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Out of Sync: Dispersed Short Selling and the Correction of Mispricing

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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

JEL Classification: G12, G14

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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 (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 prediction, 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 premise 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.

The coordination issues underlying the synchronization-risk argument are driven by a dispersion of opinions ("disagreement") among arbitrageurs. In practice, however, short orders can be desynchronized for reasons unrelated to disagreement such as differences in hedging motives. To assess the extent to which our proxy captures disagreement-related desynchronization in a stock's short selling, we regress it 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. Across our

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

tests, short-selling desynchronization is positively associated with proxies for difference of opinion such as stock turnover and the dispersion in the stock analysts' forecasts. Consistent with desynchronization capturing disagreement driven also by information asymmetries, it is significantly higher for firms with larger bid-ask spreads and smaller market capitalization. Moreover, desynchronization is higher in presence of fewer news releases related to the firm that could act as "synchronizing events" (Abreu and Brunnermeier, 2003). These relations remain strong after controlling for differences in hedging needs across a stock's traders and other stock characteristics such as return volatility, supporting the use of short sellers' profit dispersion as a proxy for disagreement-related "desynchronization" in their sales.

Using this proxy, we first examine the relation between short sellers' desynchronization and the extent of stock overpricing. Based on the insight of Abreu and Brunnermeier (2003), we hypothesize that stocks with more desynchronized short selling are more overpriced. We find support for this hypothesis across different mispricing measures and methodologies. 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 short-desynchronization portfolios of -7.6% per annum. This result holds strongly in double-sorted portfolios that first condition on short interest and other well-known cross-sectional determinants. Consistent with the theory that synchronization problems are more prevalent in firms with poorer information environments, the desynchronization effect on returns almost doubles among stocks with higher turnover and larger bid-ask spread. 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 then adopt the relative mispricing score ($MISP$) of Stambaugh, Yu, and Yuan (2015). In further support for the synchronization-risk hypothesis, we find that a stock that moves from the bottom to the top tercile of our desynchronization proxy increases the likelihood of becoming relatively overpriced in the next month by up to 16%.

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 short-sale constraints. In contrast, the positive relation between desynchronization and overpricing that we document holds strongly even for stocks with few or no short-sale restrictions. 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 a significant return spread even among stocks displaying 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 even 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.

Besides the level of overvaluation, desynchronization can affect 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 to secure the profits of the eventual correction versus the costs of holding the short position for too long. In these conditions, short sellers delay acting on their information to correct a given level of overpricing, with the delay increasing with the dispersion of their opinions. Following this prediction, we hypothesize that stocks with larger desynchronization among their short sellers experience longer delays in the correction of overpricing. To quantify this delay, we count the number of consecutive months over which a stock remains relatively overpriced according to the

mispricing score $MISP$. Consistent with the synchronization-risk hypothesis, 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 also economically meaningful, as a one standard deviation increase in the desynchronization proxy requires an additional 16 days for the overpricing to disappear. In a second approach, we follow Ofek, Richardson, and Whitelaw (2004) and Engelberg, Reed, and Ringgenberg (2018) in examining mispricing opportunities that arise from the failure of the put-call parity no-arbitrage relation in the stock option market. 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 also positively associated with our desynchronization proxy, with a one standard deviation increase in desynchronization requiring an additional 1.4 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 support to the synchronization-risk hypothesis.

Lastly, we subject our findings to a number of additional tests. First, consistent with additional implications of Abreu and Brunnermeier (2002, 2003), we find that 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 in underpricing correction.

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), and capital constraints (Gromb and Vayanos, 2002, Brunnermeier and Pedersen, 2009, Garleau and Pedersen, 2011). 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 evidence on synchronization risk is confined to specific episodes 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), synchronization risk 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.

Second, our work contributes to the literature on the relation between short selling and mispricing. 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.[3] 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, recent studies highlight the importance of considering differences across short sellers. 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 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 their profits, among short sellers. We provide evidence that this heterogeneity

[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.

[3]Indeed, 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.

reflects dispersed opinions among short sellers and can affect the ability to synchronize their trades to correct overvaluation.

The rest of the paper is organized as follows. In Section 2 we introduce our 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 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 dispersion in a stock's short-selling profits 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 the mispricing. 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. In these situations, a greater dispersion of opinions ("disagreement") among arbitrageurs translates into poorer synchronization in their trades which, in turn, exacerbates asset overpricing even in the absence of short-selling restrictions. 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 the margin accounts on their short position. 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. It is worth noting 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 our hypotheses, in the cross-section of stocks.

3 Data

For our empirical tests we combine a novel dataset on the mark-to-market profits of the short positions in a stock with an array of data on the stock, equity lending and option markets, as well with other firm and stock characteristics. We describe our data below.

3.1 Short-Selling Profits Dataset

3.1.1 Dataset Description

Our primary data source is a dataset on the profits and losses of short sellers provided by IHS Markit. IHS Markit collects transaction-level information on the securities lending market from a variety of participants (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 the IHS Markit database covers a broad cross-section of 4,000 stocks over the period spanned between January 2011 and December 2017.

For each stock i and day t, we observe the full 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 (the initiation date for new transactions and the original start date for renewing transactions) until t.[4] IHS Markit discretizes these returns over 19 bins, each of which we denote by $bin_{i,t}^{\lfloor n \rfloor}$ $(n = 1, \ldots, 19)$, representing the fraction of shares on loan for stock i whose cumulated returns fall in the nth return interval—with left and right boundaries '$\lfloor$' and '$\rfloor$'—at time t. The first 10 intervals $(n = 1, \ldots, 10)$ correspond to the negative domain of the distribution and are defined as follows: $(-\infty, -100\%]$, $(-100\%, -75\%]$, $(-75\%, -50\%]$, $(-50\%, -40\%]$, $(-40\%, -30\%]$, $(-30\%, -20\%]$, $(-20\%, -15\%]$, $(-15\%, -10\%]$, $(-10\%, -5\%]$, and $(-5\%, 0\%]$. The remaining 9 intervals $(n = 11, \ldots, 19)$ cover the positive domain of the distribution in a specular fashion, from $(0\%, 5\%]$ for $n = 11$ to $(75\%, 100\%]$ for $n = 19$. Existing data allows researchers to observe only the aggregate level of short interest (i.e. the number of shares sold short over the number of shares outstanding). Thus, our data contribute disaggregated information on the mark-to-market profits experienced by different subsets of short sellers to existing aggregate data.[5]

As an example, Figure 1 displays an instance of the data for Tesla as of September 11, 2015. The top panel highlights 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 that this profit dispersion is consistent with the uncertainty surrounding the stock around that time. The bottom panel also indicates that the stock had been attracting the attention of short sellers since the beginning of August, and that short interest reached

[4]Since U.S. equity short sellers need to borrow the stocks they sell, IHS Markit infers short-selling activity from transactions in the stock lending market. 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.

[5]Indeed, previously available data offer only aggregate information on the level of short interest and related variables (e.g., average shorting fees) at the stock level, 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.

levels close to a previous maximum of 20% in early September.[6] Nevertheless, many more short positions were established in the subsequent months, building up to a maximum short interest of 25% around March of 2016.

There are limitations to our data. First, short-selling activity is inferred from transactions in the stock lending market, which excludes short selling initiated and covered within the day ("in-and-out shorting"). As such, our data reflects the profits associated to short-selling activity other than intraday shorting. Since desynchronization in intraday shorting is unlikely to delay arbitrage activity beyond the intraday horizon, we do not expect this omission to affect the relation we examine between short sellers' desynchronization and mispricing. Second, we do not observe the identity of short sellers or their motives. This implies that we cannot distinguish speculative from other short-selling activity (e.g., shorting driven by hedging purposes), less likely to act on fundamental information. Because the profits of non-speculative short sellers can be dispersed for reasons unrelated to disagreement, we include controls for non-speculative shorting in our subsequent analyses.

3.1.2 Measuring Desynchronization in Short Selling

Our proxy for a stock's short-selling desynchronization is the dispersion in the cumulated return of its short sellers. This approach follows from the observation that all short positions in the stock that remain open throughout a day experience the same daily return, so differences in their cumulated returns must map back to a "desynchronization" (i.e., differences in timing) among them.[7] Given that for each stock i and date t we observe the fraction of shares shorted within each return interval (the variable $bin_{i,t}^{\lfloor n \rfloor}$ defined in Section 3.1.1), a natural measure of dispersion in short-selling profits, i.e., of desynchronization in short selling, is the *lack of concentration* in the associated distribution:

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

[6] This period preceded the effective start date of deliveries of Tesla's Model X on September 29, a major release that the company had been delaying since the first quarter of 2014 (https://en.wikipedia.org/wiki/Tesla_Model_X).

[7] 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.

This measure subtracts from one the Herfindahl-Hirschman index (a commonly used measure of market 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.[8] These bounds limit the potentially confounding effect of stock return volatility on profit dispersion.[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 based on the estimated standard deviation of the cumulated returns on the short positions in a stock. Because this standard deviation is more sensitive to the volatility of the stock's returns, we concentrate our subsequent analysis on the desynchronization measure (1).

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 information on the stock borrowing and lending activity from the Markit Securities Finance Buyside Analytics Datafeed. This database includes daily data on the borrowing demand and lending supply of shares, and the associated shorting fees. This information is sourced from the same contributors of the IHS Markit's short-selling profits database. Thus, our dataset accounts for the vast majority of equity loans in the United States. We obtain stock market prices and other stock characteristics data 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.

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

[9] Keeping the dispersion in the initiations of their positions constant, the profit dispersion of a stock's short sellers can increase with the volatility of the stock's returns. For this reason, we control for return volatility in our subsequent analysis.

3.3 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 short sellers were a relatively coordinated group of informed traders acting on the same or similar information, we would expect a high synchronization in their trades and, consequently, a low value for *Desync*. By contrast, we would expect *Desync* to be relatively high if varying degrees of information (e.g., differences in trading ability, as documented by Boehmer, Jones, and Zhang, 2008) or differences in opinion about the exact extent of overpricing among short sellers translated into a desynchronization in their trades. The summary statistics in Panel A are consistent with the latter scenario, as *Desync* is typically 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.

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.[10] Since the

[10]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.

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 Desynchronization and Firms' Information Environment

We first examine the relation between desynchronization across a stock's short sellers and their potential disagreement about the stock. In Abreu and Brunnermeier (2002, 2003), this disagreement follows from arbitrageurs having dispersed opinions about the stock's degree of overvaluation, as they become sequentially aware of a mispricing opportunity. More generally, it captures the variety of fundamental factors such as asymmetric information and differences in viewpoints that lead to differences in the market timing decisions (desynchronization) of arbitrageurs. In practice, however, short selling can be desynchronized for non-fundamental reasons such as the hedging of options or relative-value (e.g., convertible arbitrage) positions (Battalio and Schultz, 2011; Brown et al., 2012; Berkman, McKenzie, and Verwijmeren, 2017) on the stock.

To assess whether *Desync* actually captures disagreement-related (as opposed to hedging-related) desynchronization, 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 α_i and τ_t are stock- and time-fixed effects, and $x_{i,t}$ represents the set of regressors. We divide them into four groups:

- Variables that proxy for *difference in beliefs*: 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.

- Variables that proxy for *information asymmetry*: 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.

- Variables that proxy for *non-fundamental reasons*: Total open interest of options on the stock and amount of convertible debt. Options hedging and the implementation of convertible arbitrage strategies could require shorting the underlying stock (Battalio and Schultz, 2011; Brown et al., 2012; Berkman, McKenzie, and Verwijmeren, 2017) with no fundamental view on stock overpricing. Greater option hedging and convertible arbitrage activities could then affect desynchronization in short selling for reasons unrelated to disagreement.

- Other controls: Number of news releases related to the firm over the previous three months, Idiosyncratic volatility, Short interest, Supply, and Borrowing (Shorting) fee.[11] Following Abreu and Brunnermeier (2003), fewer news releases related to the firm could increase the uncertainty among traders about when others become informed and hinder their synchronization. We would then expect *Desync* to be negatively related to the number of news releases. We also expect *Desync* to be positively associated to the idiosyncratic volatility of returns. Lastly, we expect a low supply or demand of shares to borrow, as well as higher borrowing fees, to reduce *Desync* by limiting the number of traders able or willing to take short positions.

From this analysis we expect that *Desync* is positively related to proxies for difference in beliefs or information asymmetry. Moreover, we expect these relations to be robust to controls for non-fundamental motives for short selling and other stock characteristics. We further expect that the information in *Desync* is not completely subsumed by the disagreement proxies, so that *Desync* contributes new information about the extent of disagreement among short sellers.

[11] As is standard in the literature (see, e.g., Boehmer et al., 2017), we approximate total open short positions in a 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.

Table 2 presents our results. In column (1) we include our proxies for difference in beliefs among the stock market participants, while in column (2) we include our proxies for information asymmetry, as the only explanatory variables. In column (3) we include both types of proxies simultaneously in an augmented model that includes also proxies for the extent of hedging-related short selling. Finally, in column (4) we augment the model in (3) with our synchronizing-events proxy and with different characteristics of the stock's lending market. 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 evidence supports our priors. 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, a similarly strong and positive relation exists between *Desync* and the degree of information asymmetry surrounding a stock since in models (2) and (3) *Desync* is higher for smallcaps and for stocks with larger bid-ask spreads. With the exception of Turnover, these relations preserve their sign and significance when we account for all controls in model (4).[12] Third, there is a significantly negative relation between *Desync* and *News*, indicating that *Desync* tends to be high when there are relatively fewer news releases. This result highlights the importance of public news as synchronizing events (Abreu and Brunnermeier, 2003) among the short sellers of a stock.

The positive coefficient of open interest in the stock's options in column (3) indicates that *Desync* also increases with the level of hedging in the options market. Similarly, the negative coefficient on our convertible arbitrage proxy suggests, intuitively, that short selling tends to be more synchronized when associated with relative arbitrage strategies between a firm's stock and convertible debt prices. Inspection of column (4) indicates, as expected, a positive relation between *Desync* and idiosyncratic volatility, short interest and the supply of lendable shares. By contrast, borrowing fees have no significant impact on *Desync*. More importantly, *Desync* remains strongly related to proxies for disagreement in short selling even after adding all controls in model (4).

The set of proxies for difference in beliefs and information asymmetry explain a similar fraction of the variation of *Desync*, as indicated by the adjusted R-squared of 38% in models (1) and (2). The

[12] Given that model (4) includes idiosyncratic volatility as control, the change in sign for turnover in model (4) is not surprising. Indeed, idiosyncratic volatility and turnover are closely related both empirically (see Panel D of Table 1) and in theory (Shalen, 1993 and Harris and Raviv, 1993).

adjusted R-squared is less than 40% in all cases, implying that *Desync* reflects disagreement among short sellers beyond that conveyed by existing proxies. In sum, the results in this section support the use of *Desync* as a proxy for desynchronization arising from disagreement among short sellers about a stock.

5 Short Sellers' Desynchronization and Stock Overpricing

Following Hypothesis 1, we next investigate the relation between short sellers' desynchronization and mispricing in the cross-section of stocks. We adopt two measures of overpricing. In Section 5.1, we follow the standard approach in the literature 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 results.

5.1 Future returns

Overpriced stocks should on average exhibit inferior benchmark-adjusted performance, as measured by their abnormal returns relative to a standard pricing model. This reasoning motivated the predominant approach in the literature of associating overpricing with subsequent returns.[13] 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 and multivariate regressions, the statistical significance of this relation and its robustness to controlling for the influence of other variables.

[13] As a prominent example, Baker and Wurgler (2006) look for systematic patterns of mispricing correction via stocks' subsequent returns on the basis that mispricing is hard to identify directly.

5.1.1 Portfolio Analysis

We first examine single portfolio sorts. Our goal is not to propose a trading strategy but to assess the relation between short sellers' desynchronization and stock overpricing without imposing a parametric relationship between the two variables. 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 surrounding the firm that can lead to synchronization problems is more prevalent 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 3 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 that we observe in Figure 2. Panel A.1 evidences a strong monotonically decreasing pattern moving from the first (Q1) to the fifth (Q5) quintile. While the low-*Desync* portfolio generates a monthly alpha of 0.17% (significant at the 1% level), the high-*Desync* portfolio generates a negative 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 alpha of -0.63% per month (-7.56% per annum). As expected from the above-mentioned negative relation between *Desync* and firm size, the magnitude of the VW alpha on the hedge portfolio of Panel B.1 is a smaller -0.36% per month (-4.32% per annum), although still highly statistically significant.

To control for other cross-sectional effects, Table 3 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 that can exacerbate synchronization problems among short sellers. Within 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 are strongly supportive of 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, value stocks, and past losers, consistent with our above observation that *Desync* tends to be larger among firms with smaller capitalization. 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 the next two rows of Panels A.2 and B.2, corresponding to the proxies for the information environment of the firm, the high-minus-low *Desync* portfolio again generates negative alphas. These are particularly large (in absolute value) and significant among stocks with higher information asymmetry or difference in beliefs, as reflected by lager 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. These are indeed the types of stocks for which we expect greater uncertainty about other short sellers' trades, hence—as argued by Abreu and Brunnermeier (2003)—greater synchronization risk.

5.1.2 Fama-MacBeth Regressions

To control for multiple covariates, in Table 4 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. (2017), 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 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 β_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 a decrease of between 1.20% and 1.68% in the stock's annualized adjusted returns 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 drops of between 3.04% and 2.21% in the next-month annualized adjusted returns. 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.[14]

We conclude that $Desync$ is a robust negative predictor of future abnormal returns in the cross-section, with similar economic significance as short interest. As in our portfolio analysis, we interpret this evidence as supporting the role of synchronization problems among short sellers, following hypothesis 1, in limiting arbitrage in the cross-section of stocks.

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 relative degree of overpricing, and is available at monthly frequency from July 1965 until December 2016.[15] To determine the empirical

[14]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).

[15]We thank the authors for making these data available from Robert F. Stambaugh's website. See the Appendix in

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 falls in the top tercile of the $MISP$ distribution.[16] 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 5 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 falls in 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 $(0.91 - 0.56) \times 0.48 = 16\%$.

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-traders risk (De Long et al., 1990), short-selling risk (Engelberg, Reed, and Ringgenberg, 2018), or arbitrage asymmetries and idiosyncratic volatility (Stambaugh, Yu, and Yuan, 2015) relate to our findings.

Stambaugh, Yu, and Yuan (2015) for a description of the anomalies used to construct the score.

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

Miller (1977) hypothesizes that, in presence of disagreement between the traders in a stock, short-selling constraints can induce overpricing by curtailing the activity of the pessimists. Empirically, the hypothesis implies a negative relation between disagreement and future abnormal returns only among stocks with short-sale constraints (Boehme, Danielsen, and Sorescu, 2006; Berkman et al., 2009). In contrast, the positive relation between *Desync* and overpricing that we document holds strongly even for stocks with few or no short-sale restrictions. To show this, we repeat the double-sorted portfolio analysis of Table 3 using either *Fee*, *Supply* or *Utilization* 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 short-selling constraints in a stock. The results are displayed in Table 6. If our findings purely reflected Miller's Hypothesis, *Desync*-sorted portfolios should generate negative returns only on high-*Fee*, high-*Utilization* and low-*Supply* stocks. On the contrary, we observe that *Desync* generates significantly negative spreads also on stocks with low shorting fees, and with low utilization and high supply of lendable shares.[17]

Short sellers could delay attacking a stock overpricing 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 6, 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 3 and low-idiosyncratic volatility stocks (see below). Both results highlight the importance of considering additional factors to noise-trader risk to understand

[17]For value-weighted portfolios, *Desync* does not generate significant spreads for either of the extreme quintiles of *Utilization*. Insofar as *Utilization* proxies for short-selling constraints, this result is not in line with predictions of Miller (1977).

our findings.

Short-selling fees are highly volatile and can curtail short sellers' profits. Engelberg, Reed, and Ringgenberg (2018) find support for a "short-selling risk" channel on stock returns, i.e. the prediction of D'Avolio (2002) that 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 regressions (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 among the stocks displaying the highest volatility in fees. The results reported in the fourth row of Table 6 indicate otherwise. Moreover, *Desync* predicts negative spreads across all short-selling risk quintiles in both equal- and value-weighted portfolios.

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 not really the effect of synchronization problems on overpricing but that of arbitrage asymmetries and idiosyncratic volatility, 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 fifth row of Table 6 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 4 and 5, 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 as a distinctive and economically relevant driver of overpricing in the cross-section of stocks.

6 Short Sellers' Desynchronization and Mispricing Duration

In this section we analyze the impact of short sellers' desynchronization on the duration of overpricing. Our goal is to assess whether, following Hypothesis 2, the synchronization risk that short sellers face *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 more short lived—ex-ante 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 $MISP$ falls in 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 α_i and τ_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 Abreu and Brunnermeier (2002)'s model, and an exogenous parameter that they keep fixed throughout the analysis. In particular, they consider shorting fees to be the most important holding costs 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 the analysis of Abreu and Brunnermeier (2002). 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.[18]

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 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.

We report our estimates in Table 7 across three specifications. Following hypothesis 2, we expect the sign of β 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 relation between $Desync$ and $Delay$ across all specifications. $Desync$ shows up with coefficients of 3.35, 2.89 and 3.71 (all statistically significant at the 5% level),

[18] Controlling for short interest in our analysis is also consistent with our finding in section 4, according to which disagreement covaries positively with short interest.

respectively, in the specifications with no additional controls, with the first set of controls, and with both sets of controls. The size of these coefficients 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 an additional 16 days for the score to drop below the top tercile.[19] 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.[20] 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 8 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.[21] 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 cluster standard errors in the time dimension to control for the cross-sectional dependency in violations induced by their clustering on

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

[20] 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.

[21] 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.

certain days. 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.[22]

The results are strikingly consistent with those of Table 7. *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 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 an additional 1.38 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 section 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 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

[22]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 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).

the relation between *Desync* and the duration of *underpricing* events.

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.[23] The rest of the variables and controls are as in Section 6. According to the synchronization-risk argument in Abreu and Brunnermeier (2002, 2003), we expect $\beta_2 < 0$.

Consistent with this implication, in non-tabulated results we find an estimate for β_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 β_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 β_2 and β_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).

[23] 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.

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 9, we reproduce the results of Tables 3, 4 and 8 using the standard deviation of short sellers' cumulated returns as our measure of profit dispersion. More precisely, for each stock and day 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.[24] 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 falls in 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 in our sample, we apply our analysis of Section 6 to the duration of *underpricing* events. In the analysis of relative

[24] As in Table 3, the double-sorted portfolio analysis first conditions, alternatively, on size, market to book, bid-ask spread, turnover, or short interest.

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.[25] Our estimates, reported in Table 10, 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 mispricing 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 and 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 within-stock dispersion in their profits. Consistent with this dispersion capturing desynchronization related to disagreement, we find it to be strongly related to various measures of differences in opinions and information asymmetries surrounding the stock.

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

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

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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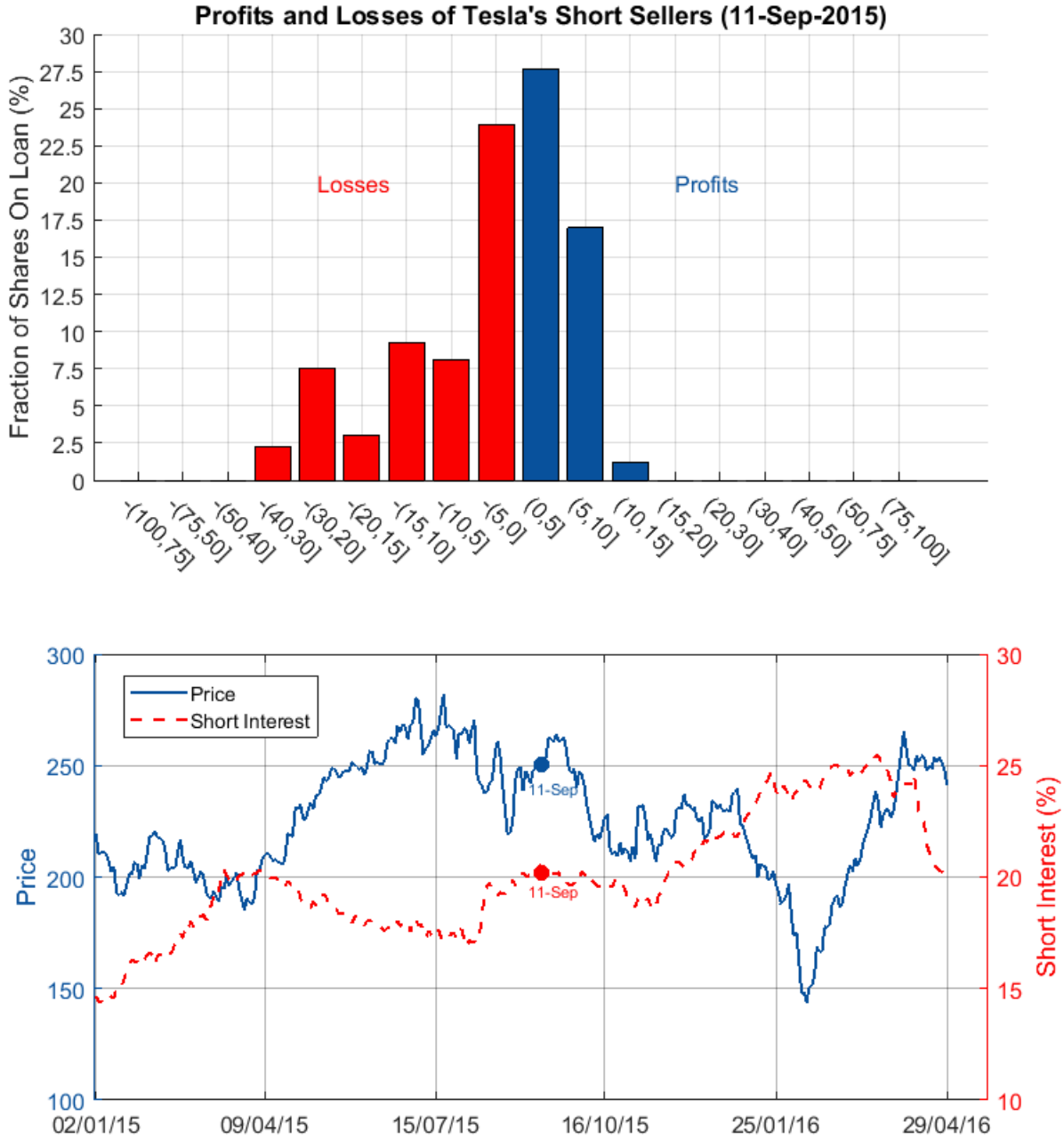
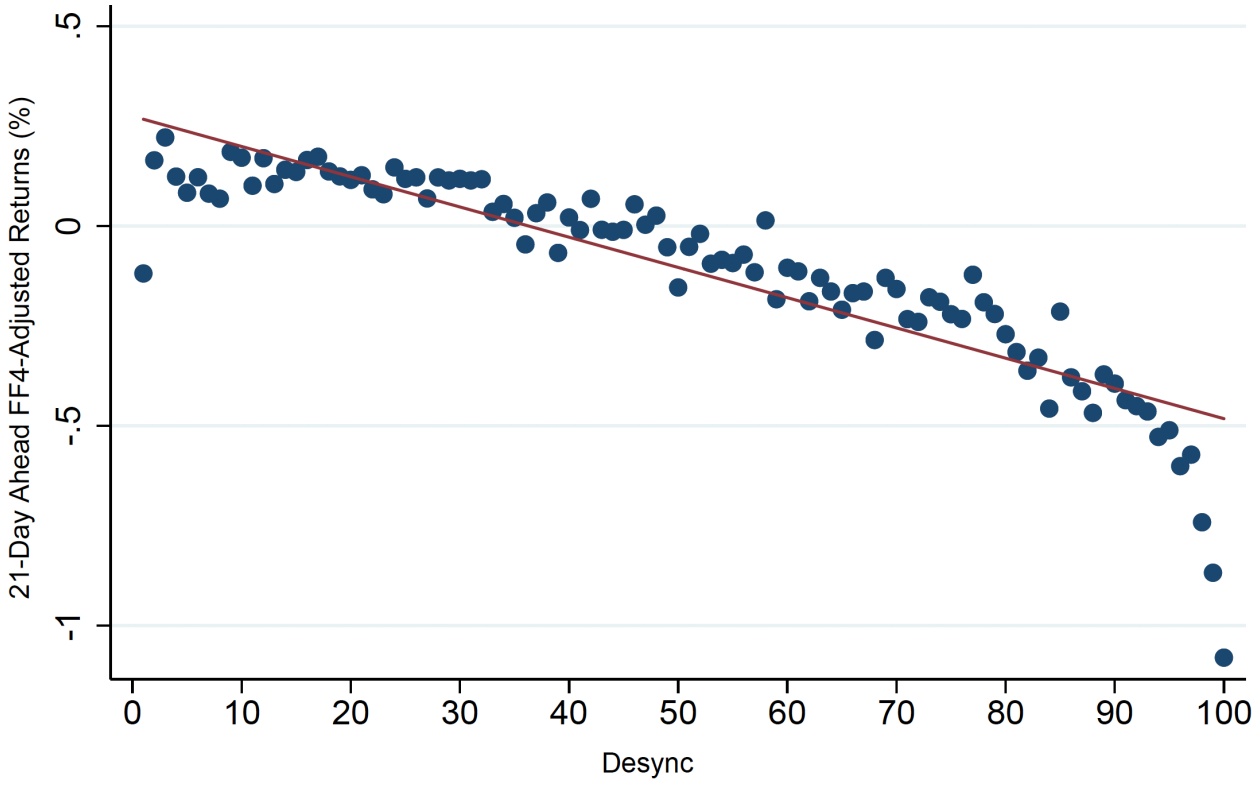
Figure 1. Shorting Tesla



The upper plot displays the distribution of profits and losses (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 on the scatterplot 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

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

	Panel B: Stock and Fundamental Characteristics						
	Mean	Median	St.Dev.	pc5	pc25	pc75	pc95
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

	Panel C: Equity Lending Market						
	Mean	Median	St.Dev.	pc5	pc25	pc75	pc95
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***		0.009***	-0.009***
	(12.80)		(9.80)	(-6.60)
Analyst Dispersion	0.006***		0.005***	0.004***
	(9.78)		(7.35)	(7.16)
Bid-Ask		0.004**	0.006***	0.009***
		(2.42)	(3.85)	(5.51)
Size		-0.036***	-0.038***	-0.023***
		(-10.88)	(-10.26)	(-6.51)
Open Interest			0.016***	0.004**
			(8.26)	(2.36)
Convertible			-0.006***	-0.002**
			(-6.79)	(-2.44)
News				-0.003**
				(-1.98)
Idio Vol				0.010***
				(6.48)
Short Interest				0.051***
				(40.65)
Supply				0.024***
				(11.92)
Fee				0.000
				(0.17)
$R^2_{adjusted}$	0.378	0.380	0.381	0.407
$Nobs$	4,652,322	5,589,080	4,652,278	4,484,203

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), α_i and τ_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; $News$, the total (log) number of news over the previous three months; $Idio\ Vol$, 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% level.

Table 3. 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; *Short Interest* is the total quantity of shares loaned out as a percentage of shares outstanding; $Return_{6M}$ is the stock return cumulated over the previous six months; *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% level.

Table 4. *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% level.

Table 5. *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 falls in 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% level.

Table 6. Short-Selling Constraints and Stock Overpricing

	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)
Utilization	-0.27**	-0.17*	-0.03	-0.20	-0.43**
	(-2.28)	(-1.70)	(-0.24)	(-1.42)	(-2.23)
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)
Utilization	-0.23	-0.41***	0.03	-0.19	-0.18
	(-1.62)	(-3.00)	(0.21)	(-1.11)	(-0.80)
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; *Utilization* is the ratio between the quantity of shares shorted over the active quantity of shares available; *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.

Table 7. *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); α_i and τ_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) 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. t-statistics are based on clustered standard errors. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 8. *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); α_i and τ_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% level.

Table 9. 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)
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)
Short Interest	-0.91***	-0.72***	-0.87***	-0.54***	-0.33*
	(-4.09)	(-2.99)	(-4.19)	(-3.04)	(-1.80)

	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

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

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 4). Column (2) of Panel B reports estimates from the following regression

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

where $y_{i,m}$ is a binary variable equal to 1 if stock i falls in 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 5. 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 α_i and τ_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 7. 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 8. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 10. *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); α_i and τ_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% level.

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 falls in 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% level.

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.

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