JOURNAL OF FINANCIAL AND QUANTITATIVE ANALYSIS Vol. 58, No. 8, Dec. 2023, pp. 3482–3520

doi:10.1017/S0022109022001089

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

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Abstract

How synchronized are short sellers? We examine a unique data set 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," that is, uncertainty among short sellers about when others will short sell, 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.

I. 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 also in situations of low or no friction.[1] Why can overpricing persist in these cases? In this paper, we take on this question by investigating whether coordination problems among short sellers explain differences across stocks in the level and persistence of overpricing.

The notion that coordination problems among arbitrageurs might limit arbitrage originates from Abreu and Brunnermeier (2002), (2003). They propose a model of dispersed opinions where the aggregate resources of all arbitrageurs are

We thank an anonymous referee, Henk Berkman, Dan diBartolomeo (discussant), Huu Nhan Duong (discussant), Yufeng Han (discussant), Jarrad Harford (the editor), Caio Machado (discussant), Giorgo Sertsios, Esad Smajlbegovic, Kumar Venkataraman, Ingrid Werner, Antti Yang, Jianfeng Yu, Rafael Zambrana, Zhuo Zhong, and seminar participants at Point72 Asset Management, Universidad Adolfo Ibañez, the 2021 Chinese International Finance Conference, and the 2019 Behavioural Finance and Capital Markets Conference for comments and suggestions. We gratefully acknowledge the support provided by the ANID Fondecyt Initiation Grant 11190917. All errors are our own.

[1]See, for example, Lamont and Stein (2004).

sufficient to correct asset mispricing, yet the correction takes place only with a delay. The dispersion of opinions creates uncertainty among the arbitrageurs about the timing decisions of other rational arbitrageurs. Crucially, it results in a synchronization problem that renders arbitrageurs temporarily unable to coordinate their strategies and eliminate the mispricing.

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

We first provide support for the use of short sellers' profit dispersion as a valid empirical proxy for disagreement-related "desynchronization" in their positions. The asset pricing implications of the synchronization-risk argument rely on the premise that coordination issues among arbitrageurs are driven by differences in their opinions ("disagreement") rather than by non-fundamental reasons such as differences in hedging motives. In line with this premise, we find that our proxy is positively associated with standard variables capturing disagreement around a stock such as turnover, dispersion in analysts' forecasts, and bid–ask spread. These relations remain strong after controlling for differences in hedging needs across a stock's traders and other stock characteristics such as return volatility. Our proxy for desynchronization drops after the release of negative public news about a firm or analyst downgrades, consistent with the theory's implication that "synchronizing events" should facilitate the coordination of arbitrageurs.

Using this proxy, we examine whether stocks with more desynchronized short selling are more overpriced, in line with the insight of Abreu and Brunnermeier (2003). Following the standard approach in the literature, we first associate overpricing with inferior future abnormal returns (i.e., lower alphas relative to a standard factor pricing model). Sorting stocks by short sellers' desynchronization, we document a decreasing pattern in future abnormal returns and a statistically significant spread between high- and low-desynchronization portfolios of -0.55% per month (-6.6% per annum). This result holds strongly in double-sorted portfolios that first condition on short interest or other well-known cross-sectional determinants of returns. Consistent with the theory that synchronization problems are more prevalent in firms with a poorer information environment, the desynchronization effect on returns almost doubles among stocks subject to greater differences in beliefs or information asymmetries. We confirm these results using Fama–MacBeth regressions that simultaneously control for stock characteristics and equity lending conditions. As an alternative proxy for overpricing, we adopt the relative mispricing score (MISP) of Stambaugh et al. (2015). In further support for the synchronization-risk hypothesis, we find that stocks in the top tercile of our desynchronization proxy are 16% more likely than stocks in the bottom tercile to become overpriced in the next month.

We differentiate our results from other mechanisms limiting arbitrage activity. First, the positive relation between desynchronization and overpricing that we document cannot be explained by Miller's (1977) hypothesis that stocks with *both* tight short-sale constraints and high dispersion in opinions are more overpriced (Boehme et al. (2006)), as it holds strongly even for stocks for which either or both of these conditions are not met. Second, our results are not driven by the risks associated with sentiment-driven traders exacerbating overpricing (De Long, Shleifer, Summers, and Waldmann (1990), Shleifer and Vishny (1997)), as desynchronization has a strong negative relation with subsequent risk-adjusted returns in both high- and low-sentiment periods. Third, the desynchronization effect prevails across different levels of fee volatility, ruling out "short-selling risk" (Engelberg, Reed, and Ringgenberg (2018)) as a primary driver of our findings. Fourth, the effect of desynchronization on overpricing is robust to the implementation of different controls for idiosyncratic volatility, indicating that arbitrage asymmetries and idiosyncratic volatility (Stambaugh et al. (2015)) cannot fully account for our results either. Finally, the combination of different frictions such as incomplete markets, low firm recognition, or lack of liquidity does not subsume the effect of desynchronization on stock overpricing, as this effect is significant across different levels of Hou and Moskowitz's (2005) measure of severity of market frictions.

We find evidence that short-selling desynchronization affects also the *duration* of overpricing. Abreu and Brunnermeier (2002) note that, in deciding when to short an overpriced asset, short sellers trade off the benefits of selling early, thus securing the profits of the eventual correction, versus the costs of holding the position for too long. In these conditions, they delay acting on their information to correct a given level of overpricing, with the delay increasing with their desynchronization. We test this implication using two measures of overpricing duration, namely the number of consecutive months over which a stock remains relatively overpriced according to the mispricing score MISP, and the duration of violations of the put–call parity no-arbitrage relation in the stock option market (Ofek et al. (2004), Engelberg et al. (2018)). Consistent with the theory, desynchronization is strongly positively associated with either overpricing duration proxy, and remains so after controlling for the level of overpricing, shorting fees, short interest, and various stock characteristics. Taken jointly, our evidence around short- and longer-lived mispricing events offers strong additional support to the synchronization-risk hypothesis.

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

Our paper contributes to two main strands of the literature. First, it contributes to the growing literature on limits to arbitrage. Several seminal theoretical studies

https://doi.org/10.1017/S0022109022001089 Published online by Cambridge University Press

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), Duffie et al. (2002)), capital constraints (Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), and Garleau and Pedersen (2011)), and fee-volatility risk (D'Avolio (2002)). While extensive empirical evidence supports the relevance of these limits to arbitrage, the impact of synchronization risk has been documented to a much lesser extent.[2] Indeed, the existing studies examining synchronization risk are confined to specific episodes of severe overpricing, as reflected in the emergence and burst of bubbles (Brunnermeier and Nagel (2004), Temin and Voth (2004)). 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 during normal times. Ljungqvist and Qian (2016) offer an opposing view on the effective impact of limits to arbitrage, according to which short sellers in the subset of stocks with the tightest short-selling constraints can induce the long shareholders to sell and accelerate a price correction by disclosing their positions ("short and disclose"). Complementing their findings, our results indicate that for the majority of the stocks in the cross-section, for which the short-and-disclose strategy is not prevalent, synchronization risk can be an economically relevant limit to arbitrage.[3]

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

[2]See Jones and Lamont (2002), Nagel (2005), Saffi and Sigurdsson (2011), and Prado et al. (2016) for evidence on the role of short-selling constraints related to lending supply and shorting costs, Kolasinksi et al. (2013) and Chague, De-Losso, De Genaro, and Giovannetti (2017) for search costs, Liu and Mello (2011) and Giannetti and Kahraman (2018) for outflow risk, Duan et al. (2010) for arbitrage risk, Engelberg et al. (2018) for fee-volatility risk, and Gargano et al. (2022) for margin constraints.

[3]In this sense, our findings can be seen as related to the more prevalent "short-and-mum" strategy of shorting and waiting for the stock price to fall, for which desynchronization problems are more likely. Indeed, the short-and-disclose strategy has been documented on a small subset of firms in the cross-section (e.g., the sample of Ljungqvist and Qian (2016) is composed of 124 stocks), consistent with the potential unprofitability of this strategy in presence of noise trading (Kovbasyuk and Pagano (2022)). Importantly, the tight constraints on these stocks imply little scope for short-selling desynchronization.

[4]The forecasting power of short selling in the cross-section has been documented using intraday (e.g., Aitken, Frino, McCorry, and Swan (1998), daily (e.g., Boehmer et al. (2008), Diether et al. (2009)), and monthly (e.g., Desai, Ramesh, Thiagarajan, and Balachandran (2002), Asquith et al. (2005), Cohen et al. (2007), and Saffi and Sigurdsson (2011)) short-selling activity. Rapach et al. (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.

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 the timing of positions, among short sellers. We provide evidence that this heterogeneity can reflect their inability to synchronize their trades to correct overvaluation.

II. Hypotheses Development

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

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

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

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

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

III. Data and Desynchronization Proxy

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

A. Short-Selling Data Sets

Our source of short-selling data is IHS Markit, from which we obtain two data sets. The first, the Securities Finance Buyside Analytics Datafeed (MSF), contains information on stock borrowing and lending activity. Since U.S. equity short sellers need to borrow the stocks they sell, this information has been used extensively in the literature to infer short-selling activity (for recent references, see, e.g., Engelberg et al. (2018), Boehmer, Huszar, Wang, and Zhang (2022), and Muravyev, Pearson, and Pollet (2021)).[5] The second data set is novel and complements MSF with information on the profits of short sellers on their open short positions. Since the equity lending market is over-the-counter (OTC), IHS Markit collects the information for both data sets at the transactions level directly from a variety of participants. These include prime brokers, custodians, asset managers, and hedge funds, who together account for about 90% of the securities lending market in developed countries. We focus on the U.S. market, for which IHS Markit databases cover a broad cross-section of 4,000 stocks for a total of approximately 5.7 million stock-day observations over the period spanned between Jan. 2011 and Dec. 2017.

From the profits database we observe, for each stock i and day t, the distribution of gross-of-fees mark-to-market (cumulated) returns being experienced by the short sellers of i from the start date of their transactions until t. Short sellers can keep their positions open over a given time span by renewing shorter-term stock loans, possibly from different lenders. To account for this, IHS Markit defines the start date of a short position as the initiation date for new transactions and the original start date for renewing transactions.[6] Returns on short positions are tabulated over 19 bins, $\text{BIN}_{i,t}^{\lfloor n \rfloor}$ ($n=1,\ldots,19$), 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 ($n=1,\ldots,10$) contain the fraction of shares on loan experiencing losses in the $(-\infty, -100\%]$, $(-100\%, -75\%]$, $(-75\%, -50\%]$, $(-50\%, -40\%]$, $(-40\%, -30\%]$, $(-30\%, -20\%]$, $(-20\%, -15\%]$, $(-15\%, -10\%]$, $(-10\%, -5\%]$, and $(-5\%, 0\%]$ ranges. The remaining 9 positive-return intervals ($n=11,\ldots,19$) are defined analogously (e.g., $(0\%, 5\%]$,$(5\%, 10\%]$,…,$(75\%, 100\%]$). Existing data allows researchers to observe only the aggregate level of short interest. Thus, our

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

[6]To determine the date on which the initial short was placed with the broker, IHS Markit uses $T-3$ from the stock lending start date assuming a 3-day settlement, unless the stock is experiencing relatively high borrowing costs, in which case they use same-day pricing assuming high demand to short the stock. IHS Markit makes these data available pre-market (typically by 7:00–8:00AM EST) on a next-day basis.

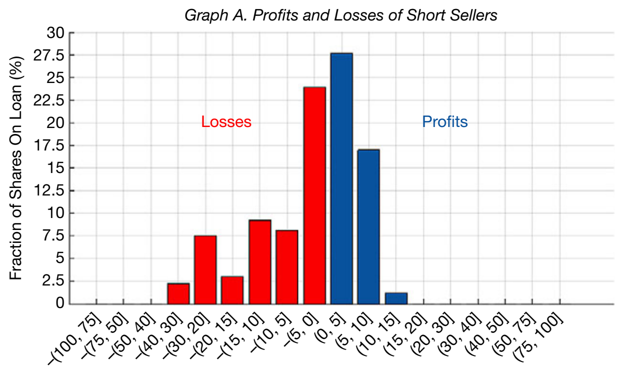
data contribute disaggregated information on the mark-to-market profits experienced by different subsets of short sellers to existing aggregate data.[7]

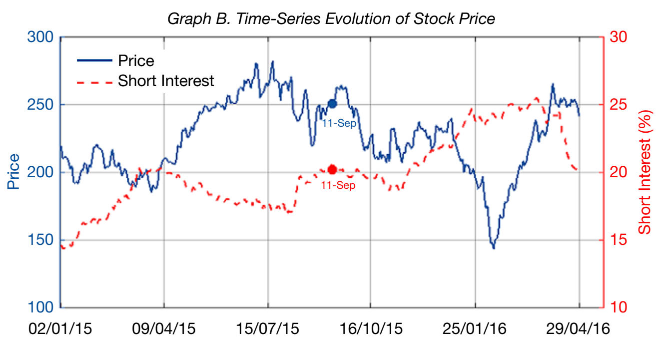
Figure 1 displays an instance of the data for Tesla as of Sept. 11, 2015. Graph A highlights a wide dispersion in the profits that the short sellers of Tesla were experiencing at that point in time. Losing positions (54.1% of the outstanding short interest) were experiencing cumulative returns in the 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 Graph B suggests a high uncertainty about Tesla around the time. In Section IV, we assess the strength of the cross-sectional relationship between this type of profit

FIGURE 1

Shorting Tesla

Graph A of Figure 1 displays the distribution of profits (in %) experienced by short sellers with positions in Tesla, Inc. on Sept. 11, 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). Graph B 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 Jan. 2, 2015, to Apr. 29, 2016.





[7]Previously available equity lending information is consolidated across all short positions in the stock. To assess differences across the short positions in a stock, Jank and Smajlbegovic (2021) and Boehmer et al. (2018) examine mandatory disclosures of large short positions in Europe and Japan, respectively, while von Beschwitz et al. (2022) and Choi, Park, Pearson, and Sandy (2020) study hedge fund trades.

dispersion, as a proxy for short-selling desynchronization, and the uncertainty surrounding a stock.

B. Auxiliary Data Sources

We use the stock's CUSIP identifier in our short-selling profits database to merge it with an array of standard data sets. We obtain stock market prices and other stock characteristics from CRSP and compute various financial accounting ratios using information from COMPUSTAT. We calculate the dispersion in stock analysts' forecasts from the IBES 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 data sets in more detail.

C. Measuring Desynchronization in Short Selling

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

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

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

$$\text{(1)} \qquad \mathrm{DESYNC}_{i,t} = 1 - \sum_{n=1}^{19} \left(\mathrm{BIN}_{i,t}^{\lfloor n \rfloor} \right)^2 .$$

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

https://doi.org/10.1017/S0022109022001089 Published online by Cambridge University Press

The DESYNC measure defined in equation (1) subtracts from one of the Herfindahl–Hirschman index (a commonly used measure of concentration) of the return bins. Higher values of DESYNC are associated with greater desynchronization in short sellers' trades. DESYNC is bounded below 0, when all of the stock's shorted shares experience a common level of profits, and above by 0.947, when the cumulated returns of the stock's shorted shares are uniformly distributed across all bins.[9]

Clearly, measuring the lack of concentration is not the only way to assess the dispersion of a distribution. In particular, in Section VII we examine two alternative dispersion measures, DESYNC_SD and DESYNC_|SPREAD|, based respectively on the estimated standard deviation and on the absolute spread between the maximum and minimum of the cumulated returns on the short positions in a stock.

1. Measure's Persistence and Relation to Return Volatility

The sequential awareness of a common mispricing opportunity underlying the synchronization problems in Abreu and Brunnermeier (2002), (2003) suggests that measured desynchronization in short selling, as captured by our DESYNC proxy, should display some persistence. We take several steps to ensure that the persistence in our proxy does not alter our results.[10] First, we verify that the hypothesis of a unit root at the stock level is predominantly rejected.[11] Second, we confirm that our main findings are essentially unaltered when we replace DESYNC with a version orthogonalized with respect to its first lag (see Panel B of Supplementary Table A.1).

The desynchronization in a stock's short selling should also be closely related to the volatility in the stock's returns. On the one hand, stocks with more uncertain prospects should exhibit *both* higher disagreement among their short sellers, hence desynchronization in their positions, *and*, following Harris and Raviv (1993), greater return volatility. Because this desynchronization is of the fundamental (information-related) type underlying the synchronization-risk theory, a desirable attribute of DESYNC is that it is positively associated with return volatility. On the other hand, the dispersion in short-selling profits upon which DESYNC is based can mechanically increase with the volatility of the stock's returns even if the fundamental desynchronization across the short positions does not change.[12] To exclude a (mechanical) effect driven by return volatility, we explicitly control for it in all of our subsequent analyses. In addition, we confirm that our main results hold when we repeat our analysis replacing DESYNC with an orthogonalized version with respect to return volatility (see Section V.C.4).

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

[10]Standard asymptotic theory does not hold when the regressor is either perfectly integrated (i.e., displays a unit root, see Phillips (1987)) or highly persistent (i.e., close to unit root, see Elliott and Stock (1994)).

[11]For each stock, we run the Dickey–Fuller test to evaluate the null that a unit root is present. We reject the null in 99% of cases, consistent with the fact that the mean (median) first-order autocorrelation coefficient in DESYNC is far from 1 and equal to 0.83 (0.84).

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

2. Impact of Offsetting Long Positions

Non-fundamental drivers, independent from arbitrageurs' uncertainty about their peers' trades, could impact our measure of short-selling desynchronization. One such driver is arbitrageurs' offsetting of their long positions when they are building net short positions. Consider 2 short sellers, A and B, aiming to build the same net short position on Tesla, Inc. Investor A, however, is long the S&P 500 index and must offset her long position by building a larger position than B. If A aims to have the same net short position as B, A may also regularly adjust her short position depending on the index's daily performance. None of the resulting differences in the short positions of A and B is related to the extent of desynchronization that our proxy aims to capture.[13]

In this example, A and B establish their positions on the same day, so they end up in the same return bin. A potential bias might then mostly occur when the fractions of investors that are like A or B vary after positions are established. For most days, however, the trading induced by the daily index fluctuations should represent only a fraction of the initial short positions, and positive and negative changes are likely to cancel out over time. Therefore, the effect of this trading activity will be relevant for our DESYNC proxy only when the S&P 500 index experiences substantial moves in one direction. Even in this scenario, cross-sectional differences in DESYNC across S&P 500 stocks are mitigated by the fact that they all link to the same move of the index. If anything, these situations are more likely to bias our tests against Hypotheses 1 and 2 because the resulting differences in DESYNC are driven by reasons unrelated to arbitrageurs' uncertainty about their peers' trades, thus should not be systematically related to the extent and duration of overpricing.

In Section VII.C, we assess the impact of these situations on our results by examining whether DESYNC affects stocks that belong to the S&P 500 index differently from those that do not.

D. Summary Statistics

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

If the short sellers of a stock acted on their information at similar points in time we would expect the initiations of their positions to be highly synchronized and the stock's DESYNC, consequently, to be low. The summary statistics in Panel A of Table 1 indicate, on the contrary, that for the typical stock in our sample DESYNC is high (its mean and median are, respectively, 0.63 and 0.68, respectively) and significantly above 0 (the 5th and 25th percentiles of its distribution are, respectively, 0.23 and 0.55).

Panel B of Table 1 shows summary statistics at the stock and firm levels. The average (median) market capitalization (SIZE) of a firm in our sample is \$6,847 (\$1,377) million. The average (median) monthly stock return (RETURN) is 1.08% (0.43%), consistent with a positive and sizable risk premium during the period.

[13]We thank an anonymous referee for drawing our attention to this possibility.

TABLE 1

Summary Statistics

Table 1 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 % per month, VOLATILITY is the stock volatility expressed in % per month, BID_ASK is the daily bid–ask spread as a percentage of mid-price, TURNOVER is the 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 SIZE 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.

	Mean	Median	St. Dev.	pc5	pc25	pc75	pc95
Panel A. Short Selling Profits							
DESYNC	0.631	0.679	0.186	0.230	0.546	0.766	0.840
Panel B. Stock and Fundamental Characteristics							
RETURN (% per month)	1.075	0.433	10.69	−61.39	−18.48	19.41	64.65
VOLATILITY (% per month)	10.02	8.429	6.563	4.029	6.181	12.03	20.86
BID_ASK (%)	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
ANALYST_DISPERSION	18.55	8.594	29.25	1.792	4.328	19.43	71.33
SIZE ($m)	6847	1377	21,552	170.3	480.3	4319	28,588
Panel C. Equity Lending Market							
SHORT_INTEREST (%)	3.916	1.856	5.231	0.144	0.759	4.833	15.09
SUPPLY (%)	21.61	23.00	10.56	2.102	13.83	29.63	36.97
FEE (% per annum)	1.244	0.375	3.677	0.373	0.375	0.464	5.041

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	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		
MTB	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

We display also summary statistics for the different proxies of the information environment surrounding a firm that we examine in Section IV, namely, stock return volatility (VOLATILITY), bid–ask spread (BID_ASK), turnover (TURNOVER), and analysts' forecast dispersion (ANALYST_DISPERSION).

Panel C of Table 1 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 (SUPPLY) is 21.6% of the total market capitalization, the mean short interest (SHORT_INTEREST) is 3.9%, and the mean borrowing fee (FEE) is 1.24% per annum.[14]

[14]As is standard in the literature (see, e.g., Boehmer et al. (2022)), 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 values that are not yet known to investors, we follow Richardson et al. (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.

https://doi.org/10.1017/S0022109022001089 Published online by Cambridge University Press

Finally, Panel D of Table 1 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 SIZE, and exhibits close to 0 correlation with the other variables considered. The pairwise correlations across variables other than DESYNC in our sample are largely as expected.[15] Since the summary statistics for stock, firm, and equity lending market characteristics displayed in Panels B and C are also consistent with prior studies, we conclude that our sample of stocks is comparable with those examined in the related literature.

IV. A Characterization of Short Sellers' Desynchronization

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

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

A. Relation to Firms' Information Environment

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

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

$$\text{DESYNC}_{i,t} = \alpha_i + \tau_t + \beta' \mathbf{x}_{i,t} + \varepsilon_{i,t},$$

where α_i and τ_t are stock- and time-fixed effects, and $x_{i,t}$ represents the set of regressors, split into three groups.

The first group consists of fundamental drivers. Given that the theory is agnostic about whether the disagreement driving desynchronization stems from differences in the arbitrageurs' beliefs or in information asymmetries, we include

[15]For instance, BID_ASK and IDIO_VOL are negatively correlated with SIZE, while FEE is positively correlated with SHORT_INTEREST but negatively correlated with SUPPLY.

both sets of proxies for the firm's information environment. Our proxies for *difference in beliefs* are stock turnover (TURNOVER) and dispersion in analysts' forecast (ANALYST_DISPERSION). 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 to generate a positive relation between belief dispersion and stock turnover. The use of dispersion in forecasts across a stock's analysts follows Diether et al. (2002), who propose using this measure as a proxy for differences in beliefs about a stock. Our proxies for *information asymmetry*, are stock bid–ask spread (BID_ASK) and firm size (SIZE). Glosten and Milgrom (1985) and Easley and O'Hara (1986), among others, argue theoretically that market makers should set wider bid–ask spreads when they expect higher levels of information asymmetry. The choice of size follows the simple intuition, used by prior studies (e.g., Chae (2005), Zhang (2006)), that more information is available for larger firms.

The second group aims to control for non-fundamental sources of short-selling desynchronization. These include the total open interest of options on the stock (OPEN_INTEREST), the amount of convertible debt (CONVERTIBLE), the stock's short interest (SHORT_INTEREST), supply of lendable shares (SUPPLY), and the borrowing (shorting) fee (FEE). Options hedging and the implementation of convertible arbitrage strategies could require shorting a stock (Battalio and Schultz (2011), Brown et al. (2012)) despite having no fundamental view on its overpricing. More option hedging or convertible arbitrage activities could then affect DESYNC for reasons unrelated to disagreement. Similarly, lower supply or demand of lendable shares, as well as higher borrowing fees, could mechanically reduce DESYNC by limiting the number of traders able or willing to take short positions. To assess the strength of the relationship between return volatility and DESYNC following our argument in Section III.C, we include idiosyncratic volatility (IDIO_VOL) as an additional control within this group.

The third group consists of other firm characteristics and short-selling-specific risks. We control for cross-sectional differences in firm characteristics using firms' leverage (LEVERAGE), market-to-book ratio (MTB), profitability (PROFITABILITY), and the extent of analyst coverage (COVERAGE). The short selling-specific risks we consider are uncertainty about future lending conditions and short squeeze risk. Following Engelberg et al. (2018), our proxy for uncertainty about future lending conditions is the variance of a stock's lending fees (VAR_FEE). Our proxy for the risk of short squeezes (SHORT_SQUEEZE) is the realized skewness measure of Neuberger (2012), as short squeeze events are more likely among stocks with a tendency to display extreme positive returns.

Table 2 reports our regression results. Column 1 includes the proxies for difference in beliefs among the stock market participants, while column 2 includes the proxies for information asymmetry, as the only explanatory variables. Column 3 includes both types of proxies. Columns 4 and 5 present results for the model in column 3 augmented, respectively, with our proxies for non-fundamental short-selling desynchronization and with the full set of controls. To facilitate the comparison across coefficients, we standardize regressors to have 0 mean and unit variance. Across models, standard errors are double-clustered in the stock and time dimension.

https://doi.org/10.1017/S0022109022001089 Published online by Cambridge University Press

TABLE 2

DESYNC and Firms' Information Environment

Table 2 reports coefficient estimates and associated t-statistics (in parentheses) of the following panel regression:

$$\text{DESYNC}_{i,t} = \alpha_i + \tau_t + \beta' \mathbf{x}_{i,t} + \varepsilon_{i,t},$$

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 $\mathbf{x}_{i,t}$ represents the set of covariates, which includes TURNOVER, the average turnover over the previous 3 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 3 months; SIZE, the (log) product of the price and the number of shares outstanding; OPEN_INTEREST, the (log) of the call and put open interest; CONVERTIBLE, the ratio between COMPUSTAT item DCTV and total assets; IDIO_VOL, the idiosyncratic volatility over the previous 3 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; FEE, the borrowing fee; LEVERAGE, the ratio of total debt to market value of assets; MTB, the (log) ratio of the market value of assets to book value of assets; PROFITABILITY, the ratio of operating income before depreciation to total assets; COVERAGE, the (log) number of analysts covering the stock; VAR_FEE, the variance of the borrowing fees, and SHORT_SQUEEZE, the realized skewness of Neuberger (2012) computed from daily returns over the previous month. Regressors are standardized to have 0 mean and unit standard deviation. t-statistics are based on standard errors clustered in the stock and time dimensions. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5
TURNOVER	0.011***		0.011***	−0.009***.	−0.008***
	(12.80)		(13.08)	(−6.95)	(−5.95)
ANALYST_DISPERSION	0.006***		0.005***	0.004***	0.003***
	(9.78)		(7.57)	(7.33)	(5.84)
BID_ASK		0.004**	0.004***	0.009***	0.005***
		(2.42)	(2.68)	(5.65)	(3.20)
SIZE		−0.036***	−0.035***	−0.021***	−0.014**
		(−10.88)	(−9.48)	(−6.28)	(−2.39)
OPEN_INTEREST				0.005***	0.001
				(2.61)	(0.43)
CONVERTIBLE				−0.004***	−0.003***
				(−5.31)	(−3.26)
IDIO_VOL				0.011***	0.007***
				(6.77)	(5.06)
SHORT_INTEREST				0.051***	0.049***
				(41.13)	(37.84)
SUPPLY				0.024***	0.026***
				(12.30)	(12.10)
FEE				0.001	0.001
				(0.65)	(1.18)
LEVERAGE					0.029***
					(12.20)
MTB					0.002
					(1.25)
PROFITABILITY					−0.003***
					(−2.69)
COVERAGE					0.001*
					(1.79)
VAR_FEE					−0.003***
					(−6.41)
SHORT_SQUEEZE					0.008***
					(25.22)
Adj. R^2	0.378	0.380	0.380	0.405	0.416
No. of obs.	4,652,322	5,589,080	4,652,278	4,627,854	3,679,820

The results broadly support the validity of DESYNC as a proxy for information-driven desynchronization. First, DESYNC is strongly positively associated with both proxies for difference in beliefs, namely TURNOVER and ANALYST_DISPERSION, in models 1 and 3. Second, DESYNC is higher for smallcaps and for stocks with larger bid–ask spreads in models 2 and 3, highlighting a strong and positive relation with the degree of information asymmetry surrounding a stock.

The adjusted R^2 of 38% in models 1 and 2 indicates that the set of proxies for difference in beliefs and information asymmetry explain a similar fraction of the variation of DESYNC. With the exception of TURNOVER, these relations preserve their sign and significance, indicating that DESYNC remains significantly related to proxies for disagreement in short selling, when we account for the partial and full set of controls in models 4 and 5.[16] The adjusted R^2 is less than 42% in all cases, implying that a substantial fraction of the information conveyed by DESYNC about short-selling desynchronization is not already contained in existing proxies.

B. Behavior Around Synchronizing Events

Abreu and Brunnermeier (2003) consider the possibility that unanticipated "synchronizing events" facilitate the coordination of arbitrageurs and accelerate the correction of mispricing. Synchronizing events include news and, more generally, any public signal that can help reduce the disagreement underlying the arbitrageurs' lack of coordination. The observation suggests assessing the empirical validity of DESYNC as a proxy for desynchronization by examining whether it falls following such events.

We consider two types of synchronizing events. The first is the release of negative public news concerning a firm.[17] News events represent not only an intuitive coordination device, but have been related to the short selling in a stock (Engelberg et al. (2012)). The second type of events is analyst downgrades of a firm's stock,[18] which extensive evidence identifies as an important trading signal for short sellers (Christophe, Ferri, and Hsieh (2010), Boehmer, Jones, Wu, and Zhang (2020)). We employ the following first-difference specification for our analysis:

$$\text{DESYNC}_{i,t} = \alpha_i + \beta \text{POST}_{i,t} + \varepsilon_{i,t},$$

where α_i is a stock fixed-effect, and $\text{POST}_{i,t}$ is a dummy variable equal to 1 (0) during the 50 days following (preceding) the information event. The coefficient of interest, β, captures the change in DESYNC across the two periods.

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

Finally, we examine the behavior of DESYNC around the release of reports by activist short sellers. Ljungqvist and Qian (2016) document a "short-and-disclose" strategy according to which arbitrageurs in overpriced but hard-to-short stocks publicly reveal their information to induce the target's shareholders to sell and

[16]The change in sign for TURNOVER in models 4 and 5 likely responds to the inclusion of IDIO_VOL, another theoretically (Shalen (1993) and Harris and Raviv (1993)) and empirically (Boehme et al. (2006)) motivated proxy for dispersion of opinions. As Panel D of Table 1 shows, stocks' idiosyncratic volatility and turnover are closely related in our sample.

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

[18]Using data from IBES, we identify analyst downgrade events with days when the average recommendation among analysts drops to either "sell" or "strong sell."

https://doi.org/10.1017/S0022109022001089 Published online by Cambridge University Press

TABLE 3

Dynamics of DESYNC Around Information Events

Table 3 reports coefficient estimates and associated t-statistics (in parentheses) of the following regression:

$$\text{DESYNC}_{i,t} = \alpha_i + \text{POST}_t + \varepsilon_{i,t},$$

where $\text{DESYNC}_{i,t}$ denotes the dispersion in profits across the short positions in stock i on day t (computed as in equation (1)), α_i is a stock fixed effects, and POST_t is a dummy variable equal to 1 (0) the 50 days after (before) the information event. Information events are defined by analyst downgrades to "sell" or "strong sell," in column 1, the release of negative news about the firm, in column 2, and the release of activist short sellers' report, in column 3. t-statistics are based on standard errors clustered in the stock and time dimensions. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	ANALYST DOWNGRADES	NEGATIVE NEWS	SHORT REPORTS
	1	2	3
POST_EVENT	−0.018***	−0.006**	0.023
	(−4.05)	(−2.52)	(1.41)
Adj. R^2	0.589	0.540	0.506
No. of obs.	84,497	337,256	4148

accelerate the price correction. Despite potentially inducing synchronized selling among *long* investors, the strategy should have little impact, precisely because of the existence of tight shorting constraints, on the coordination among the stock's *short* sellers. Accordingly, DESYNC should not exhibit systematically different behavior before and after this type of events. The insignificant coefficient of POST in the last column of Table 3 corroborates that this is indeed the case in our sample.[19]

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

V. Desynchronization and Stock Overpricing

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

A. Future Returns

Overpriced stocks should subsequently exhibit inferior average benchmark-adjusted performance, as measured by their abnormal returns relative to a standard pricing model. This reasoning motivates the predominant approach in the literature of associating overpricing with subsequent returns.[20] To preview the relationship

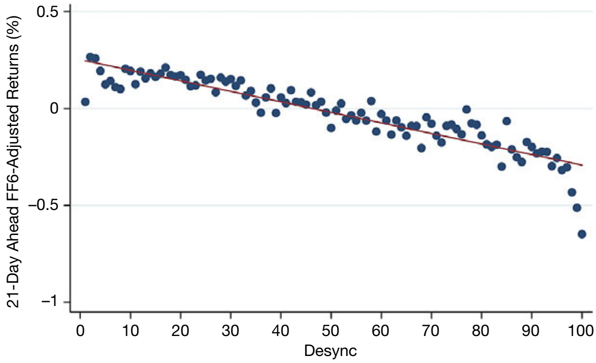
[19] We thank Antonis Kartapanis for generously facilitating these data to us. See Kartapanis (2020) for a detailed description of the data.

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

FIGURE 2

DESYNC and Future Returns: Nonparametric Evidence

This figure shows the binned scatterplot of the 21-day ahead Fama–French-Carhart 6-factor adjusted returns (in %) on DESYNC. We first group DESYNC into 100 equally-sized bins and compute the mean of DESYNC and of future adjusted returns within each bin. We then represent these data points with a scatterplot: each blue circle denotes a combination of the mean DESYNC and the mean future adjusted return across the stocks in a particular bin. The red solid line depicts the fitted line using ordinary least squares.



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 6 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 a spread of around −0.75% per month (−9.0% per annum) between the top and bottom deciles of DESYNC. In the next two subsections we analyze, using calendar portfolios and multivariate regressions, the economic and statistical significance of this relation and its robustness to controlling for the influence of other variables.

1. Portfolio Analysis

To assess the link between short sellers' desynchronization and stock overpricing without imposing a parametric relationship, we first examine single portfolio sorts. On each day *t*, we allocate stocks into five groups determined by the quintiles of DESYNC. Intuition suggests, and inspection of Table 2 confirms, that the uncertainty potentially creating synchronization problems is higher among smaller firms. In this case, while value weighting the stocks in each group makes the results comparable with other studies, it also tends to conceal the underlying patterns. We thus compute both the equal-weighted (EW) and value-weighted (VW) monthly average returns to each buy-and-hold portfolio for a 21-day holding period but discuss mainly the EW results, relegating the VW results to the Supplementary material. 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. In addition, we repeat the same exercise but work with monthly nonoverlapping returns to alleviate concerns about the overlapping nature of the portfolio returns.[21] We regress the returns to both types of portfolios on the 6 Fama–French-Carhart factors, and use Newey and West (1987) standard errors to correct for autocorrelation, with a number of lags equal to the length of the holding period. Panels A.1 and B.1 of Table 4 present the resulting alphas of the daily and monthly portfolios, respectively, corresponding to each DESYNC group.

The results confirm the negative relation between DESYNC and future alpha anticipated by Figure 2. Panels A.1 and B.1 evidence a strong decreasing pattern moving from the first (Q1) to the fifth (Q5) quintile. While the low-DESYNC portfolio generates monthly alphas of 0.19% and 0.07% in Panels A.1 and B.1 (statistically insignificant in the latter case), the high-DESYNC portfolios generate negative monthly alphas of −0.37% and −0.49% (both significant at the 1% level). As a result, the hedge overlapping and nonoverlapping portfolios long in high-DESYNC stocks and short in low-DESYNC stocks generate statistically and economically significant alphas of −0.55% and −0.56% per month (−6.6% and −6.7% per annum).

To control for other cross-sectional effects, Table 4 also presents conditional double portfolio sorts. Each day (each month for overlapping returns), we first allocate stocks into five groups based on different firm and stock characteristics. These include size (SIZE), market-to-book (MTB), past 6-month returns ($\text{RET}_{6\text{M}}$), and short interest (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 (BID_ASK) and turnover (TURNOVER), proxy for the general disagreement around the stock which, to the extent, it translates into more desynchronized short selling, should result in greater stock overpricing. Within each of these groupings, we further allocate stocks into five subgroups (from low to high) conditional on DESYNC for a total of 25 portfolios. We then compute the alphas for the hedge portfolio long in high-DESYNC and short in low-DESYNC stocks for each quintile of the first sorting variable. Panels A.2 and B.2 present, respectively, results for the overlapping and nonoverlapping portfolio analyses.

The results add strong support for Hypothesis 1. The positive relation between DESYNC and overpricing is pervasive across size, market-to-book, momentum, and short interest groupings, indicating that the effect of short sellers' desynchronization on returns is not subsumed by other well-known cross-sectional determinants. The effect is stronger among smallcaps, consistent with our above observation that DESYNC tends to be larger among firms with smaller capitalization, as well as among value stocks and past losers. Within these categories, the monthly alphas on the long-short DESYNC portfolios (−1.23% and −1.45% for small stocks, −1.21% and −1.40% for value stocks, and −0.97% and −0.85% for loser stocks) double those reported in Panels A.1 and B.1 of Table 4, respectively.

[21]This approach reduces the statistical power of our tests. Since we have a relatively short time-window of 7 years, moving from overlapping to nonoverlapping monthly returns reduces the number of portfolio returns from 1,764 to 84.

TABLE 4

Calendar Portfolios

Table 4 presents monthly Fama–French-Carhart 6-factor alphas (in percent) for overlapping (Panel A) and nonoverlapping returns (Panel B). Portfolios are rebalanced daily (monthly) in Panel A (Panel B), and are held for 21 days (1 month). The first five columns (Q1 to Q5) in subpanels A.1 and B.1 refer to portfolios formed by sorting into quintiles using the level of DESYNC, while the last column (Q5–Q1) shows returns to a portfolio long (short) in the stocks in the highest (lowest) quintile. Results in subpanels 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 into subquintiles by DESYNC. Each column shows returns to a long-short portfolio where firms with DESYNC in the highest (lowest) subquintile 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; MTB is the market-to-book ratio; RET_{6M} is the stock return cumulated over the previous 6 months; SHORT_INTEREST is the total quantity of shares loaned out as a percentage of shares outstanding; BID_ASK is the average bid–ask spread over the previous month; and TURNOVER is the average turnover over the previous month. The reported alphas are the intercept from regressing portfolio returns in excess of the risk-free rate on the excess market return (MKT), size (SMB), book-to-market (HML), momentum (MOM), profitability (RMW), and investment (CMA) 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. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Overlapping Returns

A.1. Single Sort

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
DESYNC	0.19*** (3.12)	0.09** (2.13)	0.01 (0.22)	−0.12** (−2.22)	−0.37*** (−3.41)	−0.55*** (−4.79)

A.2. Conditional Double Sorts

	Q5-Q1	Q10-Q6	Q15-Q11	Q20-Q16	Q25-Q21
SIZE	−1.23*** (−5.50)	−0.54*** (−3.23)	−0.29** (−2.18)	−0.57*** (−4.72)	−0.44*** (−4.75)
MTB	−1.21*** (−5.11)	−0.55*** (−4.01)	−0.63*** (−5.55)	−0.12 (−1.12)	−0.34* (−1.90)
RET_{6M}	−0.97*** (−5.69)	−0.37** (−2.43)	−0.48*** (−4.36)	−0.41*** (−4.11)	−0.24* (−1.82)
SHORTJNTEREST	−0.34*** (−2.69)	−0.07 (−0.49)	−0.06 (−0.47)	−0.35** (−2.14)	−0.32 (−1.60)
BID_ASK	−0.54*** (−5.82)	−0.31*** (−3.03)	−0.20* (−1.65)	−0.58*** (−3.3)	−1.20*** (−5.51)
TURNOVER	−0.48*** (−2.87)	−0.46*** (−3.80)	−0.12 (−0.95)	−0.29*** (−2.04)	−0.86*** (−4.99)

Panel B. Nonoverlapping Returns

B.1. Single Sort

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
DESYNC	0.07 (0.71)	0.21** (2.36)	0.05 (0.73)	−0.25*** (−2.89)	−0.49*** (−3.49)	−0.56*** (−3.43)

B.2. Conditional Double Sorts

	Q5-Q1	Q10-Q6	Q15-Q11	Q20-Q16	Q25-Q21
SIZE	−1.45*** (−4.11)	−0.64** (−2.24)	−0.22 (−1.09)	−0.57*** (−2.79)	−0.55*** (−3.29)
MTB	−1.40*** (−3.42)	−0.67*** (−2.97)	−0.51*** (−2.71)	−0.19 (−0.86)	−0.44 (−1.34)
RET_{6M}	−0.85** (−2.40)	−0.29 (−1.26)	−0.37** (−2.03)	−0.59*** (−2.93)	−0.17 (−0.71)
SHORTJNTEREST	−0.21 (−1.44)	−0.41** (−2.48)	−0.32** (−2.10)	−0.40** (−2.02)	−0.39 (−1.63)
BID_ASK	−0.66*** (−3.94)	−0.14 (−0.97)	−0.14 (−0.64)	−0.67** (−2.33)	−1.28*** (−3.63)
TURNOVER	−0.72*** (−3.12)	−0.46** (−2.29)	−0.21 (−1.04)	−0.42* (−1.98)	−0.68** (−2.14)

Remarkably, DESYNC generates negative alphas also among mildly and lightly shorted stocks. Conditioning on *low* levels of short interest, alpha is −0.34% per month in column Q1-Q5 of Panel A.2 of Table 4 (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 relation between DESYNC and returns is unrelated to the superior ability of short sellers—as reflected by heavy short selling—to identify overpricing.

In further support for Hypothesis 1, overpricing is greatest for the types of stocks for which we expect greater uncertainty about other short sellers' trades, hence greater synchronization risk. The high-minus-low DESYNC portfolio generates negative alphas in the bottom two rows of Panels A.2 and B.2 of Table 4, corresponding to the proxies for the information environment of the firm. These alphas are particularly large (in absolute value) and significant among stocks with higher information asymmetry or difference in beliefs, as reflected by larger values of bid–ask spread and turnover, respectively. The monthly alphas on the hedge portfolio Q25-Q21 of stocks with high bid–ask spreads and turnover are, respectively, −1.20% and −0.86% (−1.28% and −0.68%) in Panel A.2 (B.2), significant at the 1% (5%) level or higher.

2. Fama–MacBeth Regressions

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

$$\mathrm{AR}_{i,t+21} = \alpha + \beta_1 \times \mathrm{DESYNC}_{i,t} + \theta' \mathbf{x}_{i,t} + \varepsilon_{i,t+21}, \tag{2}$$

where $\mathrm{AR}_{i,t+21}$ is the factor-adjusted (abnormal) future return of stock i cumulated over 1 month (21 days), $\mathrm{DESYNC}_{i,t}$ is our short sellers' desynchronization measure for stock i at time t, and $\mathbf{x}_{i,t}$ is a vector of control variables, as described below. We compute (abnormal) returns following the approach in Boehmer et al. (2022), according to which the betas for each of the k factors in the model (where rf is the riskfree rate of return)

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

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

$$\mathrm{AR}_{i,t} = r_{i,t} - \left(rf_t + \widehat{\beta}^{(1)}_{i,q(t)-1} F_{1,t} + \ldots + \widehat{\beta}^{(k)}_{i,q(t)-1} F_{k,t} \right).$$

Our set of controls follows from previous studies, and comprises the conditioning variables in the double-sorted portfolios of Section V.A.1, along with the stock returns cumulated over the previous month ($\mathrm{RET}_{1\mathrm{M}}$), 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

TABLE 5

DESYNC and Future Returns: Fama-MacBeth Regressions

Table 5 reports Fama and MacBeth (1973) estimates and associated t-statistics (in parentheses) from the following regressions:

$$\mathrm{AR}_{i,t+h} = \alpha + \beta \times \mathrm{DESYNC}_{i,t} + \theta' \mathbf{x}_{i,t} + \varepsilon_{i,t+h},$$

where $\mathrm{AR}_{i,t+h}$ is the factor-adjusted (abnormal) future return of stock i, $\mathrm{DESYNC}_{i,t}$ denotes the dispersion in profits across the short positions in stock i at time t (computed as in equation (1)), and $\mathbf{x}_{i,t}$ is a vector of control variables. In Panel A, data are at the daily frequency and $\mathrm{AR}_{i,t+h}$ refers to abnormal returns comuluated over $h = 21$ days. In Panel B, data are at the monthly frequency and $\mathrm{AR}_{i,t+h}$ refers to next-month ($h = 1$) abnormal returns. Abnormal returns are calculated as the difference between the raw and the Fama–French-Carhart 6-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; MTB, 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 6 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. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Panel A. Overlapping Returns			*Panel B. Nonoverlapping Returns*		
	1	2	3	4	5	6
DESYNC	−0.576***	−0.490***	−0.644***	−0.59**	−0.50**	−0.70**
	(−3.523)	(−2.977)	(−4.230)	(−2.11)	(−2.10)	(−2.16)
SHORT_INTEREST	−4.799***	−4.007***	−1.849*	−3.44***	−2.78***	−0.39
	(−4.132)	(−3.894)	(−1.701)	(−3.21)	(−2.69)	(−0.30)
MTB	−0.044	0.028	0.098	0.10	0.17	0.23**
	(−0.470)	(0.297)	(1.047)	(0.83)	(1.49)	(2.20)
SIZE	−0.105**	−0.163***	−0.145***	−0.05	−0.15***	−0.14***
	(−2.349)	(−4.799)	(−4.318)	(−1.40)	(−4.85)	(−4.82)
RET_{1M}	−0.767	−0.470	−0.498	−0.66	−0.11	−0.17
	(−0.982)	(−0.621)	(−0.682)	(−1.01)	(−0.15)	(−0.24)
RET_{6M}	0.814***	0.635**	0.561**	1.03***	0.75***	0.69***
	(3.075)	(2.531)	(2.297)	(4.13)	(3.58)	(4.47)
BID_ASK		−48.607**	4.427		−106.53***	−57.57***
		(−2.153)	(0.198)		(−3.90)	(−3.60)
IDIO_VOL		−15.084***	−9.325*		−16.65***	−12.53**
		(−2.854)	(−1.896)		(−3.16)	(−2.47)
TURNOVER		−9.244	−13.244.		−10.00	−14.02
		(−0.905)	(−1.162)		(−1.25)	(−1.38)
SUPPLY			0.224			0.04
			(0.407)			(0.04)
FEE			−8.832***			−10.09***
			(−5.426)			(−7.89)
VAR_FEE			−17.967			−20.44
			(−1.002)			(−0.48)
Avg. R^2	0.02	0.03	0.04	0.02	0.02	0.03
No. of obs.	4,915,663	4,915,663	4,759,986	163,108	163,108	157,905

previous month (VAR_FEE) as a proxy for short-selling risk (Engelberg et al. (2018)). We adjust standard errors using the Newey and West (1987) methodology to correct for autocorrelation, with a number of lags equal to the length of the holding period. We report results for daily overlapping returns in Panel A of Table 5 and for monthly nonoverlapping returns in Panel B.

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 in Panel A of Table 5, at the 5% level in Panel B) coefficient across all specifications, with values ranging

https://doi.org/10.1017/S0022109022001089 Published online by Cambridge University Press

from a minimum of −0.64 to a maximum of −0.49 in Panel A (−0.70 and −0.50 in Panel B). These coefficients imply that, holding other determinants constant, 1-standard-deviation increase in DESYNC leads to annualized adjusted stock returns of between −1.38% and −1.05% (−1.51% and −1.08% when using nonoverlapping 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 1-standard-deviation increase in SHORT_INTEREST is followed (holding all else constant) by annualized adjusted returns of between −1.57% and −2.72% in the next month. However, the statistical significance of SHORT_INTEREST weakens or disappears in the specifications that controls for FEE (column 3 and 6), suggesting that shorting fees subsume short interest for predicting future returns.[22] Taken jointly, the results imply that DESYNC is a robust negative predictor of future abnormal returns in the cross-section, with similar economic significance as short interest.

B. Relative Mispricing

Stambaugh et al. (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 higher average rank proxies for a greater degree of relative overpricing, and is available at monthly frequency from July 1965 until Dec. 2016.[23] To determine the empirical relevance of synchronization risk as an arbitrage impediment, we next test whether short sellers' desynchronization and overpricing are positively associated in the cross-section.

We convert MISP into a categorical variable and employ a logit specification to model the probability that in month m stock i becomes overpriced, which we associate with the event that the stock rises to the top tercile of the MISP distribution.[24] More formally, we estimate the following model:

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

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

[22] 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 et al. (2018).

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

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

TABLE 6

DESYNC and Relative Mispricing

Table 6 reports coefficient estimates and associated t-statistics (in parentheses) from the following logit regression:

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

where $y_{i,m}$ is a binary variable equal to 1 if stock i rises to the top tercile of the MISP (the mispricing score proposed by Stambaugh et al. (2015)) distribution in month m. The vector of covariates $\mathbf{x}$ includes DESYNC, the dispersion in profits across the short positions (computed as in equation (1)); SHORT_INTEREST, the short interest in the stock; MTB, 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 6 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 square brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	1	2
DESYNC	2.228***	1.087***
	(16.22)	(7.91)
	[0.48]	[0.21]
SHORT_INTEREST		−0.205
		(−0.32)
MTB		−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
No. of obs.	163,416	146,244

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 1% level) in both specifications, implying that greater desynchronization among the stock's short sellers raises the likelihood that the stock rises to the top tercile of MISP in the following month. The estimates in the first column indicate an economically relevant effect, whereby a stock that moves from the bottom (0.56) to the top tercile (0.91) of DESYNC increases the likelihood of becoming overpriced by 16 ($=(0.91-0.56)\times 0.48\times 100$) percentage points.

C. 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's (1977) Hypothesis, noise-trader risk (De Long et al. (1990)), short-selling risk (Engelberg et al. (2018)), arbitrage asymmetries and idiosyncratic volatility (Stambaugh et al. (2015)), or a combination of several market frictions (Hou and Moskowitz (2005)) relate to our findings.

1. Miller's Hypothesis

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

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

To show that this is the case, in Table 7 we repeat the double-sorted portfolio analysis of Table 4 using either FEE or SUPPLY as the first conditioning variable. Each of these variables has been shown by prior research (see Geczy et al. (2002), Saffi and Sigurdsson (2011)) to capture the severity of the short-selling constraints in a stock. If our findings purely reflected Miller's Hypothesis, DESYNC-sorted portfolios should generate negative returns only on stocks with high fees or low supply of lendable shares. On the contrary, DESYNC generates statistically significant risk-adjusted spreads on daily overlapping portfolios (Panel A) of between −0.23% and −0.36% per month (−2.76% and 4.32% per annum) also on the stocks with the lowest shorting fees and the highest supply of lendable shares. Spreads on monthly nonoverlapping portfolios are economically similar but slightly less statistically significant for both constraint measures.[25]

We further corroborate that the effect of DESYNC on mispricing works through a different channel (i.e., desynchronization among shorts) by documenting it in tripled-sorted portfolios that control for *both* short-selling constraints *and* dispersion of opinions simultaneously in the Supplementary material. Due to an insufficient number of observations in monthly nonoverlapping portfolios, Supplementary Table A.5 reports results for daily overlapping (EW and VW) portfolios only. If the short-selling desynchronization effect is driven by Miller's Hypothesis,

[25]The generally lower statistical significance in Panel B is likely due to the loss of power induced by the significant drop in the number of observations when moving from daily portfolios in Panel A to monthly double-sorted portfolios.

TABLE 7

DESYNC and Alternative Overpricing Drivers

Table 7 presents monthly Fama–French-Carhart 6-factor alphas (in percent) for overlapping (Panel A) and nonoverlapping returns (Panel B). Portfolios are rebalanced daily (monthly) in Panel A (Panel B), and are held for 21 days (1 month). 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 subquintiles. Each column shows returns to a long-short portfolio where firms with DESYNC in the highest (lowest) subquintile are assigned to the long (short) portfolio. SUPPLY is the active quantity of shares available to be borrowed expressed as a percentage of shares outstanding; FEE is the borrowing fee; VAR_FEE is the variance of the borrowing fees over the previous month; IDIO_VOL is the idiosyncratic volatility over the previous month; SENTIMENT (BW) is the sentiment measure from Baker and Wurgler (2006); and SENTIMENT (JLMZ) is the sentiment measure from Jiang et al. (2019). FRICTIONS_SEVERITY (HM) is the measure of market frictions from Hou and Moskowitz (2005). FRICTIONS_SEVERITY⁻ (HM) is Boehmer and Wu (2013)'s refinement of FRICTIONS_SEVERITY (HM) to reflect prices' response to negative information only. The reported alphas are the intercept from regressing portfolio returns in excess of the risk-free rate on the excess market return (MKT), size (SMB), book-to-market (HML), momentum (MOM), profitability (RMW) and investment (CMA) 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. ***, **, and * indicate significantce at the 1%, 5%, and 10% levels, respectively.

	Q5-Q1	Q10-Q6	Q15-Q11	Q20-Q16	Q25-Q21
Panel A. Overlapping Returns					
SUPPLY	−1.20***	−0.60***	−0.25**	−0.34***	−0.23**
	(−5.82)	(−3.34)	(−2.15)	(−3.07)	(−2.19)
FEE	−0.36***	−0.10	−0.37***	−0.20	−0.77***
	(−4.79)	(−0.47)	(−3.63)	(−1.02)	(−3.66)
VAR FEE	−0.52***	−0.40***	−0.30***	−0.46***	−0.78***
	(−5.72)	(−3.74)	(−3.06)	(−2.78)	(−3.86)
IDIO_VOLI	−0.24**	−0.35***	−0.15	−0.09	−0.56**
	(−3.28)	(−4.29)	(−1.48)	(−0.64)	(−2.5)
SENTIMENT (BW)	−0.61***	−0.54***	−0.91***	0.04	−0.64***
	(−4.8)	(−4.92)	(−8.27)	(0.37)	(−6.56)
SENTIMENT (JLMZ)	−0.43***	−0.15	−0.83***	−0.71***	−0.67***
	(−4.57)	(−1.32)	(−6.74)	(−5.76)	(−5.86)
FRICTIONS_SEVERITY (HM)	−0.49***	−0.69***	−0.64***	−0.71***	−0.43**
	(−4.17)	(−4.42)	(−4.63)	(−4.81)	(−2.43)
FRICTIONS_SEVERITY⁻ (HM)	−0.51***	−0.71**	−0.67***	−0.48***	−0.57***
	(−4.26)	(−5.31)	(−4.65)	(−3.18)	(−3.35)
Panel B. Nonoverlapping Returns					
SUPPLY	−1.10***	−0.58**	−0.23	−0.43***	−0.14*
	(−3.12)	(−2.33)	(−1.26)	(−2.89)	(−1.87)
FEE	−0.33**	−0.72	0.09	−0.42	−1.55**
	(−2.34)	(−1.18)	(0.37)	(−0.17)	(−2.60)
VAR_FEE	−0.63***	−0.31	−0.09	−0.53*	−0.80***
	(−3.44)	(−1.31)	(−0.47)	(−1.99)	(−2.32)
IDIO_VOL	−0.31***	−0.44***	0.05	−0.44**	−0.25
	(−2.88)	(−2.69)	(0.24)	(−1.96)	(−0.69)
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)
FRICTIONS_SEVERITY (HM)	−0.32	−0.66***	−0.88***	−0.64**	−0.54*
	(−1.42)	(−2.91)	(−3.74)	(−2.48)	(−1.80)
FRICTIONS_SEVERITY ⁻ (HM)	−0.37*	−0.93**	−1.04***	−0.16	−0.69**
	(−1.67)	(−4.03)	(−4.29)	(−0.63)	(−2.04)

then the spread between high- and low-DESYNC stocks should not be meaningfully different from 0. The results in the table offer clear evidence that this is not the case. The high-minus-low DESYNC portfolio yields significantly negative (and no significantly positive) and sizable abnormal returns across several dispersion-in-beliefs and short-selling-constraints levels. These are particularly striking among stocks with little dispersion in beliefs, low short-selling constraints, or both. Given that the triple sort keeps fixed both of the characteristics resulting in stock overvaluation according to Miller, the negative DESYNC spread across these stocks provides strong indication of a different effect at play.

2. Noise-Trader Risk

Short sellers could delay attacking the overpricing in a stock not only because they face uncertainty about the information of other short sellers (synchronization risk), but also because they risk that noise traders move prices against their positions (De Long et al. (1990), 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 V.A.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), Jiang, Lee, Martin, and Zhou (2019)) in Table 7, we find a strong negative impact of DESYNC on risk-adjusted returns across both high- and low-sentiment periods. Second, we find that the effect is present even among large-cap in Table 4 and low-idiosyncratic volatility stocks (see below). Both results highlight the importance of considering additional factors to noise-trader risk to understand our findings.

3. Short-Selling Risk

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

4. Arbitrage Asymmetries and Idiosyncratic Volatility

Baker and Wurgler (2006) argue that stocks with high idiosyncratic volatility are riskier to arbitrage. Because they are also harder to value, these stocks potentially create greater dispersion of opinions and synchronization risk among their

https://doi.org/10.1017/S0022109022001089 Published online by Cambridge University Press

traders. The possibility then arises that what we are capturing is the effect of arbitrage asymmetries and idiosyncratic volatility on overpricing, as identified by Stambaugh et al. (2015). If this is the case, the relation between DESYNC and overpricing should be weak or nonexistent once we control for idiosyncratic volatility in our tests. The results in the fourth row of Table 7 rule out this possibility. The high-minus-low DESYNC conditional portfolios generate significant spreads across different IDIO_VOL 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 V.A and V.B the effect of DESYNC on overpricing is robust to controlling for IDIO_VOL, which, as expected, turns up highly statistically significant.

To further clarify the relation between our results and idiosyncratic volatility, in Supplementary 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 of Panel A refer to Fama–MacBeth regressions including abnormal returns as dependent variable, and either excluding or including IDIO_VOL in the controls. The last two columns of Panel A 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 Tables 5 and 6, the coefficients on the orthogonalized DESYNC variable are slightly smaller (in absolute value) but still strongly statistically significant.

5. Severity of Market Frictions

Even if none of the frictions above can, in isolation, account for the patterns we document, it could still be the case that a combination of some or all of them can. To investigate this possibility, we consider a parsimonious measure of the severity of market frictions affecting a stock, namely the stock's price-response delay, proposed by Hou and Moskowitz (2005). According to these authors, the average delay with which a stock's share price responds to new information captures the impact that several frictions (such as incomplete markets, limited stock market participation, low firm recognition, or lack of liquidity) can have on the speed of information diffusion in the stock market.[26] We label this measure FRICTIONS_SEVERITY.

Since we have a relatively short time series of 7 years, we follow the implementation of this measure in Boehmer and Wu (2013). Specifically, we compute FRICTIONS_SEVERITY monthly using daily observations and 5 days of lagged market returns. We further compute the alternative FRICTIONS_SEVERITY$^-$ measure, which captures price adjustment to negative information (see eq. (2) in Boehmer and Wu (2013)). We report our results in the last two rows of each panel of Table 7. If frictions other than short-selling desynchronization drive our results, we should expect that conditioning on FRICTIONS_SEVERITY or FRICTIONS_SEVERITY$^-$ portfolio sorts based on DESYNC create no significant return spreads.

[26]We thank an anonymous referee for suggesting the analysis in this subsection.

Contrary to this implication, DESYNC produces a negative spread across all (daily overlapping portfolios, Panel A of Table 7) or most (monthly nonoverlapping portfolios, Panel B) FRICTIONS_SEVERITY and FRICTIONS_SEVERITY^{-} quintiles. This implies that i) even for stocks not severely affected by frictions captured by Hou and Moskowitz's (2005) measure, higher desynchronization among the stock's short sellers leads to greater overpricing and ii) among stocks facing more severe frictions, these frictions do not subsume the effect of desynchronization on the stocks' overpricing.

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

VI. Desynchronization and Overpricing Duration

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

A. Relative Mispricing Correction

We use a 2-step approach to quantify the duration of the stock overpricing captured by MISP. For each stock i, we identify overpricing events as the months t in which the stock's MISP rises to the top tercile of the cross-sectional distribution of MISP. We then compute the length of each of these events as the number of months elapsed before MISP drops back below the top tercile. Using this delay measure, we examine the relation between DESYNC and DELAY within the following regression:

(4) $$\text{DELAY}_{i,t} = \alpha_i + \tau_t + \beta \times \text{DESYNC}_{i,t} + \gamma' \mathbf{x}_{i,t} + \varepsilon_{i,t},$$

where α_i and τ_t denote firm and time fixed-effects, and $\mathbf{x}_{i,t}$ denotes a vector of controls.

We consider two groups of controls. Our first group follows directly from the analysis of Abreu and Brunnermeier (2002). Their model explains the delay in price correction for a *given* level of mispricing. To account for the initial size of the stock overpricing, we thus include the relative mispricing score R (=MISP) at the start of the event among our controls. Arbitrageurs' holding costs are a main ingredient in the model, and an exogenous parameter that they keep fixed throughout the analysis. In particular, they consider shorting fees to be the most important holding cost among short sellers. Accordingly, we also include a stock's borrowing fees, FEE,

TABLE 8

DESYNC and Delay in Overpricing Correction

Table 8 presents coefficient estimates and associated t-statistics (in parentheses) from the following regression:

$$\text{DELAY}_{i,t} = \alpha_i + \tau_t + \beta \times \text{DESYNC}_{i,t} + \gamma' \mathbf{x}_{i,t} + \varepsilon_{i,t},$$

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 $\mathbf{x}_{i,t}$ 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 MTB, the (log) market-to-book ratio. $\text{DELAY}_{i,t}$ is constructed in two steps. For each stock i, we first identify the overpricing events, that is, the months (t) when the mispricing score (Stambaugh et al. (2015)) rises to the top tercile of the distribution. We then compute the length of the events as the number of months before the score drops below the top tercile. t-statistics are based on clustered standard errors. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	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)
MTB			−0.449*
			(−1.94)
Adj. R^2	0.135	0.215	0.235
No. of obs.	3862	3822	3722

among our first group of controls. Similarly, the number of arbitrageurs is kept constant in their analysis. To isolate the effect of synchronization risk on DELAY from the effect of the short sellers' aggregate position in the stock, we thus include SHORT_INTEREST within this first set of controls.

Our second group of controls comprises relevant stock characteristics. To account for the fact that the mispricing of more illiquid stocks could be harder to arbitrage, we include STOCK_BID_ASK, the percentage bid–ask spread in the stock market. The other two controls we consider, SIZE and MTB, are standard.

We report our estimates in Table 8 across three specifications.[27] 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 overpricing (DELAY). In line with this prior, we find a positive and statistically significant coefficient β across all specifications. β equals 3.35, 2.89, and 3.71 (all statistically significant at the 5% level), respectively, in the specifications with no additional controls, with the first set of controls, and with both sets of controls. The size of this coefficient indicates that the relationship between DESYNC and DELAY is economically meaningful. In particular, the full model implies that a 1-standard-deviation increase (0.145) in DESYNC requires

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

16 additional days for the score to drop below the top tercile.[28] Intuitively, we also find that overpricing events tend to last longer when the initial overpricing (R) is higher.

B. 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.[29] We account for transaction costs in the options market by computing an upper bound for the synthetic price using the ask price for calls and the bid price for puts. We associate stock overpricing with a positive difference between the stock's observed price and the synthetic price upper bound. Using the number of consecutive days over which this difference remains positive as our measure of the *delay* in price correction (DELAY), we re-estimate equation (4) and report our estimates in Table 9 across six specifications that differ depending on the controls included.

We consider several option characteristics as additional controls to the ones described in Section VI.A.[30] 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_VOL, the implied volatility of calls. We restrict our attention to put–call parity violation that lasts at least 2 days to avoid apparent one-day violations that are the result of misreporting. Supplementary Table A.4 presents summary statistics for our dependent variable ($\text{DELAY}_{i,t}$) and the options in our sample.[31]

The results are strikingly consistent with those of Table 8. DESYNC shows up with a positive and highly statistically significant (at the 1% level) coefficient of 14.38 in the first specification. This coefficient drops to 9.38 (significant at the 5% level) when we include the first set of controls in column 2. Nevertheless, it remains positive and significant (at the 5% level) when we also include either

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

[29]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.

[30]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.

[31]Following Ofek et al. (2004), i) we exclude stocks paying dividends and we require that both the put and call have positive open interest, and ii) we focus on the option pairs that are at-the-money ($-10\% < \ln(\text{Price}/\text{Strike}) < 10\%$) 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 et al. (2004).

TABLE 9

DESYNC and Duration of Put–Call Disparities

Table 9 presents coefficient estimates and associated *t*-statistics (in parentheses) from the following regression:

$$\text{DELAY}_{i,t} = \alpha_i + \tau_t + \beta \times \text{DESYNC}_{i,t} + \gamma' \mathbf{x}_{i,t} + \varepsilon_{i,t},$$

where $\text{DELAY}_{i,t}$ 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 $\mathbf{x}_{i,t}$ 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_VOL, the implied volatility of the call option; SIZE and MTB, computed as in Section V. *t*-statistics are based on clustered standard errors. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	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_VOL				−14.990**		−10.498
				(−2.51)		(−1.56)
MTB					0.027	−0.077
					(0.01)	(−0.03)
SIZE					4.898**	4.194*
					(2.36)	(1.79)
Adj. R^2	0.057	0.104	0.105	0.106	0.108	0.108
No. of obs.	4098	4032	4025	3981	4025	3981

stock or option controls (columns 3–5), or the full set of controls (column 6). The estimates remain consistent with economic intuition and with prior studies, as violations tend to last longer when initial overpricing (*R*) or the holding costs of short sellers (FEE) are higher. The effect of DESYNC on the duration of put–call parity-related overpricing is economically relevant. The coefficient estimate in the full model, 8.63, implies that a 1-standard-deviation increase in DESYNC requires 1.38 additional days for the put–call parity violation to close. This corresponds to a 15.5% increase relative to the mean of DELAY. By comparison, a 1-standard-deviation increase in FEE, a key determinant of put–call parity violations according to Ofek et al. (2004), is associated with an increase in DELAY of 1.25 days (13.6% relative to the mean of DELAY).

https://doi.org/10.1017/S0022109022001089 Published online by Cambridge University Press

https://doi.org/10.1017/S0022109022001089 Published online by Cambridge University Press

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

VII. Additional Results and Robustness

In this section, we show that our results do not hinge on the specific measure of dispersion in short seller's profits that we employ. We then investigate the role of negative news releases as synchronizing events that speed up the correction of mispricing. We further examine the impact of offsetting long positions on our results. Finally, we provide additional support for the limiting role of short-selling desynchronization in the correction of mispricing using a placebo test.

A. Alternative Measure of Short-Selling Profit Dispersion

To show that our results do not hinge on the specific measure of dispersion in short sellers' profits that we employ, we reproduce the analyses on both the extent (i.e., Tables 5 and 6) and the duration of overpricing (i.e., Tables 8 and 9) using two alternative measures.

The first measure is based on the standard deviation of short sellers' cumulated returns. For each stock and day, we compute the (bin-)weighted sum of the squared distance of each bin's midpoint from the mean, and take the square root of the resulting value. More formally, DESYNC_SD is equal to

$$\text{(5)}\quad \text{DESYNC\_SD}_{i,t} = \sqrt{\sum_{n=1}^{N} \text{BIN}_{i,t}^{(n)} \times \left(\text{PNL}_{i,t} - \frac{\lfloor n+n \rfloor}{2}\right)^2}$$
$$= \sqrt{\text{BIN}_{i,t}^{(-100,\ -75]} \times (\text{PNL}_{i,t} + 87.5)^2 + \ldots + \text{BIN}_{i,t}^{(75,100]} (\text{PNL}_{i,t} - 87.5)^2},$$

where $\text{PNL}_{i,t}$ is the mean of the distribution

$$\text{PNL}_{i,t} = \sum_{n=1}^{N} \text{BIN}_{i,t}^{\lfloor n \rfloor} \times \frac{\lfloor n+n \rfloor}{2}$$
$$= \text{BIN}_{i,t}^{(-100,\ -75]} \times (-87.5) + \text{BIN}_{i,t}^{(-75,\ -50]} \times (-62.5)$$
$$+ \ldots + \text{BIN}_{i,t}^{(50,\ 75]} \times 62.5 + \text{BIN}_{i,t}^{(75,100]} \times 87.5.$$

The second measure is based on the absolute spread of short sellers' cumulated returns. For each stock and day, we take the absolute difference between the midpoint of the highest ("HIGH") and lowest ("LOW") nonempty return bins. More formally, DESYNC_|SPREAD| is equal to

$$\text{(6)}\qquad \text{DESYNC\_|SPREAD|}_{i,t} = \left| \frac{\lfloor n_{\text{HIGH}} + n_{\text{HIGH}} \rfloor}{2} - \frac{\lfloor n_{\text{LOW}} + n_{\text{LOW}} \rfloor}{2} \right|$$

Results corresponding to DESYNC_SD and DESYNC_|SPREAD|, respectively, are reported in Panels A and B of Table 10. Panels A.1 and B.1 show that, in

TABLE 10

Alternative Desynchronization Measure

Column 1 of Panels A.1 and B.1 of Table 10 reports estimates from the following regression:

$$\text{AR}_{i,t+21} = \alpha + \beta \times \text{DESYNC}_{i,t} + \theta' \mathbf{x}_{i,t} + \varepsilon_{i,t+21},$$

where $\text{AR}_{i,t+21}$ is the Fama–French-Carhart 6-factor (abnormal) future return of stock i cumulated over 21 days, DESYNC is computed as in equation (5) in Panel A.1 and as in equation (6) in Panel B.1, and $\mathbf{x}$ is a vector of control variables (see Table 5). Column 2 of Panels A.1 and B.1 reports estimates from the following regression:

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

where $y_{i,m}$ is a binary variable equal to 1 if stock i rises to the top tercile of the MISP distribution in month m. The vector of covariates $\mathbf{x}$ includes DESYNC_SD in subpanel A.1 (see equation (5)) and DESYNC_|SPREAD| in Panel B.1 (see equation (6)), and the control variables in Table 6. Panels A.2 and B.2 report estimates from the following regression:

$$\text{DELAY}_{i,t} = \alpha_i + \tau_t + \beta \times \text{DESYNC}_{i,t} + \gamma' \mathbf{x}_{i,t} + \varepsilon_{i,t},$$

where α_i and τ_t are firm and time fixed-effects DESYNC is computed as in equation (5) in Panel A.2 and equation (6) in Panel B.2. In column 1, $\text{DELAY}_{i,t}$ is constructed in two steps. For each stock i, we first identify the overpricing events, that is, the months (t) when the mispricing score (Stambaugh et al. (2015)) exceeds the top tercile of the distribution. We then compute the length of the events as the number of months before the score drops below the top tercile. The vector of controls is the same as Table 8. In column 2, $\text{DELAY}_{i,t}$ is the number of days the price of stock i is above the upper-bound implied by the put–call parity, and $\mathbf{x}_{i,t}$ is the vector of controls from Table 9. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	A.1. Mispricing			*A.2. Delay*	
	AR	MISP		MISP	P-C DISPARITY
	1	2		1	2
Panel A. DESYNC_SD					
DESYNC_SD	−1.448**	1.612***	DESYNC_SD	5.398*	14.660*
	(−2.141)	(5.65)		(1.84)	(1.66)
SHORT_INTEREST	−5.002***	0.786	*R*	0.847***	2.012***
	(−4.0496)	(1.270)		(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
No. of obs.	4,915,663	146,244	No. of obs.	3722	3981
R^2	0.03	0.09	R^2	0.16	0.10
	B.1. Mispricing			*B.2. Delay*	
Panel B. DESYNC_|SPREAD|					
DESYNC_|SPREAD|	−0.273*	0.512***	DESYNC_|SPREAD|	0.629	5.531*
	(−1.830)	(6.88)		(0.79)	(1.88)
SHORT_INTEREST	−5.074***	0.382	*R*	0.778***	2.022***
	(−4.449)	(0.620)		(12.73)	(3.67)
			FEE	2.907	30.285***
				(0.31)	(2.65)
			SHORT_INTEREST	1.331	52.058***
				(0.21)	(4.18)
Controls	YES	YES	Controls	YES	YES
No. of obs.	4,915,663	146,244	No. of obs.	3,822	3,981
R^2	0.03	0.09	R^2	0.16	0.11

line with our results on the extent of overpricing in Section V, both DESYNC_SD and DESYNC_|SPREAD| are negatively related to future factor-adjusted returns and positively related to the likelihood that the stock rises to the top tercile of MISP. In line with our findings on the duration of overpricing in Section VI, Panels A.2 and B.2 show that higher values of either DESYNC_SD or DESYNC_|SPREAD| also lead to longer delays in the correction of stock overpricing. While qualitatively the same, the results are statistically weaker, particularly in the relationship between

https://doi.org/10.1017/S0022109022001089 Published online by Cambridge University Press

DESYNC_|SPREAD| and MISP duration, compared to our main results in Section VI. This is expected given that DESYNC_|SPREAD| is a more "crude" proxy for desynchronization that abstracts from relevant information about the distribution of the profits (e.g., size and number of bins).

B. 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 facilitates a stock sell out. We then repeat the analysis in Section VI but using the following specification:

$$(7) \quad \begin{aligned} \text{DELAY}_{i,t} = {} & \alpha_i + \tau_t + \beta_0 \times \text{DESYNC}_{i,t} + \beta_1 \times \text{DUMMY\_NEWS}_{i,t} \\ & + \beta_2 \times \text{DESYNC}_{i,t} \times \text{DUMMY\_NEWS}_{i,t} + \gamma' \mathbf{x}_{i,t} + \varepsilon_{i,t}, \end{aligned}$$

where $\text{DUMMY\_NEWS}_{i,t}$ is a dummy variable that equals 1 for stocks in the highest NEWS decile on a particular day, and 0 otherwise.[32] The rest of the variables and controls are as in Section VI. According to the synchronization-risk argument, we expect $\beta_2 < 0$.

Consistent with this implication, in non-tabulated results we find an estimate for β_2 in (7) 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-stat 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).

C. Impact of Offsetting Long Positions: Empirical Analysis

As mentioned in Section III.C, trading activity to offset long positions might introduce noise in the DESYNC proxy, especially for stocks that belong to the S&P 500 index. To examine this possibility, we add an interaction term between DESYNC and an S&P 500 index dummy (equal to 1 if a stock belongs to the S&P 500 index) to the tests on both the extent and the duration of overpricing of Sections V and VI. If the trading activity in S&P 500 stocks confounds our measure with noise, we should observe weaker (or no) results on this subset of stocks. Panels A and B of Supplementary Table A.2 report the results corresponding to, respectively, the extent and duration of stock overpricing.

[32]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.

Overall, the results for the stocks included in the S&P 500 index are similar to those for the stocks that are excluded. Starting from Panel A, DESYNC remains negatively related to a stock's future abnormal returns and positively related to the likelihood that the stock rises to the top tercile of MISP. The inclusion of an interaction term in the regression implies that the coefficient on DESYNC captures the short-selling desynchronization effect on stocks *excluded* from the S&P 500 index. The insignificance of the interaction term indicates that we fail to reject the null that this effect is equal to the effect on stocks included in the S&P 500 index. Moving to Panel B, DESYNC remains positively associated to the delay in the correction of stock overpricing. The interaction term is insignificant when the duration is measured based on MISP, but significant (at 10%) when based on the put–call inequality, in line with a limited amount of noise added by offsetting long positions. For the subset of stocks where we expect a lower importance of offsetting long positions, we find strongly significant effects of DESYNC in all specifications.

D. Placebo Test

Desynchronization in short selling should play no role in the correction of *underpricing*, which requires traders to establish long instead of short positions. To test whether this is indeed the case, we apply our analysis of Section VI to the duration of *underpricing* events. In the analysis of relative mispricing as captured by the MISP measure of Stambaugh et al. (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.[33] Our estimates, reported in Table 11, show that in contrast to our findings of Section VI, there is no relation between DESYNC and the delay in the correction of underpricing as gauged by either measure. The results confirm the importance of short selling-related synchronization problems in driving overpricing (and not underpricing) across stocks.

VIII. Conclusions

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

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

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

TABLE 11

DESYNC and Delay in Underpricing Correction

Table 11 presents coefficient estimates and associated t-statistics (in parentheses) from the following regression:

$$\text{DELAY}_{i,t} = \alpha_i + \tau_t + \beta \times \text{DESYNC}_{i,t} + \gamma' \mathbf{x}_{i,t} + \varepsilon_{i,t},$$

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 $\mathbf{x}_{i,t}$ is a vector of controls. In Panel A, DELAY is the number of consecutive months the mispricing score (Stambaugh et al. (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, FEE is the borrowing fee (in % per annum) and SHORT_INTEREST is the total quantity of shares loaned out as a percentage of shares outstanding. The controls include STOCK_BID_ASK, the percentage bid–ask spread; SIZE; and MTB. 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_VOL, the implied volatility of the call option. t-statistics are based on clustered standard errors. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Panel A. Mispricing Score		*Panel B. Put–Call Parity*	
	1	2	3	4
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
Adj. R^2	0.19	0.19	0.10	0.118
No. of obs.	3,895	3,785	3,477	3,262

information asymmetries surrounding the stock, and to substantially drop following information-related synchronizing events.

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

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109022001089.

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