

# Overconfidence, Information Diffusion, and Mispricing Persistence \*

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## Abstract

Short-sale constrained past-winners and losers both underperform strongly in the first year post-formation, earning market-adjusted returns of  $-13\%$ , and  $-17\%$ , respectively. However, constrained winners continue to underperform for the following four years, earning a cumulative market-adjusted return of  $-40\%$  ( $t = -6.33$ ), while past-losers earn  $6\%$  ( $t = 0.55$ ). This persistence differential cannot be explained by existing models or by simple extensions of existing models. We propose a dynamic heterogeneous agents model featuring overconfidence and slow information diffusion which is able to both explain this asymmetry in mispricing persistence among short-sale constrained stocks, and to match value and momentum effects for unconstrained stocks.

Keywords: overconfidence, information diffusion, short-sale constraints, momentum, value, mispricing

JEL-Classification: G12, G14

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A key goal of behavioral finance research is uncovering the nature of the biases in beliefs that drive price distortions in security markets. This is difficult to do with security price data alone. For example, the actions of arbitrageurs can mask these biases, and in instances where there are multiple agents who disagree about security valuations and take opposing positions, only the aggregation of these beliefs will be revealed in the price. Moreover, behavioral models of security price formation are not fully identified. For example, the models of [Barberis, Shleifer, and Vishny \(1998\)](#), [Daniel, Hirshleifer, and Subrahmanyam \(1998\)](#), [Hong and Stein \(1999\)](#) all generate value and momentum effects and match other empirical regularities, but do so with very different assumptions about belief formation. To narrow down the set of viable models requires non-standard data.

In this paper, we examine momentum and value effects for an “extreme” set of securities. High-energy physics provides a useful analogy: physics researchers examine the behavior of fundamental particles at high energies to test alternative models of particle interactions. By examining matter in extreme settings, they observe behavior that would otherwise be masked. This provides them with the additional data they need to develop models that get closer to capturing the underlying mechanisms driving basic physics. Note that they require their models to fit both the behavior in these extreme situations and in ordinary situations.

In this study we perform an analogous exercise: we examine value and momentum effects for a set of “extreme” securities that are or were short-sale constrained (i.e., hard-to-borrow). The set of securities that we examine is necessarily only a small part of the market—on average about 3% of the total stock market capitalization and 16% of the number of stocks in the US (broadly consistent with [D’Avolio, 2002](#), see p. 73).

One concern with analyzing the performance of small market capitalization portfolios is infrequent trading: that is, that the prices reported by CRSP are invalid. This is not the case for the firms in our portfolios; the extreme stocks we analyze are highly liquid as evidenced by their average monthly turnover of 28%. Additionally all portfolios we examine are value-weighted buy-and-hold portfolios, and therefore require little trading. We note

also that, for comparison, the total market capitalization of the constrained US firms we consider is, on average, about the same as the total market capitalization of the Dutch stock market.<sup>1</sup> Interestingly, we observe dramatically different behavior for these extreme securities, behavior that is *not* explained by any extant theories.

[INSERT FIGURE 1 HERE]

To begin, Figure 1 Panel A plots cumulative abnormal returns to two value-weighted portfolios which contain the 30% of US common stocks with the best and worst returns over the preceding year, excluding the month prior to portfolio formation.<sup>2</sup> The plot shows that, over about the first year after portfolio formation, the past-winner portfolio ( $W$ ) continues to earn positive abnormal returns, while the past-loser ( $L$ ) portfolio earns negative abnormal returns. However, in years 2–5 post-formation, i.e., from month 13 to 60 post-formation, both past-winners and past-losers exhibit reversal. This leads to hump-shaped impulse-response functions, consistent with the value and momentum effects in numerous securities markets (Asness, Moskowitz, and Pedersen, 2013).<sup>3</sup>

In Panel B, we plot the returns to portfolios of past-winners and losers formed in the same way except that now, rather than selecting the past-winners and losers from *all* listed US common stocks, our investment universe is instead the subset of stocks that are *short-sale constrained*. The returns from the  $W$  and  $L$  portfolios from Panel A, are dashed lines in this figure for comparison. Specifically, our universe consists of firms which have both low institutional ownership and high short interest.<sup>4</sup> Note that the vertical scale has changed dramatically. We see now that both the portfolio of constrained past-winners ( $W^*$ ) and

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<sup>1</sup>As a comparison for trading volume, the time-series average monthly turnover of the value-weighted average of all stock in the US equity market is 13% during our sample-period. For a comparison with the Dutch market, See Figure D.1 in the Appendix.

<sup>2</sup>The sort on past returns is consistent with the definition of the Fama and French (2008) “momentum” factor.

<sup>3</sup>We use CARs here for illustration purposes in awareness of its drawbacks. Based on the critique developed by Barber and Lyon (1997), Fama (1998), Lyon, Barber, and Tsai (1999), we present a new methodology that we call ‘value-weighted buy-and-hold portfolios’, which confirms and statistically validates the visual inferences depicted here. The details of the portfolio construction as well as the results are presented in Sections 3.2 and 3.3, and in the Appendix for simple momentum portfolios (Tables D.1 and D.2).

<sup>4</sup>See Section 1 for a motivation for this measure, and empirical evidence on its efficacy.

constrained past-losers ( $L^*$ ) earn strongly negative returns in the first year post-formation. However, in years 2–5 post-formation, the constrained past-loser portfolio now earns positive abnormal returns, but the constrained past-winner portfolio continues to earn strongly negative abnormal returns. Indeed, we show later that the difference in performance in years 2–5 post-formation is both large in magnitude and strongly statistically significant.<sup>5</sup>

The fact that constrained stocks earn low returns is well known. What is new and striking here is the difference in mispricing persistence between the past-winners and losers. While the past-losers earn a cumulative market-adjusted return of  $-17\%$  ( $t = -3.75$ ) in the first year post-formation, the cumulative market-adjusted return from years 2–5 years post formation is  $6\%$  ( $t = 0.55$ ). Like the past-losers, the past-winners also earn a strongly negative market-adjusted return of  $-13\%$  ( $t = -3.85$ ) in the first year post-formation but, in contrast, earn a cumulative market-adjusted return of  $-40\%$  ( $t = -6.33$ ) in years 2–5 years post formation.<sup>6</sup> Our main empirical contribution is documenting the striking difference in mispricing persistence among constrained winners and losers. Our theoretical contribution is to offer an explanation of the empirical patterns shown in Figure 1, and one that captures the difference in mispricing persistence: constrained past-winners earn large negative returns *not only* in the first year after portfolio formation, but, at statistically significant levels, for each of the five years post-formation (as we will show in Section 3.4).

Natural starting points to explain this phenomenon are, first, the existing explanations offered for momentum and reversals among unconstrained stocks, such as Daniel, Hirshleifer, and Subrahmanyam (1998), Barberis, Shleifer, and Vishny (1998), and Hong and Stein (1999), combined with the explanation for the underperformance of short-sale constrained stocks in the presence of disagreement offered in Miller (1977). Miller argues that when

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<sup>5</sup>The difference in abnormal returns in years 2–5 post-formation between constrained winners and constrained losers is  $-0.9\%/mo$  ( $t = -3.85$ ).

<sup>6</sup>The cumulative market-adjusted return from years 2–5 years post formation is calculated by taking for each portfolio the difference between the 4-year (years 2–5 post formation) buy-and-hold-return of the portfolio and the 4-year buy-and-hold-return of the market. The numbers in the text are the averages over all 295 (247 for years 2–5) cumulative market-adjusted returns for winner and loser portfolios formed during our sample period, respectively. While the methodology to calculate the cumulative market-adjusted return is different than the buy-and-hold portfolio approach, both still deliver consistent results.

there is disagreement about the value of a security and when pessimists are constrained from short-selling, only the views of the more optimistic agents will be reflected in the security price. When disagreement is resolved over time, this overvaluation is eliminated, leading to predictably low returns.

However, simple combinations of the [Miller \(1977\)](#) model with one of these explanations for momentum and reversals yield predictions that are inconsistent with the empirical facts: [Daniel, Hirshleifer, and Subrahmanyam \(1998\)](#) and [Barberis, Shleifer, and Vishny \(1998\)](#) are both representative agents models with no disagreement. Without disagreement, introducing short-sale constraints would have no effect on prices or returns, and thus could not generate the return patterns we observe. [Hong and Stein \(1999\)](#) is a heterogeneous agent model, but the nature of the *newswatcher* and *momentum-trader* belief formation in this model implies that, even in the presence of short-sale constraints, expected returns would still be positive for past-winners, inconsistent with the empirical evidence we present here.

An *ad-hoc*, empirically motivated explanation for the short-term patterns of [Figure 1](#) is what we call the *additive-effect hypothesis*: Suppose that momentum and value effects exist for all stocks, i.e., they generate the well known hump-shaped impulse response pattern as documented in [Figure 1](#) Panel A. Further suppose that constrained stocks generally underperform. We could simply add a constant negative slope, to reflect the effect of short-sale constraints, to that impulse response function of both winners and losers, and assume that this slope just cancels out with the positive long-term reversal of past-losers (i.e., the magnitudes of both effects are about the same). This could generate a picture roughly similar to what we see in Panel B. The critical proposition here is that the effect of short-sale constraints is the same for winners and losers (i.e., there is no interaction effect) both at the short and the long horizon. This would imply that the difference-in-differences (*DiD*) between constrained winners and unconstrained winners and constrained losers and unconstrained losers is the same at all horizons. It is always the effect of short-sale constraints that is added to the empirical patterns of momentum and reversals for winners and losers. In

Section 3.4 we employ a matching approach to specifically test this. The hypothesis is clearly rejected by the data: Constrained winners underperform, whereas constrained losers exhibit no significant difference, relative to their matched counterparts, in years 2–5 post-formation. The difference-in-differences is highly statistically significant (see Table 4 in Section 3.4).

Thus, none of the approaches above are able to offer an explanation of the strong asymmetry that we observe between past-winners and losers, and specifically of the long mispricing persistence of the past-winners. In Section 4, we propose a heterogeneous agents model which is calibrated to explain value and momentum in unconstrained stocks, and show that this calibrated version *also* explains the predictability in returns we document for constrained stocks. In particular, this model captures the asymmetry in mispricing persistence between constrained winners and losers that we document empirically.

Any model that can explain the striking differences in return predictability patterns between constrained and unconstrained stocks will necessarily feature a certain degree of complexity, like heterogeneous agents, disagreement and various expectation formation processes. Our model explains these empirical patterns using overconfidence and slow information diffusion, two established concepts that have been used in the behavioral literature.

The intuition behind the model is the following: first, recall that *short-term* momentum effects persist about one year (Hong, Lim, and Stein, 2000, Jegadeesh and Titman, 2001). In contrast, *long-term* value/reversal effects among unconstrained stocks last for approximately 5 years (see Figure 1 Panel A, as well as Daniel and Titman, 2006).

In our model *informed overconfident* agents receive private signals about which they are overconfident, and where this overconfidence persists about 5 years, consistent with the long-run value/reversal effect for unconstrained stocks. The momentum effect, in contrast, is explained by the *newswatchers*, modeled after the eponymous agents in Hong and Stein (1999): these agents do not incorporate information into prices until they observe it directly and ignore the information embedded in prices (see also Luo, Subrahmanyam, and Titman, 2019). Since the time required for information to diffuse through the economy is about a

year, the persistence of the momentum effect is about a year. Thus, the duration of the information diffusion and overconfidence effects in our model are dictated by the duration of the value and momentum effects for unconstrained stocks.

For unconstrained securities, the interaction of the overconfident agents and the newswatchers leads to standard momentum and value effects in our model. However, when in this model a security is “hard-to-borrow”, either the overconfident agents or the newswatchers can become constrained, meaning that they no longer set prices in the market.

To see the effect of borrowing constraints in this setting, first consider a strong positive private information shock to an unconstrained stock. The informed overconfident agents see the shock first and, owing to their overconfidence, overreact and immediately drive the price up. The newswatchers do not “see” the full information shock (and ignore the information content of prices), so their estimate of firm value is updated insufficiently. Therefore, in response to the price rise they short the stock. However, as the full positive information shock is gradually revealed to the newswatchers, they reduce their short position as they update their valuation of the firm upward. This results in a positive drift of the firm’s price, i.e., momentum, and eventual reversal as the overconfidence of the informed agents gradually fades.

However, if the firm’s stock cannot be sold short, the newswatchers will be sidelined, and the stock price will reflect only the informed overconfident agents’ views. Thus, without short-selling, the shock will result in a stronger positive reaction, as the newswatchers are completely sidelined. Moreover, there will be no momentum, as the newswatchers’ learning does not affect prices, since they are not participating in the market. There is only a long-term reversal, but one that is much stronger than would be observed for unconstrained stocks. In line with the duration of the value effect, this reversal is a long-term phenomenon in the model. Consistent with these predictions, we document empirically that for short-sale-constrained winners, there is no momentum, only a reversal which persists for about five years.

In contrast, consider now a negative private information shock for a constrained stock. The overconfident informed agents who observe this signal would like to short, but the costs of shorting prohibit them from doing so. Thus, only the newswatchers — who are the optimists in this scenario — play a role in setting prices. Now we see an enhanced momentum effect, in the sense that the stock price falls continuously over a about a year as the negative shock diffuses through the newswatcher population. Now, though, the underperformance is of a far shorter duration because information diffusion is a faster process. Furthermore, there is no long-term reversal for constrained losers as the overconfident agents, who would like to short, are sidelined. Thus, this model is able to explain all of our new empirical findings.

While the model we propose captures this and other empirical phenomena, there are certainly other models that could also capture the empirical phenomena we document here. However, simple extensions of current models do not. The distinct asymmetry in the impulse-response functions for past-losers and past-winners shows that the sidelining of pessimistic agents via short-sale restrictions has strong distinct effects depending on whether the firm has experienced a positive or negative information shock. Only models that capture this asymmetry can explain these data.

## 1 Related Literature

Much of the literature on disagreement and asset prices goes back to [Miller \(1977\)](#). Miller argues that disagreement about future prospects can lead to overpricing in the presence of short-sale constraints. Subsequent empirical research has explored this argument in great detail. Consistent with the divergence-of-opinion part of Miller’s argument, firms for which the dispersion of analysts’ forecasts of future earnings is high earn lower future stock returns ([Diether, Malloy, and Scherbina, 2002](#), [Danielsen and Sorescu, 2001](#)). Overpricing tends to be most significant if disagreement and short-sale constraints are simultaneously present ([Boehme, Danielsen, and Sorescu, 2006](#)). Shocks in the lending market have predictive power

for future returns (Asquith, Pathak, and Ritter, 2005, Cohen, Diether, and Malloy, 2007). Returns of constrained stocks are substantially negative around earnings announcements, which is consistent with the idea that earnings announcements at least partly resolve disagreement (Berkman, Dimitrov, Jain, Koch, and Tice, 2009). Anomaly returns tend to be concentrated in stocks that are expensive to short (Hirshleifer, Teoh, and Yu, 2011, Drechsler and Drechsler, 2016).<sup>7</sup> In a similar vein, Engelberg, Reed, and Ringgenberg (2018) relate loan fee uncertainty and recall risk to price inefficiencies.

D’Avolio (2002) and Geczy, Musto, and Reed (2002) are early papers that study the lending market using proprietary data. A major takeaway of these studies is that all but a few percent of common stocks can be borrowed at low cost for short selling purposes. Results reported by Kolasinski, Reed, and Ringgenberg (2013) suggest that, among the set of firms with high shorting demand, supply is fairly inelastic, meaning that further increases in borrowing demand lead to substantial increases in borrowing rates.

Our model combines key features of these literature strands in one parsimonious model, makes concrete predictions concerning empirically observable quantities, links the dynamics of disagreement to the price dynamics and stands in the tradition of other models that formalize the idea that divergence-of-opinion combined with short-sale constraints influences asset prices (see, e.g., Harrison and Kreps, 1978, Diamond and Verrecchia, 1987, Duffie, 1996, Chen, Hong, and Stein, 2002, Hong and Stein, 2003, Scheinkman and Xiong, 2003, Gallmeyer and Hollifield, 2007, Ang, Shtauber, and Tetlock, 2013, Hong and Sraer, 2016). Duffie, Gârleanu, and Pedersen (2002) explicitly model the complex search and matching process on the lending market. Our approach is to model the lending market as a market where supply and demand determine equilibrium quantities in the same way as on the stock or a standard goods market, like in the static model of Blocher, Reed, and Van Wesep (2013). This approximation of the complex search process for borrowing stocks in the real world allows us to endogenize borrowing costs in a simple way. Our approach keeps the model

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<sup>7</sup>In contrast, Israel and Moskowitz (2013) provide evidence that momentum, value and size are robust on the long side and thus do not overly rely on short-selling.

as tractable as possible, while still capturing the intertwined supply and demand mechanism on the lending and stock market that we are interested in and that is at the heart of our empirical analysis.

As discussed in more depth in the introduction and the model section, the basis for the psychological biases of our agents is the behavioral finance literature. Our modeling of the slow diffusion of information among *newswatchers* comes from [Hong and Stein \(1999\)](#), as does the assumption that these agents ignore the information impounded in prices. Implicit in our modeling is the assumption that information is costly in terms of effort. [Daniel, Hirshleifer, and Subrahmanyam \(1998\)](#) and [Daniel and Hirshleifer \(2015\)](#) argue that when agents expend effort to extract information, those agents tend to become overconfident about this information, which will lead them to overestimate its precision. This premise is based on the observations that people believe that they are better-than-average in what they are doing (see, e.g., [Svenson, 1981](#)). Our second group of agents is therefore motivated by the *informed overconfident* traders of [Daniel, Hirshleifer, and Subrahmanyam \(1998\)](#). Deeper discussions of how the investor overconfidence assumption emerges from the psychological literature as well as further applications of overconfidence in the financial literature can be found in [Odean \(1998\)](#), [Odean \(1999\)](#), [Daniel, Hirshleifer, and Subrahmanyam \(2001\)](#), [Barber and Odean \(2001\)](#), and [Scheinkman and Xiong \(2003\)](#), among others.

Theories about sort-sale constrained stocks have been approached empirically by utilizing short interest to proxy for constraints or costs in the early literature ([Figlewski, 1981](#), [Asquith and Meulbroek, 1996](#), [Dechow, Hutton, Meulbroek, and Sloan, 2001](#), [Desai, Ramesh, Thiagarajan, and Balachandran, 2002](#)). The use of short interest as a single empirical proxy for constraints has been criticized by [Chen, Hong, and Stein \(2002\)](#), among others. Stocks with high short interest are not constrained if they simultaneously face high lending supply. At the same time, stocks with low short interest can be hard-to-borrow if lending supply is already depleted.

A second set of papers proxies for short-sale constraints with institutional holdings, like mutual fund holdings (Chen, Hong, and Stein, 2002) or residual institutional ownership (Nagel, 2005), the residuals of regressing (a logit-transformation of) institutional ownership onto log-size and log-size squared. The idea is that firms with low institutional holdings are more likely to be constrained. However, similar caveats apply here. Many stocks with close-to-zero short interest may end up getting classified as constrained, even though their short interest is far below the level of institutional ownership, and shorting these stocks is easily possible.

A third set of papers relies directly on loan fees and/or loan quantities (see, e.g., Jones and Lamont, 2002, Cohen, Diether, and Malloy, 2007, Blocher, Reed, and Van Wesep, 2013). While this approach delivers reliable information about constraints, it is not suitable for studies interested in long-term returns. Proprietary data sets rely on short sample periods and even Markit data, probably the most comprehensive source of lending market data these days, does not provide sufficient coverage for our purposes pre-2004.

We therefore follow Asquith, Pathak, and Ritter (2005) and use a combination of low institutional ownership and high short interest as a characteristic of most constrained firms. Our analysis of Markit reported lending fees confirms this finding. For a shorter sub-sample, we can calculate the Markit indicative and average lending fees and find that, for low IOR firms, such fees are about three to five times higher for firms that also have high SIR at the same time, compared to firms with low SIR (see Table D.8 in the Appendix). In contrast, using residual institutional ownership leads to portfolios of firms where the fee is substantially smaller, on average, even when focusing on high SIR firms (see Table D.9, Panel N, in the Appendix). The combined use of low institutional ownership and high short interest is also consistent with our model, the model by Blocher, Reed, and Van Wesep (2013), and the empirical results reported in Asquith, Pathak, and Ritter (2005) and Cohen, Diether, and Malloy (2007).

Most papers in the literature on shorting frictions look at short-term returns up to one month.<sup>8</sup> Nagel (2005) is one of the few studies that also examines long-term returns. While some of his findings are consistent and some of them are inconsistent with our results,<sup>9</sup> the most salient difference between his study and ours is that his short- and long-term returns of constrained winners and losers are far more positive than what we find. We believe that the most likely reason for this difference in magnitudes is that Nagel uses residual institutional ownership as a proxy for short-sale constraints and therefore uses an imperfect proxy for constraints, as discussed above.

Our paper further speaks to the ongoing debate whether or not bubbles are empirically identifiable. The empirical challenge in identifying asset pricing bubbles has been the lack of observability of the fundamental value which leads to the joint hypothesis problem (Fama, 1970). Recent work by Greenwood, Shleifer, and You (2019) shows that sharp price increases of industries, along with certain characteristics of this run-up, help to forecast the probability of crashes and thereby help to identify and time a bubble. Our work adds to this strand of literature, as we show, on an individual stock basis, that price run-ups can be used to forecast low future returns when paired with indications of limits of arbitrage. Consistent with this, previous research shows that short-sale constraints are positively related to the profitability of quantitative strategies designed to exploit mispricing (Hirshleifer, Teoh, and Yu, 2011, Drechsler and Drechsler, 2016, Engelberg, Reed, and Ringgenberg, 2018). Our theoretical

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<sup>8</sup>One reason is that many data sets with detailed information about short selling activities cover just a few years (see, e.g., Boehmer, Jones, and Zhang, 2008, Diether, Lee, and Werner, 2009).

<sup>9</sup>Concretely, Nagel (2005) uses residual institutional ownership (RI) as a proxy for constraints and further decomposes cash-flow news from unexpected stock returns. He then looks at equally-weighted returns of past cash-flow winners and past cash-flow losers with low RI. Roughly consistent with our findings, Nagel finds that low-RI-cash-flow winners have negative cumulative returns over 3 years post-formation, and that low-RI-cash-flow losers have negative cumulative returns over the first year and a roughly zero cumulative return afterwards (see his Figure 1 on page 306). However, Nagel's finding that cash-flow winners *do not* underperform low-RI-stocks without cash-flow news over the first six-months post-formation is inconsistent with our findings. Furthermore, Nagel (2005, page 286) states that the main reason for using residual institutional ownership is the separation of size from institutional ownership effects, as it is well known that return predictability is more pronounced among smaller stocks. In light of this argument, the empirical evidence reported here is even more striking and inconsistent with Nagel's hypothesis, as our constrained winners have larger market capitalizations than our constrained losers, yet still exhibit greater cumulative mispricing and longer mispricing persistence (see Table 1).

and empirical approach can be interpreted as a methodology for identifying individual stock bubbles, and determining the decay rates of these bubbles.

To sum up, our paper is – to the best of our knowledge – the first study that establishes statistically reliable differences in the long-term performance (i.e., mispricing persistence) of constrained winners and losers. Additionally, we offer explanations and test them empirically. Our theoretical focus lies on the discussion of our results’ implications for leading models of momentum and reversals in the behavioral literature.

## 2 Data

We collect monthly and daily return, market capitalization and volume data from the Center for Research in Security Prices (CRSP). Our sample consists of all common ordinary NYSE, AMEX and NASDAQ stocks from 1988/07 through 2018/12.<sup>10</sup>

In the next section, we form portfolios based on a number of firm-specific variables. The first sorting variable is a measure of each firm’s cumulative *past return* from month  $t - 12$  through month  $t - 2$ , relative to formation at the beginning of month  $t$ . This is just the measure of momentum used in [Carhart \(1997\)](#), [Fama and French \(2008\)](#), and numerous other studies.

The second sorting variable, the *institutional ownership ratio (IOR)*, is based on Thomson-Reuters Institutional 13-F filings until June 2013, and on WRDS-collected SEC data after June 2013.<sup>11</sup> We divide the number of shares held by institutions by the number of shares outstanding from CRSP to get the institutional ownership ratio (IOR). We update IOR ev-

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<sup>10</sup>Specifically, we only consider stocks with exchange code 1, 2 or 3, and share code 10 or 11. Returns are adjusted for delisting ([Shumway, 1997](#)) using the CRSP delisting return, where available. Where the delisting return is missing, we follow [Scherbina and Schlusche \(2015\)](#) and assume a delisting return of -100%, or, if the delisting code is 500, 520, 551-573, 574, 580, or 584, we assume a delisting return of -30%.

<sup>11</sup>See note issued by WRDS in May 2017. We perform some data cleaning of the data before using it. For example, we identify some firms with implausibly large jumps in IOR in a given quarter, which are generally followed by roughly equal jumps in opposite direction in the following quarter. We employ a simple procedure to fix this, as described in Appendix [B.II](#).

ery quarter and assume that the holdings data is in the investors' information set with a lag of one month.<sup>12</sup>

The third sorting-variable, the *short-interest ratio* (*SIR*), is constructed based on data from two sources: From June 2003 on, we use Compustat. From June 1988 through June 2003, our short interest data comes directly from the NYSE, AMEX and NASDAQ.<sup>13</sup> The pre-2003/06 data are complemented by Compustat whenever missing, and the post-2003/06 data are complemented with exchange data whenever there is no Compustat record for a given firm-month, but there is an observation available directly from the exchanges.<sup>14</sup> We divide the number of shares held short by the number of shares outstanding from CRSP to get the short-interest-ratio SIR.

### 3 Empirical Results

Our goal is to analyze the long-term price dynamics of short-sale constrained stocks in the presence of large disagreement shocks. To identify stocks with binding short-sale constraints we follow [Asquith, Pathak, and Ritter \(2005\)](#) and independently sort on institutional ownership (IOR) and short-interest (SIR). Thereby we explicitly take into account the supply- and demand-sides of the shorting market ([Cohen, Diether, and Malloy, 2007](#)). Institutional ownership has been shown to be closely related to lending supply (see, e.g., [D'Avolio, 2002](#)). Assuming, for example, that IOR is a direct proxy for easily available lending supply, and it is at 10%, then a SIR of 10% would indicate that easily available supply is exhausted and

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<sup>12</sup>This means that the first trade based on December ownership data is in February of the following year. To avoid data coverage (which increases over time) influencing the sorts, we construct breakpoints excluding the stocks that are in CRSP but are missing ownership data. Following [Nagel \(2005\)](#), stocks with missing ownership are then assigned zero institutional ownership and consequently allocated to the low IOR portfolio.

<sup>13</sup>We apply additional procedures to better match these short interest data with CRSP. This increases the number of firm-month observations, reduces noise and strengthens all results. Details can be found in [Appendix B.II](#).

<sup>14</sup>Exchange data from NYSE starts in September 1991 and for AMEX in 1995. Compustat is used before that. Compustat coverage of NASDAQ is scarce before June 2003, which is why exchange data is the primary source for NASDAQ before that date. Furthermore, data from NASDAQ in February and July 1990 are missing, as pointed out in, e.g., [Hanson and Sunderam \(2014\)](#), and we consequently completely eliminate these months from all analyses. See [Curtis and Fargher \(2014\)](#), [Ben-David, Drake, and Roulstone \(2015\)](#), and, [Hwang and Liu \(2014\)](#) for other papers using these data sources.

short-selling is likely constrained.<sup>15</sup> Furthermore, both IOR and SIR are available from June 1988, allowing us to conduct asset pricing tests of long-term holding returns. To identify the shocks that drive disagreement, at the start of each month  $t$  we sort on each stock’s cumulative return from month  $t - 12$  through month  $t - 2$ .

For all three sorts, i.e., past return (MOM), short-interest (SIR), and institutional ownership (IOR), the breakpoints are the 30th and the 70th percentile. We use independent sorts, in order to get more independent variation in all three variables. This  $3 \times 3 \times 3$  sort provides us with 27 portfolios. Each portfolio is value-weighted, both to avoid liquidity-related-biases associated with equal-weighted portfolios (Asparouhova, Bessembinder, and Kalcheva, 2013), and to ensure that the effect we document is not driven by extremely low market capitalization stocks. We label as *constrained* the set of stocks that are in both the low institutional ownership and high short interest portfolio. Further, we designate firms with high-momentum as *past-winners* ( $W$ ), and those with low-momentum as *past-losers* ( $L$ ). Past-losers and winners which are also constrained get labeled as *constrained-winners* ( $W^*$ ) and *constrained-losers* ( $L^*$ ).

Our focus is on analyzing return patterns at different horizons. The vast majority of the literature on short-sale constrained stocks examines short-horizon returns up to one month.<sup>16</sup> Short-term negative returns could be either a sign of small and temporary mispricing or of large and persistent mispricing. With our goal of understanding the nature of the biases that result in the value and momentum effects, we examine the returns at both short- and long-horizons.

We want to make sure that we do not confound results of constrained losers by unintentionally blending in winners that are in the process of falling.<sup>17</sup> Therefore, we focus on the

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<sup>15</sup>This intuition is reflected in the design of the securities lending market in our model, outlined in more detail in Section A.IV. It is also consistent with the empirical results in Kolasinski, Reed, and Ringgenberg (2013) that search frictions strongly impact the costs of short-selling.

<sup>16</sup>Exceptions are Chen, Hong, and Stein (2002), Nagel (2005), and Lamont (2012).

<sup>17</sup>Results for all constrained losers and the subset of losers that *were* constrained winners within the past 5 years can be found in Appendix D.

constrained losers that *were not* constrained winners within the past 5 years.<sup>18</sup> Our argument is that this subset of losers better reflects the return patterns of short-sale constrained stocks with initially negative news.<sup>19</sup>

### 3.1 Characteristics

[INSERT Table 1 HERE]

Some basic characteristics of our portfolios are reported in Table 1.<sup>20</sup> We can see that, on average, each month, 52 stocks are classified as constrained winners and 39 as constrained losers.<sup>21</sup> The representative constrained winner stock has a market capitalization of \$3.74B. Constrained losers are considerably smaller. The magnitude of the average returns leading up to the formation date are large for the past-winners- and past-loser-portfolios—close to doubling/halving in size over the formation period. Institutional ownership averages 17.21% for all constrained stocks, indicating a good chance of these stocks being hard to borrow. The third sorting variable, short-interest (SIR) shows an average of 7.49%, confirming a pronounced demand for short-selling these stocks.

A firm’s book-to-market ratio can be interpreted as a noisy proxy for mispricing. Table 1 confirms that our identified constrained winners are the most expensive relative to their book-value, with a ratio of 0.29, which is in line with their relative outperformance over the ranking period. In addition to this, the constrained stocks exhibit the largest idiosyncratic volatility, consistent with disagreement among traders.

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<sup>18</sup>In our model, where *ceteris paribus*, winners will lose value over a number of years, will continue to be constrained, and potentially become constrained losers at some point. Such constrained losers are not losers based on a negative information shock, followed by slow information diffusion (as the red profile in Panel D in Figure 5). Rather, these are former constrained winners that are already somewhere in the process of disagreement (and prices) adjusting downwards, through waning overconfidence (e.g., a stock whose price behaves like the red line in Panel B of Figure 5, at period 2 or 3).

<sup>19</sup>Note that the same argument does not apply the other way around, i.e., it is not necessary to split the constrained winners into those that were/were not constrained losers in the past 5 years. The post-formation trajectory of a constrained loser is negative initially and then flat, but never positive—so it can never be classified as a constrained winner.

<sup>20</sup>For a comparison with the broader universe of stocks, averages for the remaining portfolios are displayed in Table D.8 in Appendix D.

<sup>21</sup>In addition to these, there are, on average, 52 constrained losers were that constrained winners at some point in the past 5 years.

To check whether we accurately identify stocks with binding short-sale constraints, the last few rows display the levels and 12-month changes of the Markit indicative and simple average loan fee. It clearly shows that the fees in the constrained portfolios are large, and that they have generally increased leading up to the formation date, again suggesting a high and increased level of disagreement.<sup>22</sup>

As the Markit data are only available from 2004, we calculate two additional measures for the full sample period going back to 1988. The first one is SIRIO, i.e., the number of stocks currently being shorted (short interest) divided by the number of stocks held by institutions (institutional ownership), following [Drechsler and Drechsler \(2016\)](#).<sup>23</sup>

The numbers in [Table 1](#) clearly speak in favor of our combination of low institutional ownership and high short-interest capturing shorting constraints. On average, the constrained winners exhibit a SIRIO of 125.59%, which likely pushes them above the point of cheap lending and makes short-selling these stocks highly expensive. A further proxy for short-sale costs is calculated with options data. Following [Cremers and Weinbaum \(2010\)](#), we display the volatility spread at month-end of matched put/call option pairs. A large negative number indicates a strong deviation from put-call parity in the direction of the put-option being relatively expensive. This has been linked to short-sale constraints by, e.g., [Ofek, Richardson, and Whitelaw \(2004\)](#). Again, all constrained portfolios exhibit large negative values here.

## 3.2 Short-term Performance

[INSERT [Table 2](#) HERE]

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<sup>22</sup>The loan fees displayed here are high, especially compared to the results in [D’Avolio \(2002\)](#), indicating that short-selling our constrained stocks might be prohibitively expensive. However, investors can simply benefit from the insights of this paper by avoiding past constrained winners, when running medium/small-cap momentum strategies, as indicated by [Table D.12](#) in the Appendix.

<sup>23</sup>This measure is also attractive from the perspective of our model, as it has a direct interpretation. It tells us how close or how far above we are to the institutional lending supply threshold. Assuming the unknown fraction of institutions that are willing and able to lend out for free is 100%, for instance, a SIRIO measure above 100% would indicate that the demand for short-selling is larger than institutional lending supply and thus, investors are willing to pay high search costs in order to still be able to short the stock.

We first analyze the short-term returns of these portfolios. Table 2 reports the average monthly excess returns of the 9 winner (Panel A), 9 medium momentum (Panel B) and 9 loser (Panel C) portfolios. Portfolios are displayed according to our triple-sorting procedure: Institutional ownership (IOR), going from high to low, on the x-axis; Short interest (SIR) going from low to high on the y-axis; and past-return, going from winners to losers in Panels A to C. The stocks where we expect the largest overpricing, i.e., those with the lowest institutional ownership and with the largest short-interest (“constrained” stocks), have average monthly excess returns of  $-0.33\%$  and  $-1.77\%$  for winners and losers, respectively. The returns for the most extreme past return portfolios, i.e., constrained winners and constrained losers, are larger in magnitude than those for the constrained medium past-return portfolios.<sup>24</sup>

For winners, short-sale constraints change the sign of the prediction according to both explanations, the additive-effect hypothesis and our model. Indeed, the average return for the corner winners appears particularly low when compared to the other winner portfolios. All other winner portfolios feature large positive excess returns with an average around  $1\%$  per month.<sup>25</sup> Comparing the constrained winners to the high-IOR/high-SIR winners, results in a difference of  $-1.32\%$  per month with a Newey-West  $t$ -statistic of  $-4.37$ . The rightmost column shows the alpha from a Fama-French four-factor regression, which is also highly statistically significant for high SIR stocks. Similarly, taking the low IOR column’s bottom vs. top difference produces an excess return of  $-1.38\%$  per month ( $t$ -statistic  $-3.78$ ), which can also not be explained by the four factors.

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<sup>24</sup>Notice, as shown in Table D.8 in the Appendix, that the majority of stocks is concentrated on the diagonal from bottom-left to top-right, consistent with short-selling being more (less) prevalent where it is easier (more difficult) to implement. The largest stocks are medium IOR, on average, consistent with a u-shaped association between institutional ownership and size, as also evident in the significantly negative squared-log-size regression coefficient reported in equation (2) in Nagel (2005).

<sup>25</sup>At first glance, it may appear as if there is no momentum effect, e.g., when comparing the top-left winners and losers. However, as mentioned in the previous footnote, the majority of stocks is concentrated on the diagonal from bottom-left to top-right, and the largest stocks are found in the medium IOR-buckets. Averaging returns over all but the bottom-right-corner portfolio, there is a significant momentum effect, i.e., winners outperform losers by about 63 BP/month.

The results extend to a holding period of one year. To assess longer-term holding-period returns in a way that realistically reflects a historical investor’s experience, we rely on calendar-time portfolios, as advocated by Fama (1998). In order to make the approach less trading-intensive, and thus even more realistic when taking trading-costs into account, we construct “buy-and-hold” calendar-time portfolios. Each month, we perform the triple-sort, to determine the allocation to the “most recent” portfolio. The investor then invests 1 dollar into this portfolio, and remains invested for  $T = 12$  months. The constrained winner portfolio held in month  $t$  then consists of each of the last 12 constrained winner portfolios formed in months  $t - 12$  up to  $t - 1$ . In contrast to Jegadeesh and Titman (1993), we weight each of the 12 portfolios held by its cumulated dollar value, i.e., we do not rebalance the invested amount for  $T$  (here  $T = 12$ ) months, and the portfolio return calculation reflects a buy-and-hold approach.<sup>26</sup>

[INSERT Table 3 HERE]

Due to the distinction between  $L^{*W}$  and  $L^*$ , which requires us to look back 5 years, to determine if a constrained loser stock had been a constrained winner before, our sample period shrinks by 5 years. Hence, the first time we can invest in our  $T = 12$ -month buy-and-hold strategy is June 1994, i.e., when we were, for the first time, able to allocate stocks into

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<sup>26</sup> Interpreted differently, the numerator of the buy-and-hold weight  $W$  for stock  $i$  in portfolio  $p$  at portfolio formation time  $t - 1$ , is the sum of market equity values ( $ME = PRC * SHROUT$ ) of all  $T$  occurrences at  $(t - \tau)$  this stock was allocated to portfolio  $p$  during the formation period, adjusted for the price change without dividends and adjusted for capital actions (such as splits, issuances or repurchases):

$$W_{i,p,t-1} = \sum_{\tau \in T} ME_{i,t-\tau} RET_{t-\tau,t-1}^x,$$

where  $PRC$  (price),  $SHROUT$  (shares outstanding), and  $RET^x$  (ex-dividend return), are the respective CRSP variables. The weight of stock  $i$  in portfolio  $p$  consisting of stocks  $I_{p,t-1}$  is then  $w_{i,p,t-1} = \frac{W_{i,p,t-1}}{\sum_{j \in I_{p,t-1}} W_{j,p,t-1}}$ .

Traditional equal-weight calendar-time portfolios with overlapping holding-periods, as in Jegadeesh and Titman (1993), can be found in Appendix E.III. We prefer the buy-and-hold specification as it requires less rebalancing and thus minimizes trading costs.

In addition, we also construct a version of the portfolios, where we just include any stock that falls into portfolio  $p$  at any point in time during the formation period (the past 12 months here) weighted by the stock’s market equity at the end of the formation period  $t - 1$ . The main difference to our default buy-and-hold approach is that a stock that fell into a portfolio more than once during the past  $T$  months is only considered once here. The results of this can be found in Appendix E.IV.

Results are robust to both the Jegadeesh and Titman (1993) and the simple value-weight specifications.

the  $W^*$ , and  $L^*$  portfolios for 12 months in a row. Table 3 displays the results. Panel A shows the raw monthly average excess returns as well as the number of months (T), average number of unique stocks per portfolio each month (AvgN) and the Sharpe ratio (SR). Constrained losers ( $L^*$ ) and winners ( $W^*$ ) both have negative alphas (Panels B and C).<sup>27</sup>

Returns of constrained winners and losers are not significantly different from each other (column  $W^*-L^*$ ). Hence, in the first year, there is no difference in the performance of different subgroups of short-sale constrained stocks. Also noteworthy are the loadings of the portfolios on the factors. Both losers and winners covary with growth stocks, consistent with their market prices being relatively high. Furthermore, they all have positive loadings on SMB, and constrained losers load negatively on momentum, while constrained winners seem not to covary significantly with other winners.

[INSERT Figure 2 HERE]

Panel A of Figure 2 plots the time series of cumulative first-year buy-and-hold returns to the  $W^*$  and  $L^*$  portfolios, hedged with respect to the CAPM-Mkt factor over the sample-period.<sup>28</sup> The hedged constrained past-winners and losers fall persistently over the whole sample period, confirming that our effect is not driven by a particular subperiod. An initial investment of \$1,000 into the hedged past winners (losers) is worth \$28.60 (\$2.17) at the end of June 2018.

### 3.3 Long-term Performance

Figure 1 suggests that the predictable negative abnormal returns of the constrained winners ( $W^*$ ) persist longer than do the negative abnormal returns of the constrained loser stocks

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<sup>27</sup>In Table D.6 in Appendix D Panels A and B we regress 12-month buy-and-hold excess returns of  $W^*$  and  $L^*$  on a number of other well-known factors. Their returns cannot be explained by any of the factors—not even a factor that is based on the ratio of short-interest to institutional ownership, as in Drechsler and Drechsler (2016).

<sup>28</sup>Specifically, we calculate the returns to the portfolios for each sample month. We then run a full-sample regression of the portfolio excess returns on Mkt-RF. Then, using the full-sample regression coefficient, we subtract the returns of the zero-investment hedge-portfolio [ $b_{\text{Mkt}}^*(R_{\text{Mkt}}-R_{f,t})$ ] from the respective portfolio excess returns to generate the hedged excess returns. The factor return data comes from Kenneth French’s data library.

( $L^*$ ). In order to assess the statistical significance of the differences in long-term abnormal returns, we focus on years 2–5 post formation. We calculate buy-and-hold returns, as explained in Section 3.2, but instead of holding portfolios formed in months  $t - 12$  to  $t - 1$ , we now hold portfolios formed in months  $t - 60$  to  $t - 13$ , i.e., we skip the most recent year and hold 48 portfolios from the preceding four years.<sup>29</sup>

[INSERT Table 4 HERE]

Table 4 presents the results. The number of stocks is quite large now, e.g., the portfolio of stocks that were constrained winners between 2 and 5 years prior to formation includes, on average, 378 unique stocks. Panel A presents raw excess returns and Sharpe ratios of those portfolios. We see that the portfolio of stocks that were constrained losers between 2 and 5 years before formation do not exhibit a significantly negative alpha. Winners significantly underperform relative to the Fama-French-Carhart model, with an alpha of  $-0.7$  and a  $t$ -statistic of  $-5.18$ .<sup>30</sup> The difference in abnormal returns between  $W^*$  and  $L^*$  is  $-0.9\%$  per month with a  $t$ -statistic of  $-3.7$ .<sup>31</sup> In Panel B of Figure 2, we see that the long-term return patterns are consistent over the whole sample period and the results are not driven by a particular sub-sample.

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<sup>29</sup>Each month, the most recent (12-month old) constrained portfolio is added with \$1 and then no adjustment is made to the investment amount for the remaining 48 months of holding. The first holding-month is June 1998, i.e., the first time when we were able to determine portfolio membership for 48 months in a row.

<sup>30</sup>A 60-month buy-and-hold portfolio of constrained winners, that does not skip the first 12 months after formation, yields a four-factor Information Ratio of  $-0.85$  (see Appendix D Table D.5). Such a portfolio has 434 unique stocks in it. Moreover, using the simple value-weight approach, described in footnote 26, a strategy using allocation between months  $t - 60$  and  $t - 1$  generates a four-factor Information Ratio of  $-1.1$ .

<sup>31</sup>In Table D.4 in Appendix D we contrast  $L^*$  with a portfolio of constrained losers that *were* constrained winners in the 5 years before they became constrained losers ( $L^{*W}$ ).  $L^{*W}$  has a negative (albeit insignificant) alpha. The difference between the two is significant at the 5% level. Moreover, spanning tests, shown in Table D.7 show that constrained winners help explain the long-run returns of *all* constrained losers, whereas the opposite is not true. The result holds for raw returns as well as when the the three Fama and French (1993) factors and momentum are included. Both of this is consistent with the  $L^{*W}$  stocks (i.e., those constrained losers that were constrained winners within the past 5 years) driving the low long-run returns of the combined constrained loser portfolio ( $L^{*all}$ ).

### 3.4 Matching

The exercise that we have carried out so far is to show that constrained past-winners and losers exhibit return behavior that is distinct from unconstrained past-winners and losers. One could argue that, in selecting constrained firms, the fact that these firms are constrained is not primitive, i.e., there is some other characteristic that leads these firms to be constrained and that also drives the return patterns we observe. For example, previous literature argues that short-interest is a proxy for informed demand and thus predicts future returns (Boehmer, Jones, and Zhang, 2008, Boehmer, Huszar, and Jordan, 2010, Engelberg, Reed, and Ringgenberg, 2012, Rapach, Ringgenberg, and Zhou, 2016); it is possible that it is the level of short-interest that is driving the return patterns we see. Our constrained firms also tend to be small, past-winners tend to be low-book-to-market, and past-losers tend to be high-book-to-market.

To examine this possibility, we employ a matching approach to identify a benchmark portfolio that contains firms which are as close to identical as possible to the firms in our constrained portfolio on the dimensions of size, short-interest, past-return, and book-to-market, *except that* these are *not* short-sale constrained. For each stock in the constrained winner portfolio ( $W^*$ ) and the constrained loser portfolio ( $L^*$ ), we run a matching procedure based on the Mahalanobis (1936) distance to find a statistical twin stock in a universe of unconstrained potential matches. We limit the unconstrained matching universe to be stocks above the 70% quantile of institutional ownership and to fall within the corresponding past-return bucket. For the losers, we also impose the potential matches not to have been a constrained winner stock within the past five years. We then identify, in each month, for each constrained winner (loser), the nearest neighbor based on the Mahalanobis distance considering our four matching dimensions: size, short-interest, past-return, and book-to-market.<sup>32</sup>

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<sup>32</sup>We thank our discussant Adam Reed for suggesting to use short-interest as a matching variable. In Appendix E.I we redo this exercise with an alternative set of matching variables, i.e., size, book-to-market,

The last two columns in Table 1 reveal that the value-weighted portfolios of matched stocks for  $W^*$  and  $L^*$ , i.e.,  $W_m^*$  and  $L_m^*$ , are similar along the matching dimensions. They differ substantially in all proxies for short-sale constraints, such as SIRIO, volatility spread, and Market loan-fees. Thus, it looks like they may be well-suited to uncover differences that are solely based on the fact that one set of firms is short-sale constrained while the other one is not. If our matching variables are responsible for the observed patterns of constrained winners and losers, the performance differential between a portfolio long constrained and short unconstrained winners and another portfolio that is long constrained and short unconstrained losers should be equal.

Table 3 shows that both the constrained winners and losers significantly underperform their matched unconstrained peers. The difference-in-differences (*DiD*) of the short-term performance is statistically indistinguishable from zero. That confirms that there is no asymmetric effect of short-sale constraints in the short-run, even controlling for our additional matching dimensions.

However, the picture changes for the following four years (Table 4): Constrained winners significantly underperform unconstrained ones, whereas constrained and unconstrained losers exhibit very similar returns. The difference-in-differences is statistically significant, also when controlling for the market (Panel B) or the four Fama-French-Carhart factors (Panel C). Consequently, we reject the set of hypotheses postulating that our matching variables are responsible for the observed asymmetry in mispricing persistence, including the additive-effect hypothesis and informed demand as proxied by short-interest.

[INSERT Figure 3 HERE]

Figure 3 adds more background to the matching approach. It shows the buy-and-hold performance of the constrained and matched portfolios on a year-by-year basis.<sup>33</sup> While

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idiosyncratic volatility and past-return. The results are very similar. Matching based on propensity scores instead of Mahalanobis distances also produces very similar results (available upon request).

<sup>33</sup>Specifically, we calculate the buy-and-hold return, as explained in Section 3.2 for the first holding-year, for each following year, in the same fashion. We then run a time-series regression of the monthly excess returns of these 12-month buy-and-hold portfolios on the CAPM-Mkt factor. The annualized alpha as well

the constrained stocks show distinct and significant patterns of mispricing, the matched portfolios’ returns can always be explained by the CAPM.<sup>34</sup> Note that constrained winners underperform significantly relative to the CAPM for *each* of the five years following formation (Panel A), whereas constrained losers only exhibit a significantly negative alpha in the first year (Panel B). This visual assessment is consistent with the time-series regressions presented throughout the paper.

One final concern with this matching procedure is the fact that our matched firms have much higher levels of institutional ownership. Indeed, all of our constrained firms are by definition firms with low institutional ownership and high short interest. Therefore, a firm which is matched on short interest and on other dimensions but is also unconstrained will necessarily have high institutional ownership. In this sense, we are treating institutional ownership as if it is somewhat exogenous. Of course, this is not the case. However, the argument that we are instead making is that institutional ownership does not influence the return patterns that we observe *except for* firms that also have high short interest.

Indeed, the relation between institutional ownership and future returns is examined in Panels A, B and C of Table 2. Focus on the rows labeled “Lo SIR”, i.e., the portfolios which have low short interest. For firms with low short interest, this table shows that there is no statistically significant difference between the high IOR and the low IOR portfolio average returns or alphas. That is, institutional ownership is unrelated to expected future returns or risk-adjusted returns (alphas). This is true whether the firm is a past winner, a past loser, or is in the “medium momentum” portfolio. However, the rows of the table labeled “Hi SIR” show that, among high short interest firms, institutional ownership strongly forecasts future returns for past-winners and past-losers.

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as the 95% confidence interval, constructed based on Newey-West standard errors, are plotted for each year after formation.

<sup>34</sup>Note that we cannot reject the hypotheses that the average 1st-year returns of the matched winners and losers in Figure 3 are equal to those of the winners and losers in the full sample plotted in Figure 1 Panel A and tabulated in Table D.1. The  $p$ -values from Welch-two-sample- $t$ -tests are  $p = 0.9$  for winners and  $p = 0.64$  for losers.

Thus, it is clear from this table that institutional ownership does not forecast future returns *except* among high short interest firms.<sup>35</sup> What we are arguing is that whatever the factors are that drive institutional ownership, when low institutional ownership firms experience disagreement shocks, and short interest jumps up to the point that these firms become constrained, this leads to the return patterns that we observe. For a firm that has high institutional ownership, the disagreement shocks do not result in these return patterns because the firms do not become constrained. In this section, we have identified firms with close-to-identical size, short interest, past-return and book-to-market, but high instead of low IOR. Clearly, only firms that have low IOR *and* high SIR at the same time exhibit the distinct return patterns that we highlight in this paper.

### 3.5 Fama-MacBeth Regressions

[INSERT Table 5 HERE]

We assess the robustness of our results by running Fama-MacBeth regressions.<sup>36</sup> To see whether returns of constrained winners are different than those of the other constrained stocks, turn to the coefficient on *having been a constrained winner during the past 5 years (except for the most recent 12 months)* in Table 5 Panel B, labeled “Constr.W”. It is significantly different from zero, whereas, neither the coefficient for having been a constrained loser (“Constr.L”) nor the coefficient for having been any type of constrained stock (“Constr.”) is (columns 2-3).<sup>37</sup> Hence, controlling for stocks being past (i.e., between months  $t - 60$  and  $t - 13$ ) constrained winners, constrained losers do not exhibit abnormally low long-term returns, confirming the results in Table 4.

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<sup>35</sup>Note that the same conclusions apply for longer holding-periods, as examined throughout the paper. Tables D.10 and D.11 document these results in a similar way as Table 2 does.

<sup>36</sup>Observations are weighted by the previous month’s market cap in cross-sectional weighted-least-squares regressions, to alleviate the influence of extremely small stocks on the results (see, e.g., Green, Hand, and Zhang, 2017).

<sup>37</sup>Note, however, that including the dummies for being a constrained stock in the past and being a constrained winner/loser in the past in the same regression, imposes a multicollinearity problem (as every constrained winner/loser is also constrained, and there are few constrained stocks, that were never a winner/loser at any point during the 48-month look-back-period). Hence, test-power for individual coefficients declines.

The result is robust to including well-known return predictors such as past return, the log-book-to-market ratio, log-size and idiosyncratic volatility (column 4). Even if we include the ratio of short interest to institutional ownership (SIRIO, as in [Drechsler and Drechsler, 2016](#)), as a proxy for current difficulty of short-selling, constrained past-winners underperform other constrained stocks (column 5) and all other stocks (column 6) significantly. In contrast, Panel A shows that both constrained winners and losers of the previous 12 months underperform, and the seemingly stronger underperformance of losers (column 2) disappears once the control variables are included.<sup>38</sup>

Taken together, these results are inconsistent with the additive-effect hypothesis and consistent with the predictions of our model.

### 3.6 Earnings Announcements

One point in time when disagreement is likely to be resolved is when firms announce their earnings (see, e.g., [Berkman, Dimitrov, Jain, Koch, and Tice, 2009](#)), which usually happens once per quarter. Disagreement-based explanations of the performance of constrained stocks predict that negative abnormal returns are concentrated in times of decreasing disagreement.

[INSERT Figure 4 HERE]

Figure 4 displays average cumulative abnormal returns (ACAR) of constrained winners and losers around earnings announcements, for stocks selected to one of the portfolios in the previous year (Panel A) or the 4 years preceding that year (Panel B). Daily abnormal return is defined as the return adjusted for the CAPM-MktRF factor.<sup>39</sup> Constrained winners and losers fall considerably on the first five days following the announcement for stocks selected in the preceding 12 months, and continue to underperform thereafter (Panel A). For stocks where the portfolio allocation dates back more than a year, a much stronger reaction can be

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<sup>38</sup>Notice that we lose the months March and August 1990, where NASDAQ short-interest data are missing in the respective previous month, when we use  $SIRIO_{t-1}$  as a control (columns 5-6) in Panel A. Since the sample in Panel B starts in 1993/06 due to the longer look-back-period for constraints, no observations are lost in specifications 5-6.

<sup>39</sup>The calculation of abnormal returns is explained in detail in Appendix [B.III](#).

observed for winners than for losers. Moreover, the pre-announcement rise is larger than the post-announcement drop for losers in Panel B.

## 4 Model

The empirical work presented in Section 3 suggests that the dynamics of equity prices for firms which are short-sale constrained are distinctly different from those of unconstrained firms. In particular, among constrained firms, the portfolio of past-winners earns significant negative risk-adjusted returns for 5 years following portfolio formation. In contrast, the portfolio of constrained past-losers earns an alpha indistinguishable from zero from 2–5 years post-formation. This strong asymmetry in mispricing persistence between constrained winners and losers is inconsistent with existing explanations and with straight-forward extensions of these explanations.

In this section, we propose a heterogeneous agents model in which agents differ in the way they process new information about firms. This model is completely consistent with value and momentum effects for unconstrained firms, but also matches the observed asymmetry between constrained past-winners and losers. We present an overview of the model and illustrate the main intuitions using a numerical example. A detailed and formal description of the model can be found in Appendix A.

The equilibrium price of an asset is the price at which all agents believe their holdings to be optimal. In heterogeneous agents models with frictionless markets and risk-averse agents who ignore the information contained in prices, the equilibrium price is a linear function of the weighted average of the beliefs held by these agents (see, e.g., the discussion of the competitive equilibrium in Chapter 12 of [Campbell, 2018](#)). Short-sale costs can partly or fully sideline some of these agents, leading to a different equilibrium price that no longer fully reflects the beliefs of all market participants.<sup>40</sup>

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<sup>40</sup>By “sideline,” we mean here that the agent would choose to short the security in the absence of the costs of borrowing. Agents may be partly sidelined, in the sense that they short less of the security than they

In our model, heterogeneous agents with constant absolute risk aversion (CARA) trade an asset that will pay a liquidating dividend in period  $T$  that is the sum of dividend innovations about the firm observed each period from  $t = 1, \dots, T$ . Agents may disagree about the mean and the variance of these dividend innovations, but as these agents observe the innovations each period they update their priors.

For modeling convenience, we follow recent behavioral models (see, e.g., [Barberis, Greenwood, Jin, and Shleifer, 2018](#), [Da, Huang, and Jin, 2019](#)) in assuming that each period  $t$ , each agent maximizes her utility as of period  $t + 1$ . To solve this portfolio optimization, each agent needs to determine the distribution of the equilibrium price in period  $t + 1$ , which will be based on the beliefs of all agents in the economy. We assume that, in calculating this distribution, each agent makes the strong assumption that disagreement will be resolved in the following period in such a way that all other agents will come to agree with her. This makes the solution far more tractable, and moreover is consistent with the “illusion of validity” of [Kahneman and Tversky \(1973\)](#).<sup>41</sup> In other words, agents believe that their views are correct, and that others will figure that out sooner rather than later.

A key model feature that drives our results is that access to private information is paired with overconfidence. Motivated by this, in our model there are two types of agents. The first set of agents are informed *overconfident* agents. They receive all new information immediately. Consistent with [Daniel, Hirshleifer, and Subrahmanyam \(1998\)](#) and [Gervais and Odean \(2001\)](#), this access to information makes them overconfident about the signal they receive, in that they assess the signal precision to be higher than it actually is.

The second set of agents—who we label *newswatchers*—are similar to the newswatchers of [Hong and Stein \(1999\)](#) in that the new information (that the informed observe immediately) slowly diffuses through the population of newswatchers. Crucially, we follow [Hong and](#)

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otherwise would, or fully sidelined in the sense that they choose not to participate at all (i.e., to short zero shares).

<sup>41</sup>[Kahneman and Tversky \(1973\)](#) suggest the term illusion of validity for the observation that “people are prone to experience much confidence in highly fallible judgments.” [Kahneman \(2011\)](#) links this illusion to the financial industry (see pages 212 to 216 for a discussion on what Kahneman calls “the illusion of stock-picking skills”).

Stein (1999) in assuming that newswatchers ignore the information content of prices; that is they fail to infer informed agents' signals from prices. Slow information diffusion has been put forward as an explanation of shorter-term momentum effects (Hong and Stein, 1999), while the resolution of overconfidence has been used to explain longer-term value effects (Daniel, Hirshleifer, and Subrahmanyam, 1998). Consistent with this, we assume that the resolution of overconfidence requires more time than the information diffusion process, and show that the interaction of newswatchers and overconfident agents generates standard short-term momentum and long-term value effects for unconstrained stocks.

The intuition for the key model implications is straightforward. First, consider an unconstrained stock for which there is strong positive news about cashflows. This information is first observed by the informed (and overconfident) agents who, by virtue of their overconfidence, put too much weight on the information. The newswatchers do not initially receive this information, and moreover ignore the information content of prices. Thus, the price moves up as the overconfident agents buy and the newswatchers sell. Moreover, as the new information diffuses through the population of newswatchers, the price moves up further, generating momentum, and overreaction because of the informed agents' overconfidence. Finally, as more information is released, the overreaction is corrected, producing a value effect. For unconstrained stocks, the momentum/value effect is symmetric for positive or negative information releases. This is not the case for constrained stocks.

For constrained stocks that become “winners” as a result of a strong positive information release, newswatchers will be sidelined. This implies that price dynamics largely follow the belief dynamics of overconfident agents and these firms quickly become overpriced. The resolution of overconfidence takes as long as for unconstrained stocks, resulting in low long-term returns for these stocks.

For constrained firms that become “losers” as a result of bad news about cashflows, it will generally be the overconfident agents who will be sidelined, and the newswatchers will therefore set prices. These loser stocks are overpriced as well, as the negative information

diffuses slowly into the price. However, in contrast to constrained winners, strong negative returns of constrained losers will only be observed over the short time period over which information diffuses.

Thus, our model, which produces standard value and momentum effects for unconstrained stocks, suggests that for constrained stocks, there will be no momentum effect for winners, but an exaggerated momentum effect for losers. Our model further suggests that both, constrained winners and constrained losers, earn strong negative future returns. An interesting implication of our model is that, for the past-loser firms, overpricing will be eliminated over the short horizon over which momentum is observed, i.e. about 1 year. For the past-winner firms, the elimination of overpricing will take as long as value effects, i.e. about five years. These predictions are consistent with the empirical findings documented in Section 3.

[INSERT Figure 5 HERE]

To illustrate the intuitions of the model, consider winners and losers for two extreme cases: either a stock can be shorted without any costs (unconstrained) or a stock cannot be shorted at all (constrained). Panel A of Figure 5 shows the evolution of posterior beliefs over time  $t$  of overconfident agents  $\mathbb{E}_{O_t}[D_T]$  and newswatchers  $\mathbb{E}_{N_t}[D_T]$  about the liquidating dividend  $D_T$ , as well as the rational expectation beliefs of a Bayesian who sees the dividend innovations of the overconfident agents. By construction, our stock is a winner stock in the sense that the firm experiences a large positive dividend innovation, “good news”, in the first period. Overconfident agents see all the information first, interpret it as private, overreact on it, and become far too optimistic about the value of the final liquidating dividend  $D_T$ . Over time, the overconfident agents learn (slowly) from further dividend innovations and converge towards the Bayesian price expectation. In contrast, it takes three periods for the newswatcher to see all the positive information that the overconfident agents see in the first period. However, they do not overreact, and, as a consequence, their belief step-wise approaches the rational expectation belief. In period  $t = 3$ , beliefs of newswatchers and rational expectation beliefs finally coincide.

What are the consequences for asset prices? For unconstrained assets (unconstrained winners in Panel B), our heterogeneous agent model states that the equilibrium price is simply a weighted average of single beliefs. As a consequence and given the beliefs of overconfident agents and newswatchers, the asset price in an unconstrained market, the blue line in Panel B of Figure 5, is the weighted average of the beliefs shown in Panel A. Overconfident agents are long, while newswatchers are short in the stock. The price path exhibits short-term momentum caused by slow information diffusion among the newswatchers (as in [Hong and Stein, 1999](#)). After newswatchers have learned the Bayesian expectation, the stock is overpriced, as overconfident agents are still too optimistic (as in [Daniel, Hirshleifer, and Subrahmanyam, 1998](#)) about the final liquidating dividend  $D_T$ . The overpricing vanishes in the long run, consistent with long-term value effects.<sup>42</sup>

The dynamics of prices are fundamentally different for a constrained winner. The opinions from the newswatchers, who are the pessimists in the case of “good news,” are now completely sidelined from the market and the overconfident agents are setting the price. As a consequence, the price overshoots with the large dividend innovation in period  $t = 1$ . We do not see a momentum effect. The source of the momentum effect, slow information diffusion, plays no role in the price setting process, as newswatchers’ beliefs are no longer reflected in the market price. The stock experiences long-term negative returns caused by the slow resolution of overconfidence.

Panels C and D of Figure 5 show beliefs and prices for a loser stock. The assumptions of our example are unchanged, except that all information is multiplied with  $-1$ . Beliefs in Panel C and the dynamics of prices of an unconstrained loser mirror the beliefs and price dynamics of an unconstrained winner. The overconfident agents, who overreact on the large negative surprise in the first period, are now the pessimists and short the stock. Short-term

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<sup>42</sup>Note that we have deliberately chosen a calibration of our model that predicts a short-term momentum and a long-term value effect for unconstrained stocks. It is possible to choose extreme parameterization, where there are no such effects. However, such calibrations are clearly inconsistent with the large empirical evidence on momentum and value for unconstrained stocks.

momentum is again caused by slow information diffusion and long-term value has its roots in the resolution of overconfidence over time.

The symmetry between winners and loser breaks down for the constrained case. The friction sidelines the opinion of pessimists, who are now, in the case of negative news, the overconfident agents (Panel C). The dynamics of prices reflect the newswatchers' dynamics of beliefs (Panel D). An exaggerated momentum effect results, as prices in the first and the second period are higher than they would be in the unconstrained case. After the newswatchers have seen all the negative information, there is no value effect. The opinions of pessimistic overconfident agents, who are causing the value effect in the unconstrained case, are still sidelined from the market valuation.<sup>43</sup>

## 5 Conclusion

We document a strong asymmetry in mispricing persistence between constrained winners and constrained losers. While constrained losers exhibit no abnormal returns one year after portfolio performance, constrained winners continue to underperform for another four years. The overpricing of constrained winners is economically large: they lose more than 50% relative to the market over the first 5 years post formation.

Our empirical results are inconsistent with previous explanations of constrained stocks' return patterns. While these explanations can account for the short-term performance of constrained winners and losers, they fail to account for the observed differences in mispricing persistence.

Straight-forward extensions of behavioral models originally designed to capture momentum and value for unconstrained stocks are also unable to explain the asymmetric patterns observed in the data. Neither the [Daniel, Hirshleifer, and Subrahmanyam \(1998\)](#) nor the [Barberis, Shleifer, and Vishny \(1998\)](#) models can capture the empirically observed asymme-

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<sup>43</sup>Note that in a setting where short-selling is costly but not impossible, we would see a value effect for a constrained loser. However, the effect would be smaller than in the unconstrained case, as the beliefs of overconfident agents would be partly sidelined.

try between constrained winners and constrained losers — a heterogeneous agent model is necessary. Also, the [Hong and Stein \(1999\)](#) model with momentum traders cannot explain the results, as this would imply the existence of winner momentum for constrained stocks, which is not present. However, by combining some of the key ingredients of these papers in one parsimonious heterogeneous agents model, we are able to explain the observed asymmetric behavior of both constrained and unconstrained stocks, for positive and negative news shocks, respectively.

For future research, our analysis suggests that short-sale constraints can be used as a unique testing ground for heterogeneous agents models, as their predictions for constrained and unconstrained assets will typically differ, when some agents are sidelined from the market. Understanding how prices of constrained stocks are set may help us learn about how prices are set in general.

## References

- Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang, 2006, “The Cross-Section of Volatility and Expected Returns,” *Journal of Finance*, 61(1), 259–299.
- Ang, A., A. A. Shtauber, and P. C. Tetlock, 2013, “Asset Pricing in the Dark: The Cross-Section of OTC Stocks,” *Review of Financial Studies*, 26(12), 2985–3028.
- Asness, C. S., T. J. Moskowitz, and L. H. Pedersen, 2013, “Value and Momentum Everywhere,” *Journal of Finance*, 68(3), 929–985.
- Asparouhova, E., H. Bessembinder, and I. Kalcheva, 2013, “Noisy Prices and Inference Regarding Returns,” *Journal of Finance*, 68(2), 665–714.
- Asquith, P., and L. Meulbroek, 1996, “An Empirical Investigation of Short Interest,” Harvard Business School Working Paper.
- Asquith, P., P. A. Pathak, and J. R. Ritter, 2005, “Short Interest, Institutional Ownership, and Stock Returns,” *Journal of Financial Economics*, 78(2), 243–276.
- Baker, M., and J. Wurgler, 2002, “Market Timing and Capital Structure,” *Journal of Finance*, 57(1), 1–32.
- Barber, B. M., and J. D. Lyon, 1997, “Detecting Long-Run Abnormal Stock Returns: The Empirical Power and Specification of Test Statistics,” *Journal of Financial Economics*, 43(3), 341–372.

- Barber, B. M., and T. Odean, 2001, “Boys will be Boys: Gender, Overconfidence, and Common Stock Investment,” *Quarterly Journal of Economics*, 116(1), 261–292.
- Barberis, N., R. Greenwood, L. Jin, and A. Shleifer, 2018, “Extrapolation and Bubbles,” *Journal of Financial Economics*, 129(4), 203–227.
- Barberis, N., A. Shleifer, and R. Vishny, 1998, “A Model of Investor Sentiment,” *Journal of Financial Economics*, 49(3), 307–343.
- Ben-David, I., M. S. Drake, and D. T. Roulstone, 2015, “Acquirer Valuation and Acquisition Decisions: Identifying Mispricing Using Short Interest,” *Journal of Financial and Quantitative Analysis*, 50(1-2), 1–32.
- Ben-David, I., J. R. Graham, and C. R. Harvey, 2013, “Managerial Miscalibration,” *Quarterly Journal of Economics*, 128(4), 1547–1584.
- Berkman, H., V. Dimitrov, P. C. Jain, P. D. Koch, and S. Tice, 2009, “Sell on the News: Differences of Opinion, Short-sales Constraints, and Returns around Earnings Announcements,” *Journal of Financial Economics*, 92(3), 376–399.
- Blocher, J., A. V. Reed, and E. D. Van Wesep, 2013, “Connecting two Markets: An Equilibrium Framework for Shorts, Longs, and Stock Loans,” *Journal of Financial Economics*, 108(2), 302–322.
- Boehme, R. D., B. R. Danielsen, and S. M. Sorescu, 2006, “Short Sale Constraints, Differences of Opinion, and Overvaluation,” *Journal of Financial and Quantitative Analysis*, 41(2), 455–487.
- Boehmer, E., Z. R. Huszar, and B. D. Jordan, 2010, “The Good News in Short Interest,” *Journal of Financial Economics*, 96(1), 80–97.
- Boehmer, E., C. M. Jones, and X. Zhang, 2008, “Which Shorts Are Informed?,” *Journal of Finance*, 63(2), 491–527.
- Brandt, M. W., 2010, “Portfolio Choice Problems,” in *Handbook of Financial Econometrics: Tools and Techniques*, ed. by Y. Aït-Sahalia, and L. P. Hansen, pp. 269–336. North-Holland.
- Campbell, J. Y., 2018, *Financial Decisions and Markets: A Course in Asset Pricing*. Princeton University Press, Princeton, NJ.
- Carhart, M. M., 1997, “On Persistence in Mutual Fund Performance,” *Journal of Finance*, 52(1), 57–82.
- Chen, J., H. Hong, and J. C. Stein, 2002, “Breadth of Ownership and Stock Returns,” *Journal of Financial Economics*, 66(2-3), 171–205.
- Chui, A. C. W., S. Titman, and K. C. J. Wei, 2010, “Individualism and Momentum around the World,” *Journal of Finance*, 65(1), 361–392.

- Cohen, L., K. B. Diether, and C. J. Malloy, 2007, “Supply and Demand Shifts in the Shorting Market,” *Journal of Finance*, 62(5), 2061–2096.
- Cremers, M., and D. Weinbaum, 2010, “Deviations from Put-Call Parity and Stock Return Predictability,” *Journal of Financial and Quantitative Analysis*, 45(2), 335–367.
- Curtis, A., and N. L. Fargher, 2014, “Does Short Selling Amplify Price Declines or Align Stocks with Their Fundamental Values?,” *Management Science*, 60(9), 2324–2340.
- Da, Z., X. Huang, and L. Jin, 2019, “Extrapolative Beliefs in the Cross-Section: What Can We Learn from the Crowds?,” Working Paper.
- Daniel, K., and D. Hirshleifer, 2015, “Overconfident Investors, Predictable Returns, and Excessive Trading,” *Journal of Economic Perspectives*, 29(4), 61–88.
- Daniel, K., D. Hirshleifer, and A. Subrahmanyam, 1998, “Investor Psychology and Security Market Under- and Overreactions,” *Journal of Finance*, 53(6), 1839–1885.
- , 2001, “Overconfidence, Arbitrage, and Equilibrium Asset Pricing,” *Journal of Finance*, 56(3), 921–965.
- Daniel, K., and S. Titman, 2006, “Market Reactions to Tangible and Intangible Information,” *Journal of Finance*, 61(4), 1605–1643.
- Danielsen, B. R., and S. M. Sorescu, 2001, “Why Do Option Introductions Depress Stock Prices? A Study of Diminishing Short Sale Constraints,” *Journal of Financial and Quantitative Analysis*, 36(4), 451.
- D’Avolio, G., 2002, “The Market for Borrowing Stock,” *Journal of Financial Economics*, 66(2-3), 271–306.
- Dechow, P. M., A. P. Hutton, L. Meulbroek, and R. G. Sloan, 2001, “Short-sellers, Fundamental Analysis, and Stock Returns,” *Journal of Financial Economics*, 61(1), 77–106.
- Desai, H., K. Ramesh, S. R. Thiagarajan, and B. V. Balachandran, 2002, “An Investigation of the Informational Role of Short Interest in the Nasdaq Market,” *Journal of Finance*, 57(5), 2263–2287.
- Diamond, D. W., and R. E. Verrecchia, 1987, “Constraints on Short-selling and Asset Price Adjustment to Private Information,” *Journal of Financial Economics*, 18(2), 277–311.
- Diether, K. B., K.-H. Lee, and I. M. Werner, 2009, “Short-Sale Strategies and Return Predictability,” *Review of Financial Studies*, 22(2), 575–607.
- Diether, K. B., C. J. Malloy, and A. Scherbina, 2002, “Differences of Opinion and the Cross-Section of Stock Returns,” *Journal of Finance*, 57(5), 2113–2141.
- Drechsler, I., and Q. F. Drechsler, 2016, “The Shorting Premium and Asset Pricing Anomalies,” NBER Working Paper W20282.

- Duffie, D., 1996, “Special Repo Rates,” *Journal of Finance*, 51(2), 493–526.
- Duffie, D., N. Gârleanu, and L. H. Pedersen, 2002, “Securities Lending, Shorting, and Pricing,” *Journal of Financial Economics*, 66(2-3), 307–339.
- Engelberg, J., A. V. Reed, and M. Ringgenberg, 2018, “Short Selling Risk,” *Journal of Finance*, 73(2), 755–786.
- Engelberg, J. E., A. V. Reed, and M. C. Ringgenberg, 2012, “How are Shorts Informed?,” *Journal of Financial Economics*, 105(2), 260–278.
- Fama, E. F., 1970, “Efficient Capital Markets: A Review of Theory and Empirical Work,” *Journal of Finance*, 25(2), 383–417.
- , 1998, “Market Efficiency, Long-Term Returns, and Behavioral Finance,” *Journal of Financial Economics*, 49(3), 283–306.
- Fama, E. F., and K. R. French, 1993, “Common Risk Factors in the Returns on Stocks and Bonds,” *Journal of Financial Economics*, 33(1), 3–56.
- , 2008, “Dissecting Anomalies,” *Journal of Finance*, 63(4), 1653–1678.
- Fama, E. F., and J. D. MacBeth, 1973, “Risk, Return, and Equilibrium: Empirical Tests,” *Journal of Political Economy*, 81(3), pp. 607–636.
- Figlewski, S., 1981, “The Informational Effects of Restrictions on Short Sales: Some Empirical Evidence,” *Journal of Financial and Quantitative Analysis*, 16(4), 463.
- Gallmeyer, M., and B. Hollifield, 2007, “An Examination of Heterogeneous Beliefs with a Short-Sale Constraint in a Dynamic Economy,” *Review of Finance*, 12(2), 323–364.
- Geczy, C. C., D. K. Musto, and A. V. Reed, 2002, “Stocks are Special too: An Analysis of the Equity Lending Market,” *Journal of Financial Economics*, 66(2-3), 241–269.
- Gervais, S., and T. Odean, 2001, “Learning to Be Overconfident,” *Review of Financial Studies*, 14(1), 1–27.
- Graham, J. R., and C. R. Harvey, 2001, “The Theory and Practice of Corporate Finance: Evidence from the Field,” *Journal of Financial Economics*, 60(2), 187–243.
- Green, J., J. R. M. Hand, and F. Zhang, 2017, “The Characteristics that Provide Independent Information about Average U.S. Monthly Stock Returns,” *Review of Financial Studies*, 30(12), 4389–4436.
- Greenwood, R., A. Shleifer, and Y. You, 2019, “Bubbles for Fama,” *Journal of Financial Economics*, 131(1), 20–43.
- Hanson, S. G., and A. Sunderam, 2014, “The Growth and Limits of Arbitrage: Evidence from Short Interest,” *Review of Financial Studies*, 27(4), 1238–1286.

- Harrison, J. M., and D. M. Kreps, 1978, “Speculative Investor Behavior in a Stock Market with Heterogeneous Expectations,” *Quarterly Journal of Economics*, 92(2), 323.
- Hirshleifer, D., S. H. Teoh, and J. J. Yu, 2011, “Short Arbitrage, Return Asymmetry, and the Accrual Anomaly,” *Review of Financial Studies*, 24(7), 2429–2461.
- Hong, H., T. Lim, and J. C. Stein, 2000, “Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies,” *Journal of Finance*, 55(1), 265–295.
- Hong, H., and D. Sraer, 2016, “Speculative Betas,” *Journal of Finance*, 71(5), 2095–2144.
- Hong, H., and J. C. Stein, 1999, “A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets,” *Journal of Finance*, 54(6), 2143–2184.
- , 2003, “Differences of Opinion, Short-Sales Constraints, and Market Crashes,” *Review of Financial Studies*, 16(2), 487–525.
- Hwang, B.-H., and B. Liu, 2014, “Short Sellers’ Trading on Anomalies,” Working Paper.
- Israel, R., and T. J. Moskowitz, 2013, “The Role of Shorting, Firm Size, and Time on Market Anomalies,” *Journal of Financial Economics*, 108(2), 275–301.
- Jegadeesh, N., and S. Titman, 1993, “Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency,” *Journal of Finance*, 48(1), 65–91.
- , 2001, “Profitability of Momentum Strategies: An Evaluation of Alternative Explanations,” *Journal of Finance*, 56(2), 699–720.
- Johnson, T. C., 2004, “Forecast Dispersion and the Cross Section of Expected Returns,” *Journal of Finance*, 59(5), 1957–1978.
- Jones, C. M., and O. A. Lamont, 2002, “Short-sale Constraints and Stock Returns,” *Journal of Financial Economics*, 66(2-3), 207–239.
- Kahneman, D., 2011, *Thinking, Fast and Slow*. Farrar, Straus and Giroux, New York.
- Kahneman, D., and A. Tversky, 1973, “On the Psychology of Prediction,” *Psychological Review*, 80(4), 237–251.
- Kolasinski, A. C., A. V. Reed, and M. C. Ringgenberg, 2013, “A Multiple Lender Approach to Understanding Supply and Search in the Equity Lending Market,” *Journal of Finance*, 68(2), 559–595.
- Lamont, O. A., 2012, “Go Down Fighting: Short Sellers vs. Firms,” *Review of Asset Pricing Studies*, 2(1), 1–30.
- Luo, J., A. Subrahmanyam, and S. Titman, 2019, “A Parsimonious Model of Momentum and Reversals in Financial Markets,” unpublished manuscript.
- Lyon, J. D., B. M. Barber, and C.-L. Tsai, 1999, “Improved Methods for Tests of Long-Run Abnormal Stock Returns,” *Journal of Finance*, 54(1), 165–201.

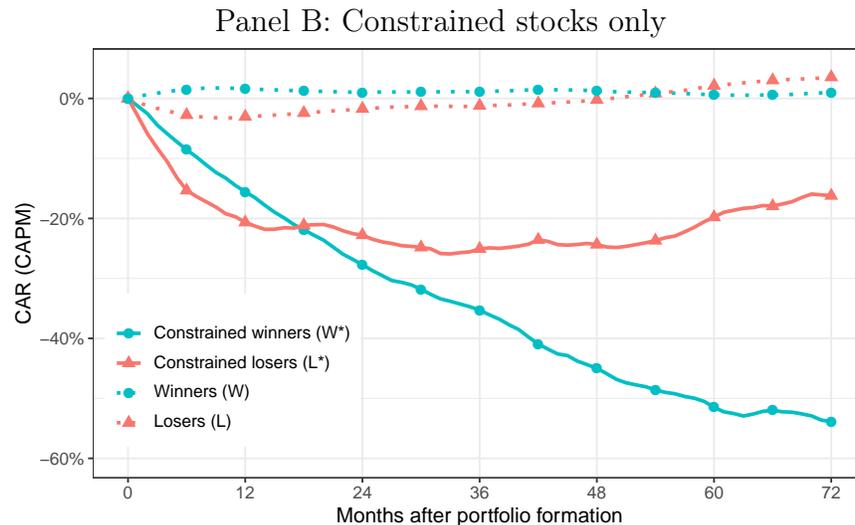
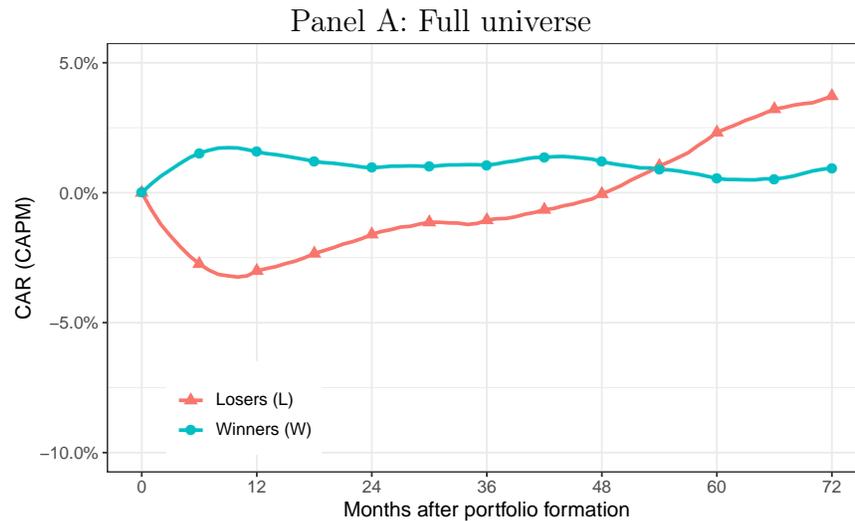
- Mahalanobis, P. C., 1936, "On the Generalised Distance in Statistics," *Proceedings of the National Institute of Sciences of India*, 2(1), 49–55.
- Miller, E. M., 1977, "Risk, Uncertainty, and Divergence of Opinion," *Journal of Finance*, 32(4), 1151–1168.
- Nagel, S., 2005, "Short Sales, Institutional Investors and the Cross-Section of Stock Returns," *Journal of Financial Economics*, 78(2), 277–309.
- Newey, W. K., and K. D. West, 1987, "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica*, 55(3), 703–708.
- Odean, T., 1998, "Volume, Volatility, Price and Profit When All Traders are Above Average," *Journal of Finance*, 53(6), 1887–1934.
- , 1999, "Do Investors Trade too Much?," *American Economic Review*, 89, 1279–1298.
- Ofek, E., M. Richardson, and R. F. Whitelaw, 2004, "Limited Arbitrage and Short Sales Restrictions: Evidence from the Options Markets," *Journal of Financial Economics*, 74(2), 305–342.
- Pontiff, J., and A. Woodgate, 2008, "Share Issuance and Cross-sectional Returns," *Journal of Finance*, 63(2), 921–945.
- Rapach, D., M. Ringgenberg, and G. Zhou, 2016, "Short Interest and Aggregate Stock Returns," *Journal of Financial Economics*, 121(1), 46–65.
- Reed, A. V., 2013, "Short Selling," *Annual Review of Financial Economics*, 5(1), 245–258.
- Scheinkman, J. A., and W. Xiong, 2003, "Overconfidence and Speculative Bubbles," *Journal of Political Economy*, 111(6), 1183–1220.
- Scherbina, A., and B. Schlusche, 2015, "Economic Linkages Inferred from News Stories and the Predictability of Stock Returns," University of California at Davis Working Paper.
- Shumway, T., 1997, "The Delisting Bias in CRSP Data," *Journal of Finance*, 52(1), 327–340.
- Svenson, O., 1981, "Are We All Less Risky and More Skillful Than Our Fellow Drivers?," *Acta Psychologica*, 47(2), 143–148.

# Figures

**Figure 1: Cumulative abnormal returns of past-return sorted portfolios.**

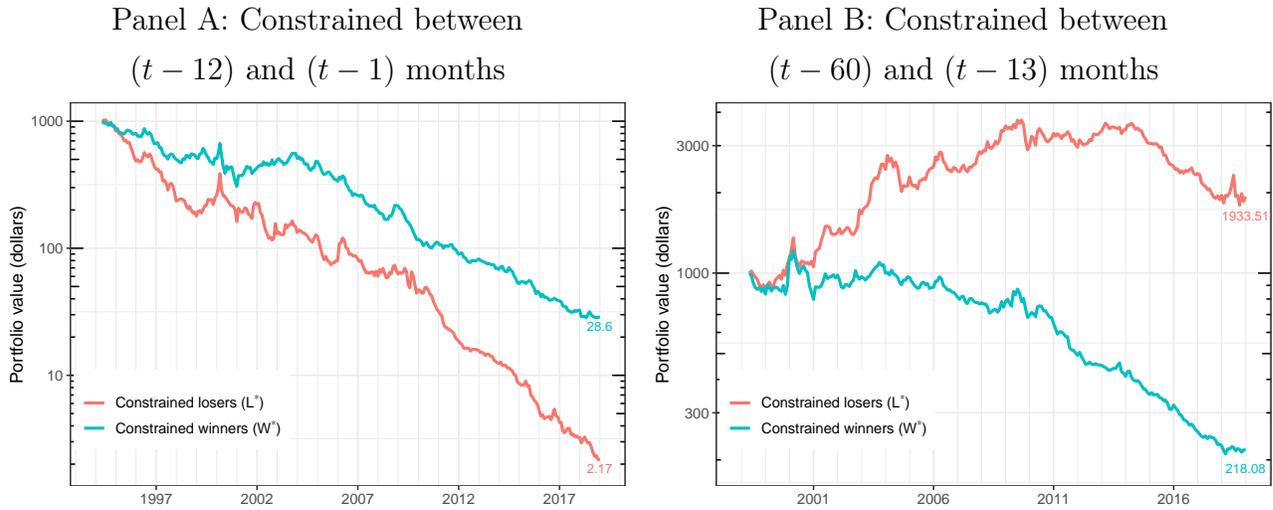
We first calculate abnormal returns for each portfolio for each holding month  $k$  by regressing the time-series of month- $k$  excess returns on the CAPM-MktRF factor. Returns are then cumulated and plotted for the past-winner and past-loser portfolio. The universe in Panel A is all US common stocks listed on the NYSE, AMEX, or NASDAQ in the sample from 1927/01–2018/12. Winners are defined as the firms whose returns from 12 months to 1 month before the portfolio formation date were in the top 30% of all firms, and the past losers are the firms in the bottom 30%.

The universe in Panel B consists of *short-sale constrained* stocks, meaning that they are in the bottom 30% of institutional ownership and the top 30% of short interest. For the constrained losers, we additionally impose the condition that they have not been in the constrained winner portfolio within the past five years, to isolate the long-run effects of winners and losers (see Section 3). The time period for constrained stocks is 1988/07–2018/12.



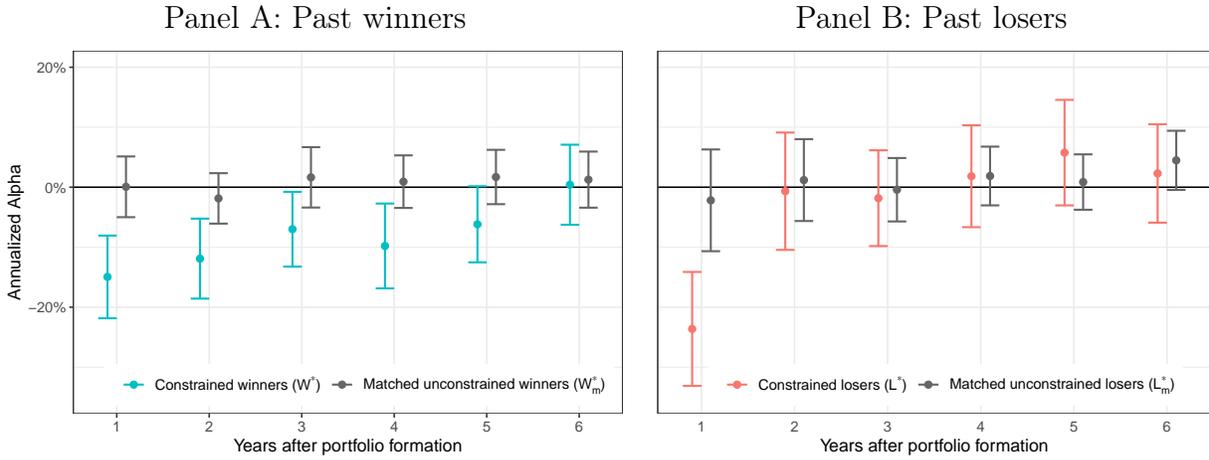
**Figure 2: Performance of hedged constrained portfolios over calendar-time.**

This figure presents the investment value for a set of hedged portfolios. To calculate the portfolio value, we assume an investment at the beginning of the sample of \$1,000. We also assume that the exposures to the market is hedged. We calculate the hedging coefficients by running a full-sample regression of the portfolio excess returns on the market excess returns. Then, using the full-sample regression coefficients, we subtract the returns of the (zero-investment) hedge-portfolio  $[b_{Mkt}(R_{Mkt}-R_{f,t})]$  from the portfolio returns and add the risk-free rate to generate the hedged portfolio returns. Panel A plots the evolution of \$1,000 invested in hedged calendar-time 12-month buy-and-hold constrained winner and loser (that were not winners in the past 5 years) portfolios. Panel B contains calendar-time 48-month buy-and-hold portfolios that skip the first 12 months.



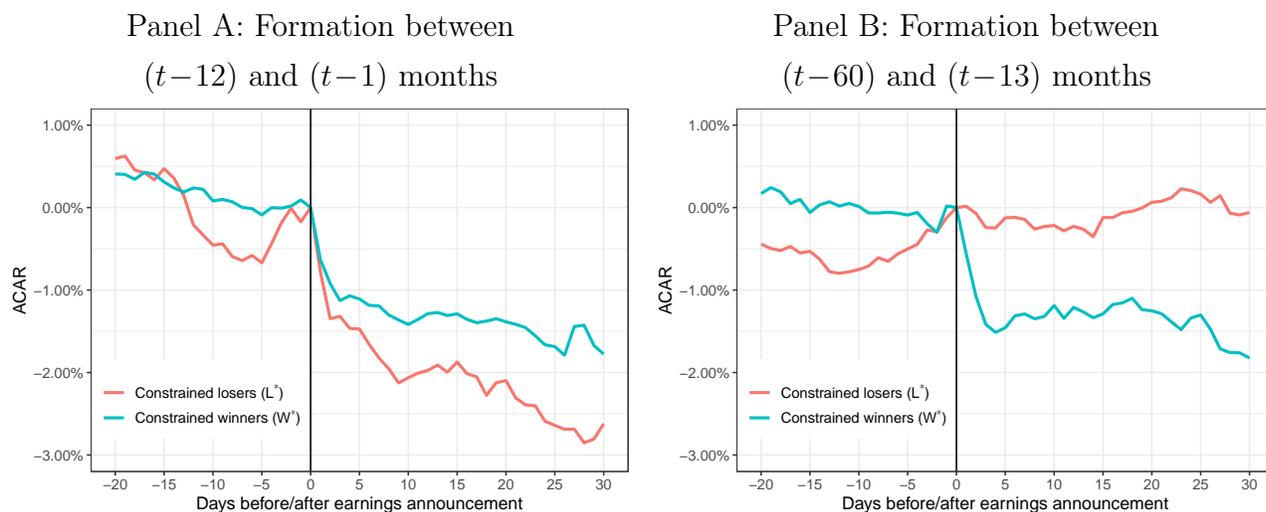
**Figure 3: Annual CAPM-alphas of constrained and matched portfolios.**

The first set of points show the the annualized CAPM-alphas of value-weighted portfolios of constrained past-winners (Panel A) and losers (Panel B), respectively, in years 1-6 post-formation. The second set of points in Panels A and B are the results of portfolios of matched stocks, based on the Mahalanobis distance calculated on size, book-to-market, past-return, and idiosyncratic volatility. For details, see Section 3.4.



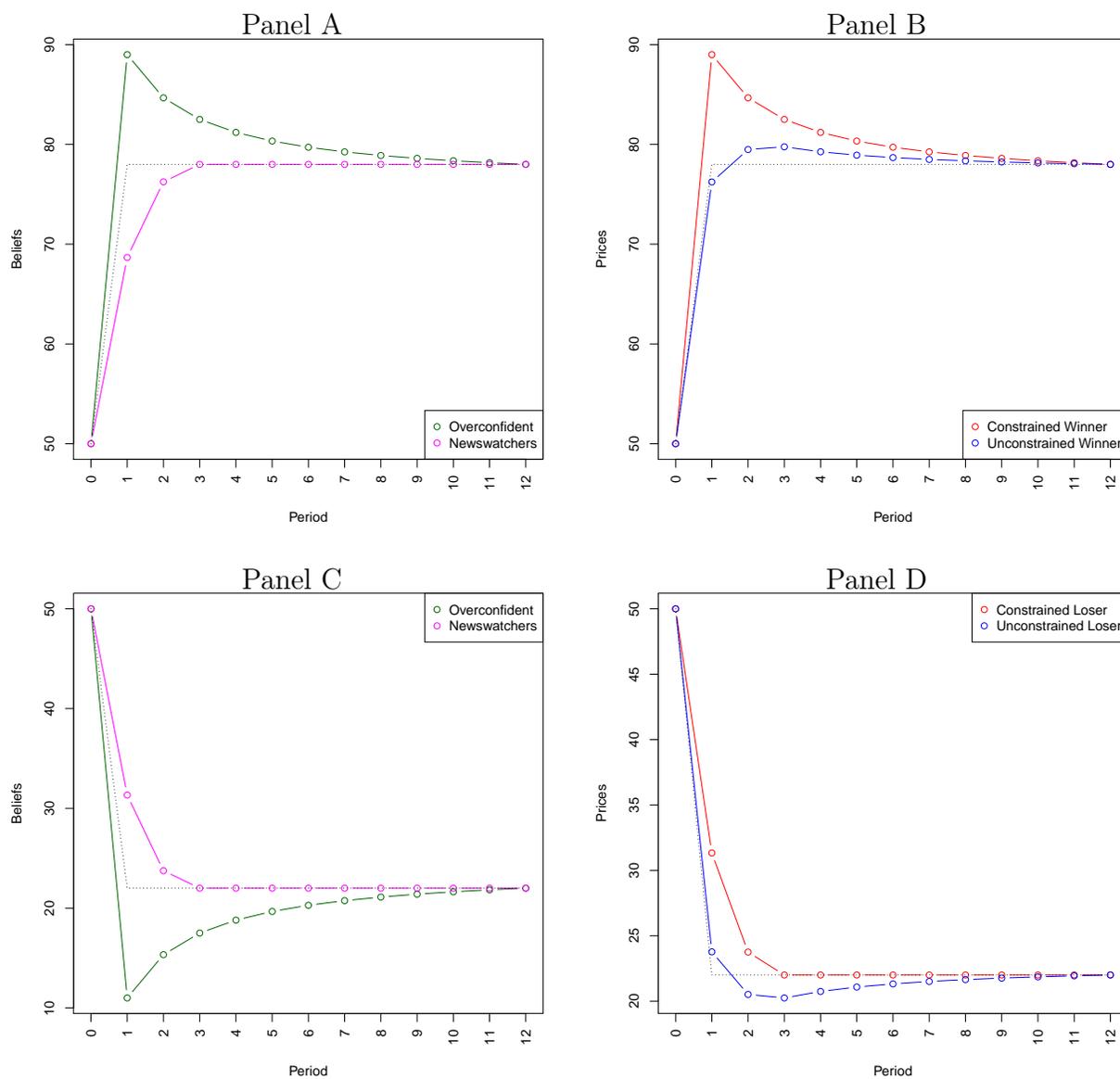
**Figure 4: CAR around earnings announcements.**

This figure shows cumulated abnormal returns of the constrained winners ( $W^*$ ) and constrained losers that were not constrained winners in the 5 preceding years ( $L^*$ ) around the day ( $D=0$ ) of an earnings announcement that occurs in the quarter after portfolio formation (months  $t$  to  $t+2$ ). We include all stocks that were in the respective portfolio in months  $t-12$  through  $t-1$  (Panel A) and  $t-60$  to  $t-13$  (Panel B) and calculate their buy-and-hold weight from formation to each day plotted by using the price change adjusted by the cumulative price adjustment factor (CFACPR in CRSP). Abnormal returns are calculated by adjusting for beta times the CAPM-Market-factor. For each stock, beta is estimated in a 1-year window of daily returns prior to the month in which the earnings announcement occurs. To construct the figure, daily abnormal returns are first centered around the day of announcement ( $D=0$ ). They are then cumulated by stock (cumulative abnormal return, CAR) and averaged (ACAR, weighted by the buy-and-hold weight) by portfolio and day relative to announcement. See Appendix B.III for details.



**Figure 5: Beliefs and prices for winners and losers - A numerical example.**

Panel A shows beliefs of overconfident agents and newswatchers after a positive surprise. These beliefs cause different price dynamics for constrained and unconstrained stocks (Panel B). Panel C and D show beliefs and prices after a negative surprise. The information structure for winners is  $(\epsilon_{O1}; \epsilon_{O2}; \epsilon_{O3}; \epsilon_{O4}; \dots; \epsilon_{O12}) = (6; 2; 2; 2; \dots; 2)$  for overconfident agents and  $(\epsilon_{N1}; \epsilon_{N2}; \epsilon_{N3}; \epsilon_{N4}; \dots; \epsilon_{N12}) = (4; 3.5; 2.5; 2; \dots; 2)$  for newswatchers. The information structure for losers is obtained by multiplying all  $\epsilon$ 's with  $-1$ , i.e.,  $(\epsilon_{O1}; \epsilon_{O2}; \epsilon_{O3}; \epsilon_{O4}; \dots; \epsilon_{O12}) = (-6; -2; -2; -2; \dots; -2)$  for overconfident agents and  $(\epsilon_{N1}; \epsilon_{N2}; \epsilon_{N3}; \epsilon_{N4}; \dots; \epsilon_{N12}) = (-4; -3.5; -2.5; -2; \dots; -2)$  for newswatchers. Parameter choices for both cases are  $D_0 = 50$ ,  $\pi_O = 2$ ,  $\pi_N = 8$ ,  $Q = 10$ ,  $\gamma_O = \gamma_N = 1$ ,  $\zeta^2 = 1$ ,  $\sigma^2 = 2$ ,  $\kappa = 1/2$ ,  $n = 3$ , and  $T = 12$ .  $\mu_\epsilon = 2$  for the winner and  $\mu_\epsilon = -2$  for the loser. All variables are defined and explained in Appendix A.



## Tables

**Table 1: Characteristics of constrained and matched portfolios.**

This table shows time-series averages of value-weighted mean characteristics of the portfolios in the month of portfolio formation. Shown are the average number of stocks, the average market equity (in billion US dollars), return from month t-12 to the end of month t-2 (in %), level of short interest two weeks prior to formation (in %) and change from 11.5 months ago to 2 weeks ago (in PP), institutional ownership (in % of number of shares outstanding) and its change over the preceding year (in PP), the ratio of book equity of the most-recently observed fiscal year to last month’s market equity, the average standard deviation of daily idiosyncratic returns in each portfolio (daily, in %) over the month prior to formation (Ang, Hodrick, Xing, and Zhang, 2006), levels (in %) and changes (in PP) over the preceding 12 months in monthly turnover, the ratio of short interest to institutional ownership (SIRIO) as in Drechsler and Drechsler (2016) (in %), the open-interest weighted average of differences in implied volatilities between matched put and call option pairs at month-end (in %), as in Cremers and Weinbaum (2010), the level (in %) and change (in PP) (over the preceding 12 months) in the Markit indicative as well as simple average loan fee. The sample period is 1993/06 (to account for the 5-year lookback period for losers that weren’t constrained winners before) to 2018/12, except for Markit data, which is available from 2004/08. For a comparison with the broader universe of stocks, averages for the remaining portfolios are displayed in Table D.8 in Appendix D.

	$W^*$	$L^*$	$W_m^*$	$L_m^*$
Number of stocks	52	39	52	39
Average Market Equity (B\$)	3.74	2.00	4.44	1.84
Formation Period Return (%)	84.61	-47.39	86.65	-46.31
Institutional Ownership (IOR, %)	17.33	18.33	83.31	79.97
Change in IOR over preceding year (PP)	-0.25	-7.31	9.40	0.01
Short-interest (SIR, %)	7.63	7.68	7.21	7.33
Change in SIR over preceding year (PP)	2.66	1.63	0.32	1.06
Book-to-market ratio	0.29	0.87	0.31	0.85
Idiosyncratic volatility (% , daily)	3.08	3.82	2.24	2.87
Turnover (%)	36.73	33.64	33.74	32.80
Change in turnover over preceding year (PP)	17.21	1.88	6.41	3.24
SIRIO (%)	125.59	115.96	8.55	9.47
Option volatility spread (%)	-4.86	-5.16	-0.69	-0.61
Ind.Fee (%)	6.04	6.09	0.53	0.86
Change in Ind.Fee over preceding year (PP)	1.14	2.08	-0.33	0.08
Simple Avg. Fee (SAF, %)	4.03	4.83	0.44	0.75
Change in SAF over preceding year (PP)	0.24	2.01	-0.31	0.15
Available lending (%)	10.50	10.71	23.55	22.76
On loan (%)	5.85	6.24	5.77	6.54
Lending utilization (%)	104.44	98.80	30.64	37.26

**Table 2: Monthly excess returns of winner and loser portfolios.**

This table contains monthly average excess returns of the 9 winner (Panel A), 9 medium momentum (Panel B) and 9 loser (Panel C) portfolios from an independent triple sort on the past 11-month return lagged by one month, institutional ownership (IOR) and short interest (SIR). The last two columns present the difference of low and high institutional ownership portfolio returns and the alpha of that difference-portfolio from a Fama-French-Carhart four-factor regression. Similarly, the bottom two rows show the return-difference between high and low SIR portfolios and the respective four-factor alpha. The sample period is 1988/07 to 2018/12. [Newey and West \(1987\)](#)  $t$ -statistics are shown in parentheses.

Panel A: Winners					
	Hi IOR	M	Lo IOR	Lo-Hi	$\alpha(Lo - Hi)$
Lo SIR	0.97	1.28	1.05	0.08 (0.34)	0.13 (0.53)
M	0.81	0.61	0.86	0.05 (0.18)	-0.01 (-0.03)
Hi SIR	0.98	0.85	-0.33	-1.32 (-4.37)	-1.33 (-4.11)
Hi-Lo	0.02	-0.43	-1.38		
$t$	(0.08)	(-1.49)	(-3.78)		
$\alpha(Hi - Lo)$	-0.29	-0.82	-1.76		
$t$	(-1.34)	(-3.02)	(-5.00)		
Panel B: Medium Momentum					
	Hi IOR	M	Lo IOR	Lo-Hi	$\alpha(Lo - Hi)$
Lo SIR	0.55	0.86	0.73	0.18 (0.75)	0.43 (1.88)
M	0.65	0.52	0.61	-0.04 (-0.22)	0.08 (0.39)
Hi SIR	0.56	0.60	0.10	-0.46 (-1.50)	-0.32 (-1.17)
Hi-Lo	0.01	-0.26	-0.63		
$t$	(0.05)	(-0.99)	(-1.79)		
$\alpha(Hi - Lo)$	-0.03	-0.37	-0.78		
$t$	(-0.17)	(-1.61)	(-2.40)		
Panel C: Losers					
	Hi IOR	M	Lo IOR	Lo-Hi	$\alpha(Lo - Hi)$
Lo SIR	0.61	0.61	0.37	-0.24 (-0.43)	0.19 (0.25)
M	0.51	0.30	-0.02	-0.53 (-1.61)	-0.35 (-1.35)
Hi SIR	0.06	-0.05	-1.77	-1.84 (-4.52)	-1.84 (-5.91)
Hi-Lo	-0.55	-0.66	-2.15		
$t$	(-1.16)	(-2.16)	(-5.23)		
$\alpha(Hi - Lo)$	-0.22	-0.72	-2.25		
$t$	(-0.38)	(-2.24)	(-6.55)		

**Table 3: Short-term (year 1) performance of constrained and matched portfolios.**

This table shows average excess returns (Panel A), as well as results from CAPM (Panel B) and Fama-French-Carhart four-factor regressions (Panel C) for calendar-time 12-month buy-and-hold portfolios. The stocks in the constrained portfolios (indicated by  $\cdot^*$ ) were in the lowest group of institutional ownership and the highest group of short interest at some point during months  $\{t - 12, \dots, t - 1\}$  before formation. To calculate the calendar-time buy-and-hold portfolio return, each month, the most recent portfolio is added with \$1 and then the investment amount is not rebalanced for the remaining 12 months of holding. The columns  $L^*$  ( $W^*$ ) are the intersections of this constrained portfolio with the lowest (highest) 11-month return lagged by 1 month. Columns containing a minus sign go long the first and short the second portfolio. Portfolios indicated by  $\cdot_m$  contain unconstrained stocks that were matched to the constrained ones based on size, past-return, book-to-market and short-interest (indicated by  $\cdot_m$ ) using the Mahalanobis distance. For details, see Section 3.4. Newey and West (1987)  $t$ -statistics are shown in parentheses. AvgN is the average number of unique stocks in the portfolio. The row labeled SR displays the Sharpe Ratios and IR the Information Ratios. The sample period is 1988/07 to 2018/12. The first return is calculated in June 1994, i.e., the first time when we invested 12 times in a row and we had the chance to see if a constrained loser had been a constrained winner over the previous 5 years.

	$W^*$	$L^*$	$W^*-L^*$	$W_m^*$	$L_m^*$	$W_m^*-L_m^*$	$W^*-W_m^*$	$L^*-L_m^*$	$DiD$
Panel A: Raw excess returns									
Average	-0.28 (-0.63)	-0.84 (-1.36)	0.56 (1.31)	0.81 (1.92)	0.99 (1.85)	-0.19 (-0.48)	-1.09 (-3.68)	-1.83 (-4.61)	0.75 (1.59)
No. of months	295	295	295	295	295	295	295	295	295
AvgN	179	107		284	196				
SR	-0.1171	-0.2686	0.2664	0.3982	0.3986	-0.1076	-0.7857	-0.9725	0.3622
Panel B: CAPM regressions									
Intercept	-1.25 (-4.25)	-1.97 (-4.88)	0.72 (1.67)	-0.08 (-0.32)	-0.05 (-0.15)	-0.02 (-0.05)	-1.17 (-4.05)	-1.92 (-4.61)	0.74 (1.50)
MktRF	1.49 (13.08)	1.75 (12.16)	-0.25 (-1.43)	1.37 (18.67)	1.62 (11.02)	-0.25 (-1.24)	0.13 (1.39)	0.13 (0.95)	0.00 (0.01)
$R^2$	0.6055	0.4834	0.0222	0.7027	0.6547	0.0335	0.0133	0.0070	0.0000
IR	-0.8297	-0.8760	0.3476	-0.0680	-0.0367	-0.0127	-0.8513	-1.0195	0.3617
Panel C: Four-factor regressions									
Intercept	-1.23 (-4.40)	-1.50 (-3.99)	0.27 (0.68)	-0.21 (-1.62)	0.26 (1.34)	-0.47 (-2.08)	-1.02 (-3.22)	-1.76 (-4.75)	0.74 (1.72)
MktRF	1.31 (20.82)	1.31 (15.79)	0.01 (0.06)	1.31 (25.99)	1.29 (22.31)	0.02 (0.20)	0.00 (0.02)	0.01 (0.19)	-0.01 (-0.10)
HML	-0.22 (-1.71)	-0.27 (-1.65)	0.06 (0.30)	-0.21 (-3.85)	0.25 (1.94)	-0.46 (-2.51)	-0.01 (-0.05)	-0.52 (-2.50)	0.51 (2.77)
SMB	0.99 (10.08)	1.24 (7.28)	-0.25 (-1.34)	0.68 (11.21)	1.03 (12.41)	-0.36 (-3.36)	0.31 (2.90)	0.20 (1.41)	0.11 (0.65)
MOM	0.03 (0.37)	-0.65 (-5.39)	0.68 (5.05)	0.27 (7.14)	-0.58 (-8.26)	0.84 (9.09)	-0.24 (-2.36)	-0.07 (-0.60)	-0.16 (-1.48)
$R^2$	0.7785	0.6777	0.2161	0.8802	0.8736	0.6026	0.0977	0.0814	0.0669
IR	-1.0912	-0.8441	0.1453	-0.2987	0.2953	-0.4341	-0.7742	-0.9743	0.3733

**Table 4: Long-term (years 2–5) performance of constrained and matched portfolios.**

See caption to Table 3. The only difference here is that we hold stocks that were allocated to one of the portfolios at some point during months  $\{t - 60, \dots, t - 13\}$  before formation. The first return is calculated in June 1998, i.e., the first time when we invested 48 times in a row.

	$W^*$	$L^*$	$W^*-L^*$	$W_m^*$	$L_m^*$	$W_m^*-L_m^*$	$W^*-W_m^*$	$L^*-L_m^*$	$DiD$
Panel A: Raw excess returns									
Average	0.02 (0.03)	0.87 (1.77)	-0.86 (-3.49)	0.80 (1.84)	0.71 (1.59)	0.10 (0.65)	-0.79 (-4.19)	0.17 (0.74)	-0.95 (-3.80)
No. of months	247	247	247	247	247	247	247	247	247
AvgN	378	213		652	459				
SR	0.0073	0.3896	-0.6731	0.4259	0.3609	0.1428	-0.7588	0.1523	-0.7333
Panel B: CAPM regressions									
Intercept	-0.69 (-2.89)	0.22 (0.73)	-0.90 (-3.85)	0.17 (1.11)	0.06 (0.34)	0.10 (0.72)	-0.85 (-3.90)	0.15 (0.72)	-1.01 (-4.20)
MktRF	1.48 (19.25)	1.39 (19.63)	0.09 (0.86)	1.34 (26.06)	1.36 (32.43)	-0.02 (-0.43)	0.14 (1.75)	0.03 (0.40)	0.11 (1.06)
$R^2$	0.7475	0.6439	0.0080	0.8514	0.8109	0.0015	0.0292	0.0012	0.0115
IR	-0.6154	0.1605	-0.7087	0.2284	0.0717	0.1570	-0.8337	0.1399	-0.7771
Panel C: Four-factor regressions									
Intercept	-0.70 (-5.18)	0.20 (0.77)	-0.90 (-3.70)	0.15 (1.33)	-0.02 (-0.18)	0.17 (1.46)	-0.85 (-5.55)	0.22 (0.94)	-1.07 (-4.23)
MktRF	1.31 (16.70)	1.17 (18.04)	0.14 (1.48)	1.24 (33.49)	1.21 (29.86)	0.02 (0.57)	0.07 (1.35)	-0.04 (-0.59)	0.12 (1.19)
HML	-0.21 (-2.98)	-0.03 (-0.32)	-0.19 (-2.03)	-0.28 (-5.04)	0.07 (1.27)	-0.35 (-6.41)	0.07 (0.62)	-0.10 (-1.19)	0.16 (1.66)
SMB	0.65 (6.09)	0.83 (10.87)	-0.19 (-2.03)	0.42 (6.87)	0.73 (12.06)	-0.31 (-9.05)	0.23 (2.39)	0.10 (1.30)	0.13 (1.20)
MOM	-0.07 (-1.00)	-0.17 (-2.49)	0.09 (0.81)	-0.00 (-0.14)	-0.04 (-1.42)	0.04 (1.22)	-0.07 (-1.15)	-0.12 (-1.77)	0.05 (0.50)
$R^2$	0.8368	0.7642	0.0502	0.9267	0.9277	0.3433	0.0745	0.0330	0.0304
IR	-0.7842	0.1844	-0.7263	0.2926	-0.0367	0.3114	-0.8539	0.2035	-0.8364

**Table 5: Fama-MacBeth regressions for stocks that were constrained in the past.** This table shows results of Fama and MacBeth (1973) regressions of excess returns on a number of predictors. The variable Constr. (Constr.W, Constr.L) is a dummy variable indicating that the stock has been a constrained stock (winner, loser) anytime during the indicated months.  $RET_{(t-12)-(t-2)}$  is the one-month lagged past 11-month-return.  $\log(BE/ME)$  is the logarithm of the previous month's book-to-market ratio,  $\log(ME)$  is the logarithm of the previous month's market equity and  $ivol$  is the volatility of daily residuals from a Fama and French (1993) three-factor regression of daily excess returns within the past month.  $SIRIO$  is the ratio of short interest to institutional ownership. Newey and West (1987)  $t$ -statistics are shown in parentheses. The sample period is 1988/07 to 2018/12.

Panel A: Constrained between $t - 12$ and $t - 1$						
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.64 (2.74)	0.64 (2.74)	0.64 (2.74)	1.44 (2.93)	1.59 (3.21)	1.59 (3.21)
$Constr._{(t-12)-(t-1)}$	-0.86 (-4.10)	-0.01 (-0.05)		-0.15 (-0.53)	-0.10 (-0.34)	
$Constr.W_{(t-12)-(t-1)}$		-0.55 (-2.11)	-0.63 (-3.13)	-0.69 (-2.74)	-0.50 (-1.94)	-0.62 (-3.18)
$Constr.L_{(t-12)-(t-1)}$		-1.13 (-3.51)	-1.13 (-3.28)	-0.54 (-2.07)	-0.35 (-1.29)	-0.42 (-1.90)
$RET_{(t-12)-(t-2)}$				0.40 (1.52)	0.40 (1.52)	0.39 (1.48)
$\log(BE/ME_{t-1})$				-0.02 (-0.19)	-0.02 (-0.19)	-0.02 (-0.20)
$\log(ME_{t-1})$				-0.07 (-1.84)	-0.08 (-2.12)	-0.08 (-2.12)
$ivol_{t-1}$				-0.19 (-2.47)	-0.18 (-2.35)	-0.18 (-2.37)
$SIRIO_{t-1}$					-0.01 (-3.97)	-0.01 (-3.87)
Avg. $R^2$	0.0018	0.0028	0.0023	0.0818	0.0834	0.0829
No. of months	354	354	354	354	352	352
Panel B: Constrained between $t - 60$ and $t - 13$						
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.64 (2.46)	0.64 (2.46)	0.64 (2.46)	1.48 (2.68)	1.60 (2.91)	1.60 (2.91)
$Constr._{(t-60)-(t-13)}$	-0.32 (-2.60)	0.09 (0.49)		-0.01 (-0.05)	-0.00 (-0.01)	
$Constr.W_{(t-60)-(t-13)}$		-0.57 (-2.70)	-0.50 (-3.76)	-0.55 (-2.80)	-0.48 (-2.50)	-0.49 (-3.28)
$Constr.L_{(t-60)-(t-13)}$		-0.03 (-0.13)	0.02 (0.08)	0.05 (0.28)	0.13 (0.73)	0.14 (0.75)
$RET_{(t-12)-(t-2)}$				0.31 (1.07)	0.31 (1.07)	0.31 (1.07)
$\log(BE/ME_{t-1})$				0.00 (0.04)	-0.00 (-0.02)	-0.00 (-0.02)
$\log(ME_{t-1})$				-0.07 (-1.72)	-0.08 (-1.97)	-0.08 (-1.96)
$ivol_{t-1}$				-0.18 (-2.03)	-0.16 (-1.86)	-0.16 (-1.87)
$SIRIO_{t-1}$					-0.01 (-3.99)	-0.01 (-4.01)
Avg. $R^2$	0.0020	0.0035	0.0028	0.0841	0.0856	0.0849
No. of months	306	306	306	306	306	306