclusions

In this paper, we use a unique dataset containing information on the dispersion in mark-to-market profits across the short positions in U.S. stocks to study i) the extent to which short sellers synchronize their timing decisions, and ii) whether any observed desynchronization among them can affect the cross-section of stock prices even in the absence of binding financial constraints or other explicit frictions limiting arbitrage activity.

Based on the observation that differences in profits across a stock's short positions must map to differences in their initiations, we infer short-selling desynchronization from the dispersion in profits across a stock's short sellers. Contrary to the view that short sellers are a homogeneous group of investors who act in a synchronous fashion, we document substantial desynchronization across their positions. Consistent with this desynchronization arising from disagreement, we find it to be strongly related to various measures of differences in opinions and information asymmetries surrounding the stock, and to substantially drop following information-related synchronizing events.

In line with the theory of Abreu and Brunnermeier (2002, 2003), we provide comprehensive evidence of the asset pricing implications of coordination problems among arbitrageurs on the cross-section of stocks. First, we find a strong positive association between the desynchronization in a stock's short selling and its overpricing. Second, we document significantly longer delays in the correction of overpricing for stocks with less synchronized short selling. We show that these effects are prevalent even among stocks facing low short-selling costs or other explicit constraints. Overall, our findings highlight the empirical relevance of synchronization risk as a distinct limit of arbitrage among short sellers.

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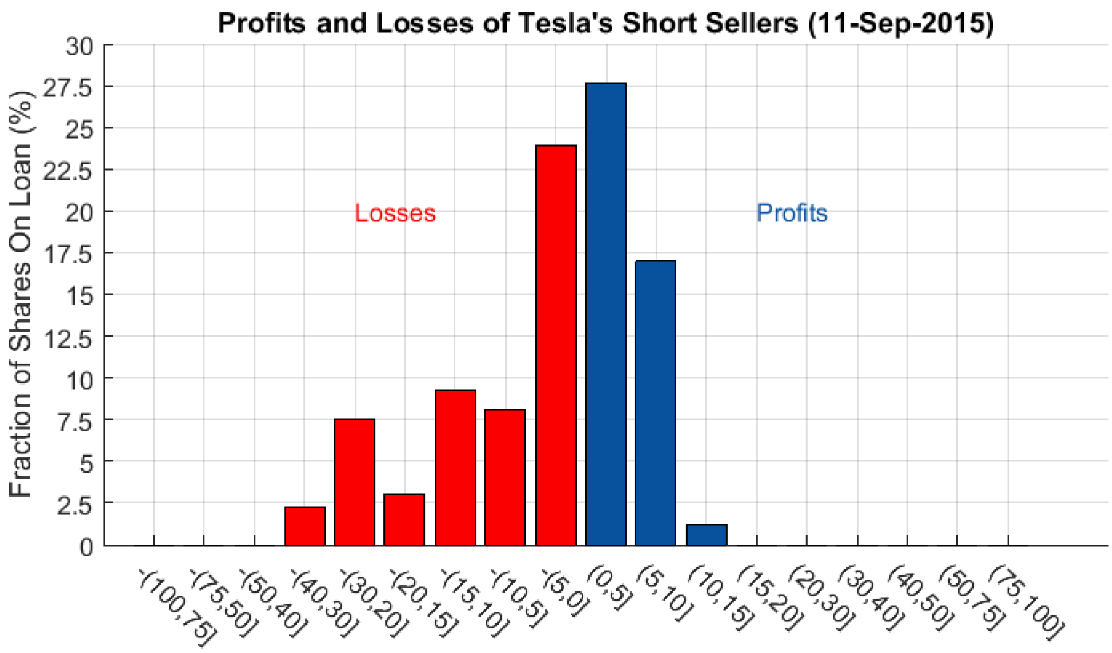
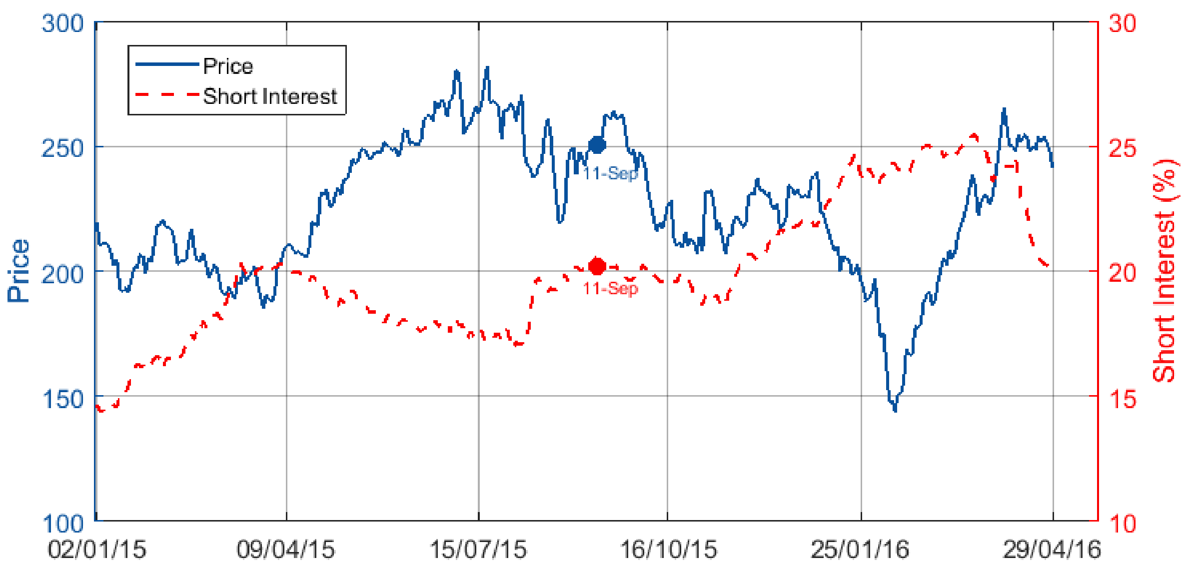
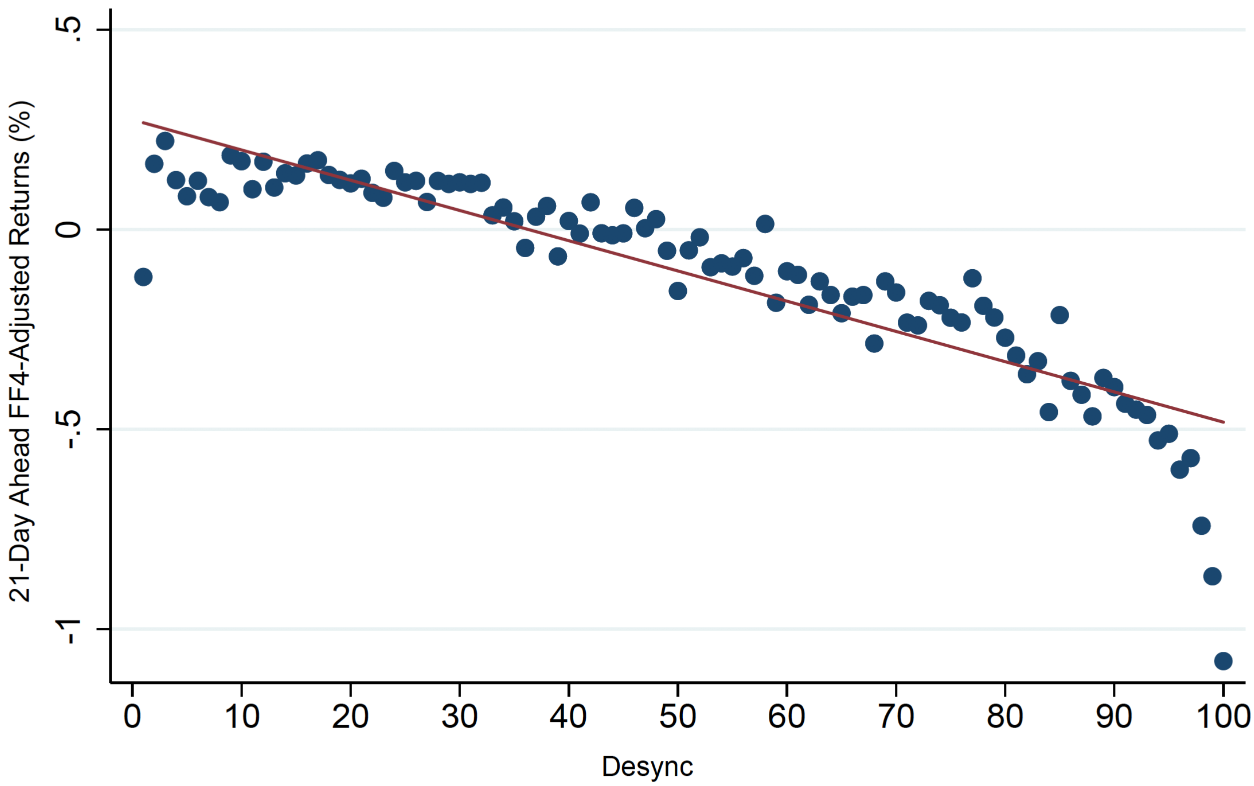
# Figure 1. Shorting Tesla




The upper plot displays the distribution of profits (in %) experienced by short sellers with positions in Tesla Inc on September 11 of 2015. Each bar denotes the fraction of shares on loan experiencing a cumulated return in its associated interval, as displayed on the x-axis. Bars in red depict losses (i.e. cumulated returns in the $-(100, 75]\%$ to $-(5, 0]\%$ ranges), while bars in blue depict gains (i.e. cumulated returns in the $(0, 5]\%$ to $(75, 100]\%$ ranges). The lower plot displays the time-series evolution of Tesla's stock price (blue solid line, left y-axis) and level of short interest (red dashed line, right y-axis) over the period January 2, 2015, to April 29, 2016.

**Figure 2.** *Desync* **and future returns: non-parametric evidence**




This figure shows the binned scatterplot of the 21-day ahead Fama-French-Carhart adjusted returns (in percentages) on *Desync*. We first group *Desync* into 100 equally sized bins and compute the mean of *Desync* and of future Fama-French-Carhart factor-adjusted returns within each bin. We then represent these data points with a scatterplot: each blue circle denotes a combination of the mean *Desync* and the mean future adjusted return across the stocks in a particular bin. The red solid line depicts the fitted line using Ordinary Least Squares.

# Table 1. Summary Statistics

| | Mean | Median | St.Dev. | pc5 | pc25 | pc75 | pc95 |
|---|---|---|---|---|---|---|---|
| | **Panel A: Short Selling Profits** | | | | | | |
| Desync | 0.631 | 0.679 | 0.186 | 0.230 | 0.546 | 0.766 | 0.840 |

| | Mean | Median | St.Dev. | pc5 | pc25 | pc75 | pc95 |
|---|---|---|---|---|---|---|---|
| | **Panel B: Stock and Fundamental Characteristics** | | | | | | |
| Return (% per month) | 1.075 | 0.433 | 10.69 | -61.39 | -18.48 | 19.41 | 64.65 |
| Volatility (% per month) | 10.02 | 8.429 | 6.563 | 4.029 | 6.181 | 12.03 | 20.86 |
| Bid-Ask Spread (%) | 0.148 | 0.0693 | 0.232 | 0.0141 | 0.0326 | 0.159 | 0.552 |
| Turnover (%) | 0.873 | 0.592 | 0.994 | 0.107 | 0.333 | 1.031 | 2.543 |
| Analysts' Forecast Dispersion | 18.55 | 8.594 | 29.25 | 1.792 | 4.328 | 19.43 | 71.33 |
| Market Equity ($m) | 6,847 | 1,377 | 21,552 | 170.3 | 480.3 | 4,319 | 28,588 |

| | Mean | Median | St.Dev. | pc5 | pc25 | pc75 | pc95 |
|---|---|---|---|---|---|---|---|
| | **Panel C: Equity Lending Market** | | | | | | |
| Short Interest (%) | 3.916 | 1.856 | 5.231 | 0.144 | 0.759 | 4.833 | 15.09 |
| Supply (%) | 21.61 | 23.00 | 10.56 | 2.102 | 13.83 | 29.63 | 36.97 |
| Fee (% per annum) | 1.244 | 0.375 | 3.677 | 0.373 | 0.375 | 0.464 | 5.041 |

[Continues on the next page]

**Panel D: Correlation Matrix**

| | Desync | Short Interest | Supply | Fee | Return | Bid-Ask Spread | Idio Vol | Turnover | Market to Book | Size |
|---|---|---|---|---|---|---|---|---|---|---|
| Desync | 1.00 | | | | | | | | | |
| Short-Interest | 0.39 | 1.00 | | | | | | | | |
| Supply | -0.03 | -0.18 | 1.00 | | | | | | | |
| Fee | 0.10 | 0.26 | -0.37 | 1.00 | | | | | | |
| Return | 0.04 | -0.03 | 0.04 | -0.04 | 1.00 | | | | | |
| Bid-Ask Spread | 0.09 | -0.05 | -0.40 | 0.22 | -0.06 | 1.00 | | | | |
| Idio Vol | 0.26 | 0.26 | -0.29 | 0.28 | -0.01 | 0.30 | 1.00 | | | |
| Turnover | 0.20 | 0.50 | 0.03 | 0.12 | -0.01 | -0.18 | 0.43 | 1.00 | | |
| Market-to-Book | 0.12 | 0.13 | -0.01 | 0.10 | 0.10 | -0.09 | 0.11 | 0.10 | 1.00 | |
| Size | -0.27 | -0.15 | 0.30 | -0.17 | 0.07 | -0.55 | -0.39 | 0.04 | 0.11 | 1.00 |

This table presents summary statistics for the main variables in our analysis. For each variable we first compute daily cross-sectional summary statistics (mean, median, standard deviation, the 5th, 25th, 75th and 95th percentiles) and report the time-series mean of each statistic. Panel A displays summary statistics relative to *Desync* computed as in equation (1). Panel B displays summary statistics relative to stock and firm fundamental characteristics. *Return* is the stock return expressed in percentage per month, *Volatility* is the stock volatility expressed in percentage per month, *Bid-Ask Spread* is the daily bid-ask spread as percentage of mid-price, *Turnover* is total number of shares sold on a day as a percentage of shares outstanding, *Analyst Dispersion*, is the ratio between the standard-deviation and the average of a quarter-ahead EPS forecasts and *Market Equity* is the market value of equity in millions. Panel C displays summary statistics relative to equity lending variables. *Short Interest* is the total quantity of shares loaned out as a percentage of shares outstanding, *Supply* is the active quantity of shares available to be borrowed expressed as a percentage of shares outstanding, and *Fee* is the borrowing fee (in % per annum). Panel D presents the correlation matrix, where *Idio Vol* is the idiosyncratic volatility over the previous month. We first compute cross-sectional correlations on each day, and then report the time-series mean.

## Table 2. *Desync* and Firms' Information Environment

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Turnover | 0.011*** | | 0.011*** | -0.009*** |
| | (12.80) | | (13.08) | (-6.95) |
| Analyst Dispersion | 0.006*** | | 0.005*** | 0.004*** |
| | (9.78) | | (7.57) | (7.33) |
| Bid-Ask | | 0.004** | 0.004*** | 0.009*** |
| | | (2.42) | (2.68) | (5.65) |
| Size | | -0.036*** | -0.035*** | -0.021*** |
| | | (-10.88) | (-9.48) | (-6.28) |
| Open Interest | | | | 0.005*** |
| | | | | (2.61) |
| Convertible | | | | -0.004*** |
| | | | | (-5.31) |
| Idio-Vol | | | | 0.011*** |
| | | | | (6.77) |
| Short_interest | | | | 0.051*** |
| | | | | (41.13) |
| Supply | | | | 0.024*** |
| | | | | (12.30) |
| Fee | | | | 0.001 |
| | | | | (0.65) |
| $R^2_{adjusted}$ | 0.378 | 0.380 | 0.380 | 0.405 |
| $Nobs$ | 4,652,322 | 5,589,080 | 4,652,278 | 4,627,854 |

This table reports coefficient estimates and associated t-statistics (in parentheses) of the following panel regression

$$Desync_{i,t} = \alpha_i + \tau_t + \beta' \boldsymbol{x_{i,t}} + \epsilon_{i,t},$$

where $Desync_{i,t}$ denotes the dispersion in profits across the short positions in stock $i$ on day $t$ (computed as in equation 1), $\alpha_i$ and $\tau_t$ are stock- and time-fixed effects, and $\boldsymbol{x_{i,t}}$ represents the set of covariates, which includes *Turnover*, the average turnover over the previous three months; *Analyst Dispersion*, the ratio between the standard deviation and the average of a quarter-ahead EPS forecasts; *Bid-Ask*, the average bid-ask spread over the previous three months; *Size*, the (log) product of the price and the number of shares outstanding; *Open Interest*, the (log) of the call and put open interest; *Convertible*, the ratio between COMPUSTAT item DCTV and total assets; *Idio Vol*, the idiosyncratic volatility over the previous three months; *Short Interest*, the total quantity of shares loaned out as a percentage of shares outstanding; *Supply*, the active quantity of shares available to be borrowed expressed as a percentage of shares outstanding; and *Fee*, the borrowing fee. Regressors are standardized to have zero mean and unit standard deviation. t-statistics are based on double-clustered standard errors. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels.

## Table 3. Dynamics of *Desync* Around Information Events

| | (1) | (2) | (3) |
|---|---|---|---|
| | Analyst Downgrades | Negative News | Short Reports |
| Post_Event | -0.018*** | -0.006** | 0.023 |
| | (-4.05) | (-2.52) | (1.41) |
| $R^2_{adjusted}$ | 0.589 | 0.540 | 0.506 |
| $Nobs$ | 84,497 | 337,256 | 4,148 |

This table reports coefficient estimates and associated t-statistics (in parentheses) of the following regression

$$Desync_{i,t} = \alpha_i + Post\_Event_t + \epsilon_{i,t},$$

where $Desync_{i,t}$ denotes the dispersion in profits across the short positions in stock $i$ on day $t$ (computed as in equation 1), $\alpha_i$ is a stock fixed effects, and $Post\_Event_t$ is a dummy variable equal to 1 (0) the fifty days after (before) the information event. Information events are defined by analyst downgrades to "sell" or "strong sell" (column (1)), the release of negative news about the firm (column (2)), and the release of activist short sellers' report (column(3)). t-statistics are based on double-clustered standard errors. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels.

# Table 4. Calendar Portfolios

**Equal-Weighted Portfolios**

| | **A.1: Single Sort** | | | | | |
|---|---|---|---|---|---|---|
| | Q1 | Q2 | Q3 | Q4 | Q5 | Q5-Q1 |
| Desync | 0.17*** | 0.07 | -0.02 | -0.15*** | -0.46*** | -0.63*** |
| | ( 2.82) | ( -1.63) | ( -0.55) | ( -2.84) | ( -4.27) | ( -5.41) |

| | **Panel A.2: Conditional Double Sorts** | | | | |
|---|---|---|---|---|---|
| | Q5-Q1 | Q10-Q6 | Q15-Q11 | Q20-Q16 | Q25-Q21 |
| Size | -1.33*** | -0.63*** | -0.35*** | -0.61*** | -0.48*** |
| | ( -6.13) | ( -3.89) | ( -2.78) | ( -4.89) | ( -4.88) |
| Market To Book | -1.26*** | -0.53*** | -0.62*** | -0.19 | -0.49* |
| | ( -5.45) | ( -3.88) | ( -5.47) | ( -1.56) | ( -1.90) |
| $Ret_{6M}$ | -1.04*** | -0.41*** | -0.50*** | -0.45*** | -0.29* |
| | ( -6.05) | ( -2.68) | ( -4.61) | ( -4.56) | ( -1.84) |
| Short Interest | -0.32*** | -0.08 | -0.10 | -0.46*** | -0.46** |
| | ( -2.61) | ( -0.60) | ( -0.69) | ( -2.80) | ( -2.30) |
| Bid-Ask | -0.52*** | -0.34*** | -0.30** | -0.65*** | -1.32*** |
| | ( -5.35) | ( -3.19) | ( -2.34) | ( -3.76) | ( -6.45) |
| Turnover | -0.44** | -0.50*** | -0.19 | -0.40*** | -0.97*** |
| | ( -2.52) | ( -4.28) | ( -1.41) | ( -2.90) | ( -5.74) |

**Value-Weighted Portfolios**

| | **B.1: Single Sort** | | | | | |
|---|---|---|---|---|---|---|
| | Q1 | Q2 | Q3 | Q4 | Q5 | Q5-Q1 |
| Desync | 0.09** | -0.06* | -0.21*** | -0.29*** | -0.27** | -0.36*** |
| | ( 2.24) | (-1.91) | (-4.53) | (-4.08) | (-2.53) | (-2.97) |

| | **Panel B.2: Conditional Double Sorts** | | | | |
|---|---|---|---|---|---|
| | Q5-Q1 | Q10-Q6 | Q15-Q11 | Q20-Q16 | Q25-Q21 |
| Size | -1.09*** | -0.48*** | -0.33*** | -0.61*** | -0.37*** |
| | (-5.11) | (-2.98) | (-2.73) | (-4.61) | (-2.98) |
| Market To Book | -0.74*** | -0.74*** | -0.45*** | -0.18 | -0.38 |
| | (-3.24) | (-4.65) | (-3.17) | (-1.21) | (-1.64) |
| $Ret_{6M}$ | -0.86*** | -0.64*** | -0.52*** | -0.24* | -0.12 |
| | ( -4.00) | ( -3.94) | ( -4.44) | ( -1.65) | ( -0.57) |
| Short Interest | -0.21 | -0.41** | -0.32** | -0.40** | -0.39 |
| | (-1.44) | (-2.48) | (-2.10) | (-2.02) | (-1.63) |
| Bid-Ask | -0.36*** | -0.27* | -0.20 | -0.81*** | -0.67** |
| | (-2.95) | (-1.90) | (-1.39) | (-3.75) | (-2.43) |
| Turnover | -0.42** | -0.26 | -0.29** | -0.25 | -0.60*** |
| | (-2.38) | (-1.51) | (-2.20) | (-1.61) | (-2.92) |

This table presents monthly Fama-French-Carhart four-factor alphas (in percent) for equal-weighted (Panel A) and value-weighted portfolios (Panel B). Portfolios are rebalanced daily, and are held for 21 days. Results in Panels A.1 and B.1 refer to portfolios formed by sorting into quintiles using the level of *Desync*; the last column in these panels (*Q5-Q1*) shows returns to a portfolio long (short) in the stocks in the highest (lowest) quintile. Results in Panel A.2 and B.2 refer to portfolios formed by first sorting by the level of one of the variables in the first column into quintiles, then sorting *Desync* into sub-quintiles. Each column shows returns to a long-short portfolio where firms with *Desync* in the highest (lowest) sub-quintile are assigned to the long (short) portfolio. *Desync* is the dispersion in profits across the short positions (computed as in equation 1); *Size* is the market capitalization; *Market to Book* is the market-to-book ratio; $Return_{6M}$ is the stock return cumulated over the previous six months; *Short Interest* is the total quantity of shares loaned out as a percentage of shares outstanding; *Bid-Ask* is the average bid-ask spread over the previous month; and *Turnover* is the average turnover over the previous month. The reported alphas are the intercept from regressing portfolio returns in excess of the riskfree rate on the excess market return (MKT), size (SMB), book-to-market (HML), and momentum (MOM) factors. t-statistics are based on adjusted standard errors using Newey and West (1987) methodology to correct for autocorrelation, with a number of lags equal to the length of the holding period. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels.

## Table 5. *Desync* and Future Returns: Fama-MacBeth Regressions

| | (1) | (2) | (3) |
|---|---|---|---|
| Desync | -0.659*** | -0.530*** | -0.739*** |
| | ( -4.021) | ( -3.288) | ( -4.910) |
| Short Interest | -5.360*** | -3.902*** | -1.178 |
| | ( -4.718) | ( -3.841) | ( -1.085) |
| Market To Book | -0.065 | 0.012 | 0.087 |
| | ( -0.645) | ( 0.126) | ( 0.920) |
| Size | -0.079* | -0.168*** | -0.153*** |
| | ( -1.950) | ( -4.810) | ( -4.416) |
| $Ret_{1M}$ | -0.248 | -0.040 | -0.102 |
| | ( -0.349) | ( -0.058) | ( -0.152) |
| $Ret_{6M}$ | 0.963*** | 0.696*** | 0.625** |
| | ( 3.580) | ( 2.692) | ( 2.464) |
| Bid-Ask | | -74.272*** | -13.190 |
| | | ( -3.344) | ( -0.636) |
| Idio Vol | | -21.376*** | -14.316*** |
| | | ( -3.679) | ( -2.769) |
| Turnover | | -16.141 | -22.637** |
| | | ( -1.588) | ( -1.982) |
| Supply | | | 0.876 |
| | | | ( 1.495) |
| Fee | | | -9.434*** |
| | | | ( -5.737) |
| Var Fee | | | -33.075* |
| | | | ( -1.756) |
| *Average-$R^2$* | 0.02 | 0.03 | 0.04 |
| *Nobs* | 4,915,663 | 4,915,663 | 4,759,986 |

This table reports Fama and MacBeth (1973) estimates and associated t-statistics (in parentheses) from the following daily regressions

$$ar_{i,t+21} = \alpha + \beta \times Desync_{i.t} + \theta' \boldsymbol{x_{i,t}} + \epsilon_{i,t+21},$$

where $ar_{i,t+21}$ is the factor-adjusted (abnormal) future return of stock $i$ cumulated over 21 days, $Desync_{i.t}$ denotes the dispersion in profits across the short positions in stock $i$ on day $t$ (computed as in equation 1), and $\boldsymbol{x_{i,t}}$ is a vector of control variables. Abnormal returns are calculated as the difference between the raw and the Fama-French-Carhart four-factor model-implied returns for the corresponding period. Model-implied returns are equal to the riskfree rate plus the sum of the products of the estimated betas from the previous quarter and the current value of the factors. Our set of controls includes: *Short Interest*, the short interest in stock $i$ at time $t$; *Market to Book*, the (log) market-to-book ratio; *Size*, the (log) market value of equity; $Ret_{1M}$, the stock returns cumulated over the previous month; $Ret_{6M}$, the stock return cumulated over the previous six months excluding the first month; *Bid-Ask*, the average bid-ask spread over the previous month; *Idio Vol*, the idiosyncratic volatility over the previous month; *Turnover*, the average turnover over the previous month; *Supply*, the active quantity of shares available to be borrowed expressed as a percentage of shares outstanding; *Fee*, the borrowing fee; and *Var Fee*, the variance of the borrowing fees. We report the time-series mean of the parameter estimates and t-statistics based on adjusted standard errors using Newey and West (1987) methodology to correct for autocorrelation, with a number of lags equal to the length of the holding period. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels.

## Table 6. *Desync* and Relative Mispricing

| | (1) | (2) |
|---|---|---|
| Desync | 2.228*** | 1.087*** |
| | (16.22) | (7.91) |
| | [0.48] | [0.21] |
| | | |
| Short Interest | | -0.205 |
| | | (-0.32) |
| Market-to-Book | | -0.108*** |
| | | (-4.19) |
| Size | | -0.224*** |
| | | (-9.89) |
| $Ret_{1M}$ | | 0.096* |
| | | (1.81) |
| $Ret_{6M}$ | | -0.813*** |
| | | (-14.45) |
| Bid-Ask | | -98.382*** |
| | | (-5.44) |
| Idio Vol | | 21.025*** |
| | | (12.91) |
| Turnover | | 18.378*** |
| | | (4.82) |
| Supply | | -3.850*** |
| | | (-11.18) |
| Fee | | 0.587 |
| | | (0.56) |
| Var Fee | | 15.544 |
| | | (1.10) |
| Pseudo $R^2$ | 0.02 | 0.09 |
| $Nobs$ | 163,416 | 146,244 |

This table reports coefficient estimates and associated t-statistics (in parentheses) from the following Logit regression

$$Pr\left(y_{i,m}=1|\boldsymbol{x}_{i,m-1}\right)=\frac{\exp\left(\boldsymbol{x}'_{i,m-1}\boldsymbol{\beta}\right)}{1+\exp\left(\boldsymbol{x}'_{i,m-1}\boldsymbol{\beta}\right)},$$

where $y_{i,m}$ is a binary variable equal to 1 if stock $i$ rises to the top tercile of the $MISP$ (the mispricing score proposed by Stambaugh, Yu, and Yuan, 2015) distribution in month $m$. The vector of covariates $\boldsymbol{x}$ includes: *Desync*, the dispersion in profits across the short positions (computed as in equation 1); $Short\ Interest$, the short interest in the stock; $Market\ to\ Book$, the (log) market-to-book ratio; *Size*, the (log) market value of equity; $Ret_{1M}$, the stock returns cumulated over a month; $Ret_{6M}$, the stock return cumulated over six months excluding the first month; $Bid-Ask$, the average bid-ask spread over the previous month; $Idio\ Vol$, the idiosyncratic volatility over the previous month; $Turnover$, the average turnover over the previous month; *Supply*, the active quantity of shares available to be borrowed expressed as a percentage of shares outstanding; $Fee$, the borrowing fee; and $Var\ Fee$, the variance of the borrowing fees. The mean marginal effect for *Desync* is reported in squared brackets. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels.

## Table 7. *Desync* and Alternative Overpricing Drivers

**Panel A: Equal-Weighted Portfolios**

| | Q5-Q1 | Q10-Q6 | Q15-Q11 | Q20-Q16 | Q25-Q21 |
|---|---|---|---|---|---|
| Supply | -1.35*** | -0.70*** | -0.28** | -0.34*** | -0.26** |
| | ( -6.65) | ( -3.97) | ( -2.45) | ( -2.90) | ( -2.51) |
| Fee | -0.38*** | -0.14 | -0.37*** | -0.24 | -0.96*** |
| | ( -4.82) | ( -0.70) | ( -3.70) | ( -1.21) | ( -4.55) |
| Var Fee | -0.54*** | -0.41*** | -0.32*** | -0.54*** | -0.99*** |
| | ( -5.42) | ( -3.78) | ( -3.10) | ( -3.19) | ( -4.94) |
| Idio Vol | -0.20** | -0.30*** | -0.12 | -0.09 | -0.70*** |
| | ( -2.54) | ( -3.44) | ( -1.08) | ( -0.70) | ( -3.18) |
| Sentiment (BW) | -0.15* | -0.43*** | -0.72*** | -0.18 | -0.29** |
| | ( -1.70) | ( -2.99) | ( -6.21) | ( -1.38) | ( -2.18) |
| Sentiment (JLMZ) | -0.42*** | -0.25** | -0.88*** | -0.73*** | -0.91*** |
| | ( -4.18) | ( -2.18) | ( -7.44) | ( -5.87) | ( -7.87) |

**Panel B: Value-Weighted Portfolios**

| | Q5-Q1 | Q10-Q6 | Q15-Q11 | Q20-Q16 | Q25-Q21 |
|---|---|---|---|---|---|
| Supply | -1.10*** | -0.44** | -0.31* | -0.11 | -0.45*** |
| | ( -4.60) | ( -2.07) | ( -1.65) | ( -0.81) | ( -3.34) |
| Fee | -0.29** | -0.01 | -0.27* | 0.04 | -0.89*** |
| | ( -2.38) | ( -0.03) | ( -1.79) | ( 0.17) | ( -4.30) |
| Var Fee | -0.40*** | -0.36*** | -0.09 | -0.20 | -0.85*** |
| | ( -2.63) | ( -2.61) | ( -0.6) | ( -1.17) | ( -4.24) |
| Idio Vol | -0.21** | -0.21* | -0.08 | 0.04 | -0.52* |
| | ( -2.16) | ( -1.74) | ( -0.49) | ( 0.26) | ( -1.85) |
| Sentiment (BW) | -0.62*** | -0.53*** | -1.1*** | -0.15 | -0.61*** |
| | ( -4.87) | ( -4.91) | ( -7.72) | ( -1.27) | ( -5.97) |
| Sentiment (JLMZ) | 0.13 | -0.41*** | -0.97*** | -0.26* | -0.39*** |
| | ( 1.35) | ( -3.40) | ( -6.72) | ( -1.84) | ( -2.64) |

This table presents monthly Fama-French-Carhart four-factor alphas (in percent) for equal-weighted (Panel A) and value-weighted (Panel B) portfolios. Portfolios are rebalanced daily, and are held for 21 days. Results refer to portfolios formed by first sorting on the level of one of the variables in the first column into quintiles, then sorting *Desync* into sub-quintiles. Each column shows returns to a long-short portfolio where firms with *Desync* in the highest (lowest) sub-quintile are assigned to the long (short) portfolio. *Supply* is the active quantity of shares available to be borrowed expressed as a percentage of shares outstanding; *Fee* is the borrowing fee; *Var Fee* is the variance of the borrowing fees over the previous month; *Idio Vol* is the idiosyncratic volatility over the previous month; Sentiment (BW) is the sentiment measure from Baker and Wurgler (2006); and Sentiment (JLMZ) is the sentiment measure from Jiang et al. (2019). The reported alphas are the intercept from regressing portfolio returns in excess of the riskfree rate on the excess market return (MKT), size (SMB), book-to-market (HML), and momentum (MOM) factors. t-statistics are based on adjusted standard errors using Newey and West (1987) methodology to correct for autocorrelation, with a number of lags equal to the length of the holding period. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels.

## Table 8. *Desync* and Delay in Overpricing Correction

| | (1) | (2) | (3) |
|---|---|---|---|
| Desync | 3.349** | 2.889** | 3.711** |
| | (2.25) | (2.00) | (2.48) |
| R | | 0.771*** | 0.777*** |
| | | (12.50) | (12.53) |
| Fee | | -0.052 | 3.351 |
| | | (-0.00) | (0.36) |
| Short Interest | | -0.271 | 2.494 |
| | | (-0.04) | (0.43) |
| Bid-Ask | | | -116.206 |
| | | | (-0.45) |
| Size | | | 4.764*** |
| | | | (6.52) |
| Market to Book | | | -0.449* |
| | | | (-1.94) |
| $R^2_{adjusted}$ | 0.135 | 0.215 | 0.235 |
| $Nobs$ | 3,862 | 3,822 | 3,722 |

This table presents coefficient estimates and associated t-statistics (in parentheses) from the following regression:

$$Delay_{i,t} = \alpha_i + \tau_t + \beta \times Desync_{i.t} + \boldsymbol{\gamma}'\boldsymbol{x_{i,t}} + \epsilon_{i,t},$$

where *Desync* is the dispersion in profits across the short positions (computed as in equation 1); $\alpha_i$ and $\tau_t$ are firm and time fixed-effects, and $\boldsymbol{x_{i,t}}$ is a vector of controls. The controls include $R$, the mispricing score; *Fee*, borrowing fee (in % per annum); *Short Interest*, the total quantity of shares loaned out as a percentage of shares outstanding; *Bid-Ask*, the average bid-ask spread; *Size* the (log) market value of equity; and *Market to Book*, the (log) market-to-book ratio. $Delay_{i,t}$ is constructed in two steps. For each stock $i$, we first identify the overpricing events, i.e. the months ($t$) when the mispricing score (Stambaugh, Yu, and Yuan, 2015) rises to the top tercile of the distribution. We then compute the length of the events as the number of months before the score drops below the top tercile. t-statistics are based on clustered standard errors. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels.

## Table 9. *Desync* and Duration of Put-Call Disparities

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Desync | 14.385*** | 9.375** | 8.882** | 9.617** | 7.790** | 8.630** |
| | (3.78) | (2.54) | (2.35) | (2.43) | (2.03) | (2.12) |
| R | | 1.221*** | 1.797*** | 2.077*** | 1.941*** | 2.114*** |
| | | (2.87) | (3.53) | (3.73) | (3.84) | (3.79) |
| Fee | | 29.209*** | 26.653** | 30.528*** | 27.543** | 30.355*** |
| | | (2.81) | (2.49) | (2.80) | (2.54) | (2.75) |
| Short Interest | | 43.356*** | 43.697*** | 46.046*** | 52.438*** | 52.206*** |
| | | (3.52) | (3.53) | (3.67) | (3.77) | (3.73) |
| Stock Bid-Ask | | | 9.059 | 9.857 | 12.822* | 12.718* |
| | | | (1.42) | (1.52) | (1.82) | (1.78) |
| Option Bid-Ask | | | -0.245** | -0.357*** | -0.213* | -0.292** |
| | | | (-2.20) | (-3.18) | (-1.93) | (-2.56) |
| Option Maturity | | | -0.017 | -0.024 | -0.019 | -0.023 |
| | | | (-0.77) | (-1.03) | (-0.85) | (-0.98) |
| Option Moneyness | | | | -0.071 | | -0.086 |
| | | | | (-0.47) | | (-0.56) |
| Option Open Interest | | | | -1.251 | | -1.003 |
| | | | | (-0.87) | | (-0.71) |
| Option Volume | | | | 1.515 | | 1.528 |
| | | | | (0.82) | | (0.83) |
| Option Implied Volatility | | | | -14.990** | | -10.498 |
| | | | | (-2.51) | | (-1.56) |
| Market to Book | | | | | 0.027 | -0.077 |
| | | | | | (0.01) | (-0.03) |
| Size | | | | | 4.898** | 4.194* |
| | | | | | (2.36) | (1.79) |
| $R^2_{adjusted}$ | 0.057 | 0.104 | 0.105 | 0.106 | 0.108 | 0.108 |
| $Nobs$ | 4,098 | 4,032 | 4,025 | 3,981 | 4,025 | 3,981 |

This table presents coefficient estimates and associated t-statistics (in parentheses) from the following regression:

$$Delay_{i,t} = \alpha_i + \tau_t + \beta \times Desync_{i,t} + \boldsymbol{\gamma}'\boldsymbol{x_{i,t}} + \epsilon_{i,t},$$

where $Delay_{i,t}$ is the number of days the price of stock $i$ is above the upper-bound implied by the put-call parity, *Desync* is the dispersion in profits across the short positions (computed as in equation 1); $\alpha_i$ and $\tau_t$ are firm and time fixed-effects, and $\boldsymbol{x_{i,t}}$ is a vector of controls. The controls include $R$, the log of the ratio between the closing stock price and the stock price derived from the options market using put-call parity; $Fee$, borrowing fee (in % per annum); $Short\ Interest$, the total quantity of shares loaned out as a percentage of shares outstanding; *Stock Bid-Ask*, the percentage bid-ask spread; *Option Bid-Ask*, the percentage bid-ask spread averaged across the call and put options for the stock; $Option\ Maturity$, the number of days until maturity; $Option\ Moneyness$, the moneyness of the option; $Option\ Volume$, the (log) option volume averaged across the stock's calls and puts; $Option\ Open\ Interest$, the (log) open interest averaged across the call and put options; $Option\ Implied\ Volatility$, the implied volatility of the call option; $Size$ and $Market\ to\ Book$, computed as in section 5. t-statistics are based on clustered standard errors. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels.

# Table 10. Alternative Desynchronization Measure

| | A.1: Single Sorted Calendar Portfolio | | | | | |
|---|---|---|---|---|---|---|
| | Q1 | Q2 | Q3 | Q4 | Q5 | Q5-Q1 |
| Desync_SD | 0.18*** | 0.04 | -0.09** | -0.24*** | -0.28* | -0.46*** |
| | (2.93) | (0.82) | (-2.14) | (-2.84) | (-1.92) | (-2.78) |

| | Panel A.2: Conditional Double Sorted Portfolios | | | | |
|---|---|---|---|---|---|
| | Q5-Q1 | Q10-Q6 | Q15-Q11 | Q20-Q16 | Q25-Q21 |
| Size | -1.43*** | -1.24*** | -0.78*** | -0.52*** | -0.95*** |
| | (-5.71) | ( -7.11) | ( -5.36) | ( -3.41) | ( -4.02) |
| Market To Book | -0.42 | -0.55*** | -0.46*** | -0.08 | -0.15 |
| | (-1.20) | ( -2.85) | ( -2.61) | ( -0.43) | ( -0.59) |
| Short Interest | -0.91*** | -0.72*** | -0.87*** | -0.54*** | -0.33* |
| | (-4.09) | ( -2.99) | ( -4.19) | ( -3.04) | ( -1.80) |
| Bid-Ask | -0.77*** | -0.42** | -0.30 | -0.67*** | -0.84*** |
| | (-3.50) | ( -2.08) | ( -1.64) | ( -3.44) | ( -2.66) |
| Idio Vol | -0.31*** | -0.06 | -0.06 | 0.08 | -0.86** |
| | (-2.59) | ( -0.39) | ( -0.40) | ( 0.30) | ( -2.54) |

| | Panel B: Mispricing | | | Panel C: Delay | |
|---|---|---|---|---|---|
| | *AdjReturn* | *MISP* | | *MISP* | *P-C Disparity* |
| | (1) | (2) | | (1) | (2) |
| Desync_SD | -0.908* | 1.612*** | Desync_SD | 5.398* | 14.660* |
| | ( -1.78) | (5.65). | | (1.84) | (1.66) |
| Short Interest | -1.901* | 0.786 | R | 0.847*** | 2.012*** |
| | | | | (11.46) | (3.66) |
| | | | Fee | 3.086 | 31.628*** |
| | | | | (0.32) | (2.87) |
| | | | Short Interest | 1.263 | 51.044*** |
| | | | | (0.21) | (4.14) |
| Controls | YES | YES | Controls | YES | YES |
| Nobs | 4,915,663 | 146,244 | Nobs | 3,722 | 3,981 |
| $R^2$ | 0.03 | 0.09 | $R^2$ | 0.16 | 0.10 |

Panels A.1 and A.2 present monthly Fama-French-Carhart four-factor alphas (in percent) for value-weighted portfolios. Portfolios are rebalanced daily, and are held for 21 days. Results in Panel A.1 refer to portfolios formed by sorting into quintiles using the level of *Desync_SD* computed following equation (6); the last column in these panels (*Q5-Q1*) shows returns to a portfolio long (short) in the stocks in the highest (lowest) quintile. Results in Panel A.2 refer to portfolios formed by first sorting by the level of one of the variables in the first column into quintiles, then sorting by *Desync_SD* into sub-quintiles. Each column shows returns to a long-short portfolio where firms with *Desync_SD* in the highest (lowest) sub-quintile are assigned to the long (short) portfolio. t-statistics are based on adjusted standard error using Newey and West (1987) methodology to correct for autocorrelation, with a number of lags equal to the length of the holding period. Column (1) of Panel B reports estimates from the following regression

$$ar_{i,t+21} = \alpha + \beta \times Desync\_SD_{i.t} + \theta' \boldsymbol{x_{i,t}} + \epsilon_{i,t+21},$$

where $ar_{i,t+21}$ is the factor-adjusted (abnormal) future return of stock $i$ cumulated over 21 days, *Desync_SD* is computed as in equation (6), and $\boldsymbol{x_{i,t}}$ is a vector of control variables (see Table 5). Column (2) of Panel B reports estimates from the following regression

$$Pr\left(y_{i,m} = 1 | \boldsymbol{x}_{i,m-1}\right) = \exp\left(\boldsymbol{x}'_{i,m-1}\boldsymbol{\beta}\right) / \left(1 + \exp\left(\boldsymbol{x}'_{i,m-1}\boldsymbol{\beta}\right)\right),$$

where $y_{i,m}$ is a binary variable equal to 1 if stock $i$ rises to the top tercile of the *MISP* distribution in month $m$. The vector of covariates $\boldsymbol{x}$ includes *Desync_SD*, (computed as in equation 6) and the control variables in Table 6. Panel C reports estimates from the following regression:

$$Delay_{i,t} = \alpha_i + \tau_t + \beta \times Desync\_SD_{i,t} + \boldsymbol{\gamma}' \boldsymbol{x_{i,t}} + \epsilon_{i,t},$$

where $\alpha_i$ and $\tau_t$ are firm and time fixed-effects. In column (1) $Delay_{i,t}$ is constructed in two steps. For each stock $i$, we first identify the overpricing events, i.e. the months ($t$) when the mispricing score (Stambaugh, Yu, and Yuan, 2015) exceeds the top tercile of the distribution. We then compute the length of the events as the number of months before the score drops below the top tercile. The vector of controls is the same as Table 8. In column (2) $Delay_{i,t}$ is the number of days the price of stock $i$ is above the upper-bound implied by the put-call parity, and $\boldsymbol{x_{i,t}}$ is the vector of controls from Table 9. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels.

## Table 11. *Desync* and Delay in Underpricing Correction

| | (1) | (2) | (4) | (5) |
|---|---|---|---|---|
| | **Panel A: Mispricing Score** | | **Panel B: Put-Call Parity** | |
| Desync | 1.011 | 0.172 | 0.001 | 0.018 |
| | (0.64) | (0.11) | (0.01) | (0.11) |
| R | -0.740*** | -0.769*** | -0.011 | -0.232*** |
| | (-9.65) | (-10.10) | (-1.22) | (-3.28) |
| Fee | 10.824 | 14.858 | -2.579 | -0.193 |
| | (0.66) | (0.89) | (-0.66) | (-0.06) |
| Short Interest | 4.511 | 4.106 | 0.330 | 1.210* |
| | (0.64) | (0.59) | (0.49) | (1.79) |
| Controls | NO | YES | NO | YES |
| $R^2_{adjusted}$ | 0.19 | 0.19 | 0.10 | 0.118 |
| $Nobs$ | 3,895 | 3,785 | 3,477 | 3,262 |

This table presents coefficient estimates and associated t-statistics (in parentheses) from the following regression:

$$Delay_{i,t} = \alpha_i + \tau_t + \beta \times Desync_{i,t} + \boldsymbol{\gamma}' \boldsymbol{x_{i,t}} + \epsilon_{i,t},$$

where *Desync* is the dispersion in profits across the short positions (computed as in equation 1); $\alpha_i$ and $\tau_t$ are firm and time fixed-effects, and $\boldsymbol{x_{i,t}}$ is a vector of controls. In Panel A, *Delay* is the number of consecutive months the mispricing score (Stambaugh, Yu, and Yuan, 2015) falls below the bottom tercile of the distribution, and $R$ is the mispricing score in the month of the underpricing event. In Panel B, *Delay* is the number of days the price of stock $i$ is below the lower-bound implied by the put-call parity, and $R$ is the log of the ratio between the closing stock price and the stock price derived from put-call parity in the options market. In both panels, the controls include: *Fee*, borrowing fee (in % per annum); *Short Interest*, the total quantity of shares loaned out as a percentage of shares outstanding; *Stock Bid-Ask*, the percentage bid-ask spread; *Size*; and *Market to Book*. In Panel B, we also include: *Option Bid-Ask*, the percentage bid-ask spread averaged across the call and put options for the stock; *Option Volume*, the (log) option volume averaged across the stock's calls and puts; *Option Maturity*, the number of days until maturity; *Option Moneyness*, the moneyness of the option; *Option Open Interest*, the (log) open interest averaged across the call and put options; and *Option Implied Volatility*, the implied volatility of the call option. t-statistics are based on clustered standard errors. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels.

## Table A.1. Orthogonalized *Desync* and Future Returns

| | Adj-Returns | | MISP | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $Desync^{\perp}$ | -0.402** | -0.476*** | 0.442*** | 0.432*** |
| | (-2.40) | (-2.92) | (4.69) | (4.52) |
| Short Interest | -1.529 | -1.983* | 0.359 | 0.963 |
| | (-1.36) | (-1.82) | (0.56) | (1.52) |
| Market-to-Book | 0.028 | 0.060 | -0.076*** | -0.099*** |
| | (0.29) | ( 0 .63) | (-3.04) | (-3.88) |
| Size | -0.097*** | -0.134*** | -0.315*** | -0.248*** |
| | (-3.06) | (-3.90) | (-14.42) | (-11.15) |
| $Ret_{1M}$ | -0.283 | -0.117 | 0.334*** | 0.119** |
| | (-0.42) | (-0.17) | (6.96) | (2.26) |
| $Ret_{6M}$ | 0.707*** | 0.618** | -0.910*** | -0.805*** |
| | (2.76) | (2.44) | (-15.93) | (-14.26) |
| Bid-Ask | -27.961 | -13.147 | -93.133*** | -99.249*** |
| | (-1.32) | (-0 .63) | (-5.17) | (-5.48) |
| Idio Vol | | -15.909*** | | 23.739*** |
| | | (-3.08) | | (13.85) |
| Turnover | -34.019*** | -22.205* | 36.363*** | 16.905*** |
| | (-2.65) | (-1.95) | (10.24) | (4.42) |
| Supply | 1 .030* | 0.729 | -3.933*** | -3.682*** |
| | (1.65) | (1.25) | (-11.37) | (-10.74) |
| Fee | -9.877*** | -9.290*** | 1.062 | 0.432 |
| | (-5.93) | (-5.65) | (1.06) | (0.42) |
| Var Fee | -33.721* | -32.761* | 12.787 | 13.414 |
| | (-1.80) | (-1.74) | (0.89) | (0.94) |
| $R^2$ | 0.03 | 0.04 | 0.08 | 0.09 |
| $Nobs$ | 4,759,986 | 4,759,986 | 146,232 | 146,232 |

This table reports coefficient estimates and associated t-statistics (in parentheses) from regression Eqs. 2 (Columns 1 and 2) and 3 (Columns 3 and 4). In Columns 1 and 2, the left-hand variable is $ar_{i,t+21}$, the factor-adjusted (abnormal) future return of stock $i$ cumulated over 21 days, while in Columns 3 and 4 is a binary variable equal to 1 if stock $i$ rises to the top tercile of the $MISP$ (the mispricing score proposed by Stambaugh, Yu, and Yuan, 2015) distribution in month $m$, and equal to 0 otherwise. $Desync^{\perp}$ denotes the residuals from regressing $Desync$ on $Idio\ Vol$. The remaining variables are: $Short\ Interest$, the short interest in the stock; $Market\ to\ Book$, the (log) market-to-book ratio; $Size$, the (log) market value of equity; $Ret_{1M}$, the stock returns cumulated over a month; $Ret_{6M}$, the stock return cumulated over six months excluding the first month; $Bid-Ask$, the average bid-ask spread over the previous month; $Idio\ Vol$, the idiosyncratic volatility over the previous month; $Turnover$, the average turnover over the previous month; $Supply$, the active quantity of shares available to be borrowed expressed as a percentage of shares outstanding; $Fee$, the borrowing fee; and $Var\ Fee$, the variance of the borrowing fees. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels.

## Table A.2. Sample of Put-Call Parity Violations

| | mean | p50 | sd | p5 | p95 |
|---|---|---|---|---|---|
| Maturity | 134.52 | 134.00 | 26.07 | 94.00 | 177.00 |
| Moneyness (ln(S/K)%) | 0.08 | 0.04 | 3.78 | -6.55 | 6.77 |
| R (ln(S/$S^*$)%) | 0.25 | 0.06 | 1.30 | -0.87 | 1.88 |
| Volume | 22.13 | 0.00 | 200.28 | 0.00 | 66.00 |
| Implied Volatility (%) | 44.27 | 41.14 | 17.17 | 23.92 | 74.61 |
| Delay | 8.91 | 3.00 | 25.10 | 2.00 | 32.00 |

This table presents pooled summary statistics for the sample of options used in our empirical tests. *Maturity* is the number of days until maturity; *Moneyness* is the moneyness of the option computed as the log of the ratio between market price (S) and the options' strike price (K); *R* is the log of the ratio between the closing stock price and the stock price derived from the options market using put-call parity; *Volume* is the (log) volume averaged across the call and put options; *Implied Volatility* is the implied volatility of the call option; and *Delay* is the number of days the price of the stock is above the upper-bound implied by put-call parity.

## Table A.3. Miller's Hypothesis and *Desync*: Triple Sort.

**Panel A: Equal-Weighted Portfolios**

| | Fee | | Supply | |
|---|---|---|---|---|
| | Low (Q1) | Hi (Q5) | Low (Q1) | Hi (Q5) |
| **Turnover** (Q1) | -0.39** | -0.97*** | -0.78*** | 0.36 |
| | (-2.45) | (-3.47) | (-3.25) | (0.62) |
| **Turnover** (Q2) | -0.48*** | -0.53* | -0.61* | -0.34* |
| | (-4.02) | (-1.77) | (-1.92) | (-1.85) |
| **Turnover** (Q3) | -0.26** | 0.09 | -0.16 | -0.02 |
| | (-2.11) | (0.25) | (-0.41) | (-0.11) |
| **Turnover** (Q4) | -0.26** | -1.05** | -1.13*** | -0.41*** |
| | (-2.43) | (-2.4) | (-3.23) | (-2.66) |
| **Turnover** (Q5) | -0.53*** | -1.96*** | -3.10*** | -0.48** |
| | (-3.71) | (-3.69) | (-5.33) | (-2.05) |

**Panel B: Valuel-Weighted Portfolios**

| | Fee | | Supply | |
|---|---|---|---|---|
| | Low (Q1) | Hi (Q5) | Low (Q1) | Hi (Q5) |
| **Turnover** (Q1) | -0.96*** | 0.12 | -0.94*** | 0.25 |
| | (-4.02) | (0.72) | (-3.34) | (0.43) |
| **Turnover** (Q2) | -0.55** | -0.33** | -0.18 | 0.04 |
| | (-2.17) | (-2.10) | (-0.5) | (0.18) |
| **Turnover** (Q3) | -0.25 | -0.17 | -0.20 | -0.22 |
| | (-1.19) | (-1.09) | (-0.44) | (-1.19) |
| **Turnover** (Q4) | -0.57** | -0.18 | -0.17 | -0.53*** |
| | (-2.30) | (-0.95) | (-0.40) | (-2.69) |
| **Turnover** (Q5) | -1.99*** | -0.69** | -2.39*** | -0.99*** |
| | (-4.25) | (-2.78) | (-4.16) | (-3.59) |

This table presents monthly Fama-French-Carhart four-factor alphas (in percent) for equal-weighted (Panel A) and value-weighted (Panel B) portfolios. Portfolios are rebalanced daily, and are held for 21 days. Results refer to portfolios formed by independently sorting in quintiles on the level of turnover, on either Fee (left Panels) or Supply (Right panels), and *Desync* for a total of 125 portfolios. Each entry shows returns to a long-short portfolio where firms with *Desync* in the highest (lowest) sub-quintile are assigned to the long (short) portfolio, keeping the other two sorting variables fixed. The reported alphas are the intercept from regressing portfolio returns in excess of the riskfree rate on the excess market return (MKT), size (SMB), book-to-market (HML), and momentum (MOM) factors. t-statistics are based on adjusted standard errors using Newey and West (1987) methodology to correct for autocorrelation, with a number of lags equal to the length of the holding period. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels.