Overconfidence, Information Diffusion, and Mispricing Persistence*

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Abstract

We propose a dynamic heterogeneous agents model which generates testable hypotheses about the formation, timing and bursting of asset price bubbles in the presence of short-sale constraints, given a calibration that is consistent with momentum and reversal effects for unconstrained assets. Consistent with the model, all short-sale constrained stocks earn strong negative risk-adjusted returns in the first year after portfolio formation. However, the calibrated model predicts strong differences in the mispricing persistence of past-winners and losers. After one year, the alpha of past-losers is approximately zero (0.23%/mo, $t = 0.85$), while the alpha for past-winners is -0.75%/mo ($t = -5.82$) over the following four years.

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

JEL-Classification: G12, G14

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1 Introduction

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 (Miller, 1977). Thus, such securities can become overvalued "bubble" stocks. We find that negative returns persist for about five years for some bubble firms. In contrast, for others, the negative abnormal returns last only about a year.

We explain the differences in these decay rates with a psychology-based model that combines approaches originally introduced several decades ago designed to explain momentum, value, and other cross-sectional return patterns among common stocks.[1] Among those proposed were representative agent models (Barberis, Shleifer, and Vishny, 1998, Daniel, Hirshleifer, and Subrahmanyam, 1998), and heterogeneous agent models (Hong and Stein, 1999). None of these three studies explored the consequences of short-sale restrictions and, to our knowledge, no subsequent work has examined the predictions of these models for the behavior of short-sale-constrained stocks, or examined how momentum and value effects are modified when firms are short-sale constrained. That is what we do here.

[INSERT FIGURE 1 HERE]

Our empirical analysis shows that, among constrained firms, the winner momentum effect "flips" in the sense that the firms with the highest past one-year return earn strikingly negative returns over the following year, and indeed over the following five years. Over the first year, the negative abnormal returns that these constrained winners earn are roughly consistent with the negative abnormal returns earned by constrained losers. However, where the constrained winners and losers differ is in the duration of the negative abnormal returns. This can be seen in Figure 1. As a proxy for short sale constraints, we use a combination of

[1] Note that we refer to value and long-term reversal interchangeably, consistent with the early behavioral finance literature.

low institutional ownership and high short interest. Finally, we consider winners and losers (highest/lowest 30% of past one-year returns).[2]

Figure 1 shows that, after the first year, the abnormal returns of constrained past losers are not statistically different from zero. In contrast, the constrained winners earn equally strong negative abnormal returns for the first year, but then continue earning negative abnormal returns for approximately four more years. Loosely speaking, we can say that both the constrained winners and the constrained losers are bubble stocks, in the sense that both portfolios earn predictable strong negative returns, consistent with the definition suggested in Fama (2014).[3] However, the bubble collapses quickly for the past losers, and over an extended period for the past winners.

The long decay rates for constrained past winners allow us to construct a large value-weighted portfolio which generates remarkably negative abnormal returns going forward. The portfolio construction relies on our finding that, even for firms that were constrained winners up to five years ago, the expected abnormal returns today are still negative. Consequently, a value-weighted buy-and-hold portfolio of all stocks that have been constrained winners in the previous 60 months, should be diversified and earn negative abnormal returns. This is what we find: The number of constrained winners in any given month, is 51 on average, but the number of firms which have been constrained winners at *any* point during the previous five years is 390, on average. The time-series average of the portfolios' monthly excess returns

[2] Specifically the stocks in the constrained portfolio are in the lowest 30% of institutional ownership, as a proxy for lending supply, and in the highest 30% of short interest, to identify stocks where agents disagree about the value. For the losers, we additionally make sure that these have not been in the constrained winner portfolio within the past five years. This is to filter out bubbles that are already in the process of bursting. The figure plots annualized alphas of 12-month buy-and-hold calendar-time portfolios by holding-year. Alphas are calculated with respect to the three Fama and French (1993) factors and the Carhart (1997) momentum factor.

[3] Fama (2014) notes that policy makers and others seem to think of a "bubble" as "an irrational strong price increase that implies a predictable strong decline." Recent discussions of bubbles from a theoretical and empirical perspective are provided by Barberis, Greenwood, Jin, and Shleifer (2018) and Greenwood, Shleifer, and You (2018).

over the risk-free rate is close to zero, and the alpha with respect to Fama and French (1993)-Carhart (1997) four-factor model is -0.88 with a t-statistic of -6.59.[4]

We show that our empirical findings are consistent with a heterogeneous agent model which features overconfidence and slow information diffusion, and 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 intuition behind the model is the following: first, recall that value effects among unconstrained stocks persist on the order of five years (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 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 value suggests that the diffusion of public information should be considerably faster than the resolution of overconfidence in an empirically sound calibration of our model.

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 shock (and ignore the information content

[4] The details of the value-weighted buy-and-hold portfolio construction are explained in Section 5.2. A simple value-weighted portfolio approach, where all stocks' weights are simply their previous month's market-capitalization, yields an alpha of -0.81 (t-statistic: -5.93).

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 positive 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 shorted, the newswatchers' views will not be fully incorporated into the price, and the price will reflect the informed overconfident agents' views only. 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. 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. So this model is consistent with the return patterns that we observe both in constrained and unconstrained stocks and captures the asymmetry between positive and negative news shocks we observe in the data.

2 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).[5] In a similar vein, Engelberg, Reed, and Ringgenberg (2018) relate loan fee uncertainty and recall risk to price inefficiencies.[6]

[5] 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.

[6] 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.

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 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 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.[7] 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 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.

[7] 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.

3 Model

The empirical work we present in Section 5 suggests that the dynamics of equity prices for firms which are short-sale constrained are distinctly different than those of unconstrained firms. Because short-sale constraints will only affect prices if there are differences across agents, the price patterns documented here and elsewhere suggest heterogeneity across agents. We therefore propose a heterogeneous agent model in which agents differ in the way that they process new information about firms. This model is completely consistent with value and momentum effects for unconstrained firms, but also matches our new empirical findings for constrained firms.

3.1 Overview

The equilibrium price of an asset is the price at which all agents believe their holdings are optimal. In heterogeneous agent models with risk-averse agents, frictionless markets and 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.[8]

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

[8] 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).

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 his utility as of period $t+1$.[9] 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 him. This makes the solution far more tractable, and moreover is consistent with the "illusion of validity" of Kahneman and Tversky (1973).[10] In other words, agents believe that their views are correct, and that others will figure that out sooner rather than later.

A key model feature that drives our results is that access to private information is paired with overconfidence. Motivated by this, in our model there are two types of agents. The first set of agents are informed *overconfident* agents. They receive all new information immediately. Consistent with Daniel, Hirshleifer, and Subrahmanyam (1998), 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

[9] Alternatively, agents might assume that they will never trade again and hold their portfolio until the final period (see, e.g., Hong and Stein, 1999). The resulting empirical predictions of such a modified model (not reported) are qualitatively the same.

[10] 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").

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, consistent with empirical findings.

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, can be labeled as "bubble" firms, as both earn strong negative future returns. An interesting implication of our model is that, for the past-loser firms, the bubble will collapse over the short horizon over which momentum is observed, i.e. about 1 year. For the past-winner firms the bubble collapse will take as long as value effects, i.e. about five years. These predictions are consistent with the empirical findings documented in Section 5.

3.2 General Model

There are two assets: a risk free asset with fully elastic supply which earns a return of zero each period, and a risky asset which pays a liquidating dividend $\tilde{D}_T$ at time T. To capture the information dynamics that drive the dynamics of return predictability, we follow Hong and Stein (1999) and specify that the liquidating dividend is a sum of dividend innovations each period $t \in \{1, \ldots, T\}$.[11] That is:

$$\tilde{D}_T = D_0 + \tilde{\epsilon}_1 + \tilde{\epsilon}_2 + \cdots + \tilde{\epsilon}_T. \tag{1}$$

Hong and Stein (1999) specify that the innovations are mean zero. In contrast, in our specification the innovations $\tilde{\epsilon}_t \sim \mathcal{N}(\mu_\epsilon, \sigma^2)$ are $i.i.d.$ draws from a distribution with constant variance σ^2 and (time invariant) mean μ_ϵ. The agents in our model do not directly observe μ_ϵ. They do have a valid, common prior distribution at time $t = 0$, $\mu_\epsilon \sim \mathcal{N}(0, \zeta^2)$, and over time agents observe, partly or completely, the realized dividend innovations (ϵ_t's) and update their beliefs about μ_ϵ based on these observations. All agents are Bayesian, but do not optimally use all information available to them.

[11] We follow Hong and Stein (1999) and call the ϵ's dividend innovations or just innovations. An alternative term in the literature is cash-flow shocks (Barberis, Greenwood, Jin, and Shleifer, 2018).

The motivation for this specification is the following: given symmetric information at $t = 0$, all agents agree on the firm value in period $t = 0$. However, because after this point they see different parts of the information set and process this information differently, they will start to disagree about the firm's value over time. Their disagreement will be captured by different posterior distributions for μ_ϵ. One group will become relatively more optimistic, meaning they think that the firm will generate higher average cashflows going forward, and the second group will be relatively more pessimistic. Our objective in writing the model this way is to develop an understanding of how this disagreement will evolve over time, and how this disagreement will affect price dynamics.

Given our modeling assumptions, each agent's posterior distribution for μ_ϵ will be normal, but the distributions will have different means and variances. Specifically, for an agent from subgroup i, we denote the mean and variance of their posterior distribution over μ_ϵ, after observing the new information at time t, as $\mu_\epsilon \sim \mathcal{N}\left(\hat{\alpha}_{it}, \hat{\eta}_{it}^2\right)$. What kind of information different agents see and how they update their priors will define the subgroup of an agent, and will be specified later.

3.2.1 Agents

There are multiple groups of agents in our model. Each group consists of a measure of agents with identical information and preferences, and who form beliefs in the same way. The first group consists of passive investors. In aggregate, the group of passive investors demands exactly the total outstanding supply of shares, independent of the share price. The set of passive investors is further stratified into institutional and individual investors. In our setting, the only difference between these sub-groups is that institutional investors are willing to lend out shares at zero cost, while individual investors do not.[12]

Any further group of agents is assumed to be active. Each active agent forms beliefs, trades, and sets prices so as to maximize individual utility. Since the passive investors

[12] This assumption is consistent with evidence presented in D'Avolio (2002) showing that lendable shares are predominantly supplied by large institutional investors like passive index funds.

demand the total outstanding supply of shares, active agents must therefore hold zero shares in aggregate; they compete with each other on the basis of their differing beliefs about the value of the risky security. Each period t, all active agents maximize utility over their period $t+1$ wealth. Their utility is exponential with risk-aversion coefficient γ_i, where index i denotes the active agents' group.

There are no trading costs. However, as in the markets we examine later on, all active agents are required to first locate and borrow any shares they sell short. Search frictions, as specified below can lead to a borrowing cost of c_t (per period, per share), which is determined endogenously. To simplify, we assume that share lending takes place in a centralized market—so the cost c_t is the same for any agent borrowing the stock. We further assume that any active agent who buys shares does not lend out these shares.[13] In the following, we refer to active agents by using the single word agents (as opposed to passive investors, who do not trade actively).

3.2.2 Demands and the equilibrium price

At time t, given a posterior distribution $\mu_\epsilon \sim \mathcal{N}\left(\hat{\alpha}_{it}, \hat{\eta}_{it}^2\right)$, an agent from group i expects a liquidating dividend of:

$$\mathbb{E}_{it}\left[D_T\right] = D_{it} + \hat{\alpha}_{it}(T-t). \tag{2}$$

where $D_{it} = D_0 + \sum_{s=1}^{t} \epsilon_{it}$ is the sum of the realized dividend innovations ϵ_t's through time t. He thinks that each upcoming piece of information will have a mean of $\hat{\alpha}_{it}$. The variance of the predictive return distribution for the upcoming dividend innovation is $\hat{\sigma}_{it}^2 = \sigma^2 + \hat{\eta}_{it}^2$, the sum of the variance of innovations and the variance of the own parameter estimate about μ_ϵ (see, for example, Brandt, 2010).

[13] Note that the existence of hard-to-borrow stocks is not possible if every agent makes their shares freely available for borrowing, for example through a margin account, and brokers lend out all available shares. In equilibrium, pessimists would just short exactly the number of shares that optimists demand and shorting fees would always be zero. Our extreme assumption is made to capture the empirical regularities that stocks do become costly to borrow and that not all investors lend out their shares (see Reed, 2013, for a recent survey of the literature on short selling).

In this CARA-normal setting, myopic demand is just the expected price next period $\mathbb{E}_{it}\left[p_{t+1}\right]$, minus the current price p_t, scaled by the risk-aversion coefficient times the payoff variance. Thus, the demand function depends on an assumption regarding agents' beliefs about the price in the next period ($\mathbb{E}_{it}\left[p_{t+1}\right]$). We assume that agents are overconfident in the sense that they believe that all other agents will agree next period that they were actually right. As a consequence, they think that there will be no disagreement in the next period, which directly implies $\mathbb{E}_{it}\left[c_{t+1}\right] = 0$ for all groups i. They further believe that the market price will be equal to their belief about the final payoff next period. As we will see shortly, this is consistent with the equilibrium price function in the sense that the equilibrium price is, in our setting, just the identical belief of all agents if there is no disagreement. Expressed mathematically, we have $\mathbb{E}_{it}\left[p_{t+1}\right] = \mathbb{E}_{it}\left[\mathbb{E}_{i,t+1}\left[D_T\right]\right]$, a term that is equal to $\mathbb{E}_{it}\left[D_T\right]$ by the law of iterated expectations. We finally obtain $\mathbb{E}_{it}\left[p_{t+1}\right] = D_{it} + \hat{\alpha}_{it}(T-t)$ by using equation (2).

So given an equilibrium price $p_t \leq \mathbb{E}_{it}\left[D_T\right]$, the demand of an agent in group i is positive and given by:[14]

$$d_t^i = \frac{\mathbb{E}_{it}\left[D_T\right] - p_t}{\gamma_i \hat{\sigma}_{it}^2} = \frac{D_{it} + \hat{\alpha}_{it}(T-t) - p_t}{\gamma_i \hat{\sigma}_{it}^2} \qquad \text{if } p_t \leq \mathbb{E}_{it}\left[D_T\right]. \tag{3}$$

However, if the price is above what the agent expects the payoff to be (i.e., if $p_t \geq \mathbb{E}_{it}\left[D_T\right]$), he may elect to borrow the stock and sell it. To do so, the agent must pay the per-unit cost of borrowing the shares from t to $t+1$, which we denote c_t. He will thus choose to go short if and only if the difference between what he receives from shorting (p_t), is greater than the the sum of the expected cost of buying back the share next period ($= \mathbb{E}_t[p_{t+1}] = \mathbb{E}_{it}\left[D_T\right]$) plus the cost of borrowing c_t. His demand—which will be negative—is:

$$d_i^t = \frac{\mathbb{E}_{it}\left[D_T\right] + c_t - p_t}{\gamma_i \hat{\sigma}_{it}^2} = -\frac{p_t - (D_{it} + \hat{\alpha}_{it}(T-t)) - c_t}{\gamma_i \hat{\sigma}_{it}^2} \qquad \text{if } p_t \geq \mathbb{E}_{it}\left[D_T\right] + c_t. \tag{4}$$

[14] Appendix A.I derives that optimal demands in period t more formally.

Note that, if $c_t > 0$, the demand of an agent in group i will be zero for a range of prices $\mathbb{E}_{it}[D_T] \leq p_t \leq \mathbb{E}_{it}[D_T] + c_t$. For an equilibrium p_t in this range, the agents in group i will be sidelined from the market – they will neither buy nor sell short the risky asset.

Let π_i denote a measure of agents in group i and L_t (S_t) denote the set of groups who are long (short) in period t. As shown in Appendix A.I, the market clearing price p_t in the stock market is

$$p_t = D_{mt} + \hat{\alpha}_{mt}(T-t) + \frac{\sum_{i \in S_t} \Pi_{it}}{\sum_{i \in (L_t \cup S_t)} \Pi_{it}} c_t \tag{5}$$

with

$$\Pi_{it} \equiv \frac{\pi_i}{\gamma_i \hat{\sigma}^2_{it}}, \tag{6}$$

$$\hat{\alpha}_{mt} \equiv \sum_{i \in (L_t \cup S_t)} \left[\frac{\Pi_{it}}{\sum_{j \in (L_t \cup S_t)} \Pi_{jt}} \hat{\alpha}_{it} \right], \tag{7}$$

and

$$D_{mt} \equiv \sum_{i \in (L_t \cup S_t)} \left[\frac{\Pi_{it}}{\sum_{j \in (L_t \cup S_t)} \Pi_{jt}} D_{it} \right]. \tag{8}$$

We can think of Π_{it} as the adjusted measure of agents belonging to group i in period t. The adjustment accounts for their risk aversion (γ_i) and their perceived parameter uncertainty ($\hat{\sigma}^2_{it}$). $\hat{\alpha}_{mt}$ is then the weighted average expectation of μ_ϵ, and D_{mt} is the weighted average of the sum of privately observed dividend innovations ϵ's. For an unconstrained stock ($c_t = 0$), equation (5) shows that the market price is simply a weighted average of single beliefs specified in equation (2). The weights depend on how aggressively a group trades. equation (5) shows further that constrained stocks are overpriced relative to the average market belief and that the degree of overpricing is proportional to the per-share shorting cost c_t.

3.2.3 The cost of borrowing shares

Consistent with US institutional restrictions, we require that stock must be borrowed before it can be sold short.[15] Borrowing costs are determined in equilibrium, and are the price at which the supply of shares are equal to the demand from agents (as in Blocher, Reed, and Van Wesep, 2013). The supply is determined by the costs of finding new shares to borrow. We model the supply of shares X_t to the lending market as a function of the borrowing cost c_t as:

$$X_t = \lambda Q + \frac{1}{\tau} c_t \tag{9}$$

where Q is the number of shares outstanding. The intuition for this specification is as follows: first, a fraction λ of the passive investors are always willing to lend out their shares in the lending market, regardless of the borrowing cost. We can think of this as institutional lending supply, coming from index funds, pension funds, etc., that have set up a stock lending program. As long as the demand to borrow shares is less than the institutional supply of λQ, the institutions compete in the lending market, driving the cost of borrowing to zero. However, after the institutional lending supply is exhausted, finding additional shares to borrow requires the payment of search costs.

We implicitly assume that the lending market is a perfectly functioning market, meaning that each stock borrower must pay the equilibrium cost per stock c_t and not the marginal cost of finding his own additional share. We can imagine a clearinghouse that collects the supply and demand schedule and then sets the equilibrium price for lending accordingly. The passive investors earn the rents from lending their shares but, by assumption, this does not affect their decision to hold the underlying shares. Similarly, those who can find shares to borrow at a cost of less than c_t are (effectively) assumed to borrow those shares at the equilibrium cost of c_t. The per-unit borrowing cost c_t, for every share borrowed, is therefore equal to the

[15] Further, stock may only be borrowed for the purpose of short selling. Thus, the number of shares borrowed is at all times equal to the number of shares sold short.

marginal cost, that is the cost of finding the last share that is borrowed. Furthermore, c_t is also equal to the average search cost per share.

Rearranging equation (9) gives the cost per share of borrowing stock as a function of the total number of shares borrowed (X_t):

$$c_t\left(X_t\right) = max\left(0, \tau\left(X_t - \lambda Q\right)\right). \tag{10}$$

The first derivative with respect to short-interest X_t (for $X_t > \lambda Q$) is equal to $\frac{\partial c}{\partial X_t} = \tau$. τ is the amount by which the borrowing cost c_t increases for each additional share borrowed. Consistent with the empirical evidence documented by Kolasinski, Reed, and Ringgenberg (2013), we specify that marginal search costs increase with the number of shares borrowed, and in our specification they increase linearly in X_t, once demand exceeds the institutional supply. Note also that, *ceteris paribus*, borrowing a share is cheaper for stocks with higher institutional lending supply.

Market clearing on the lending market requires

$$\lambda Q + \frac{1}{\tau}c_t \geq \sum_{i \in S_t} \Pi_{it}\left(p_t - \left(D_{it} + \hat{\alpha}_{it}(T-t)\right) - c_t\right). \tag{11}$$

Substituting in the equilibrium price from equation (5) and solving for c_t yields:

$$c_t = max\left\{0; \frac{\tau\left[\sum_{i \in S_t} \Pi_{it}(D_{mt} - D_{it} + (\hat{\alpha}_{mt} - \hat{\alpha}_{it})(T-t)) - \lambda Q\right]}{1 + \tau\left[\sum_{i \in S_t} \Pi_i\left(1 - \frac{\sum_{j \in S_t} \Pi_j}{\sum_{j \in (L_t \cup S_t)} \Pi_j}\right)\right]}\right\}. \tag{12}$$

Intuitively, costs increase with the adjusted measure of short-sellers ($\sum_{i \in S_t} \Pi_{it}$), and with the magnitude of the short-sellers' disagreement with the market beliefs ($(D_{mt} - D_{it} + (\hat{\alpha}_{mt} - \hat{\alpha}_{it})(T-t)$). Further intuition for equation (12) is given in Appendix A.II.

An equilibrium in period t is a situation where market clearing conditions (5) and (12) hold and where each agent acts optimally given the equilibrium prices and shorting costs. Note that this also implies that agents in set L_t choose optimally a positive demand, agents in set S_t prefer a negative demand, and agents who are in neither set have a zero demand in equilibrium.

3.3 Heterogeneous Agents

In this subsection, we specify an application of the general model outlined above. Specifically we specify that, in addition to the set of passive investors, there are two groups of actively trading agents. Each group has its own set of biases and/or information disadvantages.

As noted earlier, the key assumptions that drive the information processing of our two types of agents are that: (1) informed agents are *overconfident* (Daniel, Hirshleifer, and Subrahmanyam, 1998), and (2) the uninformed *newswatchers*, who receive this information slowly, are not overconfident.

The informed agents are all "quick", in that they receive all new information immediately. They perceive each signal to be a private signal, as all other market participants are unable to fully observe their signal ϵ_t at time t. Consistent with Daniel, Hirshleifer, and Subrahmanyam (1998), their overconfidence about their signal leads them to overestimate signal precision, and thus to overweight the signal. In contrast, the newswatchers see only a part of ϵ_t in the upcoming periods. They form beliefs by Bayesian updating, but they ignore the information contained in prices.

3.3.1 Timing of Information

We define $\delta_t = \epsilon_t - \mu_\epsilon$ as the (mean zero) surprise component of each dividend innovation release. Following Hong and Stein (1999), each surprise δ_t is decomposed into n sub-surprises δ_t^{t+i}, $i \in [0; (n-1)]$, with mean zero and variance σ^2/n.

The overconfident agents see the entire innovation $\epsilon_{Ot} = \epsilon_t = \mu_\epsilon + \delta_{Ot} = \mu_\epsilon + \sum_{j=t}^{t+n-1} \delta_t^j$ at time t. The newswatchers see signals based on sub-surprises one after another. Specifically, newswatchers observe a signal ϵ_{Nt} based on all sub-surprises with superscript t at time $n \leq t < T$, i.e.,

$$\epsilon_{Nt} = \mu_\epsilon + \delta_{Nt} = \mu_\epsilon + \sum_{j=t-n+1}^{t} \delta_j^t \tag{13}$$

INSERT Table 1 HERE

Table 1 illustrates the timing of information for a information diffusion period of $n = 3$. Each surprise δ_t has its own row in the table and is the sum of sub-surprises δ_t^{t+i}, $i \in [0; (n-1)]$. The signal's surprise component of overconfident agents (δ_{Ot}'s) are exactly equal to these row sums. The newswatchers see one sub-surprise from each previous period that lies in $[t-n+1; t]$. The surprise component δ_{Nt} of their signal is the column sum in Table 1. Newswatchers think that all of their signals δ_{Nt} have variance σ^2, which is correct except for a start- and an end-effect.[16] For example, their signal in period 3 is the sum of three sub-surprises that originate in periods one, two, and three, respectively.

3.3.2 Formation of Beliefs

In period 0, we assume that the common prior distribution of all agents accurately reflects the distribution from which μ_ϵ was drawn. In each following period, overconfident and newswatchers observe their dividend innovation ϵ_{Ot} and ϵ_{Nt}, respectively. Subsequently, trading takes place. After trading has taken place in the last period, D_T is paid out.

Agents form beliefs about the unknown value of μ_ϵ at time t after having seen their innovation ϵ_{Ot} or ϵ_{Nt} and before trading takes place. Newswatchers assume that the signal is drawn from a normal distribution with a mean equal to the unknown mean μ_ϵ and known variance σ^2. The informed (and overconfident) agents incorrectly believe that their signals have variance $\kappa\sigma^2$ with $0 < \kappa < 1$ lower than the true variance σ^2.

All agents use Bayes' rule to combine their prior belief about μ_ϵ and their signal ϵ_{Ot} or ϵ_{Nt} into a posterior belief. The beliefs of overconfident agent evolve according to $\hat{\alpha}_{Ot} =$

[16] See Table 1. In the first periods, there are not enough sub-surprises available and equation (13) effectively becomes $\epsilon_{Nt} = \mu_\epsilon + \sum_{j=1}^{t} \delta_j^t$. In the final period $t = T$, newswatchers are assumed to observe all remaining information and equation (13) reads $\epsilon_{Nt} = \mu_\epsilon + \sum_{j=t-n+1}^{t} \delta_j^t + \sum_{j=t-n+2}^{t} \delta_j^{t+1} + \cdots + \sum_{j=t}^{t} \delta_j^{t+n-1}$.

$\frac{\hat{\alpha}_{O,t-1}\kappa\sigma^2+\epsilon_{Ot}\eta_t^2}{\hat{\eta}^2_{O,t-1}+\kappa\sigma^2}$. Newswatchers' belief in period t is equal to $\hat{\alpha}_{Nt} = \frac{\hat{\alpha}_{N,t-1}\sigma^2+\epsilon_{Nt}\eta_t^2}{\hat{\eta}^2_{N,t-1}+\sigma^2}$. The posterior variances are $\hat{\eta}^2_{Ot} = \frac{\hat{\eta}^2_{O,t-1}\kappa\sigma^2}{\hat{\eta}^2_{O,t-1}+\kappa\sigma^2}$ and $\hat{\eta}^2_{Nt} = \frac{\hat{\eta}^2_{N,t-1}\sigma^2}{\hat{\eta}^2_{N,t-1}+\sigma^2}$, respectively. Agents base their demands in period t on these beliefs.

3.4 Implications

Before we turn to the asset pricing implications, we study the endogenously arising disagreement among overconfident agents and newswatchers in the case of extreme fundamental shocks. To set the stage, assume that the starting dividend $D_0 = 50$, that $T = 12$ and nature determines μ_ϵ to be equal to 2. Overconfident agents and newswatchers do not know the true value of μ_ϵ, but their uncertainty about the unknown value can be described by a common normally distributed prior with zero mean and variance $\hat{\eta}^2_{O0} = \hat{\eta}^2_{N0} = \zeta^2 = 1$. Let the known variance of dividend innovations σ^2 be 2. As in Table 1, we set the information diffusion period to $n = 3$.

Assume now that there is a large surprise $\delta_1 = \delta_{Q1} = 4$ in the first period and that all following surprises are zero. The overconfident investor thus perceives this as an initial innovation of $\epsilon_{O1} = 6$, followed by a series of $\epsilon_{Ot} = 2$ for all remaining time periods $t \in [2; 12]$.

As in Hong and Stein (1999), information travels slowly for the newswatchers. Instead of observing the large surprise in the first period immediately, they see sub-surprises assumed to be equal $\delta_1^1 = 2$, $\delta_1^2 = 1.5$, and $\delta_1^3 = 0.5$, respectively. Together with the assumption of zero surprises in periods 2 to 12, this leads, in our example, the newswatcher population to perceive dividend innovations of $\epsilon_{N1} = 4$, $\epsilon_{N2} = 3.5$, $\epsilon_{N3} = 2.5$, and $\epsilon_{Nt} = 2$ for periods $t \in [4; 12]$.

INSERT Figure 2 HERE

Panel A of Figure 2 shows posterior beliefs of overconfident agents $\mathbb{E}_{Ot}[D_T]$ and newswatchers $\mathbb{E}_{Nt}[D_T]$, as well as the rational expectation beliefs of a Bayesian who sees the dividend innovations of the overconfident agents. By construction, our stock is a winner stock in the sense that the firm experiences a large positive dividend innovation, "good news", in the first period. Overconfident agents see all the information first, interpret it as private, overreact on it, and become far too optimistic about the value of the final liquidating dividend D_t. Over time, the overconfident agents learn (slowly) from further dividend innovations the true value of μ_ϵ. 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 ($\lambda = 1$ 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 2, 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 correct value of μ_ϵ, 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.[17]

The dynamics of prices are fundamentally different for a constrained winner ($\lambda = 0$ in Panel B). For simplicity, we consider in our example an extreme short-selling constraint, modeled through a combination of no institutional lending supply ($\lambda = 0$) and unaffordable search costs ($\tau \to \infty$). The opinions from the newswatchers, who are the pessimists in the case of "good news," are now completely sidelined from the market and the overconfident agents are setting the price. As a consequence, the price overshoots with the large surprise

[17] 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.

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.

Panel C and Panel D of Figure 2 show beliefs and prices for a loser stock. The assumptions of our example are unchanged, except that all surprises and μ_ϵ are multiplied with -1. Beliefs in Panel C and the dynamics of prices of an unconstrained loser mirror the beliefs and price dynamics of a 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 the 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 newswatcher have seen all the negative information, there is no value effect. The opinions of pessimistic overconfident agents, who are causing the value in the unconstrained case, are still sidelined from the market valuation.[18] [19]

4 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 2018/06.[20]

[18] 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.

[19] Less extreme shocks lead to qualitatively similar patterns, as shown in Appendix A.III.

[20] Specifically, we only consider stocks with exchange code 1, 2 or 3, and share code 10 or 11.

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.[21] 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 portfolios every quarter and assume that the holdings data is in the investors' information set with a lag of one month.[22]

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.[23] 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.[24] Coverage starts in June 1988 and constitutes the bottleneck for all analyses. We divide the number of shares

[21] See note issued by WRDS in May 2017. Data are available until the end of 2016. 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.

[22] 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.

[23] 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.

[24] 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.

held short by the number of shares outstanding from CRSP to get the short-interest-ratio SIR.

Analyst-forecasts of fiscal-year-end earnings are from Institutional Broker's Estimate System (IBES). We use the summary file unadjusted for stock splits, to avoid the bias induced by ex-post split adjustment, as pointed out by Diether, Malloy, and Scherbina (2002). *Earnings-forecast-dispersion (EFD)* is the standard-deviation of forecasts normalized by the absolute value of its mean. We eliminate values where the mean forecast is between -0.1 and +0.1, as very low mean forecasts lead to extremely large values that bias results.[25]

5 Empirical Results

We start by assessing the model's main predictions about the price dynamics. We use institutional ownership as a proxy for lending supply. It is closely related to lending supply (see, e.g., D'Avolio, 2002) and has been used to proxy for borrowing constraints (see, e.g., Nagel, 2005). Second, high disagreement implies high short-selling activity (as agents in the model hold a zero net position in aggregate). It can be measured by calculating the short-interest ratio (SIR), which is reported in the middle of the month. Last, we use the past 12-month return (skipping the most recent month) as a proxy for the direction of fundamental shocks that can potentially be accompanied by disagreement. This choice is consistent with the large literature on momentum.

We single out candidate overpriced stocks by an independent triple sort: We divide the universe of stocks into three buckets according to their past return (MOM), short-interest (SIR) and the institutional ownership (IOR). The breakpoints are 0.3 and 0.7, as in Fama and French (1993). Making this an independent sort helps get more independent variation in all three variables. The three-by-three-by-three sort provides us with 27 portfolios. Each portfolio is value-weighted, both to avoid liquidity-related-biases associated with equal-weighted

[25] As an alternative specification, we follow Johnson (2004) and use total assets to normalize. Results are available upon request and do not change any conclusions, consistent with the findings in Johnson (2004).

portfolios, and to ensure that the effect we document is not only 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.

The model implies different return patterns for different horizons. Consistent with the literature on momentum and value, we assume information diffusion to take about a year, and the decay of overconfidence to take about five years. Consequently, over the first year after formation, all constrained stocks are predicted to underperform. Since it takes longer for overconfidence to be resolved, and overconfident agents are optimists in the case of positive news, we expect a prolonged decay of prices among winners — on the order of five years. In the empirical tests that aim at capturing the asymmetry between positive and negative news, we focus on the first 5 years, as the return-effects are predicted to be strongest in the earlier periods, and fade out towards the end (see Panel B in Figure 2).

We additionally split the constrained losers into losers that were ($\in$ W) or were not ($\notin$W) a constrained winner within the past 5 years. Our model predicts that constrained winners' prices fall for a long period of time. Ceteris paribus, they will hence still be constrained stocks after the first few years. However, they will have already lost in value over those first few years, potentially making them constrained losers. These 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 2). 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 2, at period 2 or 3). Consequently, filtering those L($\in$W) stocks out of the constrained loser portfolio should give us a portfolio that better reflects the return patterns associated with slow information diffusion and short-sale constraints. We call that portfolio "constrained losers that were not constrained winners in the past 5 years", or in short: L($\notin$W).

5.1 Characteristics

[INSERT Table 2 HERE]

Some basic characteristics about our portfolios are reported in Table 2.[26] We can see that, on average, each month, 51 stocks are classified as constrained winners, and 88 as constrained losers. 48 of those, on average, were also constrained winners in the past 5 years. The representative constrained winner stock has a market capitalization of $2.43B.[27] Constrained losers are all considerably smaller. Past returns are large in absolute magnitude for winners/losers—close to doubling/halving in size over the formation period. Institutional ownership is around 16.14% 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 6.52%, confirming a pronounced demand for short-selling these stocks.

A firm's book-to-market ratio can be interpreted as a noisy proxy for mispricing. Table 2 confirms that our identified constrained winners are the most expensive relative to their book-value, with a ratio of 27%, 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. Turnover for L(∈W) went down over the previous year, consistent with waning overconfidence and declining disagreement.

The model also predicts that the selected stocks became very expensive to sell short over the formation period. 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.[28]

[26] For a comparison with the broader universe of stocks, averages for the remaining portfolios are displayed in Table B.4 in Appendix B.IV.

[27] Table B.5 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.

[28] 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

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). This measure is particularly attractive as it has an interpretation within our model. 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 one half, for instance, a SIRIO measure above 50% 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.

The numbers in Table 2 clearly speak in favor of this phenomenon. On average, the constrained winners exhibit a SIRIO of 87.57%, which would push them above point of free lending in the example above 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 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.

5.2 Short-term Performance

[INSERT Table 3 HERE]

We first analyze the short-term return implications. Table 3 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

benefit from the insights of this paper by avoiding past constrained winners, when running medium/small-cap momentum strategies, as indicated by Table B.6 in the Appendix.

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 -0.47% and -1.54% for winners and losers, respectively. Consistent with the model, 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.[29]

For winners, short-sale constraints change the sign of the prediction, making it an ideal testing ground for our theory. 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.[30] Comparing the constrained winners to the high-IOR/high-SIR winners, results in a difference of -1.52% per month with a Newey-West t-statistic of -5.06. The rightmost column show 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 -1.54% per month (t-statistic -3.91), 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

[29] Notice, as shown in Table B.4 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).

[30] 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 65 BP/month.

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.[31]

Due to the distinction between ∈W and ∉W, and the necessity 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 July 1994, i.e., when we were, for the first time, able to allocate stocks into the W, L(∈W), and L(∉W) portfolios for 12 months in a row. Table 4 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 (Panel B).[32]

[31] 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 C.III. We prefer the buy-and-hold specification as it requires less rebalancing and thus minimizes trading costs.

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

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

[32] In Table B.1 in Appendix B.IV Panels A and B we regress 12-month buy-and-hold excess returns of W and L(∉W) 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).

Returns of winners and losers are not significantly different from each other (column W-L) and neither are L(∉W) and L(∈W). This is consistent with our model, as both constrained winners and losers underperform in the short run—albeit for different reasons. For the losers, information takes a short amount of time to diffuse—on the order of a year. For the winners, overconfidence wanes slowly, implying effects that persists about five years, which we will assess in the following section.

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(∉W) portfolios, hedged with respect to the three Fama and French (1993) factors and the Carhart (1997) momentum factor over the sample-period.[33] 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 $33.21 ($23.36) at the end of June 2018.

5.3 Long-term Performance

The model predicts strong negative returns for all constrained stocks in the first year post formation. We calibrate our model in such a way that short-term momentum is caused by slow information diffusion while the value/reversal effect is a result of the long-lasting resolution of overconfidence. In the unconstrained case, this leads to standard momentum (due to slow information diffusion) in the short term and reversal or value effects (due to

[33] 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, SMB, HML, and MOM. Then, using the full-sample regression coefficients, we subtract the returns of the zero-investment hedge-portfolio [b_{Mkt}*(R_{Mkt}-$R_{f,t}$)+b_{SMB}*SMB_t+b_{HML}*HML_t+b_{MOM}*MOM_t] from the respective portfolio excess returns to generate the hedged excess returns. The factor return data comes from Kenneth French's data library.

overconfidence) in the longer term. Short-sale constraints are predicted to have different effects depending on the sign of the news: Following negative news (i.e. for past-losers), the overconfident investor is pessimistic and short-sale constrained, and the newswatcher sets prices. This leads to more extreme negative returns, compared to other losers, in the first year post formation, but no longer-term predictability. For positive news (identified by looking at winners), the overconfident investor is optimistic and, since there are no constraints on buying, sets prices. Since overconfidence takes about five years to resolve, we expect a prolonged price decline for constrained winners.

[INSERT Table 5 HERE]

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($\notin$W)).[34] Both W and L($\notin$W) underperform significantly in the first year. However, losers never exhibit significant underperformance thereafter. In contrast, winners have significantly negative alphas up to five years and negative but mostly insignificant alphas even in years 6 to 9.[35]

In order to assess the statistical significance of the differences in long-term abnormal returns, we proceed as follows. We focus on years 2-5 post formation for two reasons. First, the model predicts similar underperformance for both winners and losers in year 1. Second, as the effect of overconfidence fades out (see Panel B in Figure 2) roughly following an exponential decay, the largest differences can be expected in the first four years that follow. Consequently, we calculate buy-and-hold returns, as explained in Section 5.2, but instead of

[34] Specifically, we calculate the buy-and-hold return, as explained in Section 5.2 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 four Fama-French-Carhart factors. The annualized alpha as well as the 95% confidence interval, constructed based on Newey-West standard errors, are plotted for each year after formation.

[35] 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 B.IV Figure B.1.

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.[36]

Table 5 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, 322 unique stocks. The upper panel 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($\in$W)) and were not (L($\notin$W)) constrained winners in the 5 years before they became constrained losers. We can see that only L($\in$W) have a negative (albeit insignificant) alpha. The difference between the two is significant at the 10% level. Winners significantly underperform relative to the Fama-French-Carhart model, with an alpha of -0.75 and a t-statistic of -5.82. The difference in abnormal returns of winners and losers is significant, and the difference between winners and L($\notin$W), is as large as -0.98 % per month with a t-statistic of -3.73.[37] [38]

In Figure 3 Panel B, we can 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.

5.4 Fama-MacBeth Regressions

[INSERT Table 6 HERE]

[36] 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 July 1998, i.e., the first time when we were able to determine portfolio membership for 48 months in a row.

[37] Moreover, spanning tests, shown in Appendix B.IV Table B.3 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($\in$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.

[38] 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 -1.08 (see Appendix B.IV Table B.2). Such a portfolio has 390 unique stocks in it. Moreover, using the simple value-weight approach, described in footnote 31, a strategy using allocation between months $t-60$ and $t-1$ generates a four-factor Information Ratio of -1.03

We assess the robustness of that result by running Fama-MacBeth regressions.[39] 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 6 Panel B, labeled "Constr.W". It is significantly different from zero, whereas, neither the coefficient for having been a constrained loser ("Constr.L") nor the coefficient for having been any type of constrained stock ("Constr.") is (columns 2-3). 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 5.

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 all other stocks significantly (column 6) and other constrained stocks (although not statistically significant, column 5).[40]

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.[41]

[39] 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).

[40] 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 becomes low.

[41] 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 1993/07 due to the longer look-back-period for constraints, no observations are lost in specifications 5-6.

5.5 Dynamics of Disagreement

Disagreement arises endogenously in the model, from the slow information incorporation of one set of agents and the overconfidence-based overreaction of the other.[42] In this subsection, we check the model's implication that an increase in disagreement in the past is quickly followed by a substantial decrease of disagreement. We use earnings forecast dispersion data as a proxy for any form of disagreement (and remain agnostic about which form it is), and examine, using this proxy, how disagreement evolves over time.[43] To analyze the dynamics of beliefs, we first sort stocks into 10 portfolios based on the preceding year's change in earnings forecast dispersion.[44]

[INSERT Figure 4 HERE]

Figure 4 plots earnings forecast dispersion from 1 year before until 5 years after portfolio formation. The high change portfolio distinctly reverses to a similar level as before within roughly 5 years, consistent with the resolution of disagreement hypothesis.[45] The timing is consistent with the return patterns we observe, where constrained winners lose significantly in value for roughly 5 years. The second highest change portfolio already exhibits a much lower increase in disagreement, indicating that large changes are very rare. There seems to be a small predictability in the other direction, as the low change portfolio slightly bounces up

[42] This highlights the close relationship between excessive optimism/pessimism and disagreement. A shock to disagreement is often assumed to be an increase in the range of beliefs, i.e., an equal rise in pessimism and optimism. Hence, such a symmetric shock affects the variance of the belief distribution but leaves the mean of the distribution unchanged. An alternative assumption is that only one side of the distribution is affected, e.g., optimists become even more optimistic, while pessimists do not change their beliefs. This also implies increase in variance, but in this case it is accompanied by an increase in the mean of the distribution as well. Such a one-sided disagreement modeling approach is thus consistent with limits-of-arbitrage models, featuring arbitrageurs and, typically, one type of biased agents (see, e.g., Shleifer and Vishny, 1997).

[43] While earnings forecast dispersion has been used in the literature to proxy for disagreement, it is only available for larger stocks where we typically do not observe binding short-sale constraints. For example, only 19% of the stock-month observations that we identify to have low institutional ownership (i.e., in the bottom 30%) have non-missing earnings forecast dispersion. Hence, to study returns, in the previous sections, we resort to the proxy generated by our model, i.e., a high past return accompanied by high short interest. By doing so, we assume that dynamics of earnings forecast dispersion apply to the dynamics of latent disagreement of all stocks in general, including those where earnings forecast dispersion is not available.

[44] Average characteristics of these portfolios are available in Appendix B.IV, Table B.7.

[45] Johnson (2004) suggests to normalize the standard deviation of earnings forecasts by total assets per share, but finds his results changing very little. Our conclusions are also unaffected—results are available upon request.

after portfolio formation. This increase is tiny in magnitude compared to the predictability of the high change portfolio, though, and the level arrives nowhere near its previous high, but rather in the neighborhood of all other stocks after 5 years.

[INSERT Table 7 HERE]

In Table 7 we predict future changes in earnings forecast dispersion over 1 year with positive and negative earnings forecast dispersion changes over the past year, using the Fama and MacBeth (1973) procedure. The results confirm that positive past changes strongly predict negative future changes. In contrast, including negative past changes to the regression barely increases the time-series average of the cross-sectional R^2. The coefficient estimate for positive past changes is larger by an order of magnitude than that of the negative past changes.

We conclude that the dynamics of beliefs approximately follow a two-state Markov process. Most stocks in the US cross-section have low levels of disagreement and fluctuate around that level. Occasionally, we observe large unpredictable jumps in disagreement. These are followed by resolution of disagreement, which is the only stylized fact we identify that is predictable with ex-ante available information. Except for this, past disagreement in beliefs does not help predict future disagreement. In particular, stocks where disagreement came down in the past are not more likely to become high disagreement stocks in the future again than other stocks.

5.6 Earnings Announcements

[INSERT Figure 5 HERE]

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. Figure 5 displays average cumulative abnormal returns (ACAR) of constrained winners and losers around earnings announcements, for stocks selected to one of the portfolios in the previous year (Panel A) or the 4 years preceding that year (Panel B).

Daily abnormal return is defined as the return adjusted for the four Fama-French-Carhart factors.[46] 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 portfolios 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.

5.7 Equity Issuance

Financial economists have now accumulated substantial empirical evidence consistent with the view that manager's try to time the market in their capital structure choices (see Baker and Wurgler, 2002, and the references therein). CFO's themselves state that they are reluctant to issue equity if they perceive their market valuation to be below the fundamental value (Graham and Harvey, 2001). Following this logic, managers who view their equity to be overvalued should issue equity to let current shareholders benefit from high market valuations. Although, perceived overvaluation is much less common than perceived undervaluation among corporate managers (Graham and Harvey, 2001, p. 219), we hypothesize that at least some managers of firms in the constrained winner portfolio think their equity is overvalued.

To test this idea, we look at the composite equity issuance measure of Daniel and Titman (2006). They define this quantity as the part of the change in a firm's market capitalization that cannot be explained by a firm's stock return (see also Pontiff and Woodgate, 2008). We build the composite equity issuance measure for each firm over a six-month time period, starting three months before portfolio formation (at the end of month t) and ranging to three months after portfolio formation. The individual measure is defined as

$$\iota_{t-2,t+3} = \log\left(\frac{ME_{t+3}}{ME_{t-2}}\right) - \log\left(1 + r_{t-2,t+3}\right) \tag{14}$$

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

where t is the month of portfolio formation. The composite equity issuance measure of a portfolio is calculated as the value-weighted average of individual composite equity issuance measures. We build $\iota_{t-2,t+3}$ for all 27 portfolios. The quantity measures the net effect of all issuance activity like equity issues, employee stock option plans, share repurchases or cash dividends around the time of portfolio formation, i.e., around the time where constrained winners are supposed to be overpriced due to a positive shock to disagreement.

INSERT Table 8 HERE

Table 8 presents the results. Consistent with previous literature, winner stocks tend to issue equity on average. The issuance in Table 8 is highest in the bottom-right-corner for all momentum buckets, and constrained winners and losers issue about twice as much as constrained medium-momentum stocks. For example, 7.48 percentage points of the increase in market capitalization of constrained winners cannot be attributed to their stock returns. Similarly, constrained losers issue substantially more than other loser stocks. Constrained stocks as a group are therefore much higher net issuers of equity than the groups of firms in any other portfolio, consistent with the idea that managers of these constrained stocks consider their equity to be overvalued and that they are trying to use this window of opportunity in favor of their shareholders. Given that most managers appear to be overoptimistic regarding their own firm's prospects (Ben-David, Graham, and Harvey, 2013), we consider the differences in the composite equity issuance measure to be substantial.

6 Conclusion

If optimists set prices for short-sale constrained firms, their stocks can become *overpriced* and such "bubbles" predictably collapse going forward (Miller, 1977). We show that constrained winners underperform for about five years, while constrained losers only lose for about a year. The finding for winners strongly contrasts with the empirical regularity of price momentum; that high past return firms continue to experience high future returns. We argue that the reason the momentum effect remains strong among winners in aggregate is because relatively few firms are short-sale-constrained (consistent with the empirical evidence on the lending market presented by D'Avolio, 2002). In line with this argument, our empirical procedure identifies 51 stocks per month as "constrained winners", on average. However, since the phenomenon is so long-lasting, we can construct a portfolio of all stocks that have been a constrained winner at some point within the last five years. Such a portfolio contains 390 unique stocks, on average, over the sample period. If we trade those overpriced winners in a value-weighted portfolio, such a well-diversified strategy generates an information ratio with respect to the four Fama-French-Carhart factors of -1.03. This drastic underperformance of such a large number of stocks, which is present during our whole sample period, also speaks to the ongoing discussion about the presence of bubbles in financial markets.

Our empirical evidence cannot be explained by behavioral models originally designed to capture momentum and value for unconstrained stocks. Neither the Daniel, Hirshleifer, and Subrahmanyam (1998) nor the Barberis, Shleifer, and Vishny (1998) models are able to 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 agent models, as their predictions for constrained and unconstrained assets will typically differ, when some agents are sidelined from the market.

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Figures

Figure 1: Annual four-factor alphas of constrained buy-and-hold portfolios. This figure plots the annualized Fama-French-Carhart four-factor alpha by holding year of calendar-time buy-and-hold portfolios, along with 95% confidence intervals based on Newey-West standard errors. The constrained winner (loser) portfolio is a value-weighted portfolio of highest (lowest) past-return firms with low institutional ownership and high 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.

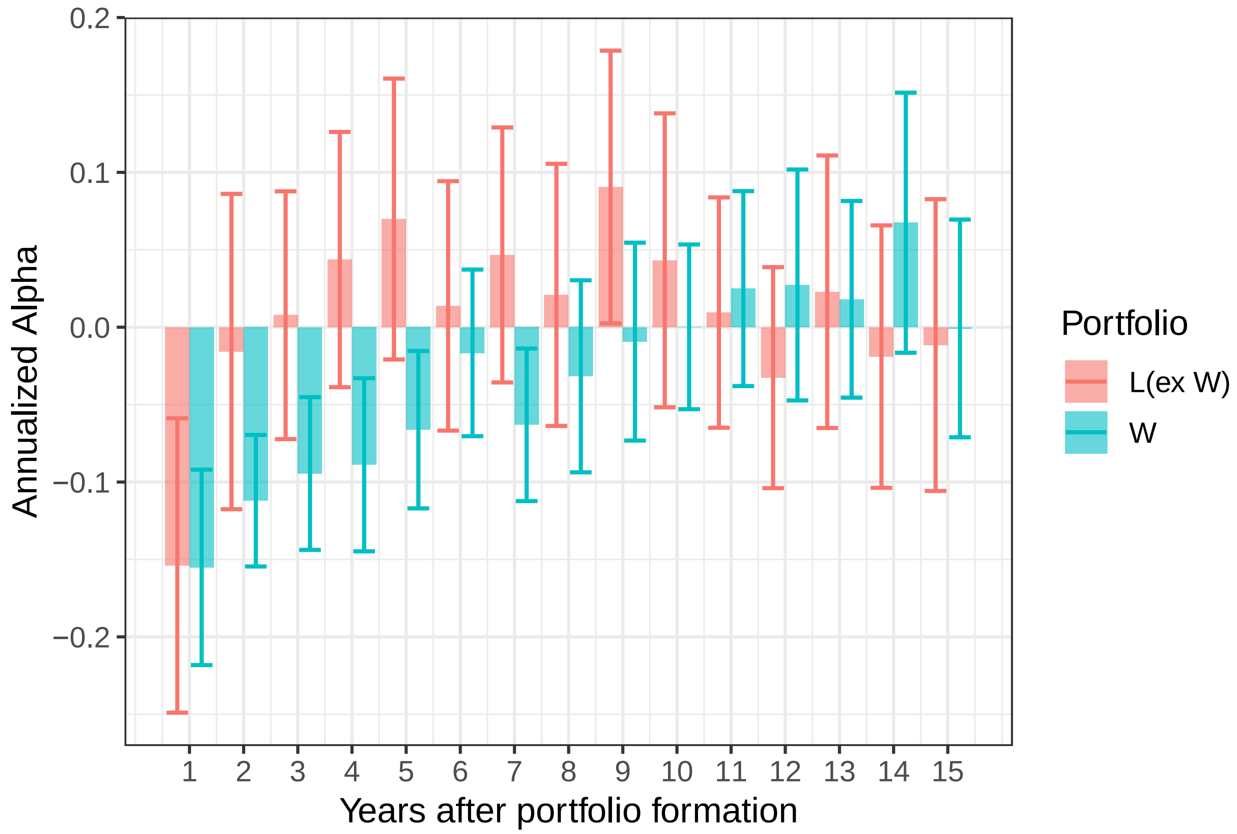


Figure 2: Beliefs and prices for winners and losers - A numerical example. Shown are beliefs and prices of a constrained winner (Panel A and B) and a constrained loser firm (Panel C and D). The information structure for winners is $(\epsilon_{O1}; \epsilon_{O2}; \epsilon_{O3}; \epsilon_{O4}; \ldots; \epsilon_{O12}) = (6; 2; 2; 2; ...; 2)$ 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.

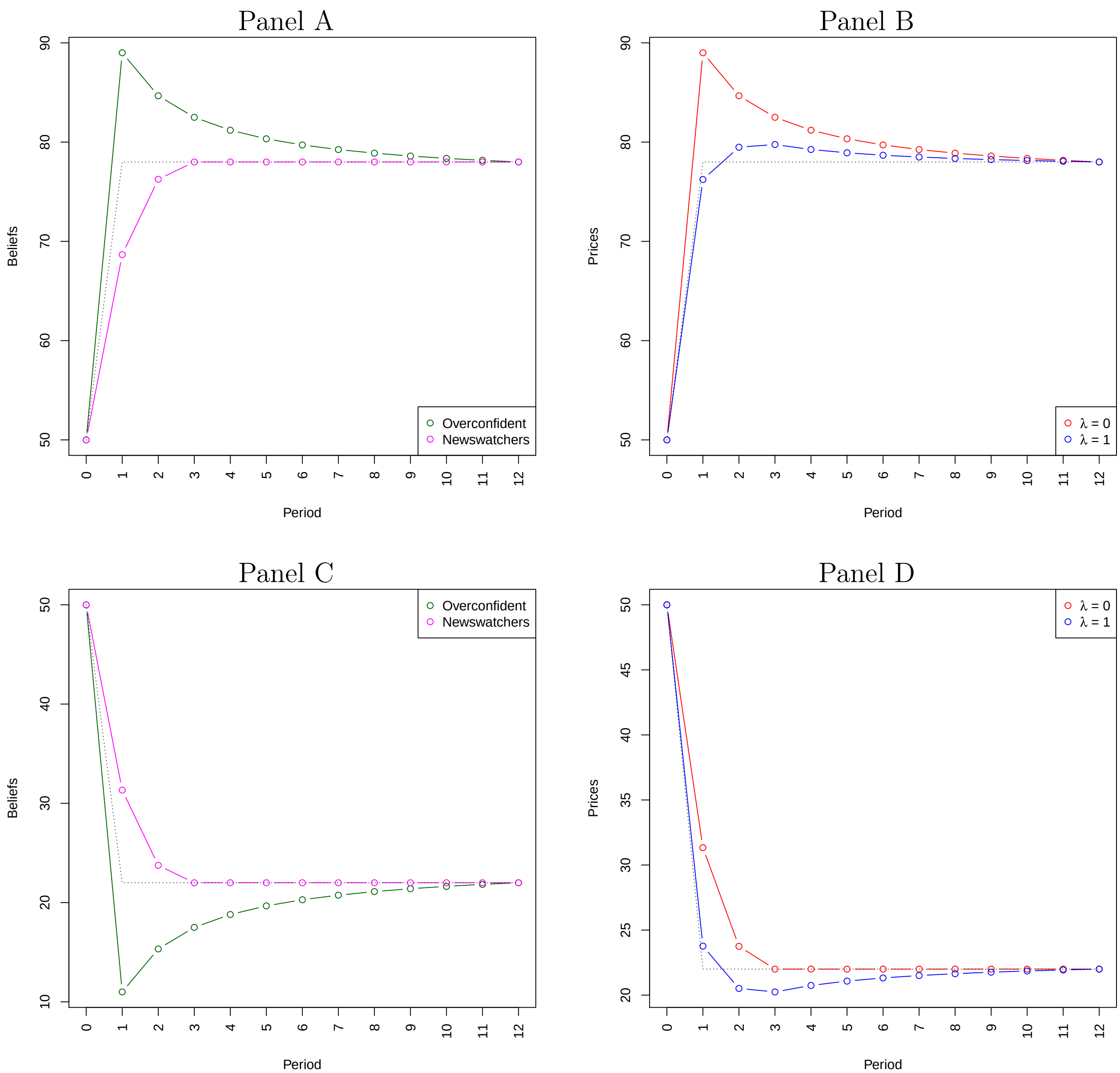
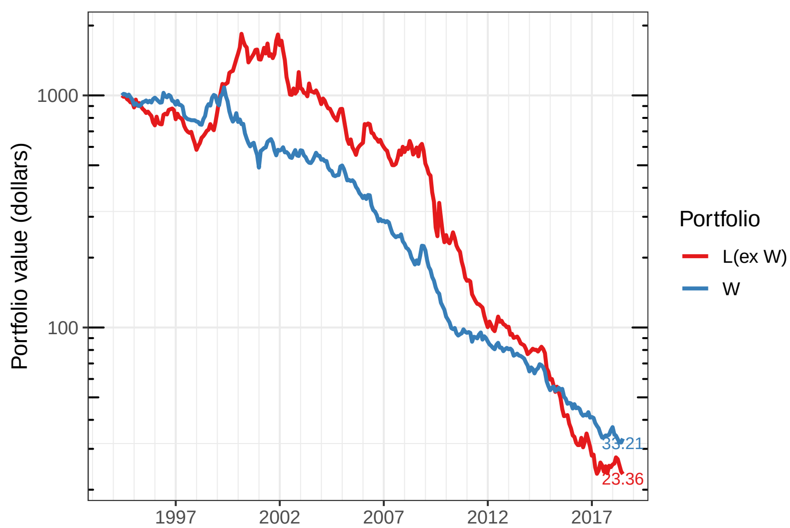


Figure 3: Performance of hedged constrained portfolios over calendar-time. This figure presents the investment value for a set of hedged portfolios. To calculate the portfolio value, we assume an investment at the beginning of the sample of \$1,000. We also assume that the exposures to Mkt-RF, SMB, HML, and MOM are hedged. We calculate the hedging coefficients by running a full-sample regression of the portfolio excess returns on Mkt-RF, SMB, HML, and MOM. Then, using the full-sample regression coefficients, we subtract the returns of the (zero-investment) hedge-portfolio [$b_{Mkt}(R_{Mkt}-R_{f,t})+b_{SMB}SMB_t+b_{HML}HML_t+b_{MOM}MOM_t$] 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

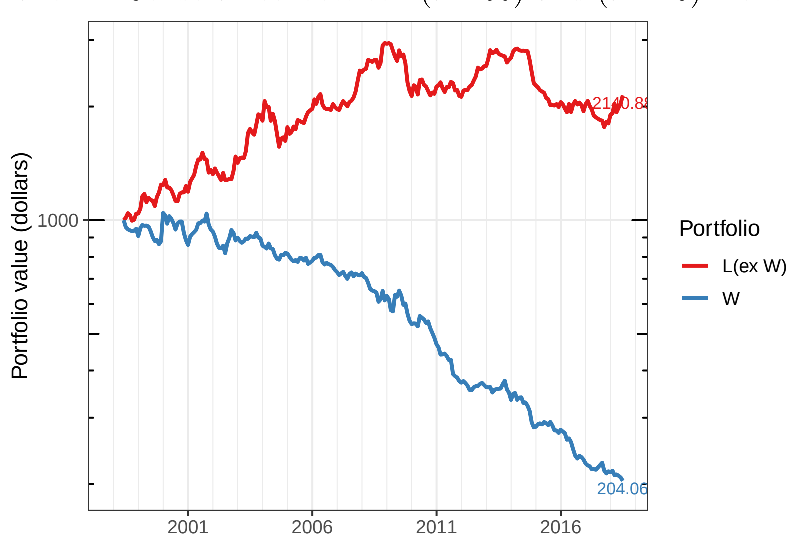


Figure 4: Dynamics of earnings forecast dispersion.
Stocks are sorted based on their past 1-year change in earnings forecast dispersion into 10 portfolios. Their level of earnings forecast dispersion is tracked over time, from 12 months before until 60 months after portfolio formation (t=0).

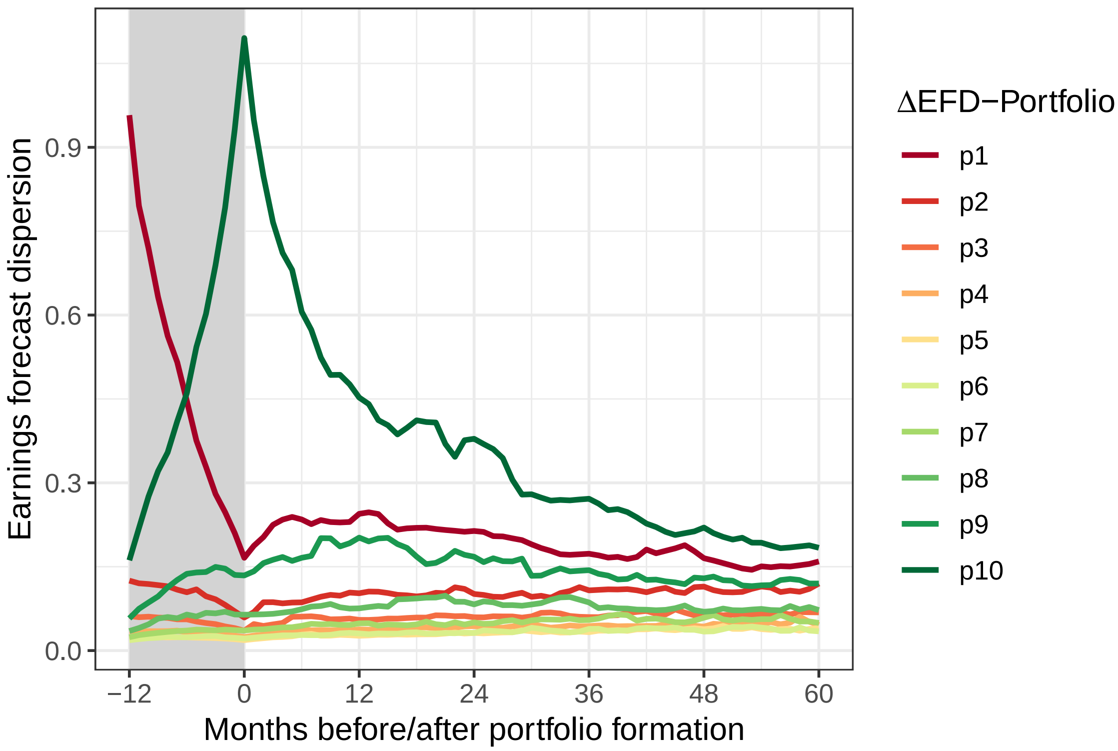
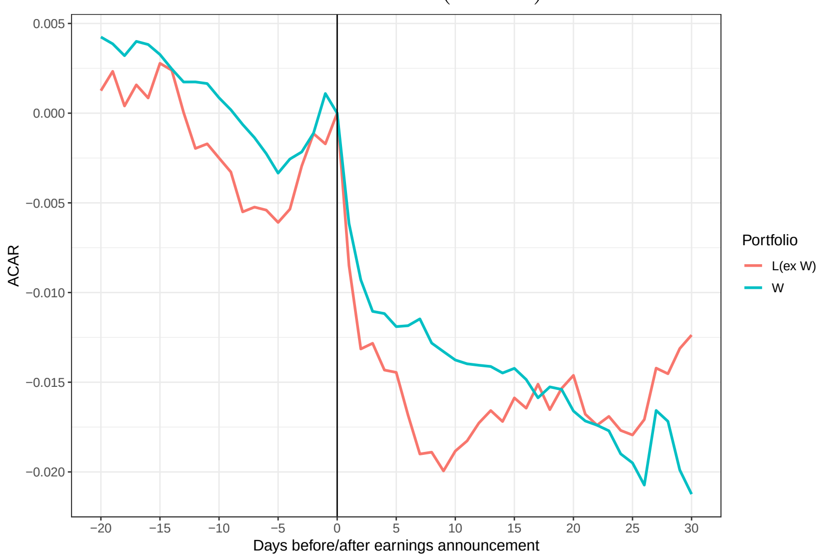
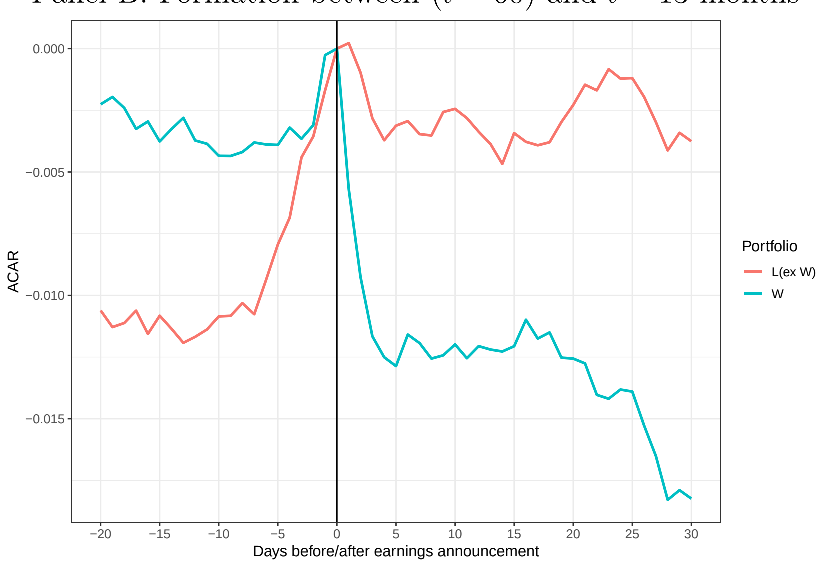


Figure 5: CAR around earnings announcements.
This figure shows cumulated abnormal returns of the constrained winners (W) and constrained losers that were not constrained winners in the 5 preceding years (L($\notin$W)) around the day (D=0) of an earnings announcement that occurs in the quarter after portfolio 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 the four Fama-French-Carhart factors. For each stock, loadings are 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



Tables

Table 1: Timing of surprises.
Sub-surprises are aggregated into surprises for overconfident agents and newswatchers. The table shows an example with $T = 5$ and $n = 3$. Overconfident agents see all information immediately, while information diffuses slowly to newswatchers.

Period	1	2	3	4	5	Overconfident
Surprise 1	δ_1^1	δ_1^2	δ_1^3			$\delta_{O1} = \sum_{t=1}^{3} \delta_1^t$
Surprise 2		δ_2^2	δ_2^3	δ_2^4		$\delta_{O2} = \sum_{t=2}^{4} \delta_2^t$
Surprise 3			δ_3^3	δ_3^4	δ_3^5	$\delta_{O3} = \sum_{t=3}^{5} \delta_3^t$
Surprise 4				δ_4^4	δ_4^5 δ_4^6	$\delta_{O4} = \sum_{t=4}^{6} \delta_4^t$
Surprise 5					δ_5^5 δ_5^6 δ_5^7	$\delta_{O5} = \sum_{t=5}^{7} \delta_5^t$
Newswatchers	$\delta_{N1} = \delta_1^1$	$\delta_{N2} = \sum_{j=1}^{2} \delta_j^2$	$\delta_{N3} = \sum_{j=1}^{3} \delta_j^3$	$\delta_{N4} = \sum_{j=2}^{4} \delta_j^4$	$\delta_{N5} = \sum_{j=3}^{5} \delta_j^5 + \sum_{j=4}^{5} \delta_j^6 + \delta_5^7$	

Table 2: Characteristics of constrained 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 1988/07 to 2018/06. For a comparison with the broader universe of stocks, averages for the remaining portfolios are displayed in Table B.4 in Appendix B.IV.

	L(∉W)	L(∈W)	L	2	W
Number of stocks	40	48	88	39	51
Average Market Equity (B$)	1.50	0.96	1.50	2.24	2.43
Formation Period Return (%)	-48.72	-42.54	-45.37	2.96	84.98
Institutional Ownership (IOR, %)	17.24	14.77	15.94	16.21	16.26
Change in IOR over preceding year (PP)	-5.39	-0.73	-2.81	0.31	1.35
Short-interest (SIR, %)	6.80	7.59	7.18	5.75	6.64
Change in SIR over preceding year (PP)	1.12	0.03	0.63	1.07	2.57
Book-to-market ratio (%)	88.55	47.00	65.30	46.13	27.25
Idiosyncratic volatility (%, daily)	4.12	3.84	3.90	2.56	3.17
Turnover (%)	28.98	19.77	24.58	14.92	32.60
Change in turnover over preceding year (PP)	1.67	-14.34	-5.88	-0.28	16.43
SIRIO (%)	77.97	88.61	83.72	81.99	87.57
Option volatility spread (%)	-6.61	-6.17	-6.24	-3.74	-5.54
Ind.Fee (%)	8.04	10.22	8.69	4.83	7.10
Change in Ind.Fee over preceding year (PP)	3.64	1.59	2.08	0.95	1.84
Simple Avg. Fee (SAF, %)	6.93	8.56	7.62	3.59	5.07
Change in SAF over preceding year (PP)	3.84	1.70	2.74	0.13	1.08

Table 3: 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 2018/06. 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	1.00	1.38	1.07	0.06 (0.25)	0.09 (0.30)
M	0.87	0.67	0.95	0.08 (0.26)	−0.02 (−0.09)
Hi SIR	1.04	0.93	−0.47	−1.52 (−5.06)	−1.56 (−5.44)
$Hi - Lo$	0.04	−0.45	−1.54		
t	(0.15)	(−1.54)	(−3.91)		
$\alpha(Hi - Lo)$	−0.29	−0.88	−1.94		
t	(−1.19)	(−3.27)	(−4.68)		

Panel B: Medium Momentum

	Hi IOR	M	Lo IOR	$Lo - Hi$	$\alpha(Lo - Hi)$
Lo SIR	0.50	0.94	0.77	0.26 (1.15)	0.46 (2.02)
M	0.75	0.58	0.66	−0.08 (−0.45)	0.06 (0.31)
Hi SIR	0.61	0.65	0.09	−0.52 (−1.76)	−0.37 (−1.31)
$Hi - Lo$	0.10	−0.30	−0.68		
t	(0.73)	(−1.20)	(−2.00)		
$\alpha(Hi - Lo)$	0.00	−0.46	−0.83		
t	(0.03)	(−2.36)	(−2.62)		

Panel C: Losers

	Hi IOR	M	Lo IOR	$Lo - Hi$	$\alpha(Lo - Hi)$
Lo SIR	0.58	0.52	0.49	−0.10 (−0.17)	0.27 (0.32)
M	0.57	0.35	0.07	−0.49 (−1.43)	−0.27 (−0.85)
Hi SIR	0.16	−0.02	−1.54	−1.69 (−4.44)	−1.63 (−5.21)
$Hi - Lo$	−0.43	−0.55	−2.03		
t	(−0.84)	(−1.91)	(−5.50)		
$\alpha(Hi - Lo)$	−0.22	−0.61	−2.11		
t	(−0.31)	(−1.91)	(−5.98)		

Table 4: Calendar-time 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 Fama-French-Carhart four-factor regressions (Panel B) 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 high 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(∉W) 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. The first return is calculated in July 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. 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 2018/06.

	L(∉W)	L(∈W)	L(∈W) - L(∉W)	L	M	W	W - L	W - L(∉W)
Panel A: Raw excess returns								
Average	-0.55	-0.49	0.05	-0.49	0.11	-0.25	0.24	0.30
	(-0.88)	(-0.90)	(0.13)	(-0.93)	(0.27)	(-0.57)	(0.66)	(0.68)
No. of months	288	288	288	288	288	288	288	288
AvgN	97	115		208	156	164		
SR	-0.1760	-0.1816	0.0256	-0.1833	0.0561	-0.1053	0.1569	0.1358
Panel B: Four-factor regressions								
Intercept	-1.28	-1.22	0.06	-1.24	-0.71	-1.30	-0.06	-0.02
	(-3.16)	(-3.58)	(0.13)	(-4.33)	(-3.48)	(-4.84)	(-0.19)	(-0.05)
MktRF	1.23	1.11	-0.11	1.19	1.08	1.28	0.09	0.05
	(14.25)	(12.85)	(-1.33)	(15.61)	(19.32)	(20.47)	(0.94)	(0.45)
HML	-0.22	-0.47	-0.25	-0.35	0.06	-0.22	0.13	0.00
	(-1.15)	(-4.19)	(-1.10)	(-2.64)	(0.73)	(-1.78)	(0.79)	(0.02)
SMB	1.26	1.28	0.02	1.22	0.78	1.07	-0.15	-0.19
	(6.76)	(10.06)	(0.15)	(10.82)	(14.30)	(11.62)	(-1.11)	(-0.95)
MOM	-0.66	-0.42	0.24	-0.51	-0.18	0.03	0.54	0.69
	(-4.85)	(-4.39)	(1.48)	(-5.53)	(-4.02)	(0.25)	(6.17)	(4.20)
R^2	0.6426	0.7226	0.0527	0.7721	0.8156	0.7806	0.2306	0.1991
IR	-0.6871	-0.8521	0.0288	-0.9662	-0.8642	-1.1656	-0.0439	-0.0113

Table 5: Calendar-time portfolio returns of stocks that were constrained within months $t-60$ to $t-13$ prior to formation.
See caption to Table 4. 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 July 1998, i.e., the first time when we invested 48 times in a row.

	L(∉W)	L(∈W)	L(∈W) - L(∉W)	L	M	W	W - L	W - L(∉W)
Panel A: Raw excess returns								
Average	1.01	0.41	-0.60	0.69	0.37	0.07	-0.61	-0.94
	(2.02)	(0.68)	(-2.07)	(1.25)	(0.85)	(0.14)	(-3.11)	(-3.72)
No. of months	240	240	240	240	240	240	240	240
AvgN	167	169		314	281	322		
SR	0.4470	0.1573	-0.4141	0.2963	0.1977	0.0324	-0.6368	-0.8081
Panel B: Four-factor regressions								
Intercept	0.23	-0.49	-0.72	-0.17	-0.41	-0.75	-0.59	-0.98
	(0.85)	(-1.85)	(-2.39)	(-0.77)	(-2.29)	(-5.82)	(-3.06)	(-3.73)
MktRF	1.19	1.23	0.04	1.23	1.06	1.27	0.04	0.09
	(17.24)	(16.94)	(0.46)	(22.24)	(18.38)	(20.38)	(0.47)	(1.05)
HML	-0.05	-0.47	-0.41	-0.23	0.04	-0.14	0.09	-0.08
	(-0.69)	(-4.63)	(-3.46)	(-2.95)	(0.59)	(-2.19)	(1.34)	(-0.80)
SMB	0.86	1.22	0.36	0.98	0.82	0.77	-0.21	-0.09
	(10.93)	(12.81)	(3.73)	(13.30)	(15.36)	(8.79)	(-2.20)	(-1.18)
MOM	-0.19	-0.08	0.10	-0.11	-0.02	-0.10	0.01	0.09
	(-2.74)	(-1.24)	(1.50)	(-1.80)	(-0.38)	(-1.49)	(0.13)	(0.79)
R^2	0.7851	0.8138	0.2005	0.8569	0.8627	0.8588	0.0555	0.0224
IR	0.2165	-0.4332	-0.5538	-0.1891	-0.5827	-0.9142	-0.6283	-0.8514

Table 6: 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 2018/06.

Panel A: Constrained between $t-12$ and $t-1$

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.67 (2.86)	0.67 (2.86)	0.67 (2.86)	1.61 (3.32)	1.79 (3.68)	1.79 (3.68)
$Constr._{(t-12)—(t-1)}$	-0.92 (-4.16)	-0.08 (-0.31)		-0.18 (-0.59)	-0.07 (-0.24)	
$Constr.W_{(t-12)—(t-1)}$		-0.49 (-1.94)	-0.59 (-3.05)	-0.66 (-2.60)	-0.40 (-1.67)	-0.46 (-2.03)
$Constr.L_{(t-12)—(t-1)}$		-0.99 (-3.22)	-1.03 (-3.19)	-0.45 (-1.53)	-0.34 (-1.12)	-0.33 (-1.38)
$RET_{(t-12)—(t-2)}$				0.45 (1.82)	0.45 (1.79)	0.45 (1.79)
$log(BE/ME_{t-1})$				-0.03 (-0.34)	-0.03 (-0.33)	-0.03 (-0.33)
$log(ME_{t-1})$				-0.08 (-2.15)	-0.09 (-2.46)	-0.09 (-2.45)
$ivol_{t-1}$				-0.22 (-2.74)	-0.20 (-2.59)	-0.20 (-2.59)
$SIRIO_{t-1}$					-0.01 (-3.98)	-0.01 (-4.02)
Avg. R^2	0.0016	0.0023	0.0021	0.0821	0.0838	0.0836
No. of months	348	348	348	348	346	346

Panel B: Constrained between $t-60$ and $t-13$

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.68 (2.57)	0.68 (2.57)	0.68 (2.57)	1.68 (3.11)	1.83 (3.41)	1.83 (3.41)
$Constr._{(t-60)—(t-13)}$	-0.36 (-2.21)	-0.13 (-0.65)		-0.24 (-1.24)	-0.24 (-1.24)	
$Constr.W_{(t-60)—(t-13)}$		-0.49 (-2.34)	-0.57 (-3.52)	-0.45 (-2.01)	-0.35 (-1.56)	-0.50 (-2.99)
$Constr.L_{(t-60)—(t-13)}$		0.27 (1.16)	0.15 (0.66)	0.34 (1.60)	0.45 (2.14)	0.28 (1.50)
$RET_{(t-12)—(t-2)}$				0.38 (1.36)	0.37 (1.36)	0.37 (1.35)
$log(BE/ME_{t-1})$				-0.01 (-0.15)	-0.02 (-0.22)	-0.02 (-0.22)
$log(ME_{t-1})$				-0.08 (-2.07)	-0.10 (-2.39)	-0.10 (-2.38)
$ivol_{t-1}$				-0.21 (-2.28)	-0.19 (-2.11)	-0.19 (-2.11)
$SIRIO_{t-1}$					-0.01 (-4.27)	-0.01 (-4.23)
Avg. R^2	0.0020	0.0030	0.0027	0.0843	0.0859	0.0857
No. of months	300	300	300	300	300	300

Table 7: Fama-MacBeth regressions of future changes on past changes in earnings forecast dispersion.
The change in earnings forecast dispersion over one calendar year is regressed on positive (Column 1) and both positive and negative changes (column 2) in earnings forecast dispersion over the previous calendar year in the cross-section of stocks. We value-weight observations in the cross-sectional regressions by their market capitalization. Following the Fama and MacBeth (1973) procedure, the time-series average of the regression coefficients is presented. Standard errors are calculated following Newey and West (1987). The time-series average of the cross-sectional R^2 is presented in the last row. The sample period is 1988 to 2017.

	(1)	(2)
Intercept	0.0312 (7.86)	0.0274 (6.93)
Positive change in disagreement (t-13 to t-1)	−0.9618 (−17.16)	−0.9590 (−17.47)
Negative change in disagreement (t-13 to t-1)		−0.1302 (−1.39)
R^2	0.4277	0.4467

Table 8: Composite equity issuance.
This table shows time-series averages of the value-weighted composite equity issuance measure of the 9 winner (Panel A), 9 medium-momentum (Panel B) and 9 loser (Panel C) portfolios. The composite equity issuance measure of a firm is the part of the change in a firm's market capitalization that cannot be explained by a firm's stock return, following Daniel and Titman (2006). It is calculated over a six-month horizon, starting three months prior to portfolio formation and ranging to three months after portfolio formation. The sample period is 1988/07 to 2018/06.

Panel A: Winners

	Hi IOR	M	Lo IOR	$Lo - Hi$
Lo SIR	0.70	−0.06	1.74	1.04 (1.71)
M	−0.16	−0.27	3.24	3.39 (5.06)
Hi SIR	2.83	2.44	7.48	4.65 (8.00)
$Hi - Lo$	2.13	2.50	5.75	
t	(4.19)	(6.45)	(9.74)	

Panel B: Medium Momentum

	Hi IOR	M	Lo IOR	$Lo - Hi$
Lo SIR	−0.93	−1.23	−0.46	0.47 (1.58)
M	−0.91	−1.17	0.48	1.39 (4.46)
Hi SIR	0.99	0.90	3.61	2.62 (5.76)
$Hi - Lo$	1.92	2.14	4.07	
t	(6.78)	(5.92)	(7.94)	

Panel C: Losers

	Hi IOR	M	Lo IOR	$Lo - Hi$
Lo SIR	0.87	−0.34	3.87	2.99 (3.88)
M	−0.78	−0.36	3.09	3.87 (11.59)
Hi SIR	0.54	2.23	7.23	6.69 (7.10)
$Hi - Lo$	−0.33	2.57	3.37	
t	(−0.67)	(4.02)	(4.06)	