The Dynamics of Disagreement

Online Appendix

Kent Daniel[△] Alexander Klos[◊] Simon Rottke[□]

[△]kd2371@columbia.edu, Columbia Business School and NBER.
[◊]alexander.klos@qber.uni-kiel.de, Kiel University.
[□]simon.rottke@uva.nl, University of Amsterdam.

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A.I 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 $t \in \{1, \ldots, T\}$.[A1] That is:

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

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.

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 $\mu_\epsilon \sim \mathcal{N}\left(\hat{\alpha}_{i,t}, \hat{\eta}^2_{i,t}\right)$. 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.

A.I.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

[A1] 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).

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.[A2]

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 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.[A3] In the following, we refer to active agents by using the single word agents (as opposed to passive investors, who do not trade actively).

A.I.2 Demands and the Equilibrium Price

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

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

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

In this CARA-normal setting, myopic demand is just the expected price next period $\mathbb{E}_{i,t}\left[p_{t+1}\right]$, 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 ($\mathbb{E}_{i,t}\left[p_{t+1}\right]$). 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 $\mathbb{E}_{i,t}\left[c_{t+1}\right] = 0$ 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

[A2] 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.

[A3] 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).

is, in our setting, just the identical belief of all agents if there is no disagreement. Expressed mathematically, we have $\mathbb{E}_{i,t}[p_{t+1}] = \mathbb{E}_{i,t}[\mathbb{E}_{i,t+1}[D_T]]$, a term that is equal to $\mathbb{E}_{i,t}[D_T]$ by the law of iterated expectations. We finally obtain $\mathbb{E}_{i,t}[p_{t+1}] = D_{i,t} + \hat{\alpha}_{i,t}(T-t)$ by using Equation (A.2).

So given an equilibrium price $p_t \leq \mathbb{E}_{i,t}[D_T]$, the demand of an agent in group i is positive and given by:[A4]

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

However, if the price is above what the agent expects the payoff to be (i.e., if $p_t \geq \mathbb{E}_{i,t}[D_T]$), she 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. She will thus choose to go short if and only if what she receives from shorting (p_t) is greater than the the sum of the expected cost of buying back the share next period ($= \mathbb{E}_t[p_{t+1}] = \mathbb{E}_{i,t}[D_T]$) plus the cost of borrowing c_t. Her demand—which will be negative—is:

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

Note that, if $c_t > 0$, the demand of an agent in group i will be zero for a range of prices $\mathbb{E}_{i,t}[D_T] \leq p_t \leq \mathbb{E}_{i,t}[D_T] + c_t$. 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.III, the market clearing price p_t in the stock market is

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

with

$$\Pi_{i,t} \equiv \frac{\pi_i}{\gamma_i \hat{\sigma}^2_{i,t}}, \tag{A.6}$$

$$\hat{\alpha}_{m,t} \equiv \sum_{i \in (L_t \cup S_t)} \left[\frac{\Pi_{i,t}}{\sum_{j \in (L_t \cup S_t)} \Pi_{j,t}} \hat{\alpha}_{i,t} \right], \tag{A.7}$$

and

$$D_{m,t} \equiv \sum_{i \in (L_t \cup S_t)} \left[\frac{\Pi_{i,t}}{\sum_{j \in (L_t \cup S_t)} \Pi_{j,t}} D_{i,t} \right]. \tag{A.8}$$

We can think of $\Pi_{i,t}$ 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 ($\hat{\sigma}^2_{i,t}$). $\hat{\alpha}_{m,t}$ is then the weighted average expectation of μ_ϵ, and $D_{m,t}$ is the weighted average of the sum of privately observed dividend innovations ϵ's. For an unconstrained stock ($c_t = 0$), Equation (A.5) shows that the market price is simply a weighted average of single beliefs specified in Equation (A.2). The weights depend on how aggressively a group trades.

[A4] Appendix A.III derives that optimal demands in period t more formally.

Equation (A.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.

A.I.3 The Cost of Borrowing Shares

Consistent with US institutional restrictions, we require that stock must be borrowed before it can be sold short.[A5] Borrowing costs are determined in equilibrium, and are the price at which the supply of shares is 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:

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

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

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

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

[A5] 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.

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

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

Substituting in the equilibrium price from Equation (A.5) and solving for c_t yields:

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

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

An equilibrium in period t is a situation where market clearing conditions (A.5) and (A.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.

A.II 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.

A.II.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 $\epsilon_{O,t} = \epsilon_t = \mu_\epsilon + \delta_{O,t} = \mu_\epsilon + \sum_{j=t}^{t+n-1} \delta_t^j$ at time t. The newswatchers see signals based on sub-surprises one after another. Specifically, newswatchers observe a signal $\epsilon_{N,t}$ based on all sub-surprises with superscript t at time $n \leq t < T$, i.e.,

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

Table A.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			$\delta_{O,1} = \sum_{t=1}^{3} \delta_1^t$
Surprise 2		δ_2^2	δ_2^3	δ_2^4		$\delta_{O,2} = \sum_{t=2}^{4} \delta_2^t$
Surprise 3			δ_3^3	δ_3^4	δ_3^5	$\delta_{O,3} = \sum_{t=3}^{5} \delta_3^t$
Surprise 4				δ_4^4	δ_4^5 δ_4^6	$\delta_{O,4} = \sum_{t=4}^{6} \delta_4^t$
Surprise 5					δ_5^5 δ_5^6 δ_5^7	$\delta_{O,5} = \sum_{t=5}^{7} \delta_5^t$
Newswatchers	$\delta_{N,1} = \delta_1^1$	$\delta_{N,2} = \sum_{j=1}^{2} \delta_j^2$	$\delta_{N,3} = \sum_{j=1}^{3} \delta_j^3$	$\delta_{N,4} = \sum_{j=2}^{4} \delta_j^4$	$\delta_{N,5} = \sum_{j=3}^{5} \delta_j^5$ $+ \sum_{j=4}^{5} \delta_j^6 + \delta_5^7$	

Table A.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 ($\delta_{O,t}$'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 $\delta_{N,t}$ of their signal is the column sum in Table A.1. Newswatchers think that all of their signals $\delta_{N,t}$ have variance σ^2, which is correct except for a start- and an end-effect.[A6] For example, their signal in period 3 is the sum of three sub-surprises that originate in periods one, two, and three, respectively.

A.II.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 $\epsilon_{O,t}$ and $\epsilon_{N,t}$, 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 $\epsilon_{O,t}$ or $\epsilon_{N,t}$ 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

[A6] See Table A.1 for an example. In the first periods, there are not enough sub-surprises available and Equation (A.13) effectively becomes $\epsilon_{N,t} = \mu_\epsilon + \sum_{j=1}^{t} \delta_j^t$. In the final period $t = T$, newswatchers are assumed to observe all remaining information and Equation (A.13) reads $\epsilon_{N,t} = \mu_\epsilon + \sum_{j=t-n+1}^{t} \delta_j^t + \sum_{j=t-n+2}^{t} \delta_j^{t+1} + \cdots + \sum_{j=t}^{t} \delta_j^{t+n-1}$.

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, i.e., they overestimate the precision of their signal.

All agents use Bayes' rule to combine their prior belief about μ_ϵ and their signal $\epsilon_{O,t}$ or $\epsilon_{N,t}$ into a posterior belief. The beliefs of overconfident agents evolve according to $\hat{\alpha}_{O,t} = \frac{\hat{\alpha}_{O,t-1}\kappa\sigma^2 + \epsilon_{O,t}\hat{\eta}_t^2}{\hat{\eta}_{O,t-1}^2 + \kappa\sigma^2}$. The newswatcher's belief in period t is equal to $\hat{\alpha}_{N,t} = \frac{\hat{\alpha}_{N,t-1}\sigma^2 + \epsilon_{N,t}\eta_t^2}{\hat{\eta}_{N,t-1}^2 + \sigma^2}$. The posterior variances are $\hat{\eta}_{O,t}^2 = \frac{\hat{\eta}_{O,t-1}^2\kappa\sigma^2}{\hat{\eta}_{O,t-1}^2 + \kappa\sigma^2}$ and $\hat{\eta}_{N,t}^2 = \frac{\hat{\eta}_{N,t-1}^2\sigma^2}{\hat{\eta}_{N,t-1}^2 + \sigma^2}$, respectively. Agents base their demands in period t on these beliefs.

A.III Solving the Model

An agent of group i maximizes the expected utility of her wealth next period. The heterogeneous agent model can be solved by using backward induction.

In period $T-1$, optimal demands follow from solving a standard static CARA-normal portfolio choice problem and are given by

$$\frac{\mathbb{E}_{i,T-1}\left[p_T - p_{T-1}\right]}{\gamma_i Var_{i,T-1}\left[p_T - p_{T-1}\right]} = \frac{D_{i,T-1} + \hat{\alpha}_{i,T-1} - p_{T-1}}{\gamma_i \hat{\sigma}_{i,T-1}^2} \tag{A.14}$$

if an agent is long in the stock or

$$-\frac{\mathbb{E}_{i,T-1}\left[p_{T-1} - p_T\right] - c_{T-1}}{\gamma_i Var_{i,T-1}\left[p_T - p_{T-1}\right]} = -\frac{p_{T-1} - (D_{i,T-1} + \hat{\alpha}_{i,T-1}) - c_{T-1}}{\gamma_i \hat{\sigma}_{i,T-1}^2} \tag{A.15}$$

if an agent is short and has to pay the per-unit cost of borrowing the shares from $T-1$ to T, which we denote c_{T-1}. Following Barberis, Greenwood, Jin, and Shleifer (2018), we assume that agents perceive the conditional variance of price changes to be equal to the predictive posterior variance of the upcoming dividend innovation.

Let π_i be a measure of agents in group i and L_{T-1} (S_{T-1}) be the set of groups who are long (short) in period $T-1$. Market clearing on the stock market requires

$$\sum_{i \in L_{T-1}} \pi_i \left(\frac{D_{i,T-1} + \hat{\alpha}_{i,T-1} - p_{T-1}}{\gamma_i \hat{\sigma}_{i,T-1}^2} \right) = \sum_{i \in S_{T-1}} \pi_i \left(\frac{p_{T-1} - (D_{i,T-1} + \hat{\alpha}_{i,T-1}) - c_{T-1}}{\gamma_i \hat{\sigma}_{i,T-1}^2} \right) \tag{A.16}$$

Solving Equation (A.16) for p_{T-1} yields

$$p_{T-1} = D_{m,T-1} + \hat{\alpha}_{m,T-1} + \frac{\sum_{i \in S_{T-1}} \Pi_{i,T-1}}{\sum_{i \in (L_{T-1} \cup S_{T-1})} \Pi_{i,T-1}} c_{T-1} \tag{A.17}$$

with $\Pi_{i,T-1} \equiv \frac{\pi_i}{\gamma_i \hat{\sigma}_{i,T-1}^2}$, $\hat{\alpha}_{m,T-1} \equiv \sum_{i \in (L_{T-1} \cup S_{T-1})} \left[\frac{\Pi_{i,T-1}}{\sum_{j \in (L_{T-1} \cup S_{T-1})} \Pi_{j,T-1}} \hat{\alpha}_{i,T-1} \right]$, and $D_{m,T-1} \equiv \sum_{i \in (L_{T-1} \cup S_{T-1})} \left[\frac{\Pi_{i,T-1}}{\sum_{j \in (L_{T-1} \cup S_{T-1})} \Pi_{j,T-1}} D_{i,T-1} \right]$.

In period $T-2$, agents maximize the expected utility of wealth in $T-1$. Their demand is equal to

$$\frac{\mathbb{E}_{i,T-2}\left[p_{T-1}\right]-p_{T-2}}{\gamma_i \hat{\sigma}^2_{i,T-2}} \tag{A.18}$$

if the agent is long or

$$-\frac{p_{T-2}-\mathbb{E}_{i,T-2}\left[p_{T-1}\right]-c_{T-2}}{\gamma_i \hat{\sigma}^2_{i,T-2}} \tag{A.19}$$

if the agent is short.

We assume that agents belief that next period all agents will hold the same belief as they do. As argued in more detail in the main text, this assumption implies that $\mathbb{E}_{i,T-2}\left[p_{T-1}\right] = \mathbb{E}_{i,T-2}\left[\mathbb{E}_{i,T-1}\left[D_T\right]\right] = D_{i,T-2}+2\hat{\alpha}_{i,T-2}$. After substituting $\mathbb{E}_{i,T-2}\left[p_{T-1}\right] = D_{i,T-2}+2\hat{\alpha}_{i,T-2}$ into Equations (A.18) and (A.19), market clearing on the stock market requires

$$\sum_{i\in L_{T-2}} \pi_i \left(\frac{D_{i,T-2}+2\hat{\alpha}_{i,T-2}-p_{T-2}}{\gamma_i \hat{\sigma}^2_{i,T-2}}\right) = \sum_{i\in S_{T-2}} \pi_i \left(\frac{p_{T-2}-(D_{i,T-2}+2\hat{\alpha}_{i,T-2})-c_{T-2}}{\gamma_i \hat{\sigma}^2_{i,T-2}}\right). \tag{A.20}$$

The equilibrium price in period $T-2$ is given by

$$p_{T-2} = D_{m,T-2}+2\hat{\alpha}_{m,T-2}+\frac{\sum_{i\in S_{T-2}} \Pi_{i,T-2}}{\sum_{i\in (L_{T-2}\cup S_{T-2})} \Pi_{i,T-2}} c_{T-2}. \tag{A.21}$$

Proceeding with backward induction from period $T-3$ to period 1, long demands, short demands, and the market clearing price p_t are given by Equations (A.3) to (A.8).

A.IV Developing an Intuition for the Equilibrium Shorting Fee

We start with a hypothetical world in which search costs of the set of short sellers S_t are covered by a third party, while, at the same time, the set of short sellers S_t is fixed. That is, other agents, who are not part of the set S_t in an equilibrium with positive shorting costs, are not allowed to sell short shares in our thought experiment. In such a world, short sellers belonging to S_t can short for free and their shorting demand is

$$\sum_{i\in S_t} \Pi_{i,t}\left(p_t-(D_{i,t}+\hat{\alpha}_{i,t}(T-t))\right) \tag{A.22}$$

Substitution of the equilibrium price from Equation (A.5) into Equation (A.22) and setting $c_t=0$ yields

$$\sum_{i\in S_t} \Pi_{i,t}\left(D_{m,t}-D_{i,t}+(\hat{\alpha}_{m,t}-\hat{\alpha}_{i,t})(T-t)\right) \tag{A.23}$$

Subtracting free lending supply λQ from Equation (A.23) and multiplying with τ gives the shorting costs per share implied by this zero-cost demand. This expression is equal to the numerator of the equilibrium per-share shorting fee (see Equation (A.12)). Multiplying the per-share shorting fee with short interest yields the total shorting costs implied by the zero-cost demand (and paid by the third party) as

$$\tau\left[\sum_{i\in S_t}\Pi_{i,t}\left(D_{m,t}-D_{i,t}+(\hat{\alpha}_{m,t}-\hat{\alpha}_{i,t})(T-t)\right)-\lambda Q\right] \left[\sum_{i\in S_t}\Pi_{i,t}\left(D_{m,t}-D_{i,t}+(\hat{\alpha}_{m,t}-\hat{\alpha}_{i,t})(T-t)\right)\right] \tag{A.24}$$

Think now of a world in which short seller have to cover their shorting costs. This will affect equilibrium quantities and thereby the shorting demand of short sellers. Assume that per-share shorting costs rise from 0 to the new equilibrium level c_t. This has two effects on shorting demand. First, shorting demand will go down because the short seller now has to cover per-unit costs c_t. We call this the direct effect. Individual demand functions are given by $\frac{p_t-(D_{i,t}+\hat{\alpha}_{i,t}(T-t))-c_t}{\gamma_i\hat{\sigma}^2_{i,t}}$ (see Equation (A.4)), so total demand decreases by $\sum_{i\in S_t}\Pi_{i,t}c_t$ due to the direct effect. Second, the equilibrium price will rise due to the non-zero shorting costs by $\frac{\sum_{i\in S_t}\Pi_{i,t}}{\sum_{i\in(L_t\cup S_t)}\Pi_{i,t}}c_t$ (see Equation (A.5)). Short sellers would now like to short more due to the increased price. We call this the indirect effect. Because of the indirect effect, aggregated demand goes up by $\sum_{i\in S_t}\Pi_{i,t}\frac{\sum_{i\in S_t}\Pi_{i,t}}{\sum_{i\in(L_t\cup S_t)}\Pi_{i,t}}c_t$. The total effect is the sum of the direct and the indirect effect. The total shorting costs change from the expression in Equation (A.24) to

$$C_t=c_tX_t=\tau\left[\sum_{i\in S_t}\Pi_{i,t}\left(D_{m,t}-D_{i,t}+(\hat{\alpha}_{m,t}-\hat{\alpha}_{i,t})(T-t)-c_t+\frac{\sum_{i\in S_t}\Pi_{i,t}}{\sum_{i\in(L_t\cup S_t)}\Pi_{i,t}}c_t\right)-\lambda Q\right] \left[\sum_{i\in S_t}\Pi_{i,t}\left(D_{m,t}-D_{i,t}+(\hat{\alpha}_{m,t}-\hat{\alpha}_{i,t})(T-t)-c_t+\frac{\sum_{i\in S_t}\Pi_{i,t}}{\sum_{i\in(L_t\cup S_t)}\Pi_{i,t}}c_t\right)\right] \tag{A.25}$$

Dividing Equation (A.25) by the total shorting demand X_t implicitly defines the new shorting costs per share

$$c_t=\tau\left[\sum_{i\in S_t}\Pi_{i,t}\left(D_{m,t}-D_{i,t}+(\hat{\alpha}_{m,t}-\hat{\alpha}_{i,t})(T-t)-c_t+\frac{\sum_{i\in S_t}\Pi_{i,t}}{\sum_{i\in(L_t\cup S_t)}\Pi_{i,t}}c_t\right)-\lambda Q\right] \tag{A.26}$$

Solving Equation (A.26) for c_t yields the equilibrium shorting cost per share (if aggregated shorting demand exceeds institutional lending supply) as given in Equation (A.12).

A.V Numerical Example

We choose the starting dividend D_0 to be equal to 50 and and the final period T to be equal to 11. Assume that 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 $\hat{\eta}^2_{O,0} = \hat{\eta}^2_{N,0} = \zeta^2 = 1$. Let the known variance of dividend innovations σ^2 be 2. As in Table A.1, we set the information diffusion period to $n = 3$.

Assume now that there is a large surprise $\delta_{O,1} = 4$ in the first period and that all following surprises are zero. The overconfident investor thus perceives this as an initial innovation of $\epsilon_{O,1} = 6$, followed by a series of $\epsilon_{O,t} = 2$ for all remaining time periods $t \in [2; 11]$.

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 $\delta^1_1 = 2$, $\delta^2_1 = 1.5$, and $\delta^3_1 = 0.5$, respectively. Together with the assumption of zero surprises in periods 2 to 11, this leads, in our example, the newswatcher population to perceive dividend innovations of $\epsilon_{N,1} = 4$, $\epsilon_{N,2} = 3.5$, $\epsilon_{N,3} = 2.5$, and $\epsilon_{N,t} = 2$ for periods $t \in [4; 11]$.

In the main text, we shift all time periods by one such that we consider time periods from -1 to 10 (as opposed to 0 to 11). The advantage is that the shock is observed at time $t = 0$. Thus, the numerical example aligns more closely with the standard practice of setting the time index at portfolio formation to $t = 0$ in empirical analyses (see, for example, Figure 1).

Panel A of Figure 3 shows posterior beliefs of overconfident agents $\mathbb{E}_{O,t}[D_T]$ (labeled "Overreacting agent") and newswatchers $\mathbb{E}_{N,t}[D_T]$ (labeled "Underreacting agent"), as well as the rational expectation beliefs of a Bayesian who sees the dividend innovations of the overconfident agents. Panel B shows the corresponding prices.

B Empirical Details

B.I Supplemental Data

To gain insights into the types of stocks in our portfolios, we calculate *idiosyncratic volatility (IVOL)*. It is based on daily CRSP returns and calculated as the residual standard deviation of a monthly regression of daily firm-excess returns on the three Fama and French (1993) factors, following Ang, Hodrick, Xing, and Zhang (2006).

One additional proxy that we use for short-sale costs is the put-call-parity violation, following Ofek, Richardson, and Whitelaw (2004). We measure it by the *volatility spread*, i.e., the open-interest-weighted average difference of implied volatilities of matched call/put option pairs. The volatility spread measure is provided by WRDS Option Suite, is based on data from Option Metrics and follows the calculation in Cremers and Weinbaum (2010).[A7]

B.II Additional Data Cleaning

We identify some issues with the short interest data as well as the institutional ownership data. These issues shrink our sample and induce additional noise, which should strictly weaken our results. First, suppose a firm is identified as having high short interest but really had low short interest. We might include this firm in the constrained portfolio, while it really was not constrained. If the firm displays "regular" returns, it will bias the results of the portfolio towards a too high return. Second, we increase our sample size and thus the pool of potentially constrained firms, which again should reduce noise.

The short interest data come from four different sources. Compustat is available from 1973, but only starts NASDAQ coverage from July 2003. We have additional files from each exchange, NYSE (1988/01 – 2005/07), AMEX (1995/01 – 2005/07) and NASDAQ (1988/06 – 2008/07, except February and July of 1990). One file typically covers one month of data for one exchange. The format varies widely – most files have tickers, some do not. Tickers typically have the share class appended at the end. In CRSP, the share class is sometimes included in the ticker and sometimes it is not. Ordinary matching on tickers misses some stocks with multiple share classes and all files that do not include tickers. We thus apply the following procedure to improve matching:

- Within each file we identify issues of the same company by name matching.
- We identify the share class from the name or the ticker within multiple issue companies.
- We match by ticker where uniquely possible.
- We match by ticker and share class where uniquely possible.
- We match the remaining firms by name and share class.

The name matching procedure for identifying multiple issues within files and for matching CRSP names with short interest file names first standardizes names by removing unnecessary whitespaces and punctuation, harmonizing abbreviations and acronyms and removing additional information (like "Class A" or "Incorporated"). We then calculate the Levenshtein

[A7] We filter time-to-expiration between 30 and 365 days, moneyness between .8 and .95 for out-of-the-money puts, .95 to 1.05 for near-the-money puts and .95 to 1.05 for near-the-money calls, and weight by open interest.

distance to assess name similarity. We discount common words like "American" and put more weight on the unique part of company names. Additionally, we allow for word rotation.

In an early version of the paper we had 1,488,655 firm month observations with short interest until December 2014. After applying the procedure above and allowing for firms from all four sources within any given month, we end up with 1,652,034 firm month observations, an 11% increase, 2/3 of which come from the new matching and 1/3 comes from allowing all sources within a month. Our short interest data now covers 81% of all observations in CRSP in our full sample period.

There are also some apparent issues with institutional ownership data, which have recently been confirmed by WRDS.[A8] We identify a few cases where institutional ownership decreases in one quarter by more than 50PP and increases by more than 50PP in the next quarter again. For example, Halliburton's institutional ownership falls from 83% to 0% in 06/2008 and is back at a level of 79% in the following quarter again. Thereby, Halliburton ends up in the constrained portfolio in one month, while it is highly unlikely that it was actually short-sale constrained.

We fix this issue by setting institutional ownership to the previous observation if we observe an extreme decrease of more than 50PP that reverses by more than 50PP in the following quarter, or a decrease by 95% that reverses to at least 50% of the previous level in the following quarter. This happens 2003 times in the sample – but even very few observations like Halliburton can have an influence on value-weighted portfolio returns. This fix further reduces noise in our results.

[A8] See the note issued by WRDS on March 6, 2017, concerning "Data Quality problems in Thomson Reuters Ownership."

B.III Bootstrapping

In order to construct a confidence interval for our cumulative abnormal return plots, we conduct two bootstrapping methodologies and finally combine both to arrive at our most conservative estimate in Figure 1 Panel D.

First, we randomly draw stocks in each month, with replacement, to form our portfolios. Effectively, this changes the weights within the portfolio: Some stocks will not be drawn at all, and others will be drawn multiple times, effectively putting a larger weight on them. Once we have conducted these draws for each month, we form our buy-and-hold strategies as before — for the year-1 and the 2–5 year holding periods. We exercise this procedure 1,000 times and calculate the standard deviation as well as the 2.5th and the 97.5th percentiles of the bootstrap runs. The results are exhibited in Figure B.1.

Second, we take the portfolios as they were actually constructed, but instead of looking at the months they were traded in reality, we randomly draw (with replacement) calendar months. Hence, in each of our 1,000 bootstrap runs, some months will be drawn multiple times, others will be dropped. This corresponds to a "random-X" bootstrap procedure, where a whole row of the "X" matrix, i.e., the matrix of right-hand-side variables, together with the y-value corresponding to that particular row (month) is drawn randomly. The results can be viewed in Figure B.2. In addition to the boostrap mean (which here corresponds to the original portfolio's CAR path) we plot two non-randomly drawn selections of months: One where we leave out all portfolio returns that occurred during 1999/01–2002/12, i.e., the dotcom era ("trade during .com"), and another one where we exclude all portfolios formed during that time-window ("formation during .com").

Finally, we combine the two methods. Hence, for each of the 1,000 random-firm draws, we randomly draw calendar months in which to record portfolio returns, also 1,000 times. From these 1,000,000 bootstrap samples, we again construct the 95% confidence interval, as shown in Figure 1 Panel D.

We also apply these bootstrap approaches to our main CAPM regression results. They can be found in Table B.1 below. We take the estimated coefficient and divide it by the bootstrap standard deviation, in order to have a value that is somewhat comparable to the t-statistics in our main tests.

Figure B.1: CAR - bootstrap firms - n=1,000

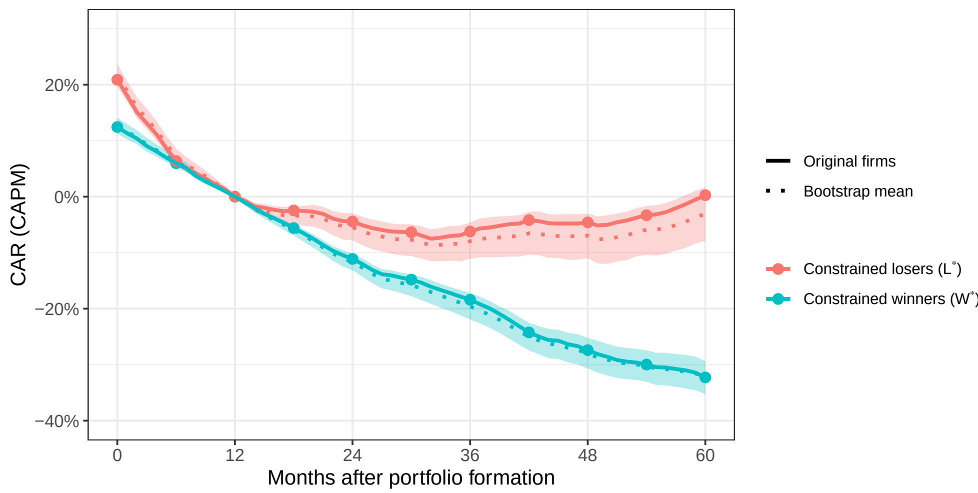


Figure B.2: CAR - bootstrap months - n=1,000

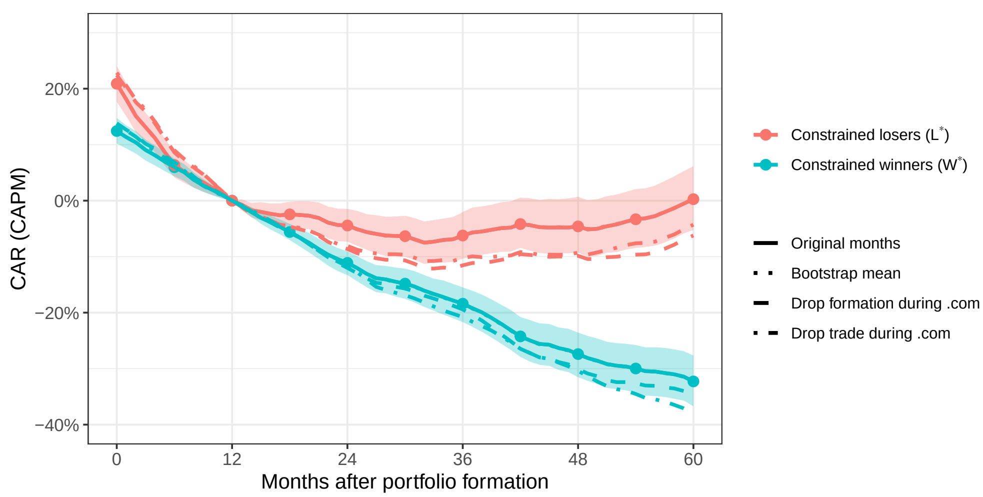


Table B.1: Bootstrap standard errors for main CAPM regressions for years 2-5. See caption to Table 3. The number in parentheses is the estimated coefficient divided by the bootstrap standard deviation, in order to have a value that is somewhat comparable to the t-statistics in our main tests.

	W_{L}^{*}	L_{L}^{*}	W_{L}^{*}-L_{L}^{*}	$W_{\mathrm{L}}^{*,m}$	$L_{\mathrm{L}}^{*,m}$	W_{L}^{*}-$W_{\mathrm{L}}^{*,m}$	L_{L}^{*}-$L_{\mathrm{L}}^{*,m}$	DiD
Panel A: Month Bootstrap, 1000 draws								
Intercept	-0.74	0.14	-0.88	0.17	-0.03	-0.90	0.17	-1.07
	(-3.56)	(0.59)	(-3.96)	(1.17)	(-0.17)	(-4.84)	(0.77)	(-4.79)
MktRF	1.43	1.32	0.11	1.25	1.27	0.18	0.05	0.14
	(22.26)	(22.79)	(1.49)	(38.13)	(30.93)	(2.99)	(0.99)	(1.91)
Panel B: Firm Bootstrap, 1000 draws								
Intercept	-0.74	0.14	-0.88	0.17	-0.03	-0.90	0.17	-1.07
	(-20.53)	(1.38)	(-10.63)	(5.86)	(-0.43)	(-19.34)	(1.44)	(-11.40)
MktRF	1.43	1.32	0.11	1.25	1.27	0.18	0.05	0.14
	(60.98)	(68.19)	(2.94)	(92.11)	(83.35)	(6.45)	(1.98)	(3.35)
Panel C: Month & Firm Bootstrap, 1000x1000 draws								
Intercept	-0.74	0.14	-0.87	0.17	-0.03	-0.90	0.17	-1.07
	(-3.53)	(0.34)	(-3.55)	(1.18)	(-0.12)	(-4.79)	(0.45)	(-4.21)
MktRF	1.43	1.32	0.11	1.25	1.27	0.18	0.05	0.14
	(21.80)	(20.92)	(1.27)	(34.29)	(28.55)	(2.76)	(0.78)	(1.69)

B.IV Long-Term Returns

Overview Two ways to communicate and to test long-term performance differences among portfolios are cumulative abnormal returns (CAR) and buy-and-hold abnormal returns (BHAR). We believe that both are great tools to get a graphical impression of impulse-response functions, that is in our context, how returns evolve after a major price shock. However, we also believe that the literature points convincingly to statistical problems that CAR and BHAR both have. We follow Fama's (1998) arguments in favor of the use of calendar-time portfolios to circumvent many of the problems. To increase diversification in our portfolio, we build rolling-portfolios in the spirit of Jegadeesh and Titman (1993). In the paper, we call the combination of these rolling-portfolios described in detail below "strategy."

To sum up, we primarily use cumulative abnormal returns (CAR) in Figure 1 to illustrate our main results and overlapping calendar-time portfolios for statistical tests. These choices are based on conceptional arguments summarized in this appendix. Our main results are not sensitive with respect to the chosen methodology.

Problems of CAR and BHAR Several problems with CAR and BHAR have been pointed out in the literature (Fama, 1998). If events cluster in certain time periods, then observations used in statistical tests of average BHAR are not independently distributed. Long-term returns tend to result in highly skewed distributions, making any testing procedure that assumes symmetric distributions difficult to apply. A major disadvantage of cumulative abnormal returns is that theses return do not correspond to a tradeable portfolio strategy, that is, they do not measure investor experience, like Barber and Lyon (1997) frame it.

Calendar-time portfolios solve or mitigate these problems. They can be problematic if events occur frequently in some time periods, as many observations are pooled in a few monthly observations, a problem that gives rise to power concerns (Loughran and Ritter, 1995).

There is one problem of BHAR that is of particular importance in any study interested in mispricing persistence. It is best explained by setting an example (Fama, 1998). Assume that you compare the buy-and-hold long-term returns of two portfolios. Portfolio 1 (PF1) makes +10% in the first year and then doubles from years 2 to 5. Portfolio 2 (PF2) has a zero return in the first year and then also doubles in the following four years. The BHAR of a portfolio that is long PF1 and short PF2 is $1.1 \cdot 2.0 - 1.0 \cdot 2.0 = 0.2$. The use of BHAR gives rise to the misleading impression that there are performance differences between PF1 and PF2 after the first year. However, this is just a compounding effect. Because of this problem, we do not use BHAR in our paper.

Overlapping Calendar-Time Portfolios The most common way to mitigate the statistical problems described above are calendar-time portfolios. Each calendar-month, all stocks that fulfill a certain criterion are grouped together in a portfolio. Criteria are flexible and can refer to events that have happened several months ago, like in Novy-Marx's (2012) comparison of recent and intermediate momentum. The returns of calendar-time portfolios are recorded monthly. Statistical significance of abnormal returns (alpha) is tested in time-series regressions under the hypothesis that a certain asset pricing model – like the CAPM or the Fama-French-three-factor model – holds.

Jegadeesh and Titman (1993, JT hereafter) propose a related approach that starts with the idea to hold portfolios for a period longer than a month. As in the calendar-time approach, portfolios are newly constructed each month based on a certain criterion. However, each of these portfolios is held for several months. This approach leads to an investment strategy holding a portfolio of several portfolios at each point in time.

Presumably, the JT approach has more power if theory or economic intuition suggests performance persistence for longer than one month. Furthermore, and of some importance in our context, if rolling portfolios are held for a considerably long-time period, say several years, then highly diversified portfolios result. This could be the case even if the average number of stocks that fulfill the portfolio inclusion criteria per month is small. To see this, it is useful to think about the portfolio in the very first period. It might well be that this portfolio contains just a few stocks. However, if the composition of stocks that fulfill the criteria changes at least to some extent from one month to another, then, over time, more and more stocks are entering the overall strategy until the number of rolling portfolios reaches its maximum number at the end of the first holding period.

Portfolio Weights of Rolling Portfolios If the holing period is K months and the maximum number of rolling portfolios has already been reached, then at each point in time t, the investor holds K portfolios. A natural question is the weight that should be put on each of theses portfolios to compute the monthly return of the overall strategy. JT rebalance every month to maintain equal weights among the K portfolios. They mention in their 1993 paper that they have also calculated returns "for a series of buy-and-hold portfolios" (page 68). A buy-and-hold approach appears to be more attractive on conceptional grounds, as the same set of biases that arise when constructing equal-weighted portfolios of stocks (Asparouhova, Bessembinder, and Kalcheva, 2013) should arise if equal weights are applied to portfolios.

How should a sensible buy-and-hold strategy of portfolios held over several months look like? We propose to start with the investment of \$1 in the first portfolio at the end of starting month s. This portfolio is now held for K months and each month between $s+1$ and $s+K-1$, we construct a new portfolio based on our criterion and invest a \$1. There is no rebalancing until the end of period $s+K$. At the beginning of period $s+K$, we hold K portfolios for the first time.

At the end of period $s+K$, we close out the first portfolio constructed K periods ago and invest in a new one. From now on, the strategy rebalances across portfolios each month. The weight of each portfolio should be proportional to the dollar value of the portfolio that has emerged endogenously. Concretely, there are K portfolios at the end of period $t-1$. We refer to the k-th portfolio as the portfolio that was formed k periods ago with $k \in 0, 1, \cdots, K-1$. Then, the non-normalized weight of portfolio k at the end of period $t-1$ is given by

$$w_{k,t-1} = \prod_{\tau=0}^{k-1}(1 + r_{k,t-1-\tau}) \text{ if } k \geq 1 \text{ and } w_{0,t-1} = 1. \tag{B.1}$$

The return of the portfolio of K portfolios (strategy) in period t can be calculated by

$$r_t = \sum_{k=0}^{K-1} \left(\frac{w_{k,t-1}}{\sum_{j=0}^{K-1} w_{j,t-1}} r_{k,t} \right), \tag{B.2}$$

where $r_{k,t}$ is the return of portfolio k in period t.

We illustrate the strategy with the help of a stylized example. Assume that a portfolio is to be held for $K = 2$ periods. Assume further that any of the rolling portfolios makes -20% in the first and $+25\%$ in the second period. A dollar invested in one of these portfolios will still be worth a dollar after the holding period. The following Table B.2 shows the portfolio returns period by period as well as the resulting time-series of equally-weighted (EW) and buy-and-hold (BH) monthly strategy returns.

Table B.2: Shown is a stylized example. Each portfolio is held over two periods and yields -20% in the first period and $+25\%$ in the second period. The row EW shows the returns of an investment strategy that holds two portfolios in each period with equal weights. The row BH shows the returns of an investment strategy that holds two portfolios in each period with weights that are proportional to the value of each portfolio at the time of portfolio formation. The initial investment under the buy-and-hold strategy is always one dollar per portfolio.

Returns	1	2	3	4	···
PF formed in 0	-0.200	0.250			···
PF formed in 1		-0.200	0.250		···
PF formed in 2			-0.200	0.250	···
PF formed in 3				-0.200	···
EW	-0.200	**0.025**	**0.025**	**0.025**	···
BH	-0.200	**0.000**	**0.000**	**0.000**	···

While the monthly returns of a strategy that rebalances to equal weights every month (EW) are rather obvious, it is useful to go through the returns of a buy-and-hold strategy (BH) step-by-step. The first dollar invested into the portfolio shrinks to 80 cents at the end of the first period. We invest another dollar into the newly formed portfolio in period 2 and continue to hold the portfolio from the first period without further rebalancing. The weight of the old portfolio is $\frac{0.8}{1.8}$ and the weight of the new portfolio is $\frac{1}{1.8}$. In this stylized example, we rebalance the portfolios every period in such a way that these weights are maintained.[A9] The per-period returns of the calendar-time portfolio are $\frac{0.8}{1.8}(0.25) + \frac{1}{1.8}(-0.2) = 0$. The dollar values invested in each portfolio at the beginning and remaining at the end of each period are shown in Panels A and B of Table B.2. Panel C reports on the necessary trades.

[A9]Note that constant portfolio weights only arise in highly stylized settings. In real-world applications, returns of portfolios vary from period to period and portfolio to portfolio and thereby create new weights according to Equations (B.1) and (B.2) endogenously.

Table B.3: This table continues on the stylized example introduced in Table B.2. Shown are more details on the buy-and-hold strategy. Panel A (B) contains the value of each portfolio at the beginning (end) of each period. Panel C shows the trades that are necessary to implement the strategy.

Panel A: Dollar values at beginning of period t under BH	1	2	3	4	···
PF formed in 0	1.0000	0.8000			
PF formed in 1		1.0000	0.8000		
PF formed in 2			1.0000	0.8000	
PF formed in 3				1.0000	···
Total value at beginning of period	1.0000	1.8000	1.8000	1.8000	···
Panel B: Dollar values at the end of period t under BH	1	2	3	4	···
PF formed in 0	0.8000	1.0000			
PF formed in 1		0.8000	1.0000		
PF formed in 2			0.8000	1.0000	
PF formed in 3				0.8000	···
Total value at end of period	0.8000	1.8000	1.8000	1.8000	···
Panel C: Trades under BH	1	2	3	4	···
Initial investment	−1.0000	−1.0000			
PF formed in 0	+1.0000		−1.0000		
PF formed in 1		+1.0000		−1.0000	
PF formed in 2			+1.0000		
PF formed in 3				+1.0000	···
Turnover	100%	55.56%	55.56%	55.56%	···

Table B.4: This table continues on the stylized example introduced in Table B.2. Shown are more details on the equally-weighted strategy. Panel A (B) contains the value of each portfolio at the beginning (end) of each period. Panel C shows the trades that are necessary to implement the strategy.

Dollar values invested at the beginning of period t under EW	1	2	3	4 ···
PF formed in 0	1.0000	0.9000		
PF formed in 1		0.9000	0.9225	
PF formed in 2			0.9225	0.9456
PF formed in 3				0.9456 ···
Total value at beginning of period	1.0000	1.8000	1.8450	1.8911 ···
Dollar values invested at end of period t under EW	1	2	3	4 ···
PF formed in 0	0.8000	1.1250		
PF formed in 1		0.7200	1.1531	
PF formed in 2			0.7380	1.1820
PF formed in 3				0.7565 ···
Total value at end of period	1.000	1.8450	1.8911	1.9385 ···
Trades under EW	1	2	3	4 ···
Initial investment	−1.0000	−1.0000		
PF formed in 0	+1.0000	+0.1000	−1.1250	
PF formed in 1		+0.9000	+0.2025	−1.1531
PF formed in 2			+0.9225	+0.2075
PF formed in 3				+0.9456 ···
Turnover	100%	55.56%	60.98%	60.98% ···

Assuming an investor starts in period 2, under BH, she invests \$1.80. At the end of period 4, there is still \$1.80 left, and continuing with this strategy would – under the same return patterns – result in a constant portfolio value. In contrast, the EW returns suggest that the investor earns positive returns from period 2 onward (see Table B.4). A comparison of Tables B.3 and B.4 reveals the reason for this difference. Equal weights imply that the investor buys more of those portfolios that have lost in value. If there is a short-term reversal effect, equal weights yield a higher return than the buy-and-hold approach that does not imply contrarian rebalancing. However, at least in our example, we would like to have a zero return for the overlapping portfolio strategy, as every single of the overlapping portfolios yields a zero buy-and-hold return by assumption.

The discussion mirrors potentially misleading returns that show up in equally-weighted portfolios of illiquid stocks. A common remedy is value-weighting (Asparouhova, Bessembinder, and Kalcheva, 2013), and BH brings this idea to strategies consisting of several portfolios, when holding periods exceed one month.

When should we expect return differences among EW and BH? Assuming that EW portfolios are mostly constructed with monthly returns, differences should be most pronounced if a strategy oversamples illquid stocks that are prone to exhibit short-term reversal (Jegadeesh, 1990). Conversely, if returns under EW and BH are very similar, an upward bias caused by short-term autocorrelation of returns is less of a concern. BH is probably the more conservative approach for most applications.

Of course, under the best of all circumstances, statistical inferences are the same, no matter which methodology is used. In the main text, we base our tests on time-series of buy-and-hold (BH) monthly returns as laid out in this appendix. In Appendix F.V, we repeat this exercise for equally-weighted (EQ) monthly returns, as used by Jegadeesh and Titman (1993). Appendix F.VI contains a robustness check where we just hold any stock that fulfills the portfolio inclusion criteria at a certain point of time in proportion to its market capitalization. In Appendix B.III, we use bootstrapping to assess the statistical significance of long-term differences in the cumulative abnormal returns of constrained winners and losers. All approaches support our main result.

B.V Calculation of Abnormal Announcement Returns

For the abnormal return $AR_{i,t}$ for calendar day t, we estimate CAPM-betas from daily returns for each individual stock i, where $m-12, m-1$ refers to the estimation window, which encompasses the 12 months prior to the earnings announcement month. Abnormal return $AR_{i,t}$ is then the difference between stock i's excess return $R_{i,t}$ and $\beta^{Mkt}_{i;m-12,m-1} \cdot MktRF_t$:

$$AR_{i,t} = R_{i,t} - \beta^{Mkt}_{i;m-12,m-1} MktRF_t$$

We then cumulate the abnormal returns for each individual stock over event days d up to D:

$$CAR_{i,D} = \sum_{d=-21}^{D} AR_{i,d}$$

and normalize by $CAR_{i,0}$:

$$CAR^0_{i,D} = CAR_{i,D} - CAR_{i,0}$$

The average CAR (ACAR) for all stocks in portfolio p is weighted by the buy-and-hold weight $w_{i,p,m}$, i.e., the weight at portfolio formation times the change in the value of that investment up to the day before the announcement:

$$ACAR^0_{D,p} = \sum_{m \in M} \sum_{j \in I_{p,m}} w_{i,p,m} CAR^0_{i,p,m,D}$$

where $w_{i,p,m} = \frac{W'_{i,p,m}}{\sum_{m \in M} \sum_{j \in I_{p,m}} W'_{j,p,m}}$ and $W'_{i,p,m} = \sum_{\tau \in T_m} \frac{ME_{i,\tau}}{\sum_{j \in J_{p,\tau}} ME_{j,\tau}} (1 + RET^x_{i;\tau,D-21})$.

$I_{p,m}$ is the set of firms in portfolio p in month m when we measure earnings announcements; and $J_{p,\tau}$ is the set of firms in portfolio p at the end of formation-month τ. $ME_{i,\tau}$ is market equity (PRC*SHROUT) of firm i in formation month τ; and $RET^x_{i;\tau,D-21}$ is the ex-dividend return between the end of the formation month τ and 21 days prior to the earnings announcemnt in month m. T_m are all months to be considered to determine whether a stock belongs to portfolio p ($m-12$ to $m-1$ in Panel A; $m-60$ to $m-13$ in Panel B). We need the summation in the calculation of $W'_{i,p,m}$ to consider the possibility that a stock could have been allocated to portfolio p multiple times during the lookback-period T_m. $W'_{i,p,m}$ can be interpreted as the dollar-amount invested in firm i 21 days prior to an earnings announcement in an overlapping buy-and-hold portfolio. M are all months where we measure earnings announcement returns (1993/06 to June 2020 in Panel A; 1998/06 to June 2020 in Panel B of Figure 6).

C Additional Empirical Results

C.I Market Capitalization and Number of Stocks

Figure C.1: Market capitalization of constrained US stocks and the Dutch stock market.

Data for the Dutch market are from Datastream and include domestic equities that are the primary quote and major security of its company (following Chui, Titman, and Wei, 2010). Data for the US include all stocks that were classified as constrained within the past 60 months, i.e., the universe of stocks on which the value-weighted buy-and-hold portfolios examined in our main tests are based on.

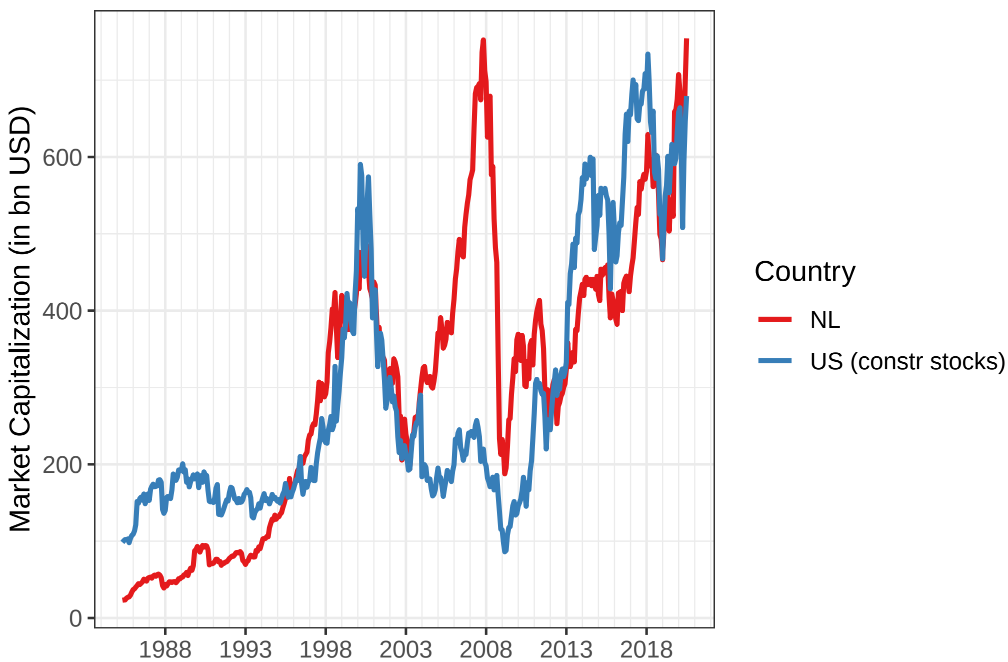


Figure C.2: Number of stocks newly assigned to portfolio each month

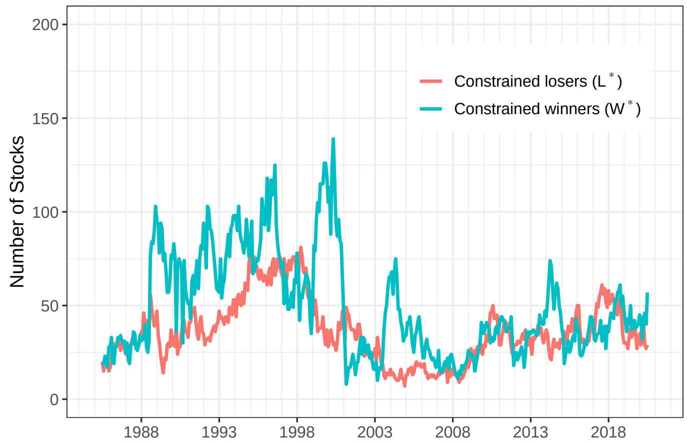


Figure C.3: Number of unique stocks in strategies containing constrained past-winners/losers from 1–12 months ago

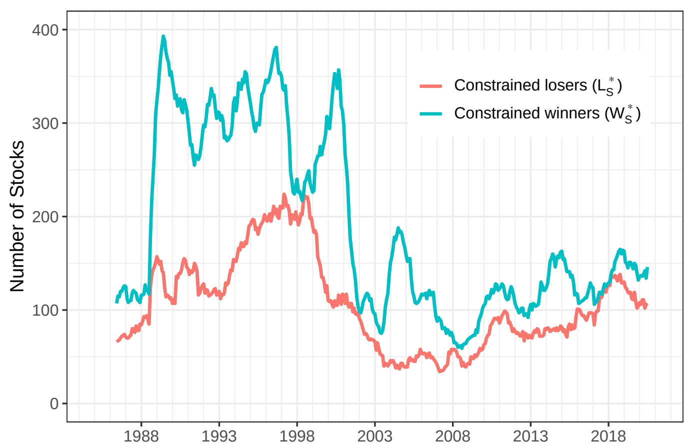
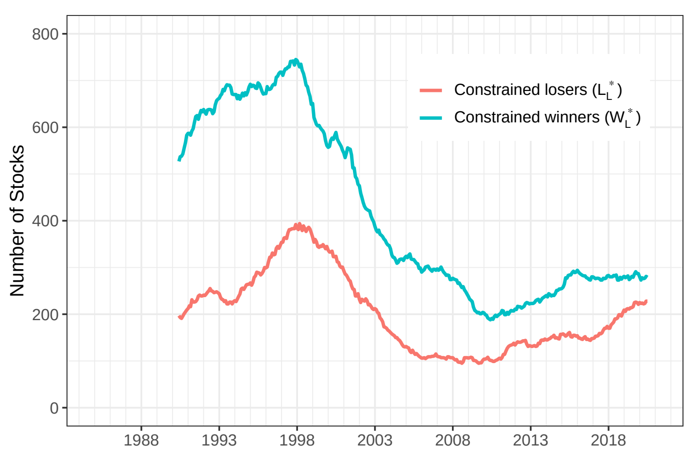


Figure C.4: Number of unique stocks in strategies containing constrained past-winners/losers from 13–60 months ago



C.II Results for one Holding Month

Table C.1 reports the average monthly excess returns of the 9 winner (Panel A), 9 medium momentum (Panel B) and 9 loser (Panel C) portfolios. Portfolios are displayed according to our triple-sorting procedure: Institutional ownership (IOR), going from high to low, on the x-axis; Short interest (SIR) going from low to high on the y-axis; and past-return, going from winners to losers in Panels A to C. The stocks where we expect the largest overpricing, i.e., those with the lowest institutional ownership and with the largest short-interest ("constrained" stocks), have average monthly excess returns of -0.14% and -1.39% for winners and losers, respectively. The returns for the most extreme past return portfolios, i.e., constrained winners and constrained losers, are larger in magnitude than those for the constrained medium past-return portfolios.[A10]

For winners, short-sale constraints change the sign of the momentum prediction. 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.[A11] Comparing the constrained winners to the high-IOR/high-SIR winners, results in a difference of -1.14% per month with a Newey-West t-statistic of -4.34. The rightmost column shows the alpha from a Fama-French four-factor regression, which is also highly statistically significant for high SIR stocks. Similarly, taking the low IOR column's bottom vs. top difference produces an excess return of -1.11% per month (t-statistic -3.50), which can also not be explained by the four factors.

[A10]Notice, as shown in Table C.7, 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).

[A11]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 57 BP/month.

Table C.1: Monthly excess returns of winner and loser portfolios.
This table contains monthly average excess returns of the 9 winner (Panel A), 9 medium momentum (Panel B) and 9 loser (Panel C) portfolios from an independent triple sort on the past 11-month return lagged by one month, institutional ownership (IOR) and short interest (SIR). The last two columns present the difference of low and high institutional ownership portfolio returns and the alpha of that difference-portfolio from a Fama-French-Carhart four-factor regression. Similarly, the bottom two rows show the return-difference between high and low SIR portfolios and the respective four-factor alpha. The sample period is May 1980 to June 2020. 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	1.25	0.98	−0.03 (−0.14)	0.04 (0.17)
M	0.84	0.64	0.83	−0.02 (−0.07)	−0.02 (−0.08)
Hi SIR	1.01	0.91	−0.14	−1.14 (−4.34)	−1.12 (−4.21)
Hi-Lo	0.00	−0.35	−1.11		
t	(0.02)	(−1.57)	(−3.50)		
$\alpha(Hi - Lo)$	−0.28	−0.61	−1.43		
t	(−1.63)	(−2.90)	(−4.54)		

Panel B: Medium Momentum

	Hi IOR	M	Lo IOR	Lo-Hi	$\alpha(Lo - Hi)$
Lo SIR	0.65	0.85	0.69	0.04 (0.22)	0.22 (1.23)
M	0.66	0.55	0.58	−0.07 (−0.47)	−0.00 (−0.01)
Hi SIR	0.55	0.62	0.09	−0.47 (−1.86)	−0.28 (−1.19)
Hi-Lo	−0.10	−0.24	−0.61		
t	(−0.69)	(−1.05)	(−2.06)		
$\alpha(Hi - Lo)$	−0.15	−0.30	−0.65		
t	(−0.99)	(−1.65)	(−2.42)		

Panel C: Losers

	Hi IOR	M	Lo IOR	Lo-Hi	$\alpha(Lo - Hi)$
Lo SIR	0.68	0.52	0.31	−0.37 (−0.91)	−0.07 (−0.13)
M	0.54	0.48	0.10	−0.44 (−1.37)	−0.18 (−0.51)
Hi SIR	0.23	0.06	−1.39	−1.61 (−4.88)	−1.53 (−5.49)
Hi-Lo	−0.46	−0.45	−1.70		
t	(−1.25)	(−1.77)	(−4.95)		
$\alpha(Hi - Lo)$	−0.18	−0.47	−1.64		
t	(−0.37)	(−1.78)	(−5.51)		

C.III Performance of Other Constrained Portfolios

Table C.2: Short-horizon (S, 1 year) strategy performance of constrained portfolios.

See caption to Table 2. Here, we do not present results for matched unconstrained stocks. Instead, we present results for constrained losers that had (L^{*W}) or had not (L^{*}) been constrained winners over the past 5 years prior to allocation, as well as the union of the two disjunct subsets of loser stocks (L^{*all}). In addition, we present the difference between L^{*W} and L^{*}, and W^{*} and L^{*all}, as well as constrained stocks that were in the medium portfolio of past-return (M^{*}).

	L^*_S	L^{*W}_S	L^{*W}_S-L^*_S	L^{*all}_S	M^*_S	W^*_S	W^*_S-L^{*all}_S	W^*_S-L^*_S
Panel A: Raw excess returns								
Average	-0.90	-0.68	0.22	-0.72	-0.00	-0.18	0.54	0.73
	(-1.81)	(-1.54)	(0.64)	(-1.67)	(-0.01)	(-0.54)	(1.94)	(2.00)
No. of months	411	411	411	411	411	411	411	411
AvgN	106	135		238	179	188		
SR	-0.3076	-0.2562	0.1167	-0.2726	-0.0021	-0.0760	0.3412	0.3528
Panel B: CAPM regressions								
Intercept	-1.89	-1.59	0.30	-1.68	-0.75	-1.07	0.61	0.82
	(-5.55)	(-4.75)	(0.86)	(-6.07)	(-4.35)	(-4.28)	(2.12)	(2.27)
MktRF	1.51	1.39	-0.11	1.47	1.14	1.37	-0.10	-0.14
	(11.97)	(17.05)	(-1.34)	(14.52)	(21.03)	(14.94)	(-0.89)	(-1.02)
R^2	0.4432	0.4644	0.0060	0.5188	0.6619	0.5783	0.0066	0.0081
IR	-0.8637	-0.8213	0.1563	-0.9185	-0.7117	-0.7096	0.3837	0.4000
Panel C: Four-factor regressions								
Intercept	-1.37	-1.14	0.23	-1.19	-0.58	-0.95	0.24	0.42
	(-3.96)	(-4.15)	(0.65)	(-4.90)	(-3.67)	(-4.07)	(0.96)	(1.20)
MktRF	1.16	1.04	-0.12	1.12	0.98	1.17	0.05	0.01
	(16.01)	(14.35)	(-1.77)	(17.18)	(22.56)	(17.18)	(0.70)	(0.11)
HML	-0.10	-0.38	-0.28	-0.25	0.05	-0.31	-0.06	-0.21
	(-0.64)	(-3.03)	(-1.73)	(-1.81)	(0.56)	(-2.73)	(-0.52)	(-1.27)
SMB	1.22	1.33	0.11	1.25	0.76	1.00	-0.25	-0.22
	(8.09)	(10.52)	(0.96)	(10.39)	(12.33)	(11.63)	(-2.00)	(-1.41)
MOM	-0.63	-0.45	0.18	-0.54	-0.18	0.01	0.55	0.64
	(-5.18)	(-4.04)	(1.45)	(-6.29)	(-4.34)	(0.09)	(7.50)	(5.04)
R^2	0.6365	0.7124	0.0511	0.7519	0.8039	0.7505	0.2241	0.1942
IR	-0.7749	-0.8014	0.1243	-0.9073	-0.7199	-0.8177	0.1722	0.2281

Table C.3: Long-horizon (L, 2–5 years) strategy performance of constrained portfolios.
See caption to Table C.2. 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.

	L^*_{L}	L^{*W}_{L}	L^{*W}_{L}-L^*_{L}	L^{*all}_{L}	M^*_{L}	W^*_{L}	W^*_{L}-L^{*all}_{L}	W^*_{L}-L^*_{L}
Panel A: Raw excess returns								
Average	1.03	0.47	-0.56	0.70	0.44	0.23	-0.47	-0.80
	(2.81)	(1.13)	(-2.24)	(1.84)	(1.37)	(0.66)	(-2.82)	(-3.87)
No. of months	363	363	363	363	363	363	363	363
AvgN	203	224		399	367	417		
SR	0.4849	0.1942	-0.3858	0.3270	0.2443	0.1094	-0.4739	-0.6061
Panel B: CAPM regressions								
Intercept	0.14	-0.51	-0.65	-0.23	-0.38	-0.74	-0.50	-0.87
	(0.59)	(-1.53)	(-2.51)	(-0.91)	(-2.21)	(-3.61)	(-3.46)	(-4.34)
MktRF	1.32	1.44	0.12	1.38	1.22	1.43	0.05	0.11
	(17.57)	(18.42)	(1.50)	(22.36)	(20.56)	(19.51)	(0.75)	(1.26)
R^2	0.6029	0.5601	0.0114	0.6493	0.7103	0.7016	0.0039	0.0115
IR	0.1039	-0.3168	-0.4460	-0.1827	-0.3920	-0.6280	-0.5088	-0.6678
Panel C: Four-factor regressions								
Intercept	0.26	-0.36	-0.61	-0.10	-0.35	-0.62	-0.52	-0.88
	(1.20)	(-1.63)	(-2.65)	(-0.54)	(-2.91)	(-4.93)	(-3.53)	(-4.33)
MktRF	1.13	1.16	0.04	1.15	1.08	1.25	0.10	0.13
	(22.15)	(20.02)	(0.54)	(25.41)	(25.28)	(18.03)	(1.27)	(1.64)
HML	0.11	-0.48	-0.59	-0.22	-0.08	-0.28	-0.06	-0.39
	(1.56)	(-5.56)	(-6.71)	(-3.30)	(-1.29)	(-5.08)	(-0.96)	(-4.99)
SMB	0.88	1.21	0.33	0.99	0.77	0.74	-0.25	-0.14
	(12.29)	(15.95)	(4.19)	(16.02)	(15.43)	(8.87)	(-2.98)	(-1.73)
MOM	-0.14	-0.08	0.06	-0.11	0.01	-0.08	0.03	0.06
	(-2.44)	(-1.47)	(0.90)	(-2.07)	(0.16)	(-1.29)	(0.35)	(0.64)
R^2	0.7352	0.8133	0.2237	0.8356	0.8601	0.8190	0.0537	0.0893
IR	0.2342	-0.3416	-0.4769	-0.1145	-0.5216	-0.6848	-0.5449	-0.7008

Table C.4: One- to five-year strategy performance of constrained portfoliosn. See caption to Table C.2. The only difference here is a holding-period of 60 instead of 12 months.

	L^{*}_{60}	L^{*W}_{60}	L^{*W}_{60}-L^{*}_{60}	L^{*all}_{60}	M^{*}_{60}	W^{*}_{60}	W^{*}_{60}-L^{*all}_{60}	W^{*}_{60}-L^{*}_{60}
Panel A: Raw excess returns								
Average	0.64	0.26	-0.38	0.41	0.34	0.22	-0.19	-0.42
	(1.70)	(0.64)	(-1.76)	(1.08)	(1.08)	(0.60)	(-1.24)	(-2.11)
No. of months	363	363	363	363	363	363	363	363
AvgN	271	277		504	454	511		
SR	0.2887	0.1095	-0.2853	0.1875	0.1913	0.1004	-0.1906	-0.3254
Panel B: CAPM regressions								
Intercept	-0.30	-0.72	-0.42	-0.55	-0.49	-0.76	-0.21	-0.46
	(-1.27)	(-2.26)	(-1.86)	(-2.16)	(-2.85)	(-3.55)	(-1.32)	(-2.25)
MktRF	1.39	1.45	0.06	1.42	1.22	1.45	0.03	0.06
	(17.57)	(19.43)	(0.72)	(23.35)	(23.80)	(16.54)	(0.40)	(0.58)
R^2	0.6178	0.5713	0.0030	0.6523	0.7293	0.6940	0.0015	0.0035
IR	-0.2197	-0.4564	-0.3152	-0.4218	-0.5190	-0.6319	-0.2113	-0.3581
Panel C: Four-factor regressions								
Intercept	-0.12	-0.51	-0.38	-0.36	-0.43	-0.68	-0.32	-0.55
	(-0.60)	(-2.46)	(-1.77)	(-1.99)	(-3.19)	(-5.10)	(-2.14)	(-2.97)
MktRF	1.16	1.14	-0.01	1.16	1.07	1.28	0.12	0.12
	(21.69)	(19.79)	(-0.21)	(26.48)	(27.33)	(16.73)	(1.51)	(1.49)
HML	0.04	-0.48	-0.52	-0.23	-0.07	-0.33	-0.10	-0.37
	(0.50)	(-5.83)	(-5.71)	(-3.38)	(-1.18)	(-4.57)	(-1.37)	(-4.43)
SMB	0.95	1.20	0.25	1.05	0.76	0.75	-0.30	-0.21
	(14.08)	(14.67)	(3.52)	(15.71)	(17.76)	(8.22)	(-2.74)	(-1.88)
MOM	-0.21	-0.16	0.05	-0.18	-0.03	-0.03	0.15	0.17
	(-3.09)	(-2.97)	(0.71)	(-3.66)	(-0.97)	(-0.57)	(2.15)	(1.97)
R^2	0.7675	0.8239	0.1861	0.8527	0.8748	0.8184	0.1020	0.1215
IR	-0.1166	-0.5031	-0.3205	-0.4221	-0.6751	-0.7281	-0.3320	-0.4561

C.IV Short-/Long-term Returns of all Triple-sorted Portfolios

Table C.5: Short-horizon (S, 1 year) strategy excess returns of winner and loser portfolios.
See caption to Table C.1. The only difference here is a holding-period of 12 months instead of 1 month.

Panel A: Winners					
	Hi IOR	M	Lo IOR	Lo-Hi	$\alpha(Lo - Hi)$
Lo SIR	0.77	0.96	0.73	−0.05 (−0.31)	0.05 (0.29)
M	0.74	0.64	0.45	−0.29 (−1.72)	−0.29 (−1.96)
Hi SIR	0.76	0.77	−0.14	−0.90 (−4.37)	−0.83 (−3.79)
Hi-Lo	−0.01	−0.19	−0.86		
t	(−0.09)	(−0.87)	(−3.85)		
$\alpha(Hi - Lo)$	−0.13	−0.32	−1.00		
t	(−1.06)	(−1.92)	(−4.71)		

Panel B: Medium Momentum					
	Hi IOR	M	Lo IOR	Lo-Hi	$\alpha(Lo - Hi)$
Lo SIR	0.64	0.80	0.80	0.16 (1.09)	0.34 (2.32)
M	0.65	0.61	0.73	0.07 (0.60)	0.14 (1.02)
Hi SIR	0.66	0.72	−0.00	−0.66 (−3.40)	−0.55 (−3.09)
Hi-Lo	0.02	−0.08	−0.80		
t	(0.22)	(−0.43)	(−3.72)		
$\alpha(Hi - Lo)$	−0.02	−0.10	−0.91		
t	(−0.20)	(−0.81)	(−4.48)		

Panel C: Losers					
	Hi IOR	M	Lo IOR	Lo-Hi	$\alpha(Lo - Hi)$
Lo SIR	0.75	0.79	0.65	−0.10 (−0.49)	0.06 (0.26)
M	0.59	0.56	0.52	−0.06 (−0.28)	−0.02 (−0.10)
Hi SIR	0.59	0.50	−0.65	−1.24 (−4.62)	−1.06 (−4.37)
Hi-Lo	−0.16	−0.30	−1.30		
t	(−1.23)	(−1.50)	(−5.71)		
$\alpha(Hi - Lo)$	−0.10	−0.38	−1.22		
t	(−0.52)	(−1.91)	(−4.75)		

Table C.6: Long-horizon (L, 2–5 years) excess returns of winner and loser portfolios.
See caption to Table C.1. The only difference here is a holding-period of 48 months, skipping the first 12, instead of 1 month.

Panel A: Winners					
	Hi IOR	M	Lo IOR	Lo-Hi	$\alpha(Lo-Hi)$
Lo SIR	0.81	0.90	0.62	−0.19 (−1.95)	−0.06 (−0.57)
M	0.77	0.70	0.59	−0.18 (−1.51)	−0.14 (−1.30)
Hi SIR	0.84	0.88	0.24	−0.61 (−4.45)	−0.61 (−4.33)
Hi-Lo	0.04	−0.02	−0.38		
t	(0.22)	(−0.10)	(−1.67)		
$\alpha(Hi-Lo)$	−0.04	−0.13	−0.59		
t	(−0.29)	(−0.94)	(−3.59)		

Panel B: Medium Momentum					
	Hi IOR	M	Lo IOR	Lo-Hi	$\alpha(Lo-Hi)$
Lo SIR	0.87	0.81	0.82	−0.05 (−0.46)	0.13 (1.09)
M	0.80	0.69	0.62	−0.18 (−1.43)	−0.11 (−0.78)
Hi SIR	0.81	0.80	0.47	−0.35 (−2.10)	−0.32 (−2.31)
Hi-Lo	−0.05	−0.01	−0.36		
t	(−0.47)	(−0.08)	(−1.61)		
$\alpha(Hi-Lo)$	−0.17	−0.11	−0.61		
t	(−1.72)	(−0.99)	(−3.73)		

Panel C: Losers					
	Hi IOR	M	Lo IOR	Lo-Hi	$\alpha(Lo-Hi)$
Lo SIR	0.80	0.88	0.69	−0.11 (−0.70)	−0.01 (−0.05)
M	0.83	0.74	0.62	−0.20 (−1.20)	−0.15 (−1.03)
Hi SIR	0.81	0.93	0.64	−0.17 (−0.86)	−0.08 (−0.47)
Hi-Lo	0.01	0.05	−0.05		
t	(0.06)	(0.31)	(−0.30)		
$\alpha(Hi-Lo)$	−0.08	−0.04	−0.16		
t	(−0.73)	(−0.30)	(−0.98)		

C.V Characteristics of all Triple-sorted Portfolios

Table C.7: Characteristics of portfolios sorted on IOR, SIR and past-return. This table shows time-series averages of value-weighted mean characteristics of the 9 winner and 9 loser portfolios in the month of portfolio formation. Panel A displays the average number of stocks. Following are average market equity in billion US dollars (Panel B), return from month t-12 to the end of month t-2 (in %, Panel C), institutional ownership in % of number of shares outstanding (Panel D) and the change over the preceding year (in PP, Panel E), level (in %, Panel F) and change (in PP, Panel G) in short interest two weeks prior to portfolio formation, the ratio of the most recent publicly available quarterly book equity to last month's market equity (Panel H) and the average standard deviation of daily idiosyncratic returns in each portfolio (in %, daily) over the month prior to formation (Ang, Hodrick, Xing, and Zhang, 2006, Panel I). Panels J and K show levels (in %) and changes (in PP) over the preceding 12 months in monthly turnover. Panel L presents the ratio of short interest to institutional ownership (in %, SIRIO) as in Drechsler and Drechsler (2016). 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) is shown in Panel M. Panels N and O display the level (in %) and change (in PP, over the preceding 12 months) in the Markit Indicative loan fee, and Panels P and Q the level (in %) and change (in PP) in the Markit simple average loan fee.

	Winners			Losers		
	Hi IOR	M	Lo IOR	Hi IOR	M	Lo IOR
Panel A: Number of stocks						
Lo SIR	29	123	197	18	121	285
M	176	239	117	91	200	168
Hi SIR	215	136	49	163	168	88
Panel B: Average Market Equity (B$)						
Lo SIR	18.12	101.08	27.44	7.55	47.06	11.76
M	33.12	62.06	9.06	14.34	44.56	4.89
Hi SIR	13.51	17.10	3.00	5.49	9.41	1.37
Panel C: Formation Period Return (%)						
Lo SIR	43	45	52	-25	-27	-34
M	44	45	59	-24	-26	-36
Hi SIR	54	58	82	-29	-34	-44

Table C.7: (continued)

	Winners			Losers		
	Hi IOR	M	Lo IOR	Hi IOR	M	Lo IOR
Panel D: Institutional Ownership (IOR, %)						
Lo SIR	73.02	44.60	13.87	72.58	43.15	11.53
M	73.01	50.12	16.47	72.67	48.71	15.16
Hi SIR	77.74	50.74	16.91	76.26	48.91	16.25
Panel E: Change in IOR over preceding year (PP)						
Lo SIR	3.41	1.39	0.03	2.70	-0.29	-1.21
M	1.97	1.37	0.05	0.38	-0.80	-1.91
Hi SIR	4.06	3.75	1.18	0.66	-1.19	-2.42
Panel F: Short-interest (SIR, %)						
Lo SIR	0.42	0.41	0.25	0.40	0.40	0.24
M	1.55	1.29	1.35	1.72	1.38	1.47
Hi SIR	6.06	5.56	6.52	6.99	6.42	6.95
Panel G: Change in SIR over preceding year (PP)						
Lo SIR	-0.50	-0.22	-0.20	-0.40	-0.30	-0.33
M	-0.44	-0.25	-0.13	-0.13	-0.03	-0.24
Hi SIR	0.33	0.42	2.28	1.65	1.35	0.58
Panel H: Book-to-market ratio						
Lo SIR	0.47	0.48	0.50	0.92	0.89	0.83
M	0.36	0.39	0.39	0.63	0.67	0.70
Hi SIR	0.35	0.37	0.30	0.70	0.75	0.68
Panel I: Idiosyncratic volatility (%, daily)						
Lo SIR	1.42	1.52	2.16	2.21	2.48	3.53
M	1.34	1.34	2.19	1.76	1.90	3.08
Hi SIR	1.68	1.81	3.04	2.12	2.41	3.77

Table C.7: (continued)

	Winners			Losers		
	Hi IOR	M	Lo IOR	Hi IOR	M	Lo IOR
Panel J: Turnover (%)						
Lo SIR	9.06	8.48	4.75	10.69	8.42	4.84
M	13.49	12.10	9.36	15.99	15.05	9.43
Hi SIR	24.97	25.39	32.64	27.71	26.54	24.51
Panel K: Change in turnover over preceding year (PP)						
Lo SIR	-0.23	-0.19	0.73	1.32	-0.22	-1.37
M	-0.42	-0.43	1.53	1.88	2.15	-2.04
Hi SIR	0.89	2.61	15.95	3.81	1.56	-5.31
Panel L: SIRIO (%)						
Lo SIR	0.50	0.68	3.98	0.47	0.76	7.26
M	1.92	2.32	22.45	2.11	2.51	32.39
Hi SIR	7.10	11.14	100.31	8.32	13.84	86.82
Panel M: Option volatility spread (%)						
Lo SIR	0.20	-0.15	-0.54	-0.13	0.29	-1.36
M	-0.36	-0.33	-1.38	-0.22	-0.18	-1.31
Hi SIR	-0.72	-1.23	-5.47	-1.01	-1.42	-6.24
Panel N: Ind.Fee (%)						
Lo SIR	0.41	0.42	1.05	0.69	0.53	2.46
M	0.40	0.40	1.38	0.42	0.41	2.58
Hi SIR	0.53	0.82	6.98	0.92	1.38	8.60
Panel O: Change in Ind.Fee over preceding year (PP)						
Lo SIR	-0.04	-0.05	-0.20	-0.01	-0.08	-0.05
M	-0.04	-0.07	-0.23	-0.03	-0.03	-0.09
Hi SIR	-0.22	-0.56	1.69	0.28	0.21	1.65

Table C.7: (continued)

	Winners			Losers		
	Hi IOR	M	Lo IOR	Hi IOR	M	Lo IOR
Panel P: Simple Avg. Fee (SAF, %)						
Lo SIR	0.29	0.30	0.72	0.43	0.33	1.85
M	0.28	0.29	0.93	0.29	0.30	1.90
Hi SIR	0.45	0.68	5.26	0.83	1.28	7.58
Panel Q: Change in SAF over preceding year (PP)						
Lo SIR	-0.06	0.01	-0.29	-0.00	-0.02	0.26
M	-0.01	-0.03	-0.24	-0.02	-0.02	-0.11
Hi SIR	-0.14	-0.59	0.67	0.27	0.23	1.85
Panel R: Available lending (%)						
Lo SIR	22.35	18.45	5.38	18.56	17.17	4.19
M	24.16	19.66	7.80	23.92	18.92	7.43
Hi SIR	25.26	18.76	9.25	24.61	18.61	9.20
Panel S: On loan (%)						
Lo SIR	0.36	0.26	0.24	0.60	0.32	0.30
M	1.63	0.98	1.73	1.64	1.20	1.86
Hi SIR	6.86	5.76	5.89	8.44	6.81	6.67
Panel T: Lending utilization (%)						
Lo SIR	3.92	2.33	16.16	10.17	3.08	25.71
M	7.39	6.34	35.77	8.16	7.92	48.65
Hi SIR	30.87	37.22	106.63	39.52	47.30	115.62

C.VI Characteristics of Residual-ownership-sorted Portfolios

Table C.8: Characteristics of portfolios sorted on residual institutional ownership (RIOR), SIR and past-return.
This table shows time-series averages of value-weighted mean characteristics of the 9 winner and 9 loser portfolios in the month of portfolio formation. The variables are the same as in Table C.7. However, here we sort on residual IOR (as in Nagel, 2005) instead of IOR.

	Winners			Losers		
	Hi RIOR	M	Lo RIOR	Hi RIOR	M	Lo RIOR
Panel A: Number of stocks						
Lo SIR	65	129	153	136	131	156
M	127	235	170	152	173	133
Hi SIR	143	165	92	161	163	93
Panel B: Average Market Equity (B$)						
Lo SIR	3.57	21.25	98.20	1.12	5.63	48.61
M	5.21	20.68	67.16	3.08	9.17	47.29
Hi SIR	4.12	11.27	22.88	2.05	4.52	12.96
Panel C: Formation Period Return (%)						
Lo SIR	47	46	46	-33	-29	-27
M	50	46	43	-30	-26	-25
Hi SIR	58	55	57	-33	-32	-31
Panel D: Institutional Ownership (IOR, %)						
Lo SIR	68.97	55.42	38.20	56.13	43.66	30.50
M	81.21	71.44	52.87	73.65	66.44	47.90
Hi SIR	85.88	72.64	51.83	79.87	67.68	46.27

Table C.8: (continued)

	Winners			Losers		
	Hi RIOR	M	Lo RIOR	Hi RIOR	M	Lo RIOR
Panel E: Change in IOR over preceding year (PP)						
Lo SIR	5.13	2.33	0.58	2.01	-0.16	-0.69
M	5.22	2.17	1.01	1.72	-0.16	-0.88
Hi SIR	7.57	4.20	2.24	2.23	-0.21	-1.35
Panel F: Short-interest (SIR, %)						
Lo SIR	0.34	0.39	0.39	0.30	0.35	0.37
M	1.73	1.51	1.28	1.82	1.66	1.35
Hi SIR	7.54	5.41	5.19	8.08	6.33	5.96
Panel G: Change in SIR over preceding year (PP)						
Lo SIR	-0.41	-0.39	-0.23	-0.46	-0.41	-0.25
M	-0.53	-0.44	-0.26	-0.34	-0.20	0.02
Hi SIR	0.97	0.19	0.30	1.89	1.23	1.39
Panel H: Book-to-market ratio						
Lo SIR	0.61	0.49	0.44	1.14	0.89	0.71
M	0.44	0.37	0.37	0.86	0.66	0.60
Hi SIR	0.37	0.36	0.35	0.78	0.70	0.70
Panel I: Idiosyncratic volatility (%, daily)						
Lo SIR	1.90	1.67	1.55	3.21	2.83	2.61
M	1.74	1.43	1.24	2.38	1.96	1.76
Hi SIR	1.93	1.74	1.68	2.44	2.26	2.25
Panel J: Turnover (%)						
Lo SIR	7.98	9.25	7.44	6.81	8.21	7.43
M	15.03	13.74	11.70	14.45	15.85	14.43
Hi SIR	28.18	24.62	26.38	27.52	27.16	27.24

Table C.8: (continued)

	Winners			Losers		
	Hi RIOR	M	Lo RIOR	Hi RIOR	M	Lo RIOR
Panel K: Change in turnover over preceding year (PP)						
Lo SIR	0.75	0.70	-0.43	-1.12	-1.04	0.11
M	1.17	-0.14	-0.85	-0.02	0.95	2.21
Hi SIR	2.59	1.40	2.08	2.69	2.32	1.78
Panel L: SIRIO (%)						
Lo SIR	0.41	0.56	1.64	0.48	0.78	4.53
M	1.97	1.98	3.08	2.35	2.48	5.50
Hi SIR	8.53	7.35	15.73	9.95	9.70	20.64
Panel M: Option volatility spread (%)						
Lo SIR	0.17	0.29	-0.38	0.00	0.20	-0.10
M	-0.43	-0.44	-0.26	-0.41	-0.26	-0.14
Hi SIR	-0.88	-0.82	-1.39	-1.07	-1.08	-2.01
Panel N: Ind.Fee (%)						
Lo SIR	0.49	0.48	0.46	1.00	1.13	1.11
M	0.41	0.41	0.44	0.48	0.48	0.53
Hi SIR	0.63	0.62	1.28	0.99	1.23	2.31
Panel O: Change in Ind.Fee over preceding year (PP)						
Lo SIR	-0.13	-0.06	-0.07	-0.03	-0.12	-0.18
M	-0.04	-0.06	-0.08	-0.06	-0.05	-0.04
Hi SIR	-0.19	-0.31	-0.53	0.29	0.23	0.35
Panel P: Simple Avg. Fee (SAF, %)						
Lo SIR	0.31	0.32	0.30	0.59	0.62	0.87
M	0.30	0.28	0.31	0.34	0.33	0.37
Hi SIR	0.54	0.52	1.10	0.90	1.13	2.19

Table C.8: (continued)

	Winners			Losers		
	Hi RIOR	M	Lo RIOR	Hi RIOR	M	Lo RIOR
Panel Q: Change in SAF over preceding year (PP)						
Lo SIR	-0.18	-0.02	-0.00	-0.03	-0.03	-0.32
M	-0.01	-0.02	-0.04	-0.06	-0.02	-0.04
Hi SIR	-0.15	-0.22	-0.64	0.32	0.22	0.27
Panel R: Available lending (%)						
Lo SIR	16.52	20.76	17.44	13.51	15.32	14.32
M	24.60	23.19	18.82	23.66	22.43	17.55
Hi SIR	25.93	22.05	16.91	25.11	20.81	16.09
Panel S: On loan (%)						
Lo SIR	0.39	0.32	0.25	0.43	0.40	0.28
M	2.07	1.46	0.99	2.07	1.56	1.17
Hi SIR	7.93	5.43	5.52	9.32	6.85	6.40
Panel T: Lending utilization (%)						
Lo SIR	6.02	4.65	3.33	15.19	10.29	7.91
M	10.21	7.15	7.37	11.93	8.91	9.69
Hi SIR	36.20	29.36	41.10	44.51	40.08	52.27

C.VII Characteristics of Forecast-dispersion-sorted Portfolios

Table C.9: Descriptive statistics of forecast dispersion change sorted portfolios. Stocks are sorted based on their past 1-year change in forecast dispersion into 5 portfolios. Constrained stocks (simultaneously in low IOR and high SIR bucket) are dropped. The time-series average of the number of stocks in the portfolios is displayed in the first column. The next columns show the time series mean of monthly value-weighted portfolio averages of market equity in B$, return of the previous year (skipping the last month) in %, institutional ownership ratio (IOR) in %, short-interest in %, and SIRIO (short interest divided by institutional ownership) in %, all in the month of portfolio formation (t-1). The sample period is May 1980 to November 2020.

ΔEFD-Portf.	No. of stocks	ME_{t-1}	$Return_{t-12-t-2}$	IOR_{t-1}	SIR_{t-1}	$SIRIO_{t-1}$	EFD_{t-1}	EFD_{t-12}
1	452	38.81	16.59	60.54	2.73	4.57	10.47	39.00
2	460	65.90	16.06	59.19	1.64	2.87	3.13	4.83
3	462	69.08	13.84	59.00	1.41	2.44	2.32	2.48
4	460	62.94	7.87	58.49	1.77	3.03	5.29	3.64
5	450	28.58	-4.60	59.25	3.00	5.20	54.43	13.82

Table C.10: Descriptive statistics of portfolios sorted on forecast dispersion change and past return.
Stocks are independently sorted based on their past 1-year change in forecast dispersion into 5 portfolios and their past return from month t-12 to the end of month t-2. Constrained stocks (simultaneously in low IOR and high SIR bucket) are dropped. The time-series average of the number of stocks in the portfolios is displayed in the first column. The next columns show the time series mean of monthly value-weighted portfolio averages of market equity in B$, return of the previous year (skipping the last month) in %, institutional ownership ratio (IOR) in %, short-interest in %, and SIRIO (short interest divided by institutional ownership) in %, all in the month of portfolio formation (t-1). The sample period is May 1980 to November 2020.

ΔEFD-Portf.	MOM-Portf.	No. of stocks	ME_{t-1}	$Return_{t-12-t-2}$	IOR_{t-1}	SIR_{t-1}	$SIRIO_{t-1}$	EFD_{t-1}	EFD_{t-12}
5	1	216	16.58	-32.52	57.81	3.79	6.90	63.98	12.61
5	2	147	29.63	4.04	59.99	2.53	4.26	46.83	13.54
5	3	86	21.92	57.08	60.69	3.46	5.75	52.70	19.33

D Additional Analyses

D.I Disagreement Around Earnings Announcements

The goal of this exercise is to check whether the release of new information (here: earnings announcements) increases or decreases disagreement among forecasters. In order to check this, we look at the dispersion in analyst forecasts about the earnings of 2 quarters ahead (q+2) that were confirmed in a narrow window (25 days) right before and right after a firm announces its earnings for the next quarter (q+1). The idea is that the q+1 announcement could contain information regarding the q+2 earnings and therefore could potentially lead to a reduction in disagreement. Furthermore, we split the cross-section of firms into terciles based on the level of earnings forecast dispersion before the announcement.

We use individual analysts' forecasts of quarterly earnings from IBES. Firm quarters for which the announcement day is more than 60 days after the quarter-end are discarded, to avoid extremely narrow windows for valid forecasts.

For the "pre"-announcement forecasts we only consider those that were confirmed after quarter (q+0)'s earnings have been announced but not earlier than 25 days before quarter (q+1)'s announcement day. For the "post"-announcement forecasts, we require them to be confirmed after (q+1)'s announcement day and they will not be considered unless they are issued within 25 days after that day. We then only consider forecasters that have a valid forecast in the "pre" and "post" window, to avoid results being driven by attrition. That forecast can be the same (if the forecaster did not change her mind), but it has to be actively confirmed after the announcement. We then calculate earnings forecast dispersion (FD) as the standard deviation of forecasts divided by the total assets per share as of the quarter where the announcement takes place (q+1).

Table D.1 shows the results for all stocks in column 1 and for the three groups based on the pre-announcement FD level (columns 2-4). The results for all stocks confirm our hypothesis: Disagreement falls from pre- to post-announcement by -0.0103, i.e., about 5.5% of the pre-announcement disagreement. However, for stocks with initially low or medium disagreement, we indeed observe the opposite effect, showing that it can go both ways. Only stocks with a high initial level of disagreement exhibit a considerable drop of -0.0409, i.e., about 9.7% of the initial disagreement.

To ensure that the effect is indeed linked to the announcement of the (q+1) earnings, and not a general effect of the passing of time, we conduct two placebo tests. First, we pick a day that falls right in the middle between the q and q+1 announcement days, and collect forecasts in the 25 days before and after that placebo day. Second, we follow the same idea, picking a day in the middle between the q+1 and q+2 announcement days. Tables D.2 and D.3 present the results. They show that there seems to be a general increase in disagreement for all groups over time. The magnitude of this increase is relatively small, however (0.0033 and 0.0043 respectively, for all stocks).

Table D.1: Earnings forecast dispersion for earnings in quarter q+2, around earnings announcement at q+1

Subset	All	Low Pre-FD	Med Pre-FD	High Pre-FD
Pre	0.1863	0.0328	0.1047	0.4208
Post	0.1760	0.0389	0.1087	0.3799
Difference	-0.0103	0.0061	0.0039	-0.0409
t-statistic	(-10.26)	(20.99)	(7.42)	(-14.61)
N	88,768	29,578	29,531	29,620

Table D.2: Placebo 1: Earnings forecast dispersion for earnings in quarter q+2, around middle-day between earnings-announcements of q and q+1

Subset	All	Low Pre-FD	Med Pre-FD	High Pre-FD
Pre	0.2014	0.0330	0.1045	0.4660
Post	0.2047	0.0353	0.1086	0.4693
Difference	0.0033	0.0023	0.0041	0.0033
t-statistic	(5.52)	(14.66)	(18.62)	(1.92)
N	82,062	27,345	27,299	27,389

Table D.3: Placebo 2: Earnings forecast dispersion for earnings in quarter q+2, around middle-day between earnings-announcements of q+1 and q+2

Subset	All	Low Pre-FD	Med Pre-FD	High Pre-FD
Pre	0.1566	0.0260	0.0833	0.3601
Post	0.1609	0.0291	0.0891	0.3642
Difference	0.0043	0.0031	0.0057	0.0041
t-statistic	(12.25)	(20.92)	(20.08)	(4.25)
N	106,422	35,471	35,421	35,519

D.II Short-/Long-term Performance of Standard Momentum Portfolios

Table D.4: Short-horizon (S, 1 year) strategy performance of stocks sorted into 3/10 portfolios on past 11-month return.
See caption to Table 2. Here, we do not focus on constrained stocks, but simply sort based on past-11-month-return (skipping one month) into three (30/70-percent breakpoints, Panel A) and ten (Panel B) portfolios, respectively. The sample-period is 1927/12 to June 2020.

	W_{S}	L_{S}	W_{S}-L_{S}
Panel A: CAPM regressions – 30/70-percentile breakpoints			
Intercept	0.13	-0.26	0.39
	(2.56)	(-3.17)	(3.20)
MktRF	1.00	1.28	-0.28
	(24.59)	(17.30)	(-2.42)
R^2	0.9221	0.8561	0.1168
No. of months	1,111	1,111	1,111
IR	0.2913	-0.3147	0.3272
Panel B: CAPM regressions – decile breakpoints			
Intercept	0.16	-0.54	0.71
	(1.55)	(-4.06)	(4.13)
MktRF	1.10	1.52	-0.41
	(13.87)	(24.14)	(-3.01)
R^2	0.7961	0.7585	0.1205
No. of months	1,111	1,111	1,111
IR	0.1897	-0.4102	0.4094

Table D.5: Long-horizon (L, 2–5 years) strategy performance of stocks sorted into 3/10 portfolios on past 11-month return.
See caption to Table 2. Here, we do not focus on constrained stocks, but simply sort based on past-11-month-return (skipping one month) into three (30/70-percent breakpoints, Panel A) and ten (Panel B) portfolios, respectively. The other difference to Table 2 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 sample-period is 1931/12 to June 2020.

	W_{L}	L_{L}	W_{L}-L_{L}
Panel A: CAPM regressions – 30/70-percentile breakpoints			
Intercept	-0.01	0.08	-0.08
	(-0.27)	(1.57)	(-1.26)
MktRF	1.03	1.15	-0.12
	(42.19)	(29.16)	(-1.90)
R^2	0.9780	0.9454	0.0906
No. of months	1,063	1,063	1,063
IR	-0.0324	0.1876	-0.1493
Panel B: CAPM regressions – decile breakpoints			
Intercept	-0.07	0.09	-0.16
	(-1.04)	(0.99)	(-1.53)
MktRF	1.15	1.30	-0.15
	(21.96)	(41.77)	(-2.10)
R^2	0.9091	0.8569	0.0631
No. of months	1,063	1,063	1,063
IR	-0.1328	0.1129	-0.1910

D.III 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

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

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.

Table D.6 presents the results. Consistent with previous literature, winner stocks tend to issue equity on average. The issuance in Table D.6 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, 6.62 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.

Table D.6: 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 May 1980 to June 2020.

Panel A: Winners				
	Hi IOR	M	Lo IOR	Lo-Hi
Lo SIR	0.17	−0.40	1.61	1.43 (3.65)
M	−0.32	−0.59	2.47	2.80 (6.01)
Hi SIR	2.47	1.95	6.62	4.15 (7.76)
Hi-Lo	2.30	2.34	5.01	
t	(6.57)	(6.64)	(10.04)	

Panel B: Medium Momentum				
	Hi IOR	M	Lo IOR	Lo-Hi
Lo SIR	−1.13	−1.44	−0.48	0.66 (2.58)
M	−1.02	−1.50	0.27	1.29 (5.13)
Hi SIR	0.91	0.87	3.01	2.11 (5.55)
Hi-Lo	2.04	2.31	3.49	
t	(8.10)	(6.94)	(8.59)	

Panel C: Losers				
	Hi IOR	M	Lo IOR	Lo-Hi
Lo SIR	0.63	−0.71	3.36	2.74 (4.09)
M	−0.95	−0.93	2.89	3.84 (11.03)
Hi SIR	0.62	1.52	6.08	5.47 (7.67)
Hi-Lo	−0.01	2.23	2.72	
t	(−0.01)	(5.00)	(4.29)	

D.IV Improving Momentum Strategies

Table D.7: Improving small-/medium-cap momentum strategies.
Shown are annualized Sharpe Ratios and monthly average excess returns as well as CAPM- and Fama-French αs of different momentum strategies. WML refers to the long-short "Winner minus Loser" portfolio and "Winners" refers to a long-only strategy that buys just past-winner stocks. "Regular" means that we form value-weighted portfolios from the universe of small- and medium-cap stocks, i.e., we exclude the 20% largest stocks in each cross-section. "Enhanced" means that we avoid constrained winners, i.e., winners that are in the top 30% of short-interest and bottom 30% of institutional ownership. The "difference" rows display statistics of a hypothetical strategy going long the enhanced and short the regular strategy. Newey and West (1987) t-statistics are shown in parentheses.

Portfolio	Style	Sharpe Ratio	Excess Return	CAPM-α	FF3-α
WML	Regular	0.83	1.20 (4.70)	1.40 (5.96)	1.47 (6.23)
	Enhanced	0.90	1.31 (5.08)	1.52 (6.41)	1.58 (6.63)
	Difference	0.68	0.11 (4.28)	0.12 (4.94)	0.11 (4.69)
Winners	Regular	0.69	1.24 (3.99)	0.48 (2.23)	0.47 (3.95)
	Enhanced	0.76	1.35 (4.29)	0.61 (2.75)	0.58 (4.70)
	Difference	0.68	0.11 (4.28)	0.12 (4.94)	0.11 (4.69)

E Out-of-Sample Results

E.I International Evidence

In this appendix, we replicate our main results on an international out-of-sample data set. We collect daily and monthly returns, market capitalization and shares outstanding from Thomson Datastream. Annual accounting data are provided by Worldscope and Compustat Global. Everything is converted to US dollars using exchange rates from Thomson Datastream. Short interest and shares available for lending are from Markit, and are available from 2004/05 to 2020/06. We apply several data cleaning steps explained in Klos, Koehl, and Rottke (2020) which follow Ince and Porter (2006), Griffin, Kelly, and Nardari (2010), Schmidt, von Arx, Schrimpf, Wagner, and Ziegler (2019). Furthermore, owing to the low data quality in micro caps in Datastream data first reported in Ince and Porter (2006), we filter out the smallest 20% of stocks from each country, and stocks with an unadjusted price below 1 (in local currency, to alleviate rounding problems reported in the papers mentioned above). We consider all developed countries (according to the definition in Fama and French, 2012), to ensure sufficient Markit data availability. Since we have no international institutional ownership data, we instead resort to the ratio of shares available for lending to shares outstanding as our lending supply proxy (available lending ratio or ALR). In contrast to the U.S. data, where we rely on a long time-series of monthly short-interest snapshots, we use the daily number of shares shorted from Markit and divide it by the total number of shares outstanding to get the short interest ratio (SIR). For both ALR and SIR we average over all days in a month to alleviate outlier problems (e.g. due to non-synchronous treatment of splits in the two datasets). The risk-free rate, market and Fama-French factor returns are those for developed markets (excluding the U.S.) from Ken French's website.

Table E.1 illustrates the time-series average of the value-weighted mean characteristics of the stocks in our sample by region (as defined in Fama and French, 2012). On average, our cross-section comprises over 4,800 stocks, the majority of which come from the regions Europe and Japan. In contrast to Fama and French (2012), we exclude the U.S. from the region "North America" to conduct a true out-of-sample exercise, leaving Canada as its own region here. The representative stock has $45B of market capitalization, short-interest of about 1.3% and 15% of its shares are available for lending. The average indicative lending fee is about 0.8% p.a..

We then perform an independent triple sort, similar to the one in the main paper, on past-return, ALR and SIR. To account for the differences in the level of some variables across regions, we specify 30% and 70% breakpoints by region. Constrained losers are additionally split into those that were and those that were not a constrained winner in the previous 5 years. Matching is performed on size, book-to-market, past-return, and SIR, and only within the same region.

Constrained stocks and their matched peers exhibit a market capitalization of around $4B and SIR between 1.74 and 3.18%. Constrained stocks have low lending supply of 2.27 to 2.64%, whereas their matched peers exhibit much higher levels. This difference is reflected in lending fees of over 6% p.a. for constrained compared to slightly over 1% for unconstrained stocks.

Table E.2 presents the results for strategies capturing the performance in the first 12 months post-formation. Constrained winners exhibit lower returns than their matched peers, but the difference is insignificant. Constrained losers' returns can also not be statistically distinguished from their matched peers' returns. The raw difference in differences (DiD) is insignificant.

We replicate the most surprising result from our U.S. sample, the return asymmetry for long-term returns, in Table E.3. Constrained losers, as in the U.S., do not show any underperformance relative to their matched counterparts. Constrained winners, however, significantly underperform their matched peers by more than 0.5% per month – regardless of the asset pricing model applied. This results in a raw DiD of -0.67 % per month (t-statistic: -2.58), a CAPM alpha of -0.69 % per month (t-statistic: -2.66), and a four-factor alpha of -0.74 % per month (t-statistic: -2.79). The results are statistically significant despite the short sample period. The reason can be found when looking at the Sharpe (SR) and information (IR) ratios at the bottom rows of the three panels: They exceed -1 with raw returns, CAPM- and four-factor-adjustment for both the difference of winners and their matched peers as well as the DiD. With point estimates below the U.S. results, this points to remarkably low volatility in these strategies, i.e., very consistent long-term underperformance of the constrained winner portfolio in international markets.

To increase the length of the time-series of portfolio returns, we drop the requirement that constrained losers cannot have been a constrained winner in any of the previous 60 months in Tables E.4 and E.5. We gain five years of data and now look at a history of more than 15 years (11 for the long-term returns). In the short-run (Table E.4), both constrained winners and losers underperform their matched peers when looking at raw excess returns (albeit insignificantly so for winners when looking at raw and CAPM adjusted returns), and their DiD is indistinguishable from zero — consistent with our U.S. results.

Looking at the long-term performance (Table E.5), constrained winners still significantly underperform their matched peers,[A12] constrained losers still do not, and the DiD remains highly statistically significant, with a t-statistic of -2.30. Again, SRs and IRs are close to -1, underlining the remarkable consistency of long-term underperformance of international constrained winners relative to matched peers.

We also track the lending fee from Markit in event time in Figure E.1. The pattern is very similar to that observed in U.S. data, i.e., the fee jumps up over the formation period and then gradually decreases over about five years. Importantly, the effect is symmetric for constrained winners and losers.

We also repeat the double sort on changes in analysts' earnings forecast dispersion (ΔFD) and past-return, as in Figure 2 Panel B, for a small subset of international stocks for which we have analyst coverage from IBES. Figure E.2 reveals that we again find the symmetric pattern of a slow decline over about five years in forecast dispersion for both high ΔFD winners and losers.

[A12]The CAPM alphas of constrained winners (first column) are close to zero. However, we would like to argue that a simple Jensen (1968) regression is inferior to the more elaborate matching approach that we conduct. By carefully selecting matching firms based on characteristics and region, we create a much more suitable benchmark than factor portfolios based on the overall broad market (consisting of firms from all developed countries except the U.S.), that exhibits higher covariance and thereby provide a more powerful test of abnormal returns (also see Daniel, Grinblatt, Titman, and Wermers, 1997).

Table E.1: Characteristics of constrained and matched portfolios - international results. For details see caption to Table 1 in the paper.

	W^{*}	L^{*}	$W^{*,m}$	$L^{*,m}$	Asia	Europe	Japan	Canada	World
Number of stocks	54.05	31.77	54.05	31.77	729.37	1839.01	1905.07	408.83	4882.28
Average Market Equity (B$)	4.04	4.84	3.45	4.34	60.93	49.83	27.64	30.25	45.57
Book-to-market ratio	0.41	1.04	0.68	0.96	0.62	0.58	0.77	0.55	0.63
Idiosyncratic volatility (%, daily)	2.69	2.23	1.82	1.90	1.52	1.21	1.43	1.33	1.32
Formation Period Return (%)	74.83	-30.32	46.74	-23.43	9.54	7.41	6.67	7.29	7.38
Short-interest (SIR, %)	2.12	2.36	1.74	3.18	0.86	1.39	1.08	2.69	1.32
Available lending (ALR, %)	2.27	2.64	13.77	18.33	10.57	16.88	11.26	24.29	15.01
Ind.Fee (%)	6.67	6.11	1.09	1.20	1.11	0.74	0.71	0.67	0.80

Table E.2: Short-horizon (S, 1 year) strategy performance of constrained and matched portfolios - international results. For details see caption to Table 2 in the paper.

	W_S^*	L_S^*	W_S^*-L_S^*	$W_S^{*,m}$	$L_S^{*,m}$	W_S^*-$W_S^{*,m}$	L_S^*-$L_S^{*,m}$	DiD
Raw excess returns								
Average	0.34	0.12	0.21	0.63	0.23	-0.29	-0.11	-0.18
	(0.76)	(0.30)	(0.42)	(1.83)	(0.66)	(-0.83)	(-0.50)	(-0.44)
No. of months	121	121	121	121	121	121	121	121
AvgN	216	121		256	171			
SR	0.1752	0.0704	0.1338	0.4591	0.1491	-0.2452	-0.1209	-0.1310
CAPM regressions								
Intercept	-0.25	-0.54	0.29	0.11	-0.40	-0.37	-0.14	-0.22
	(-0.59)	(-2.28)	(0.55)	(0.56)	(-2.31)	(-1.00)	(-0.55)	(-0.56)
MktRF	1.09	1.23	-0.14	0.95	1.17	0.14	0.06	0.08
	(8.67)	(12.04)	(-0.98)	(11.83)	(17.40)	(1.28)	(0.86)	(0.62)
R^2	0.4830	0.7357	0.0117	0.7300	0.8474	0.0216	0.0065	0.0054
IR	-0.1823	-0.5984	0.1825	0.1588	-0.6569	-0.3134	-0.1568	-0.1638
Four-factor regressions								
Intercept	-0.70	-0.06	-0.63	-0.16	0.05	-0.54	-0.12	-0.42
	(-1.76)	(-0.27)	(-1.46)	(-0.79)	(0.42)	(-1.53)	(-0.44)	(-0.92)
MktRF	1.25	1.15	0.10	1.05	1.10	0.20	0.05	0.16
	(11.59)	(15.55)	(0.74)	(16.76)	(29.06)	(1.91)	(0.59)	(1.19)
HML	-0.56	0.09	-0.65	-0.10	0.02	-0.46	0.07	-0.53
	(-1.84)	(0.63)	(-2.00)	(-1.06)	(0.23)	(-1.81)	(0.53)	(-1.81)
SMB	1.08	0.54	0.54	0.92	0.65	0.15	-0.11	0.26
	(4.72)	(3.03)	(2.08)	(8.72)	(5.50)	(0.70)	(-0.63)	(0.85)
MOM	0.22	-0.53	0.76	0.20	-0.54	0.03	0.00	0.03
	(0.86)	(-4.53)	(3.06)	(1.49)	(-7.68)	(0.19)	(0.02)	(0.18)
R^2	0.6034	0.7912	0.2821	0.8446	0.9204	0.0761	0.0113	0.0633
IR	-0.5712	-0.0793	-0.4651	-0.2907	0.1167	-0.4739	-0.1287	-0.3170

Table E.3: Long-horizon (L, 2–5 years) strategy performance for constrained and matched portfolios - international results. For details see caption to Table 3 in the paper.

	W_{L}^{*}	L_{L}^{*}	W_{L}^{*}-L_{L}^{*}	$W_{\mathrm{L}}^{*,m}$	$L_{\mathrm{L}}^{*,m}$	W_{L}^{*}-$W_{\mathrm{L}}^{*,m}$	L_{L}^{*}-$L_{\mathrm{L}}^{*,m}$	DiD
Raw excess returns								
Average	0.03	0.40	-0.37	0.57	0.28	-0.54	0.12	-0.67
	(0.08)	(0.76)	(-1.27)	(1.30)	(0.58)	(-2.39)	(0.70)	(-2.58)
No. of months	73	73	73	73	73	73	73	73
AvgN	566	321		627	426			
SR	0.0229	0.2791	-0.5145	0.4496	0.1774	-1.0434	0.2165	-1.0650
CAPM regressions								
Intercept	-0.13	0.22	-0.35	0.41	0.07	-0.54	0.15	-0.69
	(-0.56)	(1.20)	(-1.20)	(2.37)	(0.47)	(-2.44)	(0.71)	(-2.66)
MktRF	1.05	1.17	-0.12	1.05	1.33	-0.00	-0.16	0.16
	(14.27)	(18.92)	(-1.75)	(17.73)	(13.06)	(-0.06)	(-1.96)	(2.86)
R^2	0.7476	0.8452	0.0357	0.8695	0.9275	0.0001	0.1027	0.0826
IR	-0.1943	0.3838	-0.4971	0.8848	0.1606	-1.0425	0.2756	-1.1538
Four-factor regressions								
Intercept	-0.43	0.13	-0.56	0.30	0.12	-0.74	0.01	-0.74
	(-2.70)	(0.69)	(-3.00)	(1.93)	(1.05)	(-3.40)	(0.03)	(-2.79)
MktRF	1.08	1.16	-0.08	1.05	1.27	0.03	-0.11	0.14
	(19.03)	(33.30)	(-1.74)	(30.47)	(26.65)	(0.52)	(-1.67)	(2.71)
HML	-0.53	-0.05	-0.48	-0.08	0.14	-0.44	-0.19	-0.26
	(-5.30)	(-0.41)	(-4.34)	(-0.90)	(1.66)	(-6.39)	(-1.55)	(-2.46)
SMB	0.80	0.61	0.19	0.62	0.75	0.18	-0.14	0.33
	(4.47)	(4.77)	(0.76)	(5.05)	(7.07)	(1.45)	(-0.79)	(1.76)
MOM	-0.04	0.01	-0.04	0.00	-0.10	-0.04	0.10	-0.15
	(-0.28)	(0.07)	(-0.37)	(0.05)	(-1.51)	(-0.54)	(1.03)	(-1.49)
R^2	0.8732	0.8800	0.1954	0.9171	0.9668	0.2620	0.1678	0.1722
IR	-0.8874	0.2614	-0.8739	0.8266	0.4360	-1.6512	0.0114	-1.3058

Table E.4: Short-horizon (S, 1 year) strategy performance for constrained and matched portfolios - international results - longer sample/no lookback. For details see caption to Table 3 in the paper.

	W_S^*	L_S^{*all}	W_S^*-L_S^{*all}	$W_S^{*,m}$	$L_S^{*all,m}$	$W_S^{*,m}$-$L_S^{*all,m}$	W_S^*-$W_S^{*,m}$	L_S^{*all}-$L_S^{*all,m}$	DiD
Raw excess returns									
Average	0.04	-0.11	0.15	0.42	0.28	0.14	-0.38	-0.40	0.01
	(0.09)	(-0.21)	(0.37)	(1.06)	(0.58)	(0.62)	(-1.50)	(-2.21)	(0.04)
No. of months	180	180	180	180	180	180	180	180	180
AvgN	193	220		236	293				
SR	0.0198	-0.0602	0.1060	0.2863	0.1794	0.1595	-0.3674	-0.5121	0.0105
CAPM regressions									
Intercept	-0.37	-0.62	0.25	0.03	-0.16	0.20	-0.40	-0.46	0.06
	(-1.16)	(-2.81)	(0.68)	(0.20)	(-0.95)	(0.86)	(-1.48)	(-2.58)	(0.20)
MktRF	0.95	1.18	-0.24	0.91	1.04	-0.13	0.04	0.14	-0.10
	(10.29)	(18.09)	(-2.11)	(16.15)	(24.32)	(-2.06)	(0.65)	(4.04)	(-1.32)
R^2	0.5088	0.7923	0.0564	0.7538	0.8589	0.0481	0.0028	0.0683	0.0154
IR	-0.2796	-0.7230	0.1831	0.0477	-0.2690	0.2315	-0.3839	-0.6124	0.0484
Four-factor regressions									
Intercept	-0.65	-0.36	-0.29	-0.19	0.11	-0.30	-0.46	-0.47	0.00
	(-2.21)	(-1.84)	(-0.90)	(-1.26)	(1.05)	(-2.28)	(-1.97)	(-2.57)	(0.01)
MktRF	1.07	1.11	-0.04	1.00	0.96	0.03	0.08	0.15	-0.08
	(12.65)	(23.45)	(-0.55)	(22.46)	(35.78)	(0.92)	(1.13)	(3.65)	(-0.91)
HML	-0.40	0.02	-0.43	-0.03	0.15	-0.18	-0.37	-0.13	-0.24
	(-1.80)	(0.18)	(-1.95)	(-0.45)	(2.09)	(-1.91)	(-1.90)	(-0.96)	(-1.11)
SMB	0.93	0.75	0.18	0.81	0.70	0.11	0.12	0.05	0.07
	(7.60)	(6.62)	(1.01)	(10.10)	(10.07)	(1.49)	(1.00)	(0.44)	(0.39)
MOM	0.31	-0.36	0.68	0.28	-0.36	0.64	0.03	-0.01	0.04
	(2.89)	(-6.55)	(5.36)	(4.24)	(-9.80)	(8.23)	(0.61)	(-0.12)	(0.44)
R^2	0.6317	0.8478	0.3051	0.8651	0.9332	0.5235	0.0481	0.0770	0.0319
IR	-0.5743	-0.4891	-0.2487	-0.3484	0.2637	-0.4977	-0.4536	-0.6254	0.0023

Table E.5: Long-horizon (L, 2–5 years) strategy performance for constrained and matched portfolios - international results - longer sample/no lookback. For details see caption to Table 3 in the paper.

	W^*_{L}	L^{*all}_{L}	W^*_{L}-L^{*all}_{L}	$W^{*,m}_{\mathrm{L}}$	$L^{*all,m}_{\mathrm{L}}$	$W^{*,m}_{\mathrm{L}}$-$L^{*all,m}_{\mathrm{L}}$	W^*_{L}-$W^{*,m}_{\mathrm{L}}$	L^{*all}_{L}-$L^{*all,m}_{\mathrm{L}}$	DiD
Raw excess returns									
Average	0.30	0.59	-0.29	0.79	0.69	0.10	-0.49	-0.11	-0.39
	(1.12)	(1.58)	(-1.46)	(2.70)	(1.99)	(0.78)	(-3.06)	(-0.67)	(-2.30)
No. of months	132	132	132	132	132	132	132	132	132
AvgN	503	514		590	695				
SR	0.2344	0.4248	-0.4671	0.6662	0.5141	0.2482	-0.9235	-0.2021	-0.7576
CAPM regressions									
Intercept	-0.19	0.01	-0.20	0.31	0.12	0.19	-0.49	-0.11	-0.38
	(-1.03)	(0.05)	(-1.05)	(2.07)	(0.81)	(1.71)	(-3.27)	(-0.64)	(-2.14)
MktRF	0.84	1.00	-0.16	0.84	1.00	-0.16	-0.00	0.00	-0.00
	(11.39)	(21.17)	(-3.32)	(11.59)	(13.94)	(-7.02)	(-0.07)	(0.03)	(-0.08)
R^2	0.6930	0.8296	0.1072	0.7899	0.8640	0.2507	0.0000	0.0000	0.0001
IR	-0.2673	0.0152	-0.3351	0.5624	0.2358	0.5525	-0.9209	-0.2036	-0.7534
Four-factor regressions									
Intercept	-0.40	-0.12	-0.28	0.15	0.07	0.08	-0.55	-0.19	-0.36
	(-2.18)	(-0.74)	(-1.62)	(1.06)	(0.49)	(0.87)	(-2.97)	(-1.02)	(-1.88)
MktRF	0.95	1.04	-0.10	0.91	1.02	-0.11	0.04	0.02	0.01
	(16.63)	(32.64)	(-2.14)	(19.13)	(23.33)	(-5.36)	(1.19)	(0.51)	(0.29)
HML	-0.34	0.14	-0.48	-0.03	0.26	-0.28	-0.31	-0.12	-0.19
	(-3.46)	(1.59)	(-4.30)	(-0.29)	(3.78)	(-4.10)	(-3.84)	(-1.13)	(-1.67)
SMB	0.80	0.64	0.15	0.74	0.77	-0.03	0.06	-0.12	0.18
	(7.33)	(7.75)	(1.33)	(7.47)	(10.08)	(-0.42)	(0.68)	(-1.44)	(2.19)
MOM	0.05	0.11	-0.06	0.08	0.03	0.05	-0.04	0.07	-0.11
	(0.56)	(1.66)	(-0.88)	(1.16)	(0.56)	(1.14)	(-0.67)	(1.13)	(-1.63)
R^2	0.8131	0.8764	0.2824	0.8755	0.9315	0.4286	0.0948	0.0382	0.0690
IR	-0.7360	-0.2507	-0.5359	0.3482	0.1872	0.2675	-1.0753	-0.3582	-0.7319

Figure E.1: Lending fees — international sample.
We plot the indicative lending fee from Markit in event time for the constrained winners and losers, as well as portfolios containing matched unconstrained stocks for the international sample from 2004/05 to 2020/06. 95% confidence intervals are based on Newey-West standard errors.

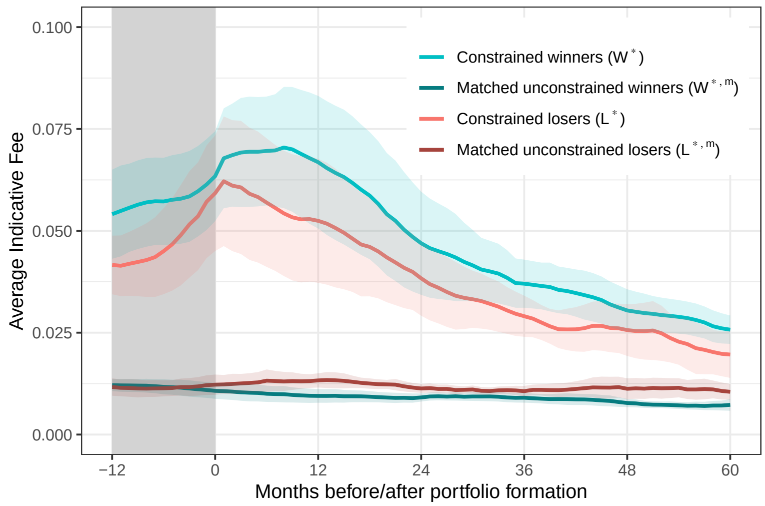
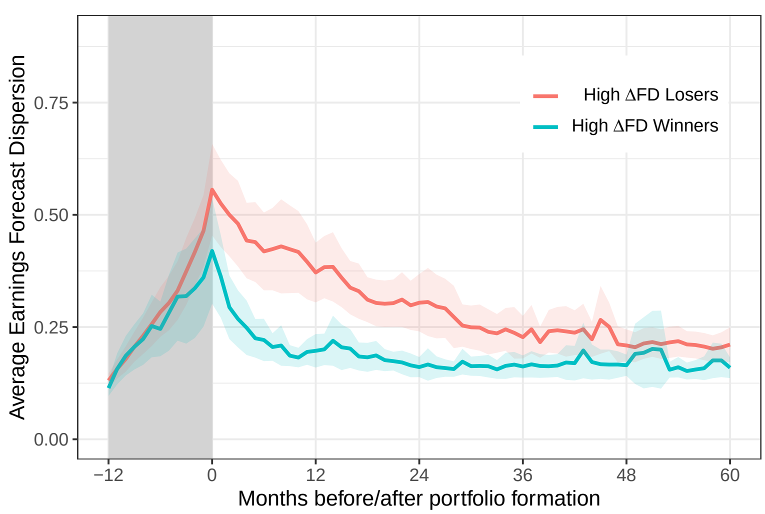


Figure E.2: Forecast dispersion — international sample.
We use earnings forecast dispersion (FD) for portfolios independently sorted on past-return (30% breakpoints) and the 1-year change in dispersion of analyst earnings forecasts (ΔFD) from IBES (30% breakpoints). The international sample goes from 2004/05 to 2020/06. 95% confidence intervals are based on Newey-West standard errors.



E.II Pre-NASDAQ Evidence

In previous versions of the paper, we started our analyses based on data starting in 1988/06, i.e., the first time when NASDAQ short interest data is available. In the current version, we include the period before that, i.e., from March of 1980, which features the first available institutional holdings snapshot. Short interest is only available for NYSE and AMEX stocks during that early period. For the backward-looking check of whether a stock was a constrained winner in the past 5 years, we use a sufficient condition, in order to keep the number of eligible stocks large enough: If a stock was not low-IOR or high-past-return during any of the last 60 months, it cannot have been a constrained winner – we do not need to know its SIR. Hence, even for NASDAQ stocks (as soon as we have SIR data for NASDAQ stocks, i.e., from June 1988 – data that is directly from NASDAQ, and not from Compustat), we are able to determine the "was not a constrained winner in the last 5 years" requirement for the vast majority of stocks.

Below, we reproduce the Tables for our main test, i.e., year-1 and years 2–5 holding periods. Table E.6 confirms that both W^* and L^* underperform strongly in the first year post-formation. The sample period of year-1 portfolio returns goes from 1986/04 to 1994/04.[A13] For the long holding period of years 2–5, Table E.7 reports that, on average, between 1990/04 and 1998/04,[A14] we have 667 unique W^* and 276 unique L^* stocks. Over that period, the DiD exhibits a CAPM-alpha of -1.03, and, despite the short sample, has a t-statistic of -2.69.

[A13] Recall that we require 60 months to determine if a losers has been a constrained winner in the past plus another 11 months before we are able to invest into all 12 portfolios that make up the year-1 buy-and-hold portfolios.

[A14] Here we need 60 months plus 59 months to form all 48 portfolios that make up the years-2–5 buy-and-hold portfolios.

Table E.6: Out-of-sample short-horizon (S, 1 year) strategy performance, 1986/04–1994/04.

See caption to Table 2. The difference here is that we use observations from the period preceding data availability for NASDAQ short interest.

	W_S^*	L_S^*	W_S^*-L_S^*	$W_S^{*,m}$	$L_S^{*,m}$	W_S^*-$W_S^{*,m}$	L_S^*-$L_S^{*,m}$	*DiD*
Raw excess returns								
Average	-0.78	-1.73	0.95	1.33	0.65	-2.11	-2.38	0.27
	(-1.14)	(-2.46)	(1.79)	(1.94)	(0.87)	(-8.46)	(-4.75)	(0.58)
No. of months	97	97	97	97	97	97	97	97
AvgN	258	118		277	193			
SR	-0.4453	-0.8658	0.6643	0.6712	0.3400	-1.8483	-1.6841	0.2065
CAPM regressions								
Intercept	-1.34	-2.22	0.88	0.62	-0.02	-1.96	-2.19	0.23
	(-5.17)	(-4.22)	(1.60)	(2.05)	(-0.07)	(-8.08)	(-4.31)	(0.49)
MktRF	1.04	0.91	0.14	1.32	1.26	-0.28	-0.35	0.07
	(20.92)	(12.27)	(1.80)	(18.96)	(15.82)	(-3.31)	(-5.34)	(0.90)
R^2	0.6344	0.3690	0.0165	0.8029	0.7784	0.1082	0.1126	0.0057
IR	-1.2611	-1.3946	0.6182	0.7080	-0.0242	-1.8184	-1.6459	0.1770
Four-factor regressions								
Intercept	-1.33	-2.14	0.81	0.79	0.38	-2.12	-2.53	0.40
	(-3.87)	(-4.18)	(1.55)	(2.68)	(1.99)	(-5.47)	(-4.87)	(0.83)
MktRF	0.92	1.00	-0.08	1.11	1.26	-0.19	-0.26	0.07
	(11.23)	(10.45)	(-0.78)	(12.10)	(26.09)	(-2.39)	(-2.67)	(0.81)
HML	0.07	0.83	-0.76	-0.55	0.06	0.62	0.77	-0.15
	(0.52)	(4.29)	(-4.75)	(-3.76)	(0.63)	(2.89)	(3.44)	(-0.65)
SMB	1.00	1.26	-0.26	0.55	0.74	0.45	0.52	-0.07
	(5.77)	(7.65)	(-1.48)	(4.21)	(8.19)	(2.18)	(3.59)	(-0.28)
MOM	0.22	-0.29	0.51	0.24	-0.45	-0.02	0.16	-0.18
	(1.83)	(-1.60)	(3.23)	(2.13)	(-5.40)	(-0.12)	(0.82)	(-1.21)
R^2	0.7924	0.6504	0.2585	0.8877	0.9131	0.2792	0.2685	0.0217
IR	-1.6671	-1.8106	0.6559	1.1910	0.6817	-2.1907	-2.0875	0.3086

Table E.7: Out-of-sample long-horizon (L, 2–5 years) strategy performance, 1990/04–1998/04.
See caption to Table 3. The difference here is that we use observations from the period preceding data availability for NASDAQ short interest.

	W^*_{L}	L^*_{L}	W^*_{L}-L^*_{L}	$W^{*,m}_{\text{L}}$	$L^{*,m}_{\text{L}}$	W^*_{L}-$W^{*,m}_{\text{L}}$	L^*_{L}-$L^{*,m}_{\text{L}}$	DiD
Raw excess returns								
Average	0.45	1.27	-0.82	1.28	1.20	-0.83	0.07	-0.89
	(0.85)	(2.26)	(-2.46)	(2.94)	(2.47)	(-3.06)	(0.22)	(-2.97)
No. of months	97	97	97	97	97	97	97	97
AvgN	667	276		789	561			
SR	0.3002	0.8623	-0.7959	0.8485	0.8780	-0.9758	0.0588	-0.8767
CAPM regressions								
Intercept	-0.81	0.30	-1.12	-0.17	-0.08	-0.64	0.39	-1.03
	(-2.26)	(0.71)	(-3.37)	(-0.69)	(-0.33)	(-2.10)	(1.43)	(-2.69)
MktRF	1.15	0.88	0.27	1.32	1.17	-0.17	-0.29	0.12
	(12.73)	(7.06)	(3.14)	(23.45)	(19.43)	(-2.12)	(-3.61)	(1.39)
R^2	0.6041	0.3668	0.0720	0.7912	0.7531	0.0410	0.0698	0.0154
IR	-0.8599	0.2599	-1.1277	-0.2502	-0.1235	-0.7727	0.3574	-1.0189
Four-factor regressions								
Intercept	-0.67	-0.04	-0.63	0.31	0.04	-0.98	-0.08	-0.89
	(-3.22)	(-0.12)	(-1.64)	(1.75)	(0.23)	(-3.60)	(-0.18)	(-2.05)
MktRF	1.03	0.93	0.11	1.15	1.12	-0.12	-0.19	0.07
	(17.23)	(9.23)	(1.14)	(29.32)	(21.60)	(-1.68)	(-1.68)	(0.66)
HML	-0.20	0.51	-0.71	-0.57	-0.03	0.37	0.54	-0.17
	(-2.93)	(3.39)	(-4.73)	(-6.39)	(-0.44)	(3.39)	(2.90)	(-0.88)
SMB	0.93	1.11	-0.17	0.33	0.69	0.60	0.42	0.18
	(11.68)	(9.51)	(-1.39)	(5.67)	(11.18)	(6.12)	(2.57)	(1.12)
MOM	0.18	0.23	-0.05	-0.03	0.03	0.22	0.20	0.01
	(3.04)	(1.71)	(-0.42)	(-0.59)	(0.60)	(2.40)	(1.27)	(0.09)
R^2	0.8570	0.6642	0.2486	0.9077	0.9103	0.3141	0.1939	0.0542
IR	-1.1816	-0.0505	-0.7046	0.6681	0.0978	-1.3929	-0.0822	-0.9025

F Robustness Checks

F.I Fama-MacBeth Regressions

We assess the robustness of our results by running Fama-MacBeth regressions.[A15] To see whether returns of constrained winners are different than those of the other constrained stocks, turn to the coefficient on *having been a constrained winner during the past 5 years (except for the most recent 12 months)* in Table F.1 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).[A16] 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 3.

The result is robust to including well-known return predictors such as past return, the log-book-to-market ratio, log-size and idiosyncratic volatility (column 4). Even if we include the ratio of short interest to institutional ownership (SIRIO, as in Drechsler and Drechsler, 2016), as a proxy for current difficulty of short-selling, constrained past-winners underperform other constrained stocks (column 5) and all other stocks (column 6) significantly. In contrast, Panel A shows that both constrained winners and losers of the previous 12 months underperform, and the seemingly stronger underperformance of losers (column 2) disappears once the control variables are included. We include additional return predictors in Table F.2 below, which does not change the conclusion.

Taken together, these results confirm the asymmetry in mispricing persistence that we find in Section 3 and are consistent with the model we present in Section 4.2.

[A15] 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).

[A16] Note, however, that including the dummies for being a constrained stock in the past and being a constrained winner/loser in the past in the same regression, imposes a multicollinearity problem (as every constrained winner/loser is also constrained, and there are few constrained stocks, that were never a winner/loser at any point during the 48-month look-back-period). Hence, test-power for individual coefficients declines.

Table F.1: 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 May 1980 to June 2020.

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

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.67 (3.17)	0.67 (3.17)	0.67 (3.17)	0.58 (1.86)	0.58 (1.86)	0.58 (1.86)
$Constr._{(t-12)—(t-1)}$	-0.75 (-4.06)	-0.03 (-0.14)		-0.06 (-0.28)	0.00 (0.02)	
$Constr.W_{(t-12)—(t-1)}$		-0.47 (-1.96)	-0.53 (-2.94)	-0.61 (-2.73)	-0.46 (-2.05)	-0.47 (-2.85)
$Constr.L_{(t-12)—(t-1)}$		-1.05 (-3.64)	-1.07 (-3.91)	-0.76 (-3.44)	-0.58 (-2.67)	-0.58 (-3.13)
$RET_{(t-12)—(t-2)}$				0.28 (2.68)	0.27 (2.43)	0.26 (2.40)
$log(BE/ME_{t-1})$				-0.03 (-0.38)	-0.04 (-0.56)	-0.04 (-0.55)
$log(ME_{t-1})$				-0.14 (-2.06)	-0.16 (-2.39)	-0.16 (-2.39)
$ivol_{t-1}$				-0.61 (-2.89)	-0.55 (-2.59)	-0.55 (-2.58)
$SIRIO_{t-1}$					-0.53 (-3.86)	-0.53 (-3.87)
Avg. R^2	0.0017	0.0028	0.0022	0.0789	0.0839	0.0833
No. of months	470	470	470	470	470	470
Avg. no. of stocks	5,183	5,183	5,183	4,320	3,672	3,672

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

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.71 (3.26)	0.71 (3.26)	0.71 (3.26)	0.61 (1.98)	0.61 (1.97)	0.61 (1.96)
$Constr._{(t-60)—(t-13)}$	-0.31 (-2.50)	-0.02 (-0.15)		-0.07 (-0.59)	-0.06 (-0.48)	
$Constr.W_{(t-60)—(t-13)}$		-0.48 (-2.82)	-0.48 (-3.56)	-0.54 (-3.51)	-0.48 (-3.15)	-0.52 (-4.28)
$Constr.L_{(t-60)—(t-13)}$		0.12 (0.64)	0.10 (0.52)	0.16 (1.05)	0.24 (1.58)	0.20 (1.31)
$RET_{(t-12)—(t-2)}$				0.29 (2.55)	0.29 (2.50)	0.29 (2.48)
$log(BE/ME_{t-1})$				-0.07 (-0.94)	-0.09 (-1.10)	-0.09 (-1.11)
$log(ME_{t-1})$				-0.13 (-1.81)	-0.16 (-2.23)	-0.16 (-2.20)
$ivol_{t-1}$				-0.58 (-2.54)	-0.52 (-2.28)	-0.52 (-2.28)
$SIRIO_{t-1}$					-0.63 (-4.20)	-0.63 (-4.21)
Avg. R^2	0.0022	0.0037	0.0031	0.0802	0.0838	0.0834
No. of months	422	422	422	422	422	422
Avg. no. of stocks	5,175	5,175	5,175	4,366	3,959	3,959

Table F.2: Fama-MacBeth regressions with additional variables.
See caption to Table F.1. Additional variables: Return over the prior 5 years, skipping the most recent year ($RET_{(t-60)—(t-13)}$, following DeBondt and Thaler, 1985), composite share issuance (over the previous 36 months, $CSI_{(t-36)—(t-1)}$, following Daniel and Titman, 2006), gross profitability (GP_{t-1}, following Novy-Marx, 2013), and standardized unexpected earnings (SUE_{t-1}, following Foster, Olsen, and Shevlin, 1984).

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.67 (2.21)	0.65 (2.11)	0.62 (2.03)	0.63 (2.08)	0.70 (2.41)	0.69 (2.34)	0.69 (2.35)
$Constr._{(t-12)—(t-1)}$	-0.06 (-0.26)	0.09 (0.45)	-0.00 (-0.01)	0.07 (0.35)	0.07 (0.24)	0.08 (0.28)	
$Constr.W_{(t-12)—(t-1)}$	-0.58 (-2.41)	-0.66 (-2.95)	-0.60 (-2.34)	-0.72 (-3.23)	-0.76 (-2.67)	-0.63 (-2.19)	-0.59 (-2.89)
$Constr.L_{(t-12)—(t-1)}$	-0.70 (-2.68)	-0.77 (-3.22)	-0.57 (-2.41)	-0.66 (-2.96)	-0.34 (-1.17)	-0.23 (-0.74)	-0.24 (-1.08)
$RET_{(t-12)—(t-2)}$	0.25 (2.18)	0.29 (2.61)	0.27 (2.61)	0.27 (2.50)	0.23 (2.09)	0.22 (1.89)	0.21 (1.87)
$log(BE/ME_{t-1})$	-0.06 (-0.94)	-0.04 (-0.49)	0.10 (1.38)	-0.01 (-0.12)	0.07 (1.26)	0.09 (1.35)	0.09 (1.35)
$log(ME_{t-1})$	-0.14 (-2.14)	-0.14 (-2.14)	-0.11 (-1.73)	-0.12 (-1.89)	-0.12 (-1.77)	-0.14 (-2.01)	-0.14 (-2.01)
$ivol_{t-1}$	-0.46 (-2.22)	-0.47 (-2.26)	-0.50 (-2.43)	-0.49 (-2.33)	-0.32 (-1.59)	-0.31 (-1.49)	-0.31 (-1.48)
$RET_{(t-60)—(t-13)}$	0.00 (0.09)				0.03 (0.63)	0.04 (0.91)	0.04 (0.90)
$CSI_{(t-36)—(t-1)}$		-0.14 (-2.44)			-0.11 (-2.23)	-0.11 (-2.17)	-0.11 (-2.21)
GP_{t-1}			0.38 (4.69)		0.34 (3.81)	0.35 (3.85)	0.35 (3.84)
SUE_{t-1}				0.08 (2.96)	0.04 (1.64)	0.04 (1.65)	0.05 (1.67)
$SIRIO_{t-1}$						-0.31 (-1.71)	-0.29 (-1.65)
Avg. R^2	0.0901	0.0861	0.0861	0.0852	0.1074	0.1134	0.1129
No. of months	470	470	470	470	470	470	470
Avg. no. of stocks	3,268	3,700	3,516	3,714	2,608	2,294	2,294

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.72 (2.37)	0.69 (2.26)	0.68 (2.22)	0.66 (2.15)	0.75 (2.54)	0.75 (2.50)	0.74 (2.50)
$Constr._{(t-60)—(t-13)}$	-0.04 (-0.28)	0.04 (0.34)	-0.09 (-0.86)	-0.05 (-0.31)	0.07 (0.38)	0.07 (0.34)	
$Constr.W_{(t-60)—(t-13)}$	-0.49 (-3.15)	-0.60 (-3.84)	-0.49 (-3.32)	-0.46 (-2.78)	-0.53 (-3.13)	-0.49 (-2.91)	-0.42 (-2.92)
$Constr.L_{(t-60)—(t-13)}$	0.06 (0.28)	0.13 (0.80)	0.15 (0.95)	0.21 (1.27)	0.15 (0.66)	0.20 (0.93)	0.22 (1.27)
$RET_{(t-12)—(t-2)}$	0.27 (2.14)	0.30 (2.49)	0.28 (2.39)	0.28 (2.52)	0.25 (2.06)	0.24 (2.01)	0.24 (1.99)
$log(BE/ME_{t-1})$	-0.11 (-1.55)	-0.07 (-0.95)	-0.05 (-0.63)	0.06 (0.80)	0.03 (0.45)	0.02 (0.36)	0.02 (0.35)
$log(ME_{t-1})$	-0.14 (-1.95)	-0.13 (-1.84)	-0.12 (-1.65)	-0.10 (-1.42)	-0.12 (-1.56)	-0.14 (-1.82)	-0.14 (-1.81)
$ivol_{t-1}$	-0.44 (-1.98)	-0.45 (-2.02)	-0.46 (-2.02)	-0.46 (-2.06)	-0.30 (-1.41)	-0.28 (-1.32)	-0.28 (-1.33)
$RET_{(t-60)—(t-13)}$	0.01 (0.28)				0.03 (0.56)	0.03 (0.67)	0.03 (0.65)
$CSI_{(t-36)—(t-1)}$		-0.10 (-1.61)			-0.08 (-1.71)	-0.08 (-1.73)	-0.08 (-1.67)
GP_{t-1}			0.08 (2.84)		0.04 (1.47)	0.04 (1.39)	0.04 (1.41)
SUE_{t-1}				0.37 (4.28)	0.34 (3.45)	0.33 (3.40)	0.33 (3.41)
$SIRIO_{t-1}$						-0.35 (-1.79)	-0.36 (-1.82)
Avg. R^2	0.0924	0.0873	0.0866	0.0872	0.1092	0.1133	0.1128
No. of months	422	422	422	422	422	422	422
Avg. no. of stocks	3,292	3,743	3,819	3,571	2,659	2,448	2,448

F.II Spanning Tests

Table F.3: Explaining the returns of constrained portfolios.
We regress monthly portfolio excess returns of constrained portfolios on well-known factor-portfolios. Panels A and B report results for the constrained winners (W^*) and constrained losers that were not constrained winners in the past 5 years (L^*), with 12-month calendar-time buy-and-hold portfolios, and in Panels C and D, we use a 48-month holding period, skipping 12 months. Column (1) shows the raw average of that strategy, (2) displays results from a CAPM regression on the market excess return. (3) represents results from a Fama and French (1993) 3-factor regression. In (4) we add momentum, and in (5), IVOL as in Ang, Hodrick, Xing, and Zhang (2006). (6) and (7) add the short- and a long-term reversal from Ken French and the value-weighted CME factor from Drechsler and Drechsler (2016), respectively. (8) includes all of the aforementioned. Newey and West (1987) t-statistics are shown in parentheses.

Panel A: W^* from months $(t-12)$—$(t-1)$								
	1	2	3	4	5	6	7	8
Intercept	-0.18	-1.07	-0.94	-0.95	-0.75	-0.98	-0.68	-0.65
	(-0.54)	(-4.28)	(-4.32)	(-4.07)	(-3.22)	(-4.39)	(-3.15)	(-3.17)
MktRF		1.37	1.17	1.17	1.08	1.12	1.00	0.93
		(14.94)	(18.49)	(17.18)	(15.17)	(15.10)	(13.86)	(12.91)
HML			-0.32	-0.31	-0.17	-0.35	-0.13	-0.07
			(-3.35)	(-2.73)	(-1.48)	(-2.77)	(-1.46)	(-0.71)
SMB			1.00	1.00	0.67	0.97	0.81	0.66
			(13.95)	(11.63)	(6.41)	(10.67)	(10.90)	(7.60)
MOM				0.01	0.13	0.03	0.09	0.18
				(0.09)	(1.35)	(0.49)	(1.31)	(2.83)
IVOL					0.24			0.13
					(4.66)			(3.57)
STRev						0.20		0.19
						(2.12)		(2.40)
LTRev						0.05		-0.06
						(0.47)		(-0.62)
CMEVW							-0.30	-0.25
							(-5.83)	(-5.00)
R^2	0.0000	0.5783	0.7505	0.7505	0.7684	0.7568	0.7853	0.7952
No. of months	411	411	411	411	411	411	411	411
IR	-0.0760	-0.7096	-0.8129	-0.8177	-0.6707	-0.8592	-0.6337	-0.6208

Table F.3: (continued)

Panel B: L^* from months $(t-12)$—$(t-1)$								
	1	2	3	4	5	6	7	8
Intercept	-0.90	-1.89	-1.82	-1.37	-0.94	-1.34	-0.95	-0.76
	(-1.81)	(-5.55)	(-5.24)	(-3.96)	(-2.80)	(-4.01)	(-3.04)	(-2.43)
MktRF		1.51	1.33	1.16	0.96	1.14	0.89	0.82
		(11.97)	(11.21)	(16.01)	(16.02)	(14.35)	(15.03)	(11.62)
HML			0.14	-0.10	0.22	-0.29	0.18	0.20
			(0.75)	(-0.64)	(1.49)	(-1.79)	(1.26)	(1.35)
SMB			1.20	1.22	0.50	1.06	0.91	0.40
			(9.52)	(8.09)	(2.85)	(7.28)	(6.36)	(2.39)
MOM				-0.63	-0.38	-0.66	-0.50	-0.38
				(-5.18)	(-3.07)	(-5.55)	(-4.91)	(-3.01)
IVOL					0.52			0.37
					(5.20)			(3.95)
STRev						-0.05		-0.05
						(-0.37)		(-0.43)
LTRev						0.45		0.29
						(2.59)		(2.10)
CMEVW							-0.48	-0.33
							(-7.13)	(-5.02)
R^2	0.0000	0.4432	0.5649	0.6365	0.6897	0.6448	0.6908	0.7167
No. of months	411	411	411	411	411	411	411	411
IR	-0.3076	-0.8637	-0.9392	-0.7749	-0.5739	-0.7698	-0.5824	-0.4850

Table F.3: (continued)

Panel C: W^* from months $(t-60)$—$(t-13)$								
	1	2	3	4	5	6	7	8
Intercept	0.23	-0.74	-0.68	-0.62	-0.46	-0.62	-0.47	-0.40
	(0.66)	(-3.61)	(-5.16)	(-4.93)	(-3.57)	(-3.99)	(-3.13)	(-2.58)
MktRF		1.43	1.28	1.25	1.16	1.26	1.15	1.11
		(19.51)	(21.72)	(18.03)	(18.38)	(17.26)	(21.50)	(17.71)
HML			-0.25	-0.28	-0.15	-0.32	-0.18	-0.11
			(-3.56)	(-5.08)	(-2.72)	(-3.02)	(-2.79)	(-1.53)
SMB			0.73	0.74	0.48	0.70	0.64	0.47
			(7.74)	(8.87)	(3.99)	(6.76)	(6.24)	(3.82)
MOM				-0.08	0.01	-0.09	-0.04	0.01
				(-1.29)	(0.15)	(-1.40)	(-0.58)	(0.18)
IVOL					0.19			0.15
					(4.69)			(4.34)
STRev						-0.03		-0.02
						(-0.25)		(-0.27)
LTRev						0.11		0.01
						(0.79)		(0.11)
CMEVW							-0.15	-0.10
							(-2.73)	(-2.10)
R^2	0.0000	0.7016	0.8169	0.8190	0.8325	0.8200	0.8298	0.8369
No. of months	363	363	363	363	363	363	363	363
IR	0.1094	-0.6280	-0.7458	-0.6848	-0.5277	-0.6792	-0.5372	-0.4571

Table F.3: (continued)

Panel D: L^* from months $(t-60)$—$(t-13)$								
	1	2	3	4	5	6	7	8
Intercept	1.03	0.14	0.15	0.26	0.51	0.26	0.43	0.55
	(2.81)	(0.59)	(0.77)	(1.20)	(2.49)	(1.24)	(1.95)	(2.55)
MktRF		1.32	1.18	1.13	0.98	1.10	1.00	0.92
		(17.57)	(17.09)	(22.15)	(17.63)	(19.15)	(15.10)	(14.68)
HML			0.16	0.11	0.31	-0.04	0.23	0.24
			(2.37)	(1.56)	(4.35)	(-0.38)	(3.03)	(2.46)
SMB			0.87	0.88	0.48	0.76	0.76	0.40
			(11.63)	(12.29)	(5.52)	(10.27)	(11.59)	(4.40)
MOM				-0.14	-0.01	-0.15	-0.10	-0.01
				(-2.44)	(-0.08)	(-2.18)	(-1.42)	(-0.14)
IVOL					0.29			0.26
					(6.03)			(4.69)
STRev						0.04		0.05
						(0.66)		(0.80)
LTRev						0.32		0.21
						(3.14)		(1.99)
CMEVW							-0.18	-0.07
							(-4.10)	(-1.57)
R^2	0.0000	0.6029	0.7281	0.7352	0.7682	0.7428	0.7500	0.7752
No. of months	363	363	363	363	363	363	363	363
IR	0.4849	0.1039	0.1329	0.2342	0.4952	0.2414	0.4045	0.5402

Table F.4: Long-horizon (L, 2–5 years) strategy performance of constrained portfolios - spanning tests.

This table shows spanning regressions for constrained calendar-time buy-and-hold strategies containing constrained stocks from months $((t-60) — (t-13))$. Portfolio formation is described in the caption to Table 3. In columns 1 to 4 (columns 5 to 8) excess returns of constrained winners (losers) are regressed on the excess return of a portfolio of constrained losers (winners) as well as constrained medium momentum (M^*). The four Fama-French-Carhart factors are also included in every other regression. Newey and West (1987) t-statistics are shown in parentheses.

	W^*_{L}	W^*_{L}	W^*_{L}	W^*_{L}	L^{*all}_{L}	L^{*all}_{L}	L^{*all}_{L}	L^{*all}_{L}
Intercept	-0.30	-0.36	-0.31	-0.29	0.45	0.30	0.17	0.22
	(-2.27)	(-2.93)	(-3.28)	(-2.71)	(2.99)	(2.12)	(1.27)	(1.77)
L	0.89	0.44	0.22	0.13				
	(26.66)	(8.73)	(3.23)	(1.91)				
W					0.90	0.43	0.21	0.12
					(18.60)	(4.01)	(2.03)	(1.37)
M			0.84	0.67			0.87	0.69
			(11.89)	(6.43)			(7.81)	(7.93)
MktRF		0.71		0.35		0.60		0.25
		(8.92)		(3.33)		(5.15)		(3.59)
HML		-0.17		-0.19		-0.06		-0.10
		(-2.95)		(-3.71)		(-0.98)		(-1.73)
SMB		0.30		0.10		0.66		0.37
		(3.82)		(1.34)		(5.96)		(5.71)
MOM		-0.04		-0.08		-0.07		-0.10
		(-0.71)		(-1.44)		(-1.24)		(-2.21)
R^2	0.8006	0.8543	0.8684	0.8844	0.8006	0.8593	0.8758	0.8913

F.III Alternative Matching

Table F.5: Characteristics of constrained and matched portfolios (based on size, past-return, log-book-to-market, and institutional ownership).
See caption to Table 1. The difference here is that the matching is based on size, past-return, log-book-to-market, and institutional ownership — short-interest is what distinguishes constrained from unconstrained stocks here.

	W^*	L^*	$W^{*,m}$	$L^{*,m}$
Number of stocks	49	36	49	36
Average Market Equity (B$)	3.00	1.47	2.13	1.08
Formation Period Return (%)	82.36	-47.37	59.39	-34.74
Institutional Ownership (IOR, %)	16.91	17.55	31.00	25.79
Change in IOR over preceding year (PP)	1.18	-5.06	1.61	-0.63
Short-interest (SIR, %)	6.52	6.41	0.32	0.29
Change in SIR over preceding year (PP)	2.28	1.05	-0.29	-0.37
Book-to-market ratio	0.30	0.91	0.42	0.85
Idiosyncratic volatility (%, daily)	3.04	3.95	2.24	3.32
Turnover (%)	32.64	28.22	6.93	5.96
Change in turnover over preceding year (PP)	15.95	1.86	1.54	-0.50
SIRIO (%)	100.31	73.30	2.54	3.56
Option volatility spread (%)	-5.47	-6.34	-0.43	-0.49
Ind.Fee (%)	6.98	7.61	0.88	1.67
Change in Ind.Fee over preceding year (PP)	1.69	3.07	-0.28	-0.03
Simple Avg. Fee (SAF, %)	5.26	6.59	0.57	1.20
Change in SAF over preceding year (PP)	0.67	3.16	-0.37	-0.19
Available lending (%)	9.25	9.38	12.88	8.49
On loan (%)	5.89	6.24	0.33	0.43
Lending utilization (%)	106.63	101.76	13.63	14.80

Table F.6: Short-horizon (S, 1 year) strategy performance of constrained and matched portfolios (based on size, past-return, log-book-to-market, and institutional ownership).

See caption to Table 2. The difference here is that the matching is based on size, past-return, log-book-to-market, and institutional ownership — short-interest is what distinguishes constrained from unconstrained stocks here.

	W_S^*	L_S^*	W_S^*-L_S^*	$W_S^{*,m}$	$L_S^{*,m}$	W_S^*-$W_S^{*,m}$	L_S^*-$L_S^{*,m}$	DiD
Panel A: Raw excess returns								
Average	-0.18	-0.90	0.73	0.81	0.82	-0.98	-1.72	0.74
	(-0.54)	(-1.81)	(2.00)	(3.30)	(2.20)	(-4.13)	(-4.84)	(2.06)
No. of months	411	411	411	411	411	411	411	411
AvgN	188	106		308	246			
SR	-0.0760	-0.3076	0.3528	0.5130	0.4435	-0.7365	-0.8689	0.3937
Panel B: CAPM regressions								
Intercept	-1.07	-1.89	0.82	0.16	0.10	-1.23	-1.99	0.76
	(-4.28)	(-5.55)	(2.27)	(0.89)	(0.39)	(-5.07)	(-5.28)	(2.12)
MktRF	1.37	1.51	-0.14	0.99	1.10	0.37	0.41	-0.04
	(14.94)	(11.97)	(-1.02)	(18.76)	(13.79)	(4.87)	(3.43)	(-0.49)
R^2	0.5783	0.4432	0.0081	0.6699	0.5912	0.1294	0.0731	0.0009
IR	-0.7096	-0.8637	0.4000	0.1719	0.0850	-0.9845	-1.0447	0.4087
Panel C: Four-factor regressions								
Intercept	-0.95	-1.37	0.42	0.11	0.26	-1.05	-1.63	0.57
	(-4.07)	(-3.96)	(1.20)	(0.96)	(1.63)	(-4.39)	(-4.42)	(1.55)
MktRF	1.17	1.16	0.01	0.91	0.95	0.26	0.21	0.05
	(17.18)	(16.01)	(0.11)	(25.39)	(22.14)	(3.70)	(2.53)	(0.62)
HML	-0.31	-0.10	-0.21	0.02	0.43	-0.33	-0.54	0.21
	(-2.73)	(-0.64)	(-1.27)	(0.28)	(4.98)	(-3.44)	(-2.99)	(1.15)
SMB	1.00	1.22	-0.22	0.75	0.85	0.25	0.37	-0.12
	(11.63)	(8.09)	(-1.41)	(16.92)	(13.52)	(2.87)	(2.50)	(-0.81)
MOM	0.01	-0.63	0.64	0.16	-0.24	-0.16	-0.39	0.23
	(0.09)	(-5.18)	(5.04)	(5.72)	(-4.85)	(-2.19)	(-2.95)	(1.94)
R^2	0.7505	0.6365	0.1942	0.8655	0.7935	0.2177	0.1966	0.0316
IR	-0.8177	-0.7749	0.2281	0.1849	0.3085	-0.8943	-0.9182	0.3112

Table F.7: Long-horizon (L, 2–5 years) strategy performance of constrained and matched portfolios (based on size, past-return, log-book-to-market, and institutional ownership).
See caption to Table 3. The difference here is that the matching is based on size, past-return, log-book-to-market, and institutional ownership — short-interest is what distinguishes constrained from unconstrained stocks here.

	W^*_{L}	L^*_{L}	W^*_{L}-L^*_{L}	$W^{*,m}_{\mathrm{L}}$	$L^{*,m}_{\mathrm{L}}$	W^*_{L}-$W^{*,m}_{\mathrm{L}}$	L^*_{L}-$L^{*,m}_{\mathrm{L}}$	DiD
Panel A: Raw excess returns								
Average	0.23	1.03	-0.80	0.65	0.88	-0.41	0.15	-0.57
	(0.66)	(2.81)	(-3.87)	(2.44)	(3.06)	(-1.87)	(0.82)	(-2.65)
No. of months	363	363	363	363	363	363	363	363
AvgN	417	203		719	504			
SR	0.1094	0.4849	-0.6061	0.4704	0.5447	-0.3478	0.1342	-0.4083
Panel B: CAPM regressions								
Intercept	-0.74	0.14	-0.87	-0.01	0.16	-0.73	-0.02	-0.71
	(-3.61)	(0.59)	(-4.34)	(-0.06)	(0.92)	(-3.31)	(-0.09)	(-3.10)
MktRF	1.43	1.32	0.11	0.97	1.07	0.46	0.25	0.21
	(19.51)	(17.57)	(1.26)	(28.00)	(22.93)	(5.40)	(4.05)	(2.25)
R^2	0.7016	0.6029	0.0115	0.7768	0.6884	0.2363	0.0754	0.0359
IR	-0.6280	0.1039	-0.6678	-0.0120	0.1728	-0.6985	-0.0147	-0.5201
Panel C: Four-factor regressions								
Intercept	-0.62	0.26	-0.88	-0.02	0.13	-0.60	0.13	-0.73
	(-4.93)	(1.20)	(-4.33)	(-0.21)	(1.24)	(-3.72)	(0.64)	(-3.58)
MktRF	1.25	1.13	0.13	0.88	0.95	0.37	0.18	0.19
	(18.03)	(22.15)	(1.64)	(34.42)	(28.64)	(4.62)	(3.90)	(2.19)
HML	-0.28	0.11	-0.39	0.17	0.21	-0.44	-0.10	-0.35
	(-5.08)	(1.56)	(-4.99)	(4.82)	(4.80)	(-5.36)	(-1.21)	(-4.18)
SMB	0.74	0.88	-0.14	0.58	0.83	0.16	0.05	0.11
	(8.87)	(12.29)	(-1.73)	(19.38)	(18.37)	(2.27)	(0.87)	(1.34)
MOM	-0.08	-0.14	0.06	0.01	0.04	-0.09	-0.18	0.09
	(-1.29)	(-2.44)	(0.64)	(0.62)	(1.35)	(-1.62)	(-2.95)	(1.04)
R^2	0.8190	0.7352	0.0893	0.9088	0.8872	0.3658	0.1160	0.1123
IR	-0.6848	0.2342	-0.7008	-0.0468	0.2410	-0.6374	0.1168	-0.5570

F.IV Sort on Past-Return and SIRIO

Table F.8: Short-horizon (S, 1 year) strategy performance of constrained portfolios.
See caption to Table C.2. The only difference here is that we use one sort on SIRIO (ratio of short interest to institutional ownership) instead of the double sort on SIR and IOR to identify constrained stocks. We define constrained stocks as those with a SIRIO above the 97.5th percentile in a particular month, following Drechsler and Drechsler (2016).

	L^*_S	L^{*W}_S	L^{*W}_S-L^*_S	L^{*all}_S	M^*_S	W^*_S	W^*_S-L^{*all}_S	W^*_S-L^*_S
Panel A: Raw excess returns								
Average	-2.14	-1.54	0.60	-1.60	-0.67	-1.07	0.53	1.08
	(-3.33)	(-3.31)	(1.26)	(-3.46)	(-1.89)	(-3.15)	(1.85)	(2.14)
No. of months	411	411	411	411	411	411	411	411
AvgN	124	191		309	229	221		
SR	-0.6117	-0.5487	0.2342	-0.5771	-0.3003	-0.3840	0.2802	0.3574
Panel B: CAPM regressions								
Intercept	-3.07	-2.54	0.53	-2.57	-1.49	-2.02	0.55	1.05
	(-6.10)	(-7.73)	(1.01)	(-8.31)	(-5.54)	(-6.46)	(1.89)	(1.98)
MktRF	1.42	1.53	0.11	1.49	1.25	1.47	-0.03	0.04
	(12.31)	(16.63)	(1.07)	(16.21)	(21.62)	(12.50)	(-0.23)	(0.28)
R^2	0.2760	0.4933	0.0029	0.4860	0.5225	0.4665	0.0003	0.0003
IR	-1.0313	-1.2701	0.2073	-1.2970	-0.9639	-0.9989	0.2896	0.3481
Panel C: Four-factor regressions								
Intercept	-2.58	-2.07	0.52	-2.10	-1.27	-1.80	0.30	0.78
	(-4.97)	(-7.69)	(1.07)	(-7.58)	(-5.63)	(-6.82)	(1.08)	(1.43)
MktRF	1.07	1.18	0.11	1.15	1.03	1.20	0.05	0.13
	(8.94)	(18.27)	(0.95)	(17.88)	(21.51)	(16.16)	(0.62)	(0.94)
HML	0.02	-0.35	-0.38	-0.25	-0.09	-0.42	-0.17	-0.45
	(0.10)	(-2.77)	(-1.82)	(-1.87)	(-1.05)	(-3.18)	(-1.39)	(-1.92)
SMB	1.41	1.23	-0.17	1.26	1.04	1.24	-0.02	-0.16
	(8.11)	(11.23)	(-1.14)	(11.53)	(10.45)	(12.57)	(-0.18)	(-0.86)
MOM	-0.59	-0.51	0.08	-0.52	-0.19	-0.09	0.43	0.50
	(-3.96)	(-6.11)	(0.60)	(-5.47)	(-2.52)	(-0.94)	(5.30)	(3.16)
R^2	0.4331	0.6935	0.0234	0.6956	0.6972	0.6520	0.1033	0.0745
IR	-0.9800	-1.3270	0.2047	-1.3753	-1.0302	-1.1021	0.1650	0.2691

Table F.9: Long-horizon (L, 2–5 years) strategy performance of constrained portfolios.
See caption to Table C.3. The only difference here is that we use one sort on SIRIO (ratio of short interest to institutional ownership) instead of the double sort on SIR and IOR to identify constrained stocks. We define constrained stocks as those with a SIRIO above the 97.5th percentile in a particular month, following Drechsler and Drechsler (2016).

	L^*_{L}	L^{*W}_{L}	L^{*W}_{L}-L^*_{L}	L^{*all}_{L}	M^*_{L}	W^*_{L}	W^*_{L}-L^{*all}_{L}	W^*_{L}-L^*_{L}
Panel A: Raw excess returns								
Average	0.56	0.42	-0.14	0.56	0.29	-0.32	-0.88	-0.88
	(1.59)	(0.87)	(-0.40)	(1.29)	(0.91)	(-0.82)	(-2.42)	(-3.25)
No. of months	363	363	363	363	363	363	363	363
AvgN	230	311		497	453	472		
SR	0.2208	0.1569	-0.0711	0.2273	0.1268	-0.1402	-0.7403	-0.5212
Panel B: CAPM regressions								
Intercept	-0.44	-0.59	-0.15	-0.45	-0.61	-1.25	-0.80	-0.81
	(-1.43)	(-1.64)	(-0.45)	(-1.44)	(-2.25)	(-4.50)	(-2.31)	(-2.63)
MktRF	1.47	1.48	0.01	1.49	1.32	1.38	-0.11	-0.09
	(13.74)	(16.00)	(0.12)	(17.31)	(18.13)	(20.83)	(-1.53)	(-1.24)
R^2	0.5310	0.4885	0.0001	0.5747	0.5412	0.5719	0.0138	0.0049
IR	-0.2523	-0.3085	-0.0751	-0.2795	-0.3995	-0.8386	-0.6815	-0.4845
Panel C: Four-factor regressions								
Intercept	-0.15	-0.42	-0.27	-0.23	-0.48	-1.03	-0.80	-0.89
	(-0.50)	(-1.28)	(-0.78)	(-0.82)	(-2.46)	(-5.04)	(-2.98)	(-2.63)
MktRF	1.19	1.19	0.01	1.21	1.07	1.10	-0.11	-0.09
	(14.85)	(12.79)	(0.07)	(15.30)	(21.63)	(23.78)	(-1.78)	(-1.16)
HML	-0.11	-0.39	-0.28	-0.30	-0.39	-0.32	-0.03	-0.21
	(-1.08)	(-4.12)	(-2.32)	(-3.46)	(-6.49)	(-4.37)	(-0.45)	(-1.94)
SMB	0.95	1.24	0.29	1.07	1.10	1.07	-0.01	0.12
	(8.75)	(8.29)	(1.46)	(10.50)	(14.87)	(13.26)	(-0.08)	(0.86)
MOM	-0.34	-0.12	0.22	-0.20	-0.07	-0.20	-0.00	0.14
	(-3.95)	(-1.56)	(2.14)	(-3.05)	(-1.20)	(-2.55)	(-0.01)	(1.18)
R^2	0.6650	0.6917	0.0727	0.7503	0.7761	0.7776	0.0142	0.0423
IR	-0.1002	-0.2839	-0.1422	-0.1887	-0.4511	-0.9591	-0.6787	-0.5367

F.V Jegadeesh-Titman Calendar-Time Portfolios

Table F.10: Short-horizon (S, 1 year) strategy performance of constrained Jegadeesh-Titman-style portfolios.
See caption to Table 2. The only difference here is that, to get the calendar-time portfolio return, each month, the portfolios formed in in each of the last 12 months are held with equal weight (following Jegadeesh and Titman, 1993), while within portfolios, stocks are still value-weighted.

	W_S^*	L_S^*	W_S^*-L_S^*	$W_S^{*,m}$	$L_S^{*,m}$	W_S^*-$W_S^{*,m}$	L_S^*-$L_S^{*,m}$	DiD
Panel A: Raw excess returns								
Average	-0.20	-0.83	0.63	0.96	0.81	-1.16	-1.64	0.48
	(-0.63)	(-1.71)	(1.77)	(3.53)	(2.11)	(-4.61)	(-4.58)	(1.48)
No. of months	411	411	411	411	411	411	411	411
AvgN	188	106		262	203			
SR	-0.0863	-0.2786	0.3022	0.5159	0.3620	-0.7956	-0.8447	0.2571
Panel B: CAPM regressions								
Intercept	-1.09	-1.84	0.74	0.15	-0.12	-1.24	-1.72	0.48
	(-4.44)	(-5.54)	(2.15)	(0.90)	(-0.43)	(-4.72)	(-4.75)	(1.44)
MktRF	1.37	1.54	-0.17	1.23	1.42	0.13	0.12	0.01
	(14.97)	(11.30)	(-1.09)	(31.04)	(13.40)	(1.57)	(1.03)	(0.13)
R^2	0.5798	0.4446	0.0114	0.7400	0.6742	0.0142	0.0067	0.0001
IR	-0.7275	-0.8267	0.3583	0.1581	-0.0937	-0.8620	-0.8890	0.2532
Panel C: Four-factor regressions								
Intercept	-0.96	-1.27	0.31	0.11	0.19	-1.07	-1.45	0.39
	(-4.19)	(-3.65)	(0.88)	(0.85)	(1.31)	(-3.93)	(-3.87)	(1.13)
MktRF	1.17	1.17	-0.01	1.15	1.21	0.02	-0.03	0.05
	(17.35)	(16.11)	(-0.08)	(31.24)	(35.78)	(0.21)	(-0.41)	(0.58)
HML	-0.32	-0.07	-0.25	-0.04	0.44	-0.28	-0.51	0.22
	(-2.82)	(-0.43)	(-1.39)	(-0.57)	(4.50)	(-1.81)	(-2.34)	(1.54)
SMB	1.01	1.24	-0.23	0.69	0.95	0.32	0.29	0.03
	(12.01)	(8.12)	(-1.46)	(8.12)	(19.24)	(2.77)	(1.80)	(0.24)
MOM	-0.01	-0.72	0.71	0.16	-0.46	-0.17	-0.26	0.09
	(-0.08)	(-5.87)	(5.07)	(3.95)	(-5.46)	(-1.55)	(-1.73)	(0.77)
R^2	0.7550	0.6535	0.2355	0.8652	0.8910	0.0975	0.0914	0.0107
IR	-0.8370	-0.7217	0.1678	0.1553	0.2516	-0.7729	-0.7856	0.2067

Table F.11: Long-horizon (L, 2–5 years) strategy performance of constrained Jegadeesh-Titman-style portfolios.
See caption to Table 3. The only difference here is that, to get the calendar-time portfolio return, each month, the portfolios formed in in each of the 48 formation-months are held with equal weight (following Jegadeesh and Titman, 1993), while within portfolios, stocks are still value-weighted.

	W^*_{L}	L^*_{L}	W^*_{L}-L^*_{L}	$W^{*,m}_{\mathrm{L}}$	$L^{*,m}_{\mathrm{L}}$	W^*_{L}-$W^{*,m}_{\mathrm{L}}$	L^*_{L}-$L^{*,m}_{\mathrm{L}}$	DiD
Panel A: Raw excess returns								
Average	0.26	0.98	-0.72	0.99	0.84	-0.74	0.13	-0.87
	(0.76)	(2.66)	(-4.08)	(3.87)	(3.04)	(-4.89)	(0.68)	(-6.65)
No. of months	363	363	363	363	363	363	363	363
AvgN	417	203		621	461			
SR	0.1245	0.4616	-0.6388	0.5872	0.4693	-0.7648	0.1180	-0.7605
Panel B: CAPM regressions								
Intercept	-0.69	0.07	-0.77	0.16	-0.02	-0.85	0.10	-0.95
	(-3.64)	(0.32)	(-4.38)	(1.28)	(-0.15)	(-5.45)	(0.52)	(-5.91)
MktRF	1.40	1.33	0.06	1.23	1.28	0.17	0.05	0.12
	(25.31)	(18.08)	(0.94)	(37.51)	(31.78)	(3.09)	(0.82)	(1.80)
R^2	0.7294	0.6239	0.0051	0.8325	0.7953	0.0501	0.0036	0.0165
IR	-0.6475	0.0570	-0.6792	0.2305	-0.0276	-0.9088	0.0855	-0.8369
Panel C: Four-factor regressions								
Intercept	-0.55	0.22	-0.78	0.16	-0.02	-0.71	0.25	-0.96
	(-4.51)	(1.13)	(-4.00)	(1.70)	(-0.22)	(-4.57)	(1.14)	(-5.02)
MktRF	1.20	1.13	0.08	1.14	1.15	0.07	-0.03	0.09
	(27.12)	(22.51)	(1.40)	(44.96)	(35.70)	(1.18)	(-0.48)	(1.60)
HML	-0.21	0.07	-0.28	-0.10	0.20	-0.11	-0.12	0.02
	(-4.91)	(1.02)	(-3.77)	(-1.67)	(4.14)	(-1.17)	(-1.22)	(0.24)
SMB	0.79	0.89	-0.11	0.53	0.80	0.26	0.10	0.16
	(13.03)	(13.52)	(-1.67)	(12.16)	(19.32)	(3.81)	(1.22)	(2.32)
MOM	-0.12	-0.18	0.05	0.04	0.00	-0.17	-0.18	0.02
	(-3.12)	(-2.88)	(0.68)	(1.72)	(0.18)	(-2.98)	(-2.28)	(0.18)
R^2	0.8628	0.7658	0.0617	0.9211	0.9427	0.1582	0.0534	0.0330
IR	-0.7271	0.2184	-0.7096	0.3283	-0.0536	-0.8040	0.2246	-0.8513

F.VI Simple Value-Weighted Portfolios

Table F.12: Short-horizon (S, 1 year) strategy performance of constrained simple value-weight portfolios.
See caption to Table 2. Here, we just include any stock, that falls into portfolio p at any point in time during the formation period (months $t-12$ to $t-1$ here) with the market equity at the end of the formation period $t-1$ as the weight. The main difference to the buy-and-hold approach is that a stock that fell into a portfolio more than once is only considered once.

	W_S^*	L_S^*	W_S^*-L_S^*	$W_S^{*,m}$	$L_S^{*,m}$	W_S^*-$W_S^{*,m}$	L_S^*-$L_S^{*,m}$	DiD
Panel A: Raw excess returns								
Average	-0.20	-0.73	0.53	0.79	0.78	-0.99	-1.51	0.52
	(-0.58)	(-1.39)	(1.45)	(2.95)	(2.03)	(-4.48)	(-3.96)	(1.56)
No. of months	411	411	411	411	411	411	411	411
AvgN	188	106		261	202			
SR	-0.0943	-0.2552	0.2834	0.4367	0.3492	-0.8166	-0.8149	0.2932
Panel B: CAPM regressions								
Intercept	-1.07	-1.77	0.70	-0.01	-0.16	-1.06	-1.61	0.55
	(-5.08)	(-5.19)	(1.98)	(-0.06)	(-0.57)	(-4.76)	(-3.96)	(1.56)
MktRF	1.33	1.59	-0.26	1.22	1.43	0.10	0.15	-0.05
	(21.42)	(10.90)	(-2.17)	(25.75)	(12.83)	(1.95)	(1.17)	(-0.46)
R^2	0.6410	0.5116	0.0321	0.7614	0.6860	0.0119	0.0113	0.0013
IR	-0.8335	-0.8832	0.3802	-0.0101	-0.1249	-0.8770	-0.8737	0.3119
Panel C: Four-factor regressions								
Intercept	-0.96	-1.32	0.36	-0.02	0.13	-0.94	-1.45	0.51
	(-4.53)	(-4.10)	(1.19)	(-0.20)	(0.88)	(-3.83)	(-4.00)	(1.63)
MktRF	1.16	1.29	-0.13	1.14	1.24	0.02	0.06	-0.04
	(21.54)	(14.37)	(-1.87)	(27.18)	(34.97)	(0.32)	(0.64)	(-0.49)
HML	-0.25	-0.06	-0.19	-0.11	0.44	-0.13	-0.50	0.37
	(-2.23)	(-0.32)	(-1.22)	(-1.83)	(4.43)	(-1.02)	(-1.68)	(1.93)
SMB	0.85	1.02	-0.16	0.59	0.92	0.26	0.09	0.17
	(9.19)	(8.25)	(-1.24)	(7.82)	(16.97)	(2.10)	(0.77)	(1.48)
MOM	-0.01	-0.56	0.55	0.12	-0.43	-0.13	-0.13	0.00
	(-0.11)	(-5.25)	(5.89)	(3.04)	(-4.47)	(-1.60)	(-0.87)	(0.00)
R^2	0.7835	0.6582	0.2010	0.8636	0.8873	0.0715	0.0669	0.0336
IR	-0.9635	-0.7860	0.2134	-0.0365	0.1714	-0.7982	-0.8063	0.2930

Table F.13: Long-horizon (L, 2–5 years) strategy performance of constrained simple value-weight portfolios.
See caption to Table 3. Here, we just include any stock, that falls into portfolio p at any point in time during the formation period (months $t-60$ to $t-13$ here) with the market equity at the end of the formation period $t-1$ as the weight. The main difference to the buy-and-hold approach is that a stock that fell into a portfolio more than once is only considered once.

	W^*_{L}	L^*_{L}	W^*_{L}-L^*_{L}	$W^{*,m}_{\mathrm{L}}$	$L^{*,m}_{\mathrm{L}}$	W^*_{L}-$W^{*,m}_{\mathrm{L}}$	L^*_{L}-$L^{*,m}_{\mathrm{L}}$	DiD
Panel A: Raw excess returns								
Average	0.21	0.69	-0.48	0.80	0.72	-0.59	-0.03	-0.56
	(0.63)	(1.82)	(-2.33)	(2.74)	(2.50)	(-4.59)	(-0.14)	(-2.90)
No. of months	363	363	363	363	363	363	363	363
AvgN	417	203		621	461			
SR	0.1125	0.3349	-0.4214	0.4820	0.4093	-0.7163	-0.0262	-0.4914
Panel B: CAPM regressions								
Intercept	-0.67	-0.19	-0.48	-0.04	-0.14	-0.63	-0.05	-0.58
	(-4.55)	(-0.81)	(-2.22)	(-0.34)	(-1.06)	(-4.78)	(-0.25)	(-2.93)
MktRF	1.29	1.29	0.00	1.23	1.26	0.06	0.03	0.04
	(21.27)	(19.97)	(0.01)	(33.17)	(34.78)	(1.43)	(0.51)	(0.46)
R^2	0.7584	0.6237	0.0000	0.8710	0.8218	0.0096	0.0011	0.0015
IR	-0.7280	-0.1495	-0.4221	-0.0616	-0.1905	-0.7729	-0.0445	-0.5128
Panel C: Four-factor regressions								
Intercept	-0.65	-0.13	-0.52	0.00	-0.17	-0.66	0.04	-0.70
	(-5.22)	(-0.67)	(-2.51)	(0.05)	(-1.64)	(-4.49)	(0.19)	(-3.23)
MktRF	1.19	1.12	0.07	1.14	1.16	0.05	-0.04	0.09
	(23.49)	(21.87)	(1.01)	(43.93)	(43.44)	(1.00)	(-0.68)	(1.35)
HML	-0.11	0.07	-0.19	-0.20	0.13	0.09	-0.06	0.15
	(-2.14)	(1.01)	(-2.21)	(-5.10)	(3.00)	(1.51)	(-0.65)	(1.81)
SMB	0.56	0.88	-0.32	0.38	0.69	0.18	0.18	-0.00
	(6.68)	(9.77)	(-2.30)	(8.57)	(22.99)	(2.67)	(1.88)	(-0.04)
MOM	0.02	-0.05	0.08	-0.01	0.05	0.03	-0.10	0.13
	(0.61)	(-1.07)	(1.12)	(-0.37)	(2.76)	(0.79)	(-1.66)	(1.79)
R^2	0.8401	0.7619	0.0778	0.9339	0.9421	0.0502	0.0385	0.0299
IR	-0.8781	-0.1289	-0.4823	0.0098	-0.4007	-0.8246	0.0376	-0.6231

Table F.14: One- to five-year strategy performance of constrained simple value-weight portfolios.

See caption to Table C.4. Here, we just include any stock, that falls into portfolio p at any point in time during the formation period (months $t-60$ to $t-1$ here) with the market equity at the end of the formation period $t-1$ as the weight. The main difference to the buy-and-hold approach is that a stock that fell into a portfolio more than once is only considered once.

	W^*_{60}	L^*_{60}	W^*_{60}-L^*_{60}	$W^{*,m}_{60}$	$L^{*,m}_{60}$	W^*_{60}-$W^{*,m}_{60}$	L^*_{60}-$L^{*,m}_{60}$	DiD
Panel A: Raw excess returns								
Average	0.16	0.44	-0.28	0.78	0.73	-0.62	-0.28	-0.34
	(0.47)	(1.13)	(-1.43)	(2.70)	(2.41)	(-5.01)	(-1.48)	(-1.93)
No. of months	363	363	363	363	363	363	363	363
AvgN	512	271		752	573			
SR	0.0871	0.2046	-0.2533	0.4721	0.4076	-0.8116	-0.2651	-0.3163
Panel B: CAPM regressions								
Intercept	-0.72	-0.50	-0.21	-0.06	-0.15	-0.66	-0.36	-0.30
	(-4.95)	(-2.20)	(-1.03)	(-0.55)	(-1.05)	(-4.58)	(-1.80)	(-1.64)
MktRF	1.29	1.40	-0.10	1.24	1.29	0.06	0.11	-0.05
	(24.05)	(20.77)	(-1.33)	(35.18)	(37.67)	(1.36)	(1.78)	(-0.66)
R^2	0.7718	0.6534	0.0136	0.8765	0.8243	0.0091	0.0151	0.0031
IR	-0.8110	-0.3941	-0.1915	-0.0957	-0.1976	-0.8670	-0.3341	-0.2868
Panel C: Four-factor regressions								
Intercept	-0.72	-0.38	-0.34	-0.03	-0.12	-0.68	-0.25	-0.43
	(-5.76)	(-1.93)	(-1.77)	(-0.46)	(-1.18)	(-4.77)	(-1.25)	(-2.26)
MktRF	1.20	1.20	-0.00	1.15	1.17	0.04	0.03	0.01
	(27.17)	(24.14)	(-0.01)	(52.18)	(55.14)	(0.99)	(0.58)	(0.21)
HML	-0.10	0.06	-0.17	-0.18	0.17	0.08	-0.11	0.18
	(-1.98)	(0.62)	(-1.89)	(-4.73)	(4.14)	(1.24)	(-1.10)	(1.97)
SMB	0.56	0.89	-0.33	0.41	0.73	0.16	0.17	-0.01
	(7.41)	(8.88)	(-2.55)	(8.61)	(23.46)	(2.96)	(2.36)	(-0.11)
MOM	0.04	-0.14	0.19	0.02	-0.03	0.02	-0.11	0.14
	(1.12)	(-2.51)	(3.07)	(0.86)	(-1.26)	(0.60)	(-2.05)	(1.97)
R^2	0.8560	0.7865	0.1369	0.9433	0.9488	0.0447	0.0565	0.0421
IR	-1.0214	-0.3759	-0.3269	-0.0881	-0.3010	-0.9114	-0.2450	-0.4093

F.VII Alternative Formation Period

We repeat our main exercise for shorter momentum signals, i.e., instead of the 11-month return, we consider the previous 3 and 6 months (still skipping 1 month to avoid confusion with short-term reversal). Figures F.1 and F.2 show the subsequent CAPM-alphas of annual buy-and-hold strategies (as constructed in the main paper) – Figure 5 (in the main paper) contains results for our main specification as well as the detailed description of how the plots are constructed. We always get strong underperformance in year 1, no matter which momentum signal, and for both winners and losers. Constrained losers only underperform in year 1 and for the very short momentum signal, their year-2 performance is borderline significantly negative. Most importantly, constrained winners exhibit significantly negative alphas for at least 4 years in all specifications.

Figure F.1: Alphas by year for momentum signal based on returns from t-4 through t-2

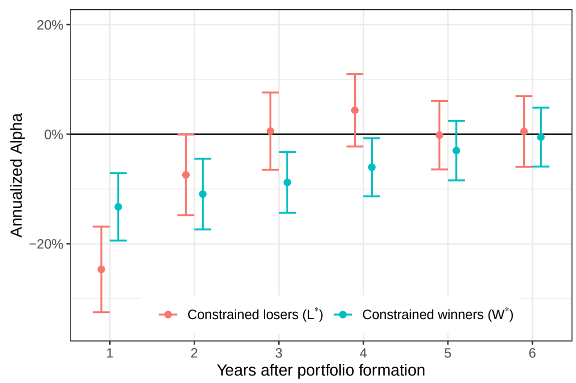
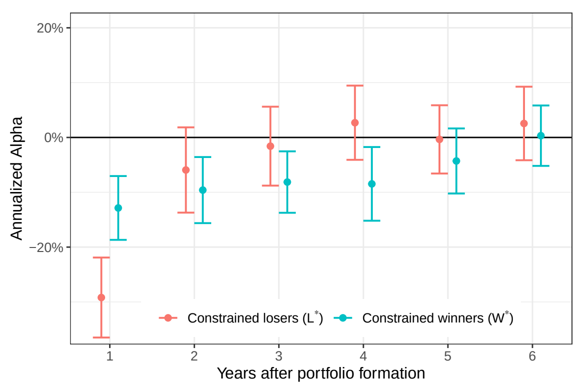


Figure F.2: Alphas by year for momentum signal based on returns from t-7 through t-2



F.VIII Alternative Measures of Past Performance

Here, we want to test whether the reaction of agents to different types of news shocks vary. In particular, we want to explore, if there are a difference between "hard" information, such as cashflow news or accounting numbers, and "soft information", such as news about products, rumors, etc.

Inspired by Bernard and Thomas (1989), we distinguish returns that are realized around earnings announcements, from those that occur on all other days. We calculate "hard information" abnormal log-returns, by summing up the abnormal (with respect to the market) log-returns of the 3-day windows around all earnings announcements that happen during the 11-month pre-formation window (skipping the most recent month). As "soft information" abnormal log-returns, we use the difference between the abnormal log-return over the full 11-month pre-formation window and the "hard information" abnormal log-return. We estimate beta over the same 11-month window of daily returns. Portfolios are formed by triple-sorting on IOR, SIR and one of the abnormal return measures.

We observe very similar patterns as with our main specification for both constrained "hard information" and "soft information" stocks, as depicted in Figure F.3. All of them lose substantially in year 1. Constrained winners continue to lose until year 4–5, whereas losers exhibit CAPM alphas that are statistically indistinguishable from zero in all but the first year.

To gain statistical power, we, again, combine years 2–5 into buy-and-hold portfolios, and examine the performance differential between constrained losers and winners for that "long" holding period (Tables F.15 and F.16). For both "hard information" and "soft information" sorted portfolios, we find no evidence of loser underperformance but strong evidence of winner underperformance. The difference is statistically significant in both cases. The alphas become even more negative when we look at the difference in differences (DiD) that first subtracts the returns of matched portfolios from W^* and L^* respectively. Hence, it looks like the type of news, at least measured in this way, is not an important determinant of agents' belief patterns. It is possible that our measure is not precise in distinguishing the types of news, as we know from the accounting literature, that firms disclose numerous items on announcement days – not merely "hard information" such as accounting data and cashflow news, but all sorts of other information.

The fact that the magnitude of the difference coefficient is smaller than in our main specification is likely attributable to an errors-in-variables problem. It appears that a comprehensive measure of return identifies relevant news shocks more cleanly, whereas our "hard/soft information" split induces error into that measurement.

Figure F.3: CAPM alphas of constrained Portfolios sorted by the sum of all 3-day EA-CARs in the 12-2 formation window, and on abnormal returns that occurred on the remaining days during the formation window ($t-12$ to $t-1$)

Panel A: Sort on "hard information" returns Panel B: Sort on "soft information" returns

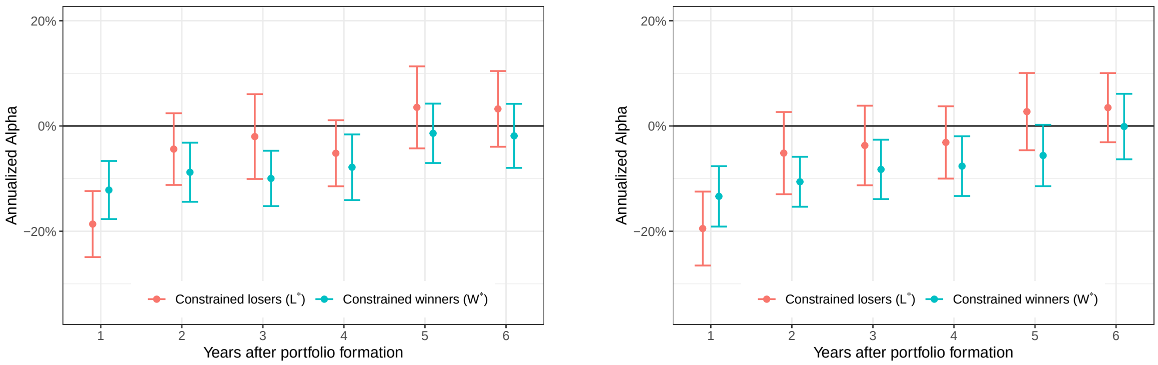


Table F.15: Long-horizon (L, 2–5 years) strategy performance of constrained portfolios sorted on "hard information"

See caption to Table 3. Here, we use "hard information" abnormal log-returns instead of the standard momentum signal to allocate into "winner" and "loser" portfolios. We calculate "hard information" abnormal log-returns, by summing up the abnormal (with respect to the market) log-returns of the 3-day windows around all earnings announcements that happen during the 11-month pre-formation window (skipping the most recent month). We estimate beta over the same 11-month window of daily returns.

	W^*_{L}	L^*_{L}	W^*_{L}-L^*_{L}	$W^{*,m}_{\mathrm{L}}$	$L^{*,m}_{\mathrm{L}}$	W^*_{L}-$W^{*,m}_{\mathrm{L}}$	L^*_{L}-$L^{*,m}_{\mathrm{L}}$	DiD
Panel A: Raw excess returns								
Average	0.32	0.81	-0.50	0.97	0.84	-0.66	-0.03	-0.63
	(0.80)	(2.13)	(-2.19)	(3.29)	(2.84)	(-3.44)	(-0.12)	(-2.88)
No. of months	363	363	363	363	363	363	363	363
AvgN	417	203		468	452			
SR	0.1479	0.3622	-0.3973	0.5594	0.4713	-0.6737	-0.0196	-0.4979
Panel B: CAPM regressions								
Intercept	-0.66	-0.12	-0.54	0.12	-0.03	-0.78	-0.09	-0.69
	(-2.99)	(-0.45)	(-2.28)	(0.96)	(-0.26)	(-4.09)	(-0.41)	(-3.19)
MktRF	1.44	1.37	0.06	1.25	1.28	0.18	0.09	0.09
	(20.62)	(17.34)	(0.71)	(34.61)	(39.38)	(3.32)	(1.15)	(1.06)
R^2	0.7160	0.5936	0.0040	0.8203	0.8234	0.0551	0.0079	0.0081
IR	-0.5801	-0.0846	-0.4325	0.1655	-0.0448	-0.8234	-0.0677	-0.5488
Panel C: Four-factor regressions								
Intercept	-0.53	0.03	-0.55	0.10	-0.03	-0.63	0.05	-0.68
	(-3.13)	(0.12)	(-2.54)	(1.34)	(-0.34)	(-3.40)	(0.25)	(-2.87)
MktRF	1.24	1.15	0.09	1.16	1.18	0.09	-0.03	0.11
	(21.01)	(18.75)	(1.06)	(40.99)	(33.70)	(1.42)	(-0.29)	(1.53)
HML	-0.27	-0.22	-0.05	-0.04	-0.03	-0.23	-0.19	-0.04
	(-2.57)	(-2.49)	(-0.42)	(-1.02)	(-0.88)	(-2.14)	(-1.61)	(-0.39)
SMB	0.79	0.93	-0.14	0.63	0.62	0.16	0.31	-0.15
	(9.76)	(13.03)	(-1.39)	(13.74)	(9.60)	(2.04)	(3.03)	(-1.50)
MOM	-0.10	-0.13	0.02	0.06	0.02	-0.17	-0.15	-0.02
	(-1.58)	(-2.31)	(0.34)	(2.58)	(1.27)	(-2.62)	(-2.45)	(-0.25)
R^2	0.8486	0.7489	0.0150	0.9335	0.9241	0.1512	0.0885	0.0196
IR	-0.6371	0.0239	-0.4485	0.2233	-0.0545	-0.6991	0.0432	-0.5426

Table F.16: Long-horizon (L, 2–5 years) strategy performance of constrained portfolios sorted on "soft information"

See caption to Table 3. Here, we use "soft information" abnormal log-returns instead of the standard momentum signal to allocate into "winner" and "loser" portfolios. We calculate "hard information" abnormal log-returns, by summing up the abnormal (with respect to the market) log-returns of the 3-day windows around all earnings announcements that happen during the 11-month pre-formation window (skipping the most recent month). As "soft information" abnormal log-returns, we use the difference between the abnormal log-return over the full 11-month pre-formation window and the "hard information" abnormal log-return. We estimate beta over the same 11-month window of daily returns.

	W_{L}^{*}	L_{L}^{*}	W_{L}^{*}-L_{L}^{*}	$W_{\mathrm{L}}^{*,m}$	$L_{\mathrm{L}}^{*,m}$	W_{L}^{*}-$W_{\mathrm{L}}^{*,m}$	L_{L}^{*}-$L_{\mathrm{L}}^{*,m}$	DiD
Panel A: Raw excess returns								
Average	0.23	0.77	-0.54	0.94	0.88	-0.71	-0.11	-0.60
	(0.62)	(1.96)	(-2.45)	(3.37)	(2.88)	(-3.72)	(-0.50)	(-2.80)
No. of months	363	363	363	363	363	363	363	363
AvgN	417	203		527	410			
SR	0.1112	0.3492	-0.4458	0.5574	0.4813	-0.7125	-0.0904	-0.4931
Panel B: CAPM regressions								
Intercept	-0.71	-0.17	-0.54	0.11	-0.00	-0.82	-0.17	-0.65
	(-3.58)	(-0.70)	(-2.66)	(0.90)	(-0.00)	(-4.46)	(-0.82)	(-3.05)
MktRF	1.39	1.40	-0.01	1.22	1.30	0.17	0.10	0.07
	(22.41)	(20.55)	(-0.13)	(39.95)	(29.77)	(2.61)	(1.63)	(1.02)
R^2	0.7085	0.6267	0.0001	0.8239	0.7949	0.0447	0.0114	0.0049
IR	-0.6363	-0.1283	-0.4402	0.1598	-0.0008	-0.8458	-0.1490	-0.5322
Panel C: Four-factor regressions								
Intercept	-0.57	-0.07	-0.50	0.08	-0.01	-0.65	-0.06	-0.59
	(-4.21)	(-0.34)	(-2.28)	(0.89)	(-0.09)	(-3.67)	(-0.28)	(-2.49)
MktRF	1.19	1.20	-0.01	1.14	1.18	0.05	0.03	0.02
	(21.61)	(20.39)	(-0.17)	(45.62)	(35.71)	(0.79)	(0.48)	(0.32)
HML	-0.19	0.09	-0.28	-0.09	0.14	-0.11	-0.05	-0.06
	(-3.04)	(1.20)	(-3.44)	(-1.81)	(2.22)	(-1.17)	(-0.42)	(-0.72)
SMB	0.81	0.94	-0.13	0.56	0.80	0.25	0.14	0.11
	(10.89)	(13.40)	(-1.39)	(13.44)	(18.60)	(3.38)	(1.69)	(1.21)
MOM	-0.12	-0.11	-0.01	0.08	0.02	-0.21	-0.14	-0.07
	(-2.21)	(-1.91)	(-0.12)	(3.00)	(1.01)	(-3.59)	(-1.97)	(-0.80)
R^2	0.8441	0.7630	0.0426	0.9256	0.9385	0.1618	0.0432	0.0177
IR	-0.7008	-0.0666	-0.4194	0.1742	-0.0191	-0.7154	-0.0553	-0.4852

F.IX Alternative Definitions Analyst Disagreement

Table F.17: Fama-MacBeth regressions of future changes on past changes in forecast dispersion – scaled by asset.
See caption to Table 5. The difference here is that the standard deviation of forecasts is scaled by total assets per share instead of the mean forecast.

	$\Delta FD_{t—(t+12)}$	$\Delta FD_{t—(t+12)}$	$\Delta FD_{(t+12)—(t+60)}$	$\Delta FD_{(t+12)—(t+60)}$	$\Delta FD_{t—(t+60)}$	$\Delta FD_{t—(t+60)}$
Intercept	0.00	0.00	-0.00	-0.00	0.00	0.00
	(5.18)	(5.71)	(-0.41)	(-0.04)	(4.22)	(4.33)
$\Delta FD^{+}_{(t-12)—t}$	-0.70	-0.69	-0.14	-0.14	-0.89	-0.89
	(-12.87)	(-12.73)	(-5.87)	(-5.93)	(-34.49)	(-33.71)
$\lvert\Delta FD^{-}_{(t-12)—t}\rvert$		0.14		-0.03		0.01
		(2.67)		(-2.14)		(0.97)
Avg. R^2	0.2928	0.3126	0.0172	0.0247	0.2846	0.2912
No. of months	470	470	427	427	427	427
Avg. no. of stocks	1,816	1,816	1,266	1,266	1,315	1,315

Table F.18: Fama-MacBeth regressions of future changes on past changes in forecast dispersion – using quarterly earnings.
See caption to Table 5. The difference here is that we use forecasts of earnings of the nearest fiscal quarter.

	$\Delta FD_{t—(t+12)}$	$\Delta FD_{t—(t+12)}$	$\Delta FD_{(t+12)—(t+60)}$	$\Delta FD_{(t+12)—(t+60)}$	$\Delta FD_{t—(t+60)}$	$\Delta FD_{t—(t+60)}$
Intercept	0.05	0.05	0.02	0.02	0.06	0.07
	(7.07)	(7.02)	(1.63)	(1.88)	(6.44)	(6.56)
$\Delta FD^{+}_{(t-12)—t}$	-0.84	-0.83	-0.15	-0.16	-0.97	-0.97
	(-42.69)	(-41.60)	(-6.79)	(-6.78)	(-54.82)	(-55.53)
$\lvert\Delta FD^{-}_{(t-12)—t}\rvert$		0.04		-0.07		-0.01
		(2.86)		(-4.23)		(-1.44)
Avg. R^2	0.3767	0.3833	0.0124	0.0225	0.3623	0.3681
No. of months	413	411	368	368	368	368
Avg. no. of stocks	1,663	1,671	1,169	1,169	1,228	1,228

Table F.19: Fama-MacBeth regressions of future changes on past changes in forecast dispersion – long-term-growth.
See caption to Table 5. The difference here is that we use the standard deviation of long-term-growth forecasts instead of fiscal-year end forecasts.

	$\Delta FD_{t—(t+12)}$	$\Delta FD_{t—(t+12)}$	$\Delta FD_{(t+12)—(t+60)}$	$\Delta FD_{(t+12)—(t+60)}$	$\Delta FD_{t—(t+60)}$	$\Delta FD_{t—(t+60)}$
Intercept	0.49	0.44	0.25	0.30	0.71	0.70
	(8.02)	(8.22)	(2.57)	(3.27)	(7.70)	(8.62)
$\Delta FD^{+}_{(t-12)—t}$	-0.67	-0.66	-0.25	-0.27	-0.92	-0.92
	(-23.91)	(-22.60)	(-8.41)	(-8.35)	(-32.28)	(-32.26)
$\lvert\Delta FD^{-}_{(t-12)—t}\rvert$		0.05		-0.09		-0.02
		(2.70)		(-3.38)		(-0.77)
Avg. R^2	0.2389	0.2470	0.0241	0.0349	0.2251	0.2351
No. of months	439	439	396	396	396	396
Avg. no. of stocks	1,160	1,160	800	800	836	836

References

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang, 2006, "The Cross-Section of Volatility and Expected Returns," *Journal of Finance*, 61(1), 259–299.

Asparouhova, E., H. Bessembinder, and I. Kalcheva, 2013, "Noisy Prices and Inference Regarding Returns," *Journal of Finance*, 68(2), 665–714.

Baker, M., and J. Wurgler, 2002, "Market Timing and Capital Structure," *Journal of Finance*, 57(1), 1–32.

Barber, B. M., and J. D. Lyon, 1997, "Detecting Long-Run Abnormal Stock Returns: The Empirical Power and Specification of Test Statistics," *Journal of Financial Economics*, 43(3), 341–372.

Barberis, N., R. Greenwood, L. Jin, and A. Shleifer, 2018, "Extrapolation and Bubbles," *Journal of Financial Economics*, 129(4), 203–227.

Ben-David, I., J. R. Graham, and C. R. Harvey, 2013, "Managerial Miscalibration," *Quarterly Journal of Economics*, 128(4), 1547–1584.

Bernard, V. L., and J. K. Thomas, 1989, "Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium?," *Journal of Accounting Research*, 27, 1–36.

Blocher, J., A. V. Reed, and E. D. Van Wesep, 2013, "Connecting two Markets: An Equilibrium Framework for Shorts, Longs, and Stock Loans," *Journal of Financial Economics*, 108(2), 302–322.

Brandt, M. W., 2010, "Portfolio Choice Problems," in *Handbook of Financial Econometrics: Tools and Techniques*, ed. by Y. Aït-Sahalia, and L. P. Hansen, pp. 269–336. North-Holland.

Chui, A. C. W., S. Titman, and K. C. J. Wei, 2010, "Individualism and Momentum around the World," *Journal of Finance*, 65(1), 361–392.

Cremers, M., and D. Weinbaum, 2010, "Deviations from Put-Call Parity and Stock Return Predictability," *Journal of Financial and Quantitative Analysis*, 45(2), 335–367.

Daniel, K., M. Grinblatt, S. Titman, and R. Wermers, 1997, "Measuring Mutual Fund Performance with Characteristic-Based Benchmarks," *Journal of Finance*, 52(3), 1035–1058.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam, 1998, "Investor Psychology and Security Market Under- and Overreactions," *Journal of Finance*, 53(6), 1839–1885.

Daniel, K., and S. Titman, 2006, "Market Reactions to Tangible and Intangible Information," *Journal of Finance*, 61(4), 1605–1643.

D'Avolio, G., 2002, "The Market for Borrowing Stock," *Journal of Financial Economics*, 66(2-3), 271–306.

DeBondt, W. F. M., and R. H. Thaler, 1985, "Does the Stock Market Overreact?," *Journal of Finance*, 40(3), 793–805.

Drechsler, I., and Q. F. Drechsler, 2016, "The Shorting Premium and Asset Pricing Anomalies," Working Paper.

Fama, E. F., 1998, "Market Efficiency, Long-Term Returns, and Behavioral Finance," *Journal of Financial Economics*, 49(3), 283–306.

Fama, E. F., and K. R. French, 1993, "Common Risk Factors in the Returns on Stocks and Bonds," *Journal of Financial Economics*, 33(1), 3–56.

——— , 2012, "Size, Value, and Momentum in International Stock Returns," *Journal of Financial Economics*, 105(3), 457–472.

Fama, E. F., and J. D. MacBeth, 1973, "Risk, Return, and Equilibrium: Empirical Tests," *Journal of Political Economy*, 81(3), 607–636.

Foster, G., C. Olsen, and T. Shevlin, 1984, "Earnings Releases, Anomalies, and the Behavior of Security Returns," *The Accounting Review*, 59(4), 574–603.

Graham, J. R., and C. R. Harvey, 2001, "The Theory and Practice of Corporate Finance: Evidence from the Field," *Journal of Financial Economics*, 60(2), 187–243.

Green, J., J. R. M. Hand, and F. Zhang, 2017, "The Characteristics that Provide Independent Information about Average U.S. Monthly Stock Returns," *Review of Financial Studies*, 30(12), 4389–4436.

Griffin, J. M., P. J. Kelly, and F. Nardari, 2010, "Do Market Efficiency Measures Yield Correct Inferences? A Comparison of Developed and Emerging Markets," *Review of Financial Studies*, 23(8), 3225–3277.

Hong, H., and J. C. Stein, 1999, "A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets," *Journal of Finance*, 54(6), 2143–2184.

Ince, O. S., and R. B. Porter, 2006, "Individual Equity Return Data from Thomson Datastream: Handle with Care!," *Journal of Financial Research*, 29(4), 463–479.

Jegadeesh, N., 1990, "Evidence of Predictable Behavior of Security Returns," *Journal of Finance*, 45(3), 881–898.

Jegadeesh, N., and S. Titman, 1993, "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency," *Journal of Finance*, 48(1), 65–91.

Jensen, M. C., 1968, "The Performance of Mutual Funds in the Period 1945-1964," *Journal of Finance*, 23(2), 389–416.

Klos, A., A. Koehl, and S. Rottke, 2020, "Streaks in Daily Returns," Working Paper.

Kolasinski, A. C., A. V. Reed, and M. C. Ringgenberg, 2013, "A Multiple Lender Approach to Understanding Supply and Search in the Equity Lending Market," *Journal of Finance*, 68(2), 559–595.

Loughran, T., and J. R. Ritter, 1995, "The New Issues Puzzle," *Journal of Finance*, 50(1), 23–51.

Nagel, S., 2005, "Short Sales, Institutional Investors and the Cross-Section of Stock Returns," *Journal of Financial Economics*, 78(2), 277–309.

Newey, W. K., and K. D. West, 1987, "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica*, 55(3), 703–708.

Novy-Marx, R., 2012, "Is Momentum Really Momentum?," *Journal of Financial Economics*, 103(3), 429–453.

——— , 2013, "The Other Side of Value: The Gross Profitability Premium," *Journal of Financial Economics*, 108(1), 1–28.

Ofek, E., M. Richardson, and R. F. Whitelaw, 2004, "Limited Arbitrage and Short Sales Restrictions: Evidence from the Options Markets," *Journal of Financial Economics*, 74(2), 305–342.

Pontiff, J., and A. Woodgate, 2008, "Share Issuance and Cross-sectional Returns," *Journal of Finance*, 63(2), 921–945.

Reed, A. V., 2013, "Short Selling," *Annual Review of Financial Economics*, 5(1), 245–258.

Schmidt, P. S., U. von Arx, A. Schrimpf, A. F. Wagner, and A. Ziegler, 2019, "Common Risk Factors in International Stock Markets," *Financial Markets and Portfolio Management*, 33(3), 213–241.