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% ($t = -6.31$), while past-losers earn 6% ($t = 0.56$). 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 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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[INSERT FIGURE 1 HERE]

Across a number of different asset classes and time periods, we see momentum effects at horizons up to about one year, and reversal or value effects over the subsequent 2–5 years (Asness, Moskowitz, and Pedersen, 2013). As a way of illustrating this, we form value-weighted portfolios of the 30% of US common stocks with the best and worst returns from months $t-12$ through $t-2$ at the start of each month t. The sort on past returns is consistent with the definition of the Fama and French (2008) "momentum" factor. Panel A of Figure 1 plots the annualized CAPM alphas for these past winners and losers, and shows that past-winner stocks (W) outperform past-loser stocks (L) in the first year after portfolio formation, consistent with the large literature on momentum. Two to five years after portfolio formation, we observe reversed performance differences between initial winners and losers.[1]

In Panel B of Figure 1, we plot the returns to portfolios of past-winners and losers formed in the same way, except here, rather than using all listed US common stocks, we use the subset of stocks that are *short-sale constrained*. Specifically, as a proxy for short-sale constraints, we use a combination of low institutional ownership and high short interest.[2] Thus, the prices of the stocks in these portfolios are likely to reflect the beliefs of the more optimistic agents, while the less optimistic are "sidelined" (Miller, 1977). We see here that both constrained winners and losers earn strong negative returns in the first year post formation. Interestingly, from 2–5 years post formation, the alpha of the past-loser portfolio is 0.21%/year ($t = 0.71$, see Table 4). In contrast, the constrained past-winner portfolio earns economically and statistically large negative alphas in each year 2–5 post-formation. The annualized CAPM alphas range from -15% to -6% per year, indicating large and persistent mispricing. The

[1] The details of the value-weighted buy-and-hold portfolio construction are explained in Section 3.2. Note that while the alpha of the momentum effect in year 1 is statistically significant ($t = 3.06$), the reversal effect in years 2-5 is not ($t = -1.73$). For more extreme sorts, e.g., deciles, the alpha of the reversal effect becomes statistically significant ($t = -2.01$). See Tables D.1 and D.2 in the Appendix for the details of these tests.

[2] See Section 3 for a motivation for this measure, and empirical evidence on the efficacy of this measure.

difference in abnormal returns in years 2–5 post-formation between constrained winners and constrained losers amounts to $-0.89\%/\text{mo}$ ($t = -3.68$).

[INSERT FIGURE 2 HERE]

One concern with any such analysis should be that the constrained past-winner and loser stocks are different from the unconstrained past-winner and loser stocks on dimensions other than just the simple fact that they are constrained. To examine this, in Figure 2 we plot the performance of the constrained past-winner and loser stocks (i.e., exactly what is plotted in Figure 1 Panel B), and the equivalent annualized CAPM alphas for a portfolio of stocks which are, each month, matched based on a propensity score, calculated based on size, book-to-market, idiosyncratic volatility and past-return. Loosely speaking, we compare the performance of the constrained stocks with their characteristics-matched twins in the universe of unconstrained stocks.[3] Assuming that the propensity-score matched sample is sufficiently similar on all dimensions other than whether the firm is short-sale constrained, it is clear that the fact that a firm is constrained results in a very different "impulse response" to the information that is leading to the large positive or negative returns in the pre-formation year.

The fact that constrained stocks earn low returns is well known. What is new and striking here is the difference in persistence between the past-winners and losers, and the difference in the cumulative returns post-formation between the past-winners and losers. While the past-losers earn a cumulative market-adjusted return of -17% ($t = -3.73$) in the first year, the cumulative market-adjusted return from years 2–5 years post formation is 6% ($t = 0.56$). In contrast, the past-winners earn a cumulative market-adjusted return of -13% ($t = -3.72$) in year 1 and -40% ($t = -6.31$) from 2–5 years post formation.[4] Our main

[3] Also note that we cannot reject the hypotheses that the average 1st-year returns of the matched winners and losers in Figure 2 are equal to those of the winners and losers in the full sample plotted in Figure 1. The p-values from Welch-two-sample-t-tests are $p = 0.73$ for winners and $p = 0.45$ for losers.

[4] 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

empirical contribution is to document the striking difference in mispricing persistence among constrained winners and losers. A satisfying explanation of the empirical patterns shown in Figure 1 needs to explain the difference in mispricing persistence: constrained firms that have experienced a large positive return 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.

Natural starting points to explain this phenomenon are the existing explanations for momentum and reversals among unconstrained stocks, such as those of Daniel, Hirshleifer, and Subrahmanyam (1998), Barberis, Shleifer, and Vishny (1998), and Hong and Stein (1999), and for the underperformance of short-sale constrained stocks in the presence of disagreement (Miller, 1977). When there is disagreement about the value of a security, and when pessimists are constrained from short-selling, only the views of the most optimistic agents will be reflected in the security price. The overvaluation is gradually eliminated with the resolution of disagreement and/or less binding short sale constraints.

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 representative agents models with no disagreement. On their own, both of these models predict no short selling and no differences in the return patterns of constrained and unconstrained stocks. While Hong and Stein (1999) is a heterogeneous agent model, the addition of short-sale constraints would still imply momentum for constrained winners, inconsistent with the evidence we present here.

An empirically motivated explanation for the short-term patterns of Figures 1 and 2 is proposed in Nagel (2005): suppose that momentum exists for all stocks and constrained stocks generally underperform. If we assume, first, that these effects do not interact and can just be *added up*, and, second, that the short-sale-constrained stock effect is considerably

is different than the buy-and-hold portfolio approach used to compile Figure 1, both still deliver consistent results.

stronger than the momentum effect, we have a valid explanation of the first-year alphas.[5] Nagel (2005) further shows that these short-term effects do not reverse in years two and three after portfolio formation.[6] However, such an *additive-effect hypothesis* does not explain why there is mispricing persistence for constrained winners but not for constrained losers, or put differently, why constrained winners so significantly underperform constrained losers at longer horizons.

A second possible explanation would be an extension of the additive-effect hypothesis. Assume, in addition to the assumptions above, that long-term reversals exist for all stocks. Assume further that the constrained stock effect is roughly as large as the long-term reversal effect at longer horizons. This hypothesis would predict long-term mispricing persistence for winners but not for losers, in addition to no winner-momentum and amplified loser-momentum in the short-run. The most fundamental prediction of this *extended-additive-effect hypothesis* is 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 constrained stock effect that is added to the empirical patterns of momentum and reversals for winners and losers. However, this 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-difference is highly statistically significant (see Table 6 in Section 3.4).

[5] Specifically, Nagel (2005) uses the terms "overreaction" for constrained winners and "underreaction" for constrained losers. The idea is that optimists set prices for constrained winners leading to an overreaction in the sense that prices overshoot. Optimists set prices for constrained losers as well, leading to an underreaction in the sense that prices do not fall as much as they would for an unconstrained stock.

[6] Figure 3 in Nagel (2005) does not show evidence of the strong patterns that we document here. A potential reason could be that he uses residual institutional ownership, i.e., the residuals from a regression of logit institutional ownership on log size, as a measure of short-sale constraints. As a consequence, two groups of stocks are classified as short-sale constrained, although they are presumably unconstrained: first, stocks with low institutional ownership and almost zero short interest; second, stocks with relatively high institutional ownership and even higher predicted values. Nagel (2005, p. 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).

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. Disagreement, a key feature in our model, arises endogenously with the arrival of new information. The model is consistent with the return patterns that we observe both in constrained and unconstrained stocks. It is especially able to capture the asymmetry in mispricing persistence between constrained winners and losers that we observe in the data. Any model that explains both, the short-term symmetry and the long-term asymmetry between constrained winners and losers, will feature a certain degree of complexity, like heterogeneous agents, disagreement and various expectation formation processes. Our model explains these empirical patterns by 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 value effects among unconstrained stocks persist on the order of five years (see Figure 1 Panel A, as well as Daniel and Titman (2006)), a time-frame that we label as long-term. In contrast, momentum effects are short-term, in that they persist about one year (Hong, Lim, and Stein, 2000, Jegadeesh and Titman, 2001). Our model features "informed overconfident" agents who receive private signals about which they are overconfident, and where this overconfidence persists in the long run, leading to a long-run value/reversal effect for unconstrained stocks. The momentum effect, in contrast, is explained by a different set of agents who are like the "newswatchers" in Hong and Stein (1999). The fact that the momentum effect is far less persistent than the value effect suggests that the diffusion of public information should be considerably faster than the resolution of overconfidence in an empirically sound calibration of our model. Stated differently, an alternative assumption, declaring that information diffusion lasts as long or even longer than the resolution of overconfidence, is inconsistent with the empirical evidence on 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 set of securities are "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 of course eventual reversal as the overconfidence of the informed agents is gradually reduced.

However, if the firm's stock cannot be sold short, the newswatchers' views will not be fully incorporated into the price, and the 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. Moreoever, 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 as it is not moderated by the newswatchers, who are sidelined here. 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 the release of a negative private signal. For constrained stocks, the overconfident informed agents 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 on the information release date as the overconfident agents leave the market, and continues falling subsequently as the information diffuses through the newswatchers population. Here however, the duration of the constrained stock's underperformance is far shorter because information diffusion is a faster process. Furthermore, there is no long-term reversal for constrained losers as the overconfident agents, who are causing this effect for unconstrained stocks and constrained winners, are sidelined.

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). Demand shocks in the lending market have predictive power for future returns (Asquith, Pathak, and Ritter, 2005, Cohen, Diether, and Malloy, 2007), while shocks to lending supply have no significant effect (Cohen, Diether, and Malloy, 2007, Kaplan, Moskowitz, and Sensoy, 2013). 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 (Nagel, 2005, Hirshleifer, Teoh, and Yu, 2011, Drechsler and Drechsler, 2016).[7]

[7] 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.

In a similar vein, Engelberg, Reed, and Ringgenberg (2018) relate loan fee uncertainty and recall risk to price inefficiencies.[8]

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 demands, 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

[8] Miller's idea has been approached empirically by utilizing short interest to proxy for short-sale constraints or costs, including Figlewski (1981), Asquith and Meulbroek (1996), Desai, Ramesh, Thiagarajan, and Balachandran (2002), or, alternatively, using data on loan fees and/or loan quantities (Jones and Lamont, 2002, Cohen, Diether, and Malloy, 2007, Blocher, Reed, and Van Wesep, 2013). Asquith, Pathak, and Ritter (2005) consider institutional ownership to proxy for supply and short-interest for demand. The use of short interest as a single empirical proxy to test Miller (1977) has been criticized by Chen, Hong, and Stein (2002), among others. Previous research, such as Asquith and Meulbroek (1996), Dechow, Hutton, Meulbroek, and Sloan (2001), Desai, Ramesh, Thiagarajan, and Balachandran (2002), Asquith, Pathak, and Ritter (2005), Boehmer, Jones, and Zhang (2008), Diether, Lee, and Werner (2009), or Drechsler and Drechsler (2016), generally reach significantly abnormal returns based on short-sale activity with equal weighting or for short-term horizons. The empirical approach we develop here provides robust negative long-term return predictability from high short-interest with value-weighted portfolios.

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) 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.

Our paper further speaks to the ongoing debate whether or not bubbles are empirically identifiable.[9] 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 (2018) 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

[9] The theoretical literature on limits of arbitrage highlights the possibility of persistent mispricing by identifying numerous forces that inhibit arbitrage. For example, Shleifer and Vishny (1997) show how biased beliefs can have an impact on asset prices in the presence of noise trader risk, while Abreu and Brunnermeier (2002, 2003) introduce synchronization risk to explain why prices can be disconnected from fundamentals. Gromb and Vayanos (2010) survey and summarize the literature on limits of arbitrage.

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 (Nagel, 2005, Hirshleifer, Teoh, and Yu, 2011, Drechsler and Drechsler, 2016, Engelberg, Reed, and Ringgenberg, 2018). Our theoretical and empirical approach can be interpreted as a methodology for identifying individual stock bubbles, and determining the decay rates of these bubbles.

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 to 2018/12.[10]

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 $t-12$ to $t-2$, relative to formation at the beginning of month t. This is just the measure of momentum used in Carhart (1997).

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.[11] 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-

[10] 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%.

[11] 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.[12]

The third sorting-variable, the *short-interest ratio (SIR)*, is constructed based on data from two sources: From June 2003 on, we use Compustat. Short interest data prior to June 2003 data come directly from the NYSE, AMEX and NASDAQ.[13] 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.[14] Coverage starts in June 1988 and constitutes the bottleneck for all analyses. 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) and

[12] Therefore, the first trade based on December ownership data is on February 1st. 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.

[13] 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.

[14] 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.

has been used, even in isolation, to proxy for borrowing constraints (see, e.g., Nagel, 2005).[15] 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 short-selling is likely constrained.[16] Furthermore, both IOR and SIR are available from the 1980s, allowing us to conduct asset pricing tests of long-term holding returns.

To identify shocks that we argue drive disagreement, at the start of each month t we sort on each stock's momentum, and specifically its cumulative return from month $t-12$ through month $t-2$ (i.e., the past 12-month return, skipping the most recent month). This is consistent with the definition of momentum in Fama and French (2008), and numerous other studies.

For all three sorts, i.e., past return (MOM), short-interest (SIR), and institutional ownership (IOR), the breakpoints are the 30th and 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. The portfolio of stocks that are in the low institutional ownership and high short interest bucket will be called the "constrained" portfolio, for each past-return bucket (winners or W, medium momentum or M, and, losers or L), respectively.

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.[17] Short-term negative returns could be either a sign of small and temporary mispricing or of large and

[15] Nagel (2005) uses residuals of regressing logit-transformations of IOR on log-size and log-size squared. In order to focus on stocks with strongly binding constraints, we think that the proxy proposed by Asquith, Pathak, and Ritter (2005) is more suitable in our context. In fact, for a 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.6). Using residual institutional ownership (RIOR) also leads to portfolios of firms where the fee is substantially smaller, on average, even when focusing on high SIR firms (see Table D.7).

[16] This intuition is reflected in the design of the securities lending market in our model, outlined in more detail in Section 4.

[17] Nagel (2005) is one of the few exceptions, as he also considers returns up to three years after formation.

persistent mispricing. Ultimately, we would like to provide a more complete test of the *extended-additive-effect hypothesis* stated in the introduction.

The extended-additive-effect hypothesis and our model predict that constrained winners exhibit strong long-term reversals. 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. Therefore, we additionally split the constrained losers into losers that either *were* or *were not* constrained winners within the past 5 years. We denote these two groups, respectively with L^W and L^*.[18] Our argument is that the L^* portfolio better reflects the return patterns of short-sale-constrained losers.

3.1 Characteristics

[INSERT Table 1 HERE]

Some basic characteristics about our portfolios are reported in Table 1.[19] We can see that, on average, each month, 49 stocks are classified as constrained winners, and 87 as constrained losers. On average 50 of the constrained losers were constrained winners at some point in the past 5 years. The representative constrained winner stock has a market capitalization of \$3.64B.[20] Constrained losers are all considerably smaller. The magnitude of the average returns leading up to the formation date are large for the past- winners and loser-portfolios—close to doubling/halving in size over the formation period. Institutional ownership averages 17.32% 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 7.55%, confirming a pronounced demand for short-selling these stocks.

[18] 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).

[19] For a comparison with the broader universe of stocks, averages for the remaining portfolios are displayed in Table D.6 in Appendix D.

[20] Table D.8 in the Appendix shows the distribution of our portfolio by size quintiles. It becomes apparent that all but the largest constrained winner stocks exhibit significantly negative returns and alphas.

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 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 relative to a Fama and French 3-factor model within the month prior to portfolio formation, as well as large levels and increases in turnover, consistent with disagreement among traders. Past-losers that were previously past-winners (L^W) experience a remarkable decline in turnover, consistent with waning overconfidence and declining disagreement.

To check if we identify stocks with binding short-sale constraints, the last few rows display the levels and changes of the Markit indicative and simple average loan fee. It clearly shows that the fees in the constrained portfolios are large and that there was a large increase over the previous 12 months.[21]

As the Markit data is 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).[22]

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 124.67%, which would push them above the point of cheap lending and make 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

[21] 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.9 in the Appendix.

[22] 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.

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]

We first analyze the short-term return implications. 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 -0.35% and -1.72% 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.[23]

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.[24] Comparing the constrained winners to the high-IOR/high-SIR winners, results in a difference of -1.34% per month with a Newey-West t-statistic of -4.16. The rightmost

[23] Notice, as shown in Table D.6 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).

[24] 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.

column shows the alpha from a Fama-French four-factor regression, which is also highly statistically significant. Similarly, taking the column's bottom vs. top difference produces an excess return of -1.44% per month (t-statistic -4.05), which can also not be explained by the four factors.

The results extend to a holding period of one year. To assess longer-term holding-period returns in 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.[25]

[INSERT Table 3 HERE]

[25] 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):

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

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.II. 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.III.

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

Due to the distinction between $\cdot^W$ and $\cdot^*$, which requires us to look back 5 years, to determine if a 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 the W, L^W, and L^* portfolios for 12 months in a row. Table 3 displays the results. Panel A shows the raw monthly average 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), medium momentum (M) and winners (W) all have negative alphas (Panels B and C).[26]

Returns of constrained winners and losers are not significantly different from each other (column W-L) and neither are L^* and L^W. 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 3 HERE]

Panel A of Figure 3 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.[27] 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 $30.56 ($2.36) at the end of June 2018.

[26] In Table D.3 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).

[27] 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.

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 (L^*).[28] Both W and L^* underperform significantly in the first year. However, losers never exhibit significant underperformance thereafter. In contrast, winners have significantly negative alphas up to five years.[29]

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.[30]

[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, 369 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. In columns (1) and (2) we split the loser portfolio into stocks that were (L^W) and were not (L^*) constrained

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

[29] Some readers might wonder why we do not present a traditional cumulative abnormal return (CAR) plot here. The reason is that averaging historical returns by holding month first and then cumulating over averages, does not represent the historical experience of any actual investor. Depending on distributional characteristics of returns, visual inferences can be strongly biased. Furthermore, we advocate for the yearly buy-and-hold approach as it gives us the opportunity to calculate reasonable standard errors. Each monthly return observation corresponds to a perfectly tradable portfolio. A CAR plot can nevertheless be found in Appendix D Figure D.1.

[30] 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.

winners in the 5 years before they became constrained losers. We can see that only L^W have a negative (albeit insignificant) alpha (Panels B and C). The difference between the two is significant at the 5% level. Winners significantly underperform relative to the Fama-French-Carhart model, with an alpha of -0.69 and a t-statistic of -5.12. The difference in abnormal returns of winners and losers is significant, and the difference between winners and L^*, is as large as -0.89% per month with a t-statistic of -3.59.[31] [32] In Panel B of Figure 3, 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.

3.4 Matching

Nagel's (2005) additive-effect can explain the short-term performance of constrained winners and losers in Section 3.2, but does not predict the differences in mispricing persistence reported in Section 3.3. The extended-additive-effect hypothesis and our model can potentially explain both. However, the explanations differ in their predictions of the constrained stocks' long-term performance. The extended-additive-effect hypothesis posits that two independent effects, long-term reversal and short-sale constraints, just add up, while our model predicts an interaction effect in mispricing persistence. Mispricing persistence in the long-run should be observed only for constrained winners. In this subsection, we provide a test that allows to differentiate between these two competing explanations.

A rigorous test of an additive effect of short-sale constraints, momentum and reversals, requires comparing past-winners and losers among constrained and unconstrained stocks. According to the extended-additive-effect hypothesis, the performance differences among

[31] Moreover, spanning tests, shown in Appendix D Table D.5 show that constrained winners help explain the long-run returns of 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. This is consistent with the L^W stocks driving the low long-run returns of the combined constrained loser portfolio, i.e., those constrained losers that were constrained winners within the past 5 years.

[32] 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 -0.83 (see Appendix D Table D.4). Such a portfolio has 424 unique stocks in it. Moreover, using the simple value-weight approach, described in footnote 25, a strategy using allocation between months $t-60$ and $t-1$ generates a four-factor Information Ratio of -1.08.

constrained and unconstrained stocks are always the same, no matter what the time horizon is or if we consider winners or losers.

We have to take into account that constrained stocks differ from unconstrained ones among certain dimensions, such as size, book-to-market ratio, idiosyncratic volatility, and past-return. We therefore employ a matching procedure. For each stock in the constrained winner portfolio (W) and the constrained loser portfolio (L^*), we run propensity score matching (PSM) to find a statistical twin stock in a universe of unconstrained potential matches. We limit the unconstrained matching universe to be stocks above the 30% quantile of institutional ownership and below the 70% quantile of short-interest and within the corresponding past-return bucket. We then run, in each month, a cross-sectional logistic regression of a dummy variable that is one for each constrained winner (loser) on the four matching dimensions (size, book-to-market, idiosyncratic volatility, past-one-year-return, excluding the last month). The predicted probability from that regression is assigned to each stock as the propensity score. We then apply nearest neighbor matching to find the closest match for each "treated" stock in the W or L^* portfolio.

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 Markit 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.

[INSERT Table 5 HERE]

The extended-additive-effect hypothesis postulates that there is no interaction between the constrained stock effect and momentum/reversals. This would require that, once we take out the momentum/reversal effect that exists between winners and losers, the effect of short-sale constraints is exactly the same across all horizons for each portfolio. In other words, the performance difference between a portfolio long constrained and short unconstrained winners and another portfolio that is long constrained and short unconstrained losers, is equal in the short- and in the long-run.

Table 5 confirms that the difference-in-difference (DiD) of the performance is statistically indistinguishable from zero in the first year. Based on the short-term evidence, we cannot reject the additive-effect hypothesis, consistent with Nagel (2005).

[INSERT Table 6 HERE]

However, the picture changes for the following four years: Constrained winners significantly underperform unconstrained ones, whereas constrained and unconstrained losers exhibit very similar returns (Table 6). The difference-in-difference is statistically significant, also when controlling for the market (Panel B) or the four Fama-French-Carhart factors (Panel C). Consequently, we reject the extended-additive-effect hypothesis.

Figure 2 in the introduction adds more background to the matching approach. It shows the buy-and-hold performance of the matched portfolios on a year-by-year basis. While the constrained stocks show distinct and significant patterns of mispricing, the matched portfolios' returns can always be explained by the CAPM. Constrained winners underperform unconstrained ones for at least five years (Panel A), whereas constrained losers only exhibit significantly negative alpha in the first year. This visual assessment is consistent with the time-series regressions presented throughout the paper.

3.5 Fama-MacBeth Regressions

[INSERT Table 7 HERE]

We assess the robustness of our results by running Fama-MacBeth regressions.[33] To see whether returns of constrained winners are different than 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 7 Panel B, labeled "Constr.W". It is significantly different

[33] 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).

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).[34] 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.

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.[35]

Taken together, these results are inconsistent with the extended-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]

[34] 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.

[35] 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.

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 CAPM-MktRF factor.[36] 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 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.

[36] The calculation of abnormal returns is explained in detail in Appendix B.III.

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.[37]

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 $t = 1, \ldots, T$. 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, 2018) 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).[38] In other words, agents believe that their views are correct, and that others will figure that out sooner rather than later.

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

[38] 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").

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 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 and differ qualitatively from the extended-additive-effect hypothesis.

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).[39] Panel A of Figure 5 shows posterior beliefs of overconfident

[39] The more detailed model in the Appendix allows for intermediate cases.

agents $\mathbb{E}_{Ot}[D_T]$ and newswatchers $\mathbb{E}_{Nt}[D_T]$ about the liquidating dividend D_T at time 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 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.[40]

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

[40] 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.

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 price changes 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 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 the overconfident agents. The dynamics of prices reflect the newswatchers' dynamics of beliefs. 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.[41]

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.

[41] 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.

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 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 asymmetry 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.

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Figure 1: Annual CAPM-alphas of unconstrained and constrained portfolios. Panel A plots the annualized CAPM-alphas of value-weighted portfolios of past one-year winners and losers in years 1-6 post-formation. The universe here 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%. We report 95% confidence intervals based on Newey and West (1987) standard-errors with automated lag-detection (Newey and West, 1994).

Panel B performs the same exercise, only for a universe 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 Panel B is 1988/07–2018/12.

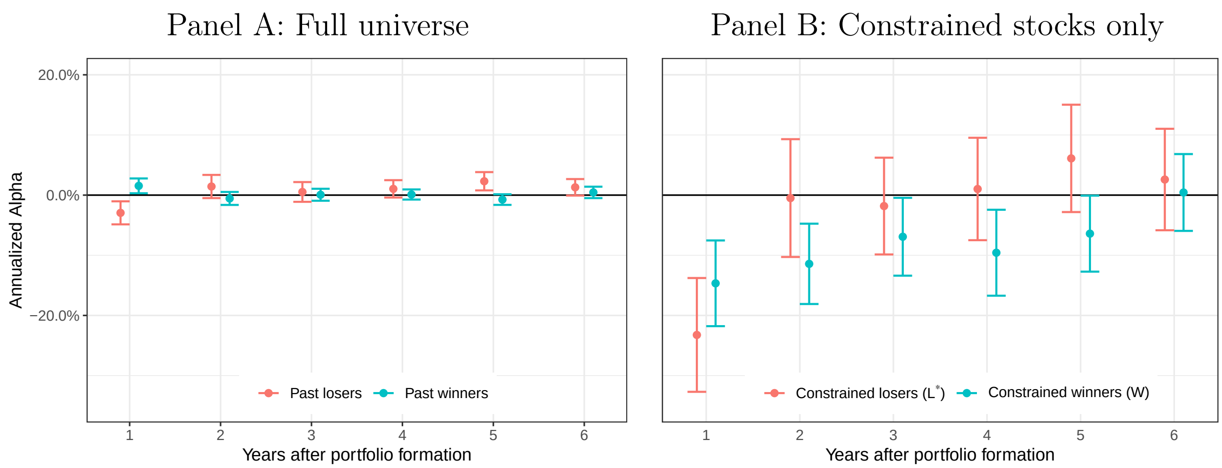


Figure 2: Annual CAPM-alphas of constrained and matched portfolios.
The first set of points show the the annualized CAPM-alphas of value-weighted portfolios of constrained past one-year winners (Panel A) and losers (Panel B), respectively, in years 1-6 post-formation (as in Figure 1 Panel B). The second set of points in Panels A and B are the results of portfolios of matched stocks, based on propensity score matching on size, book-to-market, past-return, and idiosyncratic volatility. For details, see Section 3.4.

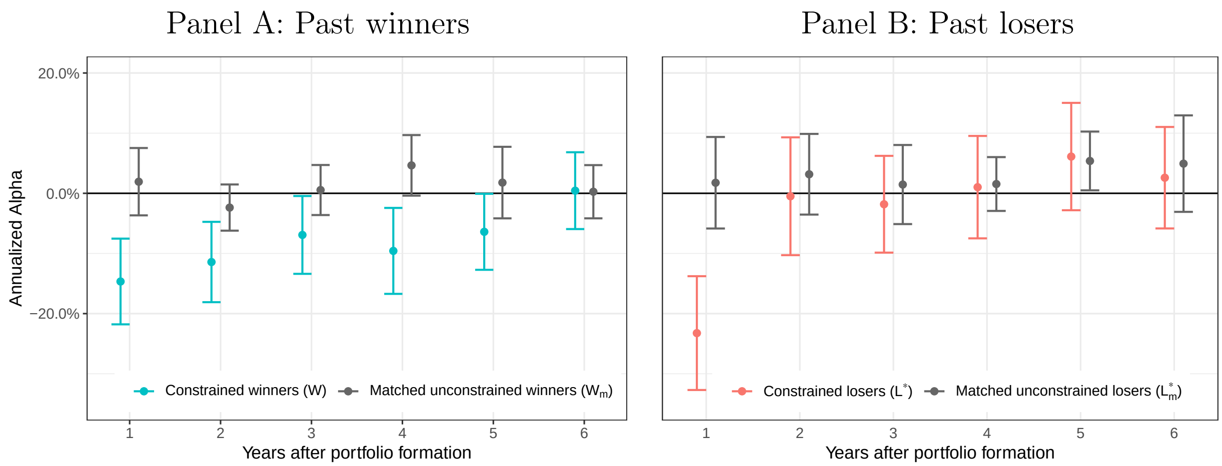
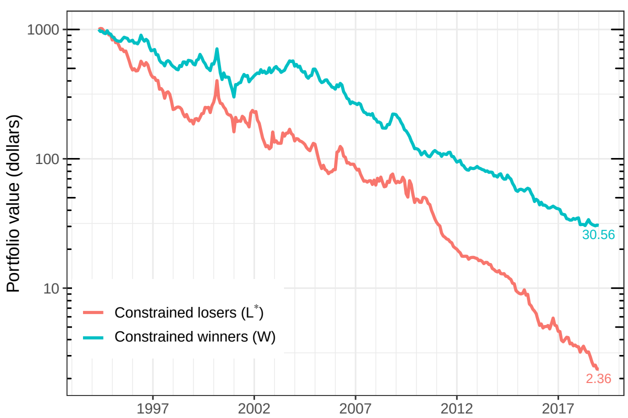


Figure 3: Performance of hedged constrained portfolios over calendar-time. This figure presents the investment value for a set of hedged portfolios. To calculate the portfolio value, we assume an investment at the beginning of the sample of $1,000. We also assume that the exposures to the market is hedged. We calculate the hedging coefficients by running a full-sample regression of the portfolio excess returns on the market excess returns. Then, using the full-sample regression coefficients, we subtract the returns of the (zero-investment) hedge-portfolio [$b_{Mkt}(R_{Mkt}$-$R_{f,t})$] from the portfolio returns to generate the hedged portfolio returns. Panel A plots the evolution of the $1,000 invested in calendar-time 12-month buy-and-hold constrained winners and losers (that were not winners in the past 5 years). Panel B contains calendar-time 48-month buy-and-hold portfolios that skip the first 12 months.

Panel A: Constrained between $(t-12)$ and $(t-1)$ months



Panel B: Constrained between $(t-60)$ and $(t-13)$ months

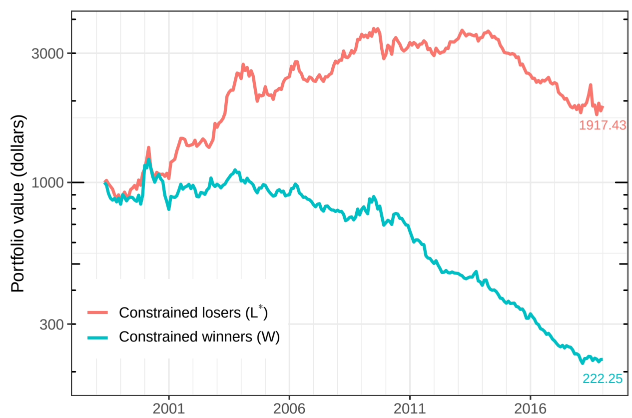


Figure 4: CAR around earnings announcements.
This figure shows cumulated abnormal returns of the constrained winners (W) and constrained losers that were not constrained winners in the 5 preceding years (L^*) around the day (D=0) of an earnings announcement that occurs in the quarter after portfolio 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.

Panel A: Formation between $(t-12)$ and $(t-1)$ months

Panel B: Formation between $(t-60)$ and $(t-13)$ months

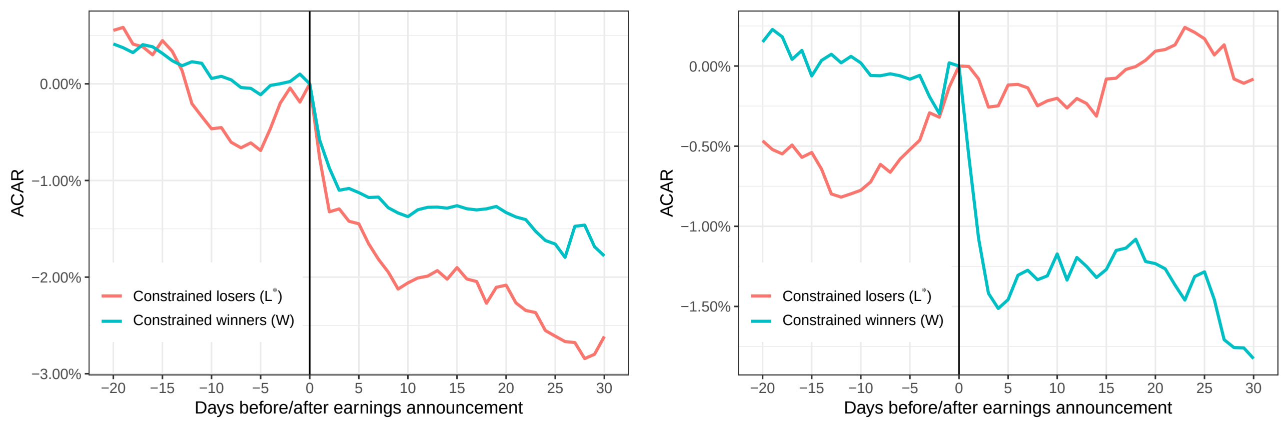


Figure 5: Beliefs and prices for winners and losers - A numerical example. Panel A shows beliefs of overconfident agents and newswatchers after a positive innovation. These beliefs cause different price dynamics for constrained and unconstrained stocks (Panel B). Panel C and D show beliefs and prices after a negative innovation. The information structure for winners is $(\epsilon_{O1}; \epsilon_{O2}; \epsilon_{O3}; \epsilon_{O4}; \ldots; \epsilon_{O12}) = (6; 2; 2; 2; ...; 2)$ for overconfident agents and $(\epsilon_{N1}; \epsilon_{N2}; \epsilon_{N3}; \epsilon_{N4}; \ldots; \epsilon_{N12}) = (4; 3.5; 2.5; 2; ...; 2)$ for newswatchers. The information structure for losers is obtained by multiplying all ϵ's with -1, i.e., $(\epsilon_{O1}; \epsilon_{O2}; \epsilon_{O3}; \epsilon_{O4}; \ldots; \epsilon_{O12}) = (-6; -2; -2; -2; ...; -2)$ for overconfident agents and $(\epsilon_{N1}; \epsilon_{N2}; \epsilon_{N3}; \epsilon_{N4}; \ldots; \epsilon_{N12}) = (-4; -3.5; -2.5; -2; ...; -2)$ 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 the Appendix.

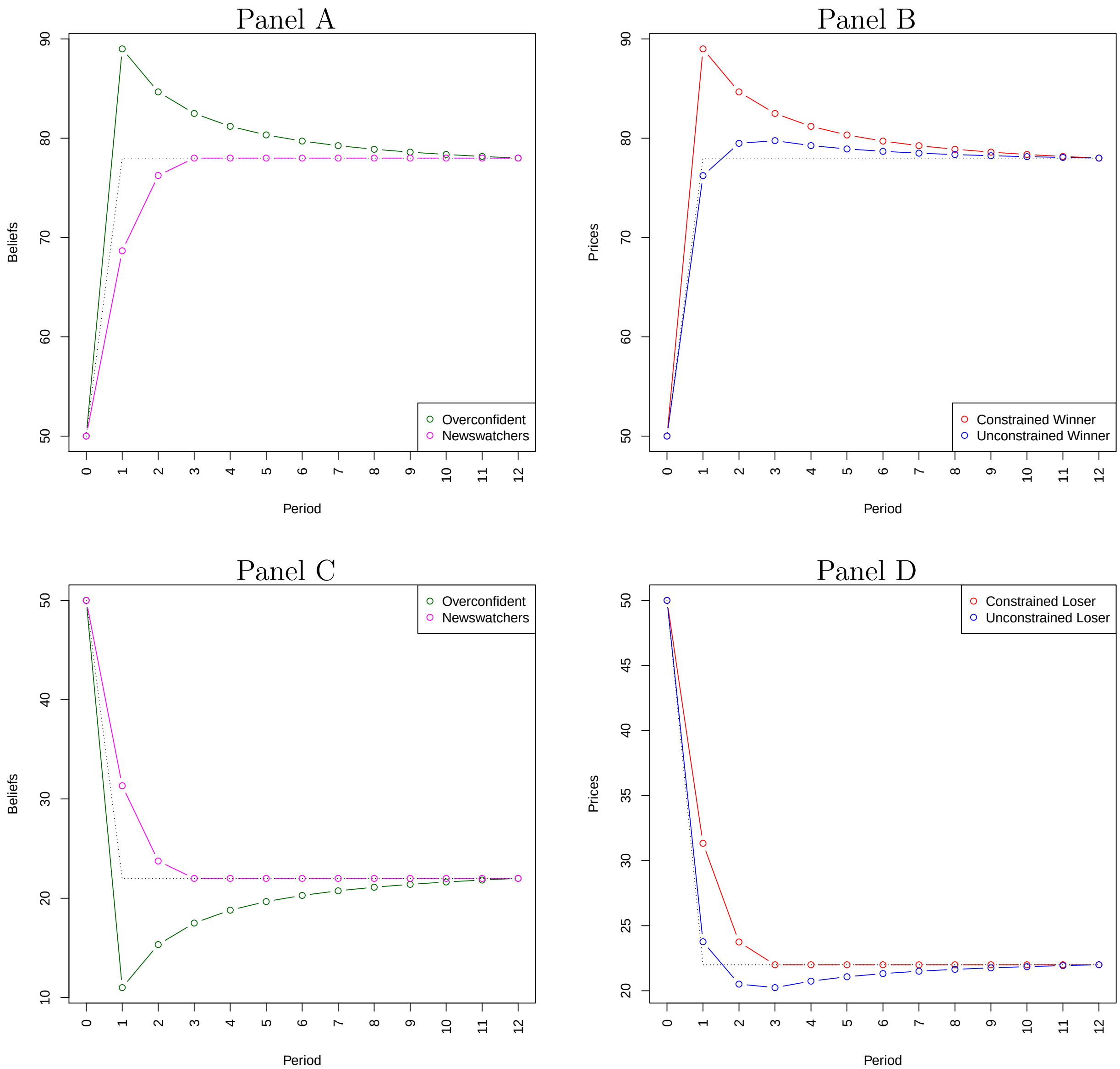


Table 1: Characteristics of constrained and matched portfolios.
This table shows time-series averages of value-weighted mean characteristics of the constrained portfolios in the month of portfolio formation. Shown are the average number of stocks, the average market equity (in billion US dollars), return 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 percent 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 (in %), 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 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.6 in Appendix D.

	L	M	W	L^*	L^W	W_m	L^*_m
Number of stocks	87	38	49	37	50	49	37
Average Market Equity (B$)	2.04	2.89	3.64	2.17	1.27	2.54	2.70
Formation Period Return (%)	-44.56	3.31	84.90	-47.17	-42.59	76.98	-44.45
Institutional Ownership (IOR, %)	17.07	17.54	17.36	18.42	15.86	58.37	57.00
Change in IOR over preceding year (PP)	-4.75	-1.84	0.00	-7.35	-1.56	7.22	-0.32
Short-interest (SIR, %)	8.25	6.74	7.66	7.81	8.71	1.78	1.89
Change in SIR over preceding year (PP)	1.00	1.37	2.66	1.78	0.11	-0.20	-0.63
Book-to-market ratio (%)	68.16	44.92	28.51	86.20	52.29	32.66	86.37
Idiosyncratic volatility (%, daily)	3.69	2.48	3.09	3.81	3.70	2.91	3.49
Turnover (%)	29.50	17.87	36.77	33.42	24.14	19.69	17.52
Change in turnover over preceding year (PP)	-6.12	-0.11	17.25	1.63	-15.14	6.78	1.14
SIRIO (%)	116.89	108.13	124.67	113.41	118.83	3.11	3.74
Option volatility spread (%)	-5.32	-3.58	-4.87	-5.25	-6.12	-0.45	-0.27
Ind.Fee (%)	7.27	4.32	6.06	6.11	9.70	0.58	0.94
Change in Ind.Fee over preceding year (PP)	1.46	0.70	1.15	2.11	1.62	-0.34	-0.19
Simple Avg. Fee (SAF, %)	6.01	3.15	4.04	4.73	7.95	0.40	0.90
Change in SAF over preceding year (PP)	1.79	-0.23	0.24	1.99	1.69	-0.18	0.00

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 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	1.08	0.12 (0.45)	0.16 (0.63)
M	0.81	0.62	0.89	0.08 (0.24)	0.01 (0.05)
Hi SIR	0.98	0.85	−0.35	−1.34 (−4.16)	−1.35 (−4.00)
Hi-Lo	0.02	−0.43	−1.44		
t	(0.08)	(−1.49)	(−4.05)		
$\alpha(Hi-Lo)$	−0.29	−0.82	−1.80		
t	(−1.34)	(−3.02)	(−4.98)		

Panel B: Medium Momentum

	Hi IOR	M	Lo IOR	Lo-Hi	$\alpha(Lo-Hi)$
Lo SIR	0.55	0.85	0.74	0.19 (0.77)	0.43 (1.90)
M	0.65	0.51	0.60	−0.05 (−0.28)	0.07 (0.33)
Hi SIR	0.56	0.60	0.11	−0.45 (−1.45)	−0.30 (−1.14)
Hi-Lo	0.01	−0.25	−0.63		
t	(0.04)	(−0.98)	(−1.73)		
$\alpha(Hi-Lo)$	−0.03	−0.37	−0.77		
t	(−0.18)	(−1.61)	(−2.34)		

Panel C: Losers

	Hi IOR	M	Lo IOR	Lo-Hi	$\alpha(Lo-Hi)$
Lo SIR	0.60	0.61	0.42	−0.18 (−0.33)	0.26 (0.34)
M	0.51	0.29	−0.01	−0.53 (−1.61)	−0.35 (−1.34)
Hi SIR	0.06	−0.05	−1.72	−1.79 (−4.36)	−1.77 (−5.57)
Hi-Lo	−0.54	−0.66	−2.14		
t	(−1.14)	(−2.13)	(−5.11)		
$\alpha(Hi-Lo)$	−0.21	−0.72	−2.23		
t	(−0.36)	(−2.22)	(−6.42)		

Table 3: Calendar-time buy-and-hold portfolio returns of stocks that were constrained within months $t-12$ to $t-1$ prior to formation.
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 constrained calendar-time 12-month buy-and-hold portfolios. The stocks in the portfolios were in the lowest group of institutional ownership and the highest group of short interest at some point during months $\{t-12, ..., t-1\}$ before formation. To calculate the calendar-time buy-and-hold portfolio return, each month, the most recent portfolio is added with \$1 and then no adjustment is made to the investment amount for the remaining 12 months of holding. The columns L (W) are the intersection of this constrained portfolio with the lowest (highest) 11-month return lagged by 1 month; M is the portfolio in between. L^W / L^* contain constrained losers that had / had not been constrained winners over the past 5 years prior to allocation. Columns containing a minus sign go long the first and short the second portfolio. 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.

	L^*	L^W	L^W-L^*	L	M	W	W-L	W-L^*
Panel A: Raw excess returns								
Average	-0.81	-0.54	0.28	-0.65	0.08	-0.26	0.38	0.55
	(-1.32)	(-0.99)	(0.69)	(-1.21)	(0.20)	(-0.60)	(0.99)	(1.29)
No. of months	295	295	295	295	295	295	295	295
AvgN	103	120		219	167	172		
SR	-0.2599	-0.1998	0.1377	-0.2366	0.0413	-0.1108	0.2467	0.2617
Panel B: CAPM regressions								
Intercept	-1.94	-1.51	0.43	-1.70	-0.74	-1.22	0.48	0.71
	(-4.82)	(-3.62)	(1.11)	(-4.78)	(-2.96)	(-4.03)	(1.23)	(1.65)
MktRF	1.74	1.50	-0.23	1.63	1.26	1.48	-0.15	-0.26
	(12.14)	(18.80)	(-2.17)	(16.29)	(20.47)	(14.40)	(-1.12)	(-1.47)
R^2	0.4772	0.4846	0.0208	0.5523	0.6714	0.5963	0.0142	0.0232
IR	-0.8555	-0.7818	0.2149	-0.9304	-0.6703	-0.8056	0.3108	0.3448
Panel C: Four-factor regressions								
Intercept	-1.45	-1.15	0.30	-1.30	-0.62	-1.19	0.11	0.26
	(-4.00)	(-3.48)	(0.73)	(-4.65)	(-2.95)	(-4.12)	(0.34)	(0.66)
MktRF	1.29	1.11	-0.17	1.22	1.07	1.29	0.06	0.00
	(16.05)	(12.76)	(-2.06)	(16.44)	(18.16)	(20.20)	(0.73)	(0.01)
HML	-0.29	-0.44	-0.15	-0.33	0.05	-0.22	0.11	0.07
	(-1.78)	(-3.82)	(-0.74)	(-2.54)	(0.64)	(-1.71)	(0.74)	(0.39)
SMB	1.24	1.25	0.01	1.22	0.77	1.00	-0.22	-0.24
	(7.67)	(9.64)	(0.06)	(10.56)	(13.80)	(9.64)	(-1.62)	(-1.32)
MOM	-0.67	-0.42	0.24	-0.52	-0.20	0.01	0.53	0.68
	(-5.65)	(-4.09)	(1.77)	(-5.27)	(-4.96)	(0.11)	(6.99)	(5.05)
R^2	0.6754	0.7239	0.0590	0.7792	0.8135	0.7704	0.2314	0.2145
IR	-0.8147	-0.8158	0.1540	-1.0147	-0.7504	-1.0407	0.0817	0.1413

Table 4: Calendar-time buy-and-hold portfolio returns of stocks that were constrained within months $t-60$ to $t-13$ prior to formation.
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 $\{t-60, ..., t-13\}$ before formation. The first return is calculated in June 1998, i.e., the first time when we invested 48 times in a row.

	L^*	L^W	L^W-L^*	L	M	W	W-L	W-L^*
Panel A: Raw excess returns								
Average	0.88	0.26	-0.61	0.58	0.25	0.03	-0.55	-0.85
	(1.74)	(0.45)	(-2.50)	(1.08)	(0.58)	(0.05)	(-2.74)	(-3.36)
No. of months	247	247	247	247	247	247	247	247
AvgN	210	201		381	333	369		
SR	0.3880	0.1034	-0.4054	0.2543	0.1329	0.0117	-0.5216	-0.6620
Panel B: CAPM regressions								
Intercept	0.21	-0.45	-0.66	-0.11	-0.34	-0.68	-0.56	-0.89
	(0.71)	(-1.18)	(-2.23)	(-0.39)	(-1.45)	(-2.82)	(-2.82)	(-3.68)
MktRF	1.40	1.50	0.10	1.46	1.26	1.48	0.02	0.08
	(19.36)	(18.68)	(1.22)	(25.58)	(22.37)	(19.02)	(0.25)	(0.79)
R^2	0.6421	0.5748	0.0077	0.6894	0.7293	0.7440	0.0007	0.0069
IR	0.1581	-0.2672	-0.4392	-0.0892	-0.3457	-0.6012	-0.5312	-0.6948
Panel C: Four-factor regressions								
Intercept	0.20	-0.48	-0.68	-0.14	-0.44	-0.69	-0.55	-0.89
	(0.77)	(-1.82)	(-2.28)	(-0.71)	(-2.56)	(-5.12)	(-2.89)	(-3.59)
MktRF	1.17	1.20	0.02	1.22	1.10	1.31	0.09	0.14
	(17.88)	(15.72)	(0.27)	(23.71)	(20.24)	(16.37)	(0.87)	(1.41)
HML	-0.04	-0.50	-0.46	-0.24	-0.04	-0.22	0.02	-0.18
	(-0.48)	(-4.54)	(-3.61)	(-3.01)	(-0.60)	(-2.96)	(0.21)	(-1.98)
SMB	0.84	1.15	0.31	0.93	0.78	0.65	-0.28	-0.19
	(10.74)	(12.00)	(2.95)	(13.48)	(15.26)	(6.08)	(-2.31)	(-1.96)
MOM	-0.17	-0.10	0.07	-0.12	-0.00	-0.07	0.04	0.10
	(-2.46)	(-1.43)	(1.03)	(-2.07)	(-0.10)	(-0.98)	(0.41)	(0.84)
R^2	0.7639	0.8090	0.1688	0.8552	0.8805	0.8353	0.0621	0.0486
IR	0.1828	-0.4304	-0.4963	-0.1643	-0.6634	-0.7695	-0.5375	-0.7139

Table 5: Calendar-time buy-and-hold portfolio returns of stocks that were constrained within months $t-12$ to $t-1$ prior to formation and their statistical matches.

See caption of Table 3 for details. Here, we add portfolios of unconstrained stocks that were propensity-score matched to the constrained ones based on size, book-to-market, past-return and idiosyncratic volatility (indicated by $\cdot_m$). For details, see Section 3.4.

	W	W_m	W-W_m	L^*	L^*_m	L^*-L^*_m	W-L^*	W_m-L^*_m	DiD
Panel A: Raw excess returns									
Average	-0.26	0.99	-1.26	-0.81	1.07	-1.89	0.55	-0.08	0.63
	(-0.60)	(2.65)	(-4.58)	(-1.32)	(2.15)	(-5.15)	(1.29)	(-0.23)	(1.47)
No. of months	295	295	295	295	295	295	295	295	295
AvgN	172	316		103	237				
SR	-0.1108	0.4958	-1.0113	-0.2599	0.4733	-1.0391	0.2617	-0.0540	0.3326
Panel B: CAPM regressions									
Intercept	-1.22	0.16	-1.38	-1.94	0.15	-2.08	0.71	0.01	0.70
	(-4.03)	(0.68)	(-4.99)	(-4.82)	(0.45)	(-5.78)	(1.65)	(0.04)	(1.74)
MktRF	1.48	1.29	0.19	1.74	1.43	0.30	-0.26	-0.15	-0.11
	(14.40)	(17.33)	(3.05)	(12.14)	(12.87)	(2.47)	(-1.47)	(-0.86)	(-0.96)
R^2	0.5963	0.6399	0.0379	0.4772	0.6195	0.0432	0.0232	0.0150	0.0051
IR	-0.8056	0.1339	-1.1341	-0.8555	0.1046	-1.1728	0.3448	0.0098	0.3707
Panel C: Four-factor regressions									
Intercept	-1.19	0.04	-1.23	-1.45	0.41	-1.86	0.26	-0.37	0.63
	(-4.12)	(0.39)	(-4.13)	(-4.00)	(2.17)	(-4.84)	(0.66)	(-1.81)	(1.61)
MktRF	1.29	1.17	0.12	1.29	1.12	0.17	0.00	0.05	-0.05
	(20.20)	(28.97)	(1.40)	(16.05)	(24.73)	(2.05)	(0.01)	(0.66)	(-0.41)
HML	-0.22	-0.12	-0.10	-0.29	0.23	-0.52	0.07	-0.36	0.43
	(-1.71)	(-2.44)	(-0.93)	(-1.78)	(2.07)	(-2.42)	(0.39)	(-2.21)	(2.38)
SMB	1.00	0.99	0.00	1.24	1.08	0.16	-0.24	-0.09	-0.15
	(9.64)	(23.27)	(0.03)	(7.67)	(14.98)	(1.08)	(-1.32)	(-1.12)	(-0.84)
MOM	0.01	0.21	-0.20	-0.67	-0.49	-0.17	0.68	0.71	-0.03
	(0.11)	(6.36)	(-1.91)	(-5.65)	(-7.11)	(-1.36)	(5.05)	(8.21)	(-0.25)
R^2	0.7704	0.9147	0.0849	0.6754	0.8679	0.1198	0.2145	0.5388	0.0603
IR	-1.0407	0.0703	-1.0358	-0.8147	0.4966	-1.0932	0.1413	-0.3617	0.3436

Table 6: Calendar-time buy-and-hold portfolio returns of stocks that were constrained within months $t-60$ to $t-13$ prior to formation and their statistical matches.

See caption of Table 4 for details. Here, we add portfolios of unconstrained stocks that were propensity-score matched to the constrained ones based on size, book-to-market, past-return and idiosyncratic volatility (indicated by $\cdot_m$). For details, see Section 3.4.

	W	W_m	W-W_m	L^*	L^*_m	L^*-L^*_m	W-L^*	W_m-L^*_m	DiD
Panel A: Raw excess returns									
Average	0.03	0.78	-0.75	0.88	0.90	-0.03	-0.85	-0.12	-0.73
	(0.05)	(1.85)	(-3.34)	(1.74)	(1.95)	(-0.11)	(-3.36)	(-0.78)	(-2.91)
No. of months	247	247	247	247	247	247	247	247	247
AvgN	369	791		210	555				
SR	0.0117	0.4216	-0.7422	0.3880	0.4540	-0.0225	-0.6620	-0.1973	-0.5886
Panel B: CAPM regressions									
Intercept	-0.68	0.20	-0.87	0.21	0.28	-0.07	-0.89	-0.08	-0.81
	(-2.82)	(1.01)	(-4.16)	(0.71)	(1.35)	(-0.26)	(-3.68)	(-0.56)	(-3.33)
MktRF	1.48	1.23	0.25	1.40	1.31	0.09	0.08	-0.08	0.17
	(19.02)	(26.00)	(3.83)	(19.36)	(26.81)	(1.24)	(0.79)	(-1.90)	(1.67)
R^2	0.7440	0.7415	0.1040	0.6421	0.7294	0.0096	0.0069	0.0294	0.0301
IR	-0.6012	0.2091	-0.9088	0.1581	0.2715	-0.0587	-0.6948	-0.1365	-0.6622
Panel C: Four-factor regressions									
Intercept	-0.69	0.07	-0.77	0.20	0.15	0.05	-0.89	-0.07	-0.82
	(-5.12)	(0.63)	(-4.20)	(0.77)	(1.29)	(0.21)	(-3.59)	(-0.55)	(-3.08)
MktRF	1.31	1.10	0.21	1.17	1.13	0.05	0.14	-0.03	0.16
	(16.37)	(28.26)	(2.91)	(17.88)	(31.25)	(0.58)	(1.41)	(-0.80)	(1.75)
HML	-0.22	-0.14	-0.08	-0.04	0.06	-0.10	-0.18	-0.21	0.03
	(-2.96)	(-2.52)	(-0.80)	(-0.48)	(1.61)	(-1.02)	(-1.98)	(-3.69)	(0.32)
SMB	0.65	0.75	-0.09	0.84	0.98	-0.14	-0.19	-0.23	0.04
	(6.08)	(10.98)	(-0.72)	(10.74)	(15.48)	(-1.30)	(-1.96)	(-5.96)	(0.46)
MOM	-0.07	0.08	-0.15	-0.17	-0.00	-0.17	0.10	0.08	0.01
	(-0.98)	(2.15)	(-2.85)	(-2.46)	(-0.11)	(-2.17)	(0.84)	(2.23)	(0.10)
R^2	0.8353	0.9215	0.1628	0.7639	0.9393	0.0703	0.0486	0.2393	0.0316
IR	-0.7695	0.1422	-0.8274	0.1828	0.3005	0.0483	-0.7139	-0.1345	-0.6758

Table 7: 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)	1.43 (2.92)	1.61 (3.26)	1.61 (3.27)
$Constr._{(t-12)—(t-1)}$	-0.89 (-3.88)	-0.03 (-0.11)		-0.14 (-0.52)	-0.07 (-0.23)	
$Constr.W_{(t-12)—(t-1)}$		-0.51 (-1.93)	-0.60 (-2.62)	-0.65 (-2.55)	-0.41 (-1.59)	-0.50 (-2.54)
$Constr.L_{(t-12)—(t-1)}$		-1.11 (-3.27)	-1.10 (-3.25)	-0.53 (-1.94)	-0.39 (-1.36)	-0.43 (-1.89)
$RET_{(t-12)—(t-2)}$				0.40 (1.53)	0.40 (1.50)	0.39 (1.48)
$log(BE/ME_{t-1})$				-0.02 (-0.18)	-0.02 (-0.19)	-0.02 (-0.20)
$log(ME_{t-1})$				-0.07 (-1.83)	-0.08 (-2.13)	-0.08 (-2.14)
$ivol_{t-1}$				-0.19 (-2.48)	-0.18 (-2.34)	-0.18 (-2.37)
$SIRIO_{t-1}$					-0.01 (-4.63)	-0.01 (-4.62)
Avg. R^2	0.0017	0.0028	0.0023	0.0819	0.0836	0.0831
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 (2.45)	0.64 (2.45)	0.64 (2.46)	1.47 (2.68)	1.62 (2.97)	1.61 (2.96)
$Constr._{(t-60)—(t-13)}$	-0.29 (-2.46)	0.11 (0.61)		0.01 (0.08)	0.02 (0.11)	
$Constr.W_{(t-60)—(t-13)}$		-0.58 (-2.86)	-0.49 (-3.98)	-0.58 (-3.04)	-0.51 (-2.67)	-0.51 (-3.36)
$Constr.L_{(t-60)—(t-13)}$		-0.03 (-0.11)	0.03 (0.12)	0.07 (0.37)	0.16 (0.90)	0.18 (1.01)
$RET_{(t-12)—(t-2)}$				0.31 (1.06)	0.31 (1.06)	0.30 (1.06)
$log(BE/ME_{t-1})$				0.00 (0.03)	-0.00 (-0.04)	-0.00 (-0.03)
$log(ME_{t-1})$				-0.07 (-1.72)	-0.08 (-2.01)	-0.08 (-2.00)
$ivol_{t-1}$				-0.18 (-2.04)	-0.16 (-1.86)	-0.16 (-1.87)
$SIRIO_{t-1}$					-0.01 (-4.76)	-0.01 (-4.76)
Avg. R^2	0.0019	0.0034	0.0027	0.0841	0.0857	0.0850
No. of months	306	306	306	306	306	306