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Stock prices' overreaction corrections: Firm-specific and market-wide attributes*

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ABSTRACT

We study the effects of overreaction corrections in stock prices. To this end, we exogenously specify dynamics for the stock price which include a short-term overreaction correction effect as well as long-term mean reversal. This proposed framework allows us to estimate the strength of the overreaction correction parameter for each stock. We conduct a cross-sectional analysis to investigate the relation between the overreaction correction and traditional measures of market frictions and firm characteristics. We find that overreaction corrections are not well explained by any of these variables. Finally, a long-short trading strategy based on yearly portfolios formed according to their overreaction correction strength exhibits a significant abnormal return of more than 6% per year, about two thirds of which can be explained by systematic liquidity risk.

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1. Introduction

Negative very short-term autocorrelation, positive short-term autocorrelation and long-term reversal of stock returns are well-known and have been widely documented empirically.[1] Because these predictabilities in asset returns are inconsistent with standard asset pricing models, the literature has proposed behavioral theories and explanations. In particular, one strand of literature departs from the assumption of rational investors and considers the implications of psychological biases (behavioral finance). Within the field of behavioral finance, the theory of overreaction has received considerable attention.[2]

Specifically, an essential contribution in the theory of overreaction in stock prices is the paper by Daniel, Hirshleifer, and Subrahmanyam (1998). In their model, investors are overconfident about the precision of their private signals and suffer from biased self-attribution. As a result, investors overreact to private information and underreact to public information. In particular, upon the arrival of a positive private signal, the stock price tends to increase more than the rationale expected value ('overreaction phase'). Subsequently, this inefficient deviation is partially corrected due to the arrivals of noisy private signals ('correction phase'). Daniel, Hirshleifer, and Subrahmanyam (1998) use a discrete-time three-period model to derive these results, and investigate the stock price behavior in a dynamic framework later in the paper. However, in the dynamic framework, only one overreaction and subsequent correction phase is considered, given the arrival of private signals and updated investor's beliefs. This framework cannot be applied in a straightforward manner to empirical analyzes for two reasons. First, overreaction and subsequent correction might occur to a stock price process more than once; and, second, private signals are not observable, and can, hence, not directly be estimated. In this paper, we suggest stock price dynamics which are consistent with the overreaction effect of Daniel, Hirshleifer, and Subrahmanyam (1998), and which, in particular, allow for an overreaction phase and a correction phase. Importantly, imposing the dynamics exogenously allows us to investigate overreaction and correction in empirical applications.

The contribution of this paper is twofold. First, we offer a simple approach to estimate a stock price overreaction correction parameter by proposing stock price dynamics, which incorporate such an effect. This parameter is only weakly predictable at the individual firm level. Second, we document that, at the aggregate level, the overreaction correction factor is priced, yielding a premium of more than 6% per year, after controlling for the Fama - French factors, and for the momentum factor.

For this purpose, we borrow from physics the idea of the dynamics describing the motion of a (small) particle in a force field with frictions. This theory was developed by Ornstein and Uhlenebeck as a new theory of Brownian motion, building on the earlier work of Einstein and Smolu-

[1] For evidence on very short-term (monthly) negative autocorrelation, see Jegadeesh (1990) or Lehmann (1990); Short-term momentum, is, for example, documented in Jegadeesh and Titman (1993); concerning long-term reversal, see, e.g., Fama and French (1988) or Poterba and Summers (1988).

[2] For a survey on the early literature on mean reversion and overreaction, see Forbes (1996).

chowski. The proposed dynamics capture stock prices' overreaction corrections in a parsimonious way, and, in particular, allow to estimate a stock specific overreaction correction parameter.

Even though the mean-reverting stochastic process of Ornstein and Uhlenbeck is widely used in continuous-time finance, the financial literature, to the best of our knowledge, did not adopt the friction effect of the Ornstein-Uhlenbeck theory to financial setups. This paper presents such an attempt. The physic's friction is comparable to an overreaction correction effect in stock prices. To differentiate between the overreaction correction effect and long - term mean-reversion, we also assume that the stock price fluctuates in a mean reverting way around its linear long-term mean process. The overreaction correction effect then determines the characteristics of the fluctuation: If the overreaction effect is strong, we see stronger price swings, followed by correction phases.

Long, Shleifer, Summers, and Waldmann (1990) and Shleifer and Vishny (1997) explain why deviations from efficient prices may persist. If irrational noise traders are present (Long, Shleifer, Summers, and Waldmann, 1990) or if the arbitrage requires substantial capital and is risky (Shleifer and Vishny, 1997), an arbitrageur has an incentive to limit his position in the arbitrage. As a result, mispricing may persist. Conversely, for a diminishing overreaction correction effect, the stock price process approaches the solution of a standard first order stochastic differential equation, in this case an Ornstein-Uhlenbeck process.[3]

We apply our setup to US non-financials stock market data from 1963-2009 and first show how the overreaction correction parameter for each stock can be estimated. We then conduct a cross-sectional analysis to investigate whether the overreaction correction parameter is predictable. In particular, we analyze the relation between the overreaction correction parameter and firm characteristics as well as other measures of market frictions. We consider size and leverage as firm characteristics, and illiquidity measures, information uncertainty measures, and probabilities of informed trading as measures of market frictions. The results suggest that the overreaction correction parameter cannot be explained by any of the friction measures or firm characteristics. While some explanatory variables turn out to be significant or marginally significant, the explanatory power (adjusted R^2) remains, in general, very low: The five best models according to the Akaike or Bayes Information Criterion do not exceed an adjusted R^2 of 8%. We conclude that the predictability of the overreaction correction parameter with common measures of individual market frictions and firm characteristics is very low.

Finally, we examine whether the overreaction correction factor, at the aggregate level, is a priced risk factor. To this end, we estimate a yearly overreaction correction parameter and sort stocks into portfolios based on the magnitude of the overreaction correction parameter. We then compute abnormal returns resulting from a three- (Fama French), four- (Carhart) and five- (including liquidity risk) factor models. Using the Fama-French and Carhart models, we obtain abnormal yearly returns just above 6%. Additional inclusion of a systematic risk liquidity factor decreases

[3]In physics, the analogous convergence result justifies the usage of first order stochastic differential equations in order to model the motion of a small particle in a force field with frictions.

the abnormal return to about 2%. We conclude that the overreaction correction factor is indeed a priced factor, of which about two thirds can be explained by a systematic liquidity risk premium.

Literature review. De Bondt and Thaler (1985) and De Bondt and Thaler (1987) were the first to explore the consistency of the overreaction theory in the context of an empirical study using stock market data. In detail, they form stock portfolios based on past performance and find systematic price reversals. By excluding alternative explications such as a size or a risk effect, the authors conclude that this systematical pattern is evidence of overreaction. Similarly, Lakonishok, Shleifer, and Vishny (1994) argue that the performance of value strategies can be explained by suboptimal behavior of the typical investor. Several models have been proposed to explain the effects of overreaction on stock prices, notably by Daniel, Hirshleifer, and Subrahmanyam (1998), who assume overconfident investors with biased self-attribution to generate an overreaction effect in stock prices, or by Barberis, Shleifer, and Vishny (1998), who present a model of investor sentiment to generate both under- and overreaction.[4] Hong and Stein (1999) obtain underreaction at short horizons and overreaction at long horizons in a model with two groups of investors, namely, newswatchers and momentum traders. In a laboratory setting, Bloomfield, Tayler, and Zhou (2009) confirm that uninformed traders are causing long-term mean reversion. Consistent with Hong and Stein (1999), the two possible mechanisms are either that uninformed traders engage in momentum trade when informed traders do not observe prices, or that uninformed traders engage in contrarian strategies when informed traders can condition on prices. An early empirical contribution is the paper by La Porta (1994), who considers stock portfolios based on analysts' growth forecasts. The author finds that the portfolio consisting of stocks with the highest growth forecast earns a much lower return than the portfolio consisting of stocks with the lowest growth forecast. This result is consistent with an overreaction effect not only in analysts' forecast, but, importantly, also in stock prices. Further, Daniel and Titman (2005) decompose returns into tangible returns, i.e., accounting based, and intangible returns, i.e., the component of returns that is orthogonal to the firm's past performance. Their results suggest that investors overreact to intangible information, but not to tangible information. Extending the setup to a dynamic framework, Lee (2006) confirms that investors tend to overreact to intangible information. Recently, Wei and Yang (2012) proposed a model based on investor's moderated confidence, which leads to underreaction and overreaction in different types - with respect to volatility levels - of large cap stocks. As a result, momentum and reversal can coexist in large cap stocks over horizons from one to six months.

The remainder of the paper is structured as follows. Section 2 introduces, explains, and illustrates the stock price dynamics. In Section 3, we estimate the overreaction correction parameter for a universe of non-financial firms and provide an empirical analysis of the determinants of the

[4]Importantly, Kyle and Wang (1997) show that overconfidence can persist in the long run by using a duopoly model of informed speculation. Further, in the literature, overconfidence has also been used to explain a number phenomenons other than overreaction, as in Daniel, Hirshleifer, and Subrahmanyam (1998). For example, Odean (1998) documents that overconfidence increases expected trading volume, market depth, and expected utility, while under- and overreaction occur depending on the type of information. Scheinkman and Xiong (2003) explain speculative bubbles in asset prices using a model in which overconfidence generates disagreement among agents.

individual stocks' overreaction correction parameters. Section 4 investigates, if at the aggregate level, the overreaction correction factor is priced. Finally, Section 6 concludes.

2. Stock price dynamics and the overreaction correction effect

2.1. Assumptions and intuition

We now specify the mean-reverting stock price dynamics that accounts for the overreaction correction effect. More specifically, to describe the evolution of a coupled price and infinitesimal log return process including an overreaction effect, we borrow ideas from physics using Newton's law describing the motion of a particle with mass m in an external field of force, given that the friction is proportional to the velocity with some constant β. We denote the log-price process by X_t, and the infinitesimal annualized log return process by Y_t. Precisely, we assume that X_t and Y_t solve the following system of stochastic differential equations:

$$\mathrm{d}X_t = Y_t \mathrm{d}t \tag{1}$$
$$\mathrm{d}Y_t = -\tilde{a}\left(\mu_t - X_t\right)\mathrm{d}t + \tilde{\sigma}\mathrm{d}W_t - \beta \mathrm{d}X_t, \tag{2}$$

in which $\tilde{a} \in (-\infty, 0)$ is the mean-reversion coefficient, μ_t is a deterministic but time-dependent trend process, $\beta \in \mathbb{R}_+$ is a coefficient, and $\tilde{\sigma} \in \mathbb{R}_+$ is the volatility.[5] W_t is a standard Brownian motion. We set

$$\mu_t := \mu_0 + Et, \tag{3}$$

with $\mu_0 \in \mathbb{R}$ being the initial value of the trend process, and E the long-run (annualized) log return of the stock. To understand the mechanics of the assumed dynamics, we rewrite (2) as

$$\mathrm{d}X_t = -a\left(\mu_t - X_t\right)\mathrm{d}t + \sigma \mathrm{d}W_t - \gamma \mathrm{d}Y_t, \tag{4}$$

with $a := \frac{\tilde{a}}{\beta}$, $\sigma := \frac{\tilde{\sigma}}{\beta}$, and the overreaction parameter $\gamma := \frac{m}{\beta} = \frac{1}{\beta}$. The log-price X_t is assumed to fluctuate around its long-term mean process $\mu(t)$. This fluctuation is determined not only by the realizations of a Brownian motion, but also by the overreaction correction term $-\gamma \mathrm{d}Y_t$. We presume that an overreaction causes the stock price to deviate in the short term from its fundamentals (overreaction phase), and that, subsequently, this deviation is corrected (correction phase). Because the overreaction phase consists of a large and rapid price swing, the stock price process increases [decreases] such that returns are also increasing [decreasing], i.e., $\mathrm{d}Y_t > 0$ [$\mathrm{d}Y_t < 0$]. In particular, the last term in (4) is negative [positive]. Hence, the actual price change $\mathrm{d}X_t$ is decreased [increased]. Therefore, the last term induces the correction phase of the stock price,

[5] In physics, this system describes the evolution of a particle with a mass of m, in which it is assumed without loss of generality that $m = 1$. Westermann (2006) proposes to use second-order stochastic differential equation based on Newton's law in the context of financial markets. Technically, our setup constitutes a special case in the class of processes considered in Westermann (2006).

during which the price recovers from the strong price swing in the overreaction phase. Importantly, the overreaction parameter γ measures the magnitude of the effect.[6] From (4), we see that the overreaction correction effect is stronger the larger is γ.

The overreaction correction effect is consistent with the model results of Daniel, Hirshleifer, and Subrahmanyam (1998). In their model, investors are overconfident in private information. Initially, a private signal arrives, and because investors are overconfident in this signal, the price overreacts. Subsequently, noisy public information arrives, and the inefficient deviation is partially corrected. The resulting pattern consisting of the overreaction and the correction phase is displayed in Fig. 1 on page 1847 in Daniel, Hirshleifer, and Subrahmanyam (1998). As explained above, this pattern is also reflected by our proposed dynamics. Importantly, this approach allows us to investigate the effects of overreaction in a dynamic framework, without the need to identify its origin as stemming from private or public information events.

The first term of the dynamics (4) captures the long-term mean reversion property of stocks, the parameter a measuring the extend or speed of mean-reversion. In particular, the mean-reverting drift function ensures a limiting log-return that can be different from zero. The second term is the conventional volatility term, which is the source of randomness in the dynamics. Neglecting the last term, the price dynamics are described by the standard Ornstein-Uhlenbeck dynamics. The long-term mean reversion property of stock price has first been investigated empirically in the late 80ies (Fama and French, 1988; Poterba and Summers, 1988), and it has been shown that mean-reverting stock price dynamics are consistent with an equilibrium setup (Marcus, 1989). Importantly, the long-term mean reversion is also in line with the model of Daniel, Hirshleifer, and Subrahmanyam (1998). In their model, long-lag negative autocorrelation stems from changes in investors' confidence due to biased self-attribution upon arrival of noisy public signals.

Both mean-reversion and overreaction correction affect the stock price dynamics. However, it is important to note that the mechanism and concepts are fundamentally different. Mean-reversion affects the stock price dynamics depending on the level of the stock price relative to its long-term mean. Overreaction correction affects the stock price dynamics depending on the magnitude of the change in instantaneous returns.

[6] From a physic's point of view, the intuition corresponds to an overdamped system. The overdamped case occurs in a system which returns to equilibrium without oscillating. Here, the system is overdamped if the overreaction correction parameter γ is sufficiently small compared to the mean reversion parameter a (in detail, if $\gamma < \sqrt{(\frac{1}{-4a})}$). As expected, in our empirical application, we always find the overdamped case to hold. On the contrary, in an underdamped system, i.e. for a large overreaction correction parameter γ, the explained effect overcompensates extreme returns, causing the price process to oscillate.

The dynamics (1)-(2) imply a bivariate normal distribution of the two-dimensional random variable $\begin{pmatrix} X_t \\ Y_t \end{pmatrix} |\mathcal{F}_0$ (cf. Nelson (2001). The moments are listed in Appendix 7.1. It can be shown that, as time approaches infinity,

$$\lim_{t\to\infty} \mathbb{E}\left[X_t - \mu_t\right] = \frac{E}{a} \tag{5}$$

$$\lim_{t\to\infty} \mathbb{E}\left[Y_t\right] = E. \tag{6}$$

In words, the annualized log returns converge to the equilibrium rate E, and the log prices converge to the corresponding long-run mean process plus a correction term due to the combined effect of overreaction and mean-reversion (recall that $a = \tilde{a}\gamma$). For the variance-covariance matrix, the limits are given by

$$\lim_{t\to\infty} Var\left(X_t\right) = \frac{\sigma^2}{2\left(-a\right)} \tag{7}$$

$$\lim_{t\to\infty} Var\left(Y_t\right) = \frac{1}{2}\sigma^2\gamma^3 \tag{8}$$

$$\lim_{t\to\infty} cov\left(X_t, Y_t\right) = 0. \tag{9}$$

(9) shows that the covariance for equal times approaches zero. The intuition is that the correlation between the infinitesimal log return and the log price diminishes as t is large, since the log price process X_t is the result of all former log returns, i.e., the integral, and the process Y_t constitutes only the most recent log return in time.

For sufficiently small γ (compared to the other parameters and the considered time interval), the Smoluchowski approximation (see e.g. Karatzas and Shreve, 1998) can be applied (Nelson, 2001). The Smoluchowski approximation is given by the solution X^{smol} to the Ornstein-Uhlenbeck SDE

$$\mathrm{d}X_t^{smol} = -a\left(\mu_t - X_t^{smol}\right)\mathrm{d}t + \sigma\mathrm{d}W_t. \tag{10}$$

This approximation shows that for stocks with a small overreaction correction, the price process can be represented by a mean-reverting process with constant volatility according to (10). These dynamics are consistent with mean- or trend-reverting stochastic price processes, and extend the literature by explicitly allowing for an overreaction correction effect in stock prices.This descriptive approach of the stock price dynamics can also accommodate the two most important model results of Daniel, Hirshleifer, and Subrahmanyam (1998): Short-term price swings and subsequent correction due to overreaction and long-term mean reversal due to biased self-attribution.

2.2. Simulation results

This subsection presents simulation results for the stochastic process defined in (1)-(3). We illustrate the impact of the overreaction correction parameter γ on stock prices and returns. We

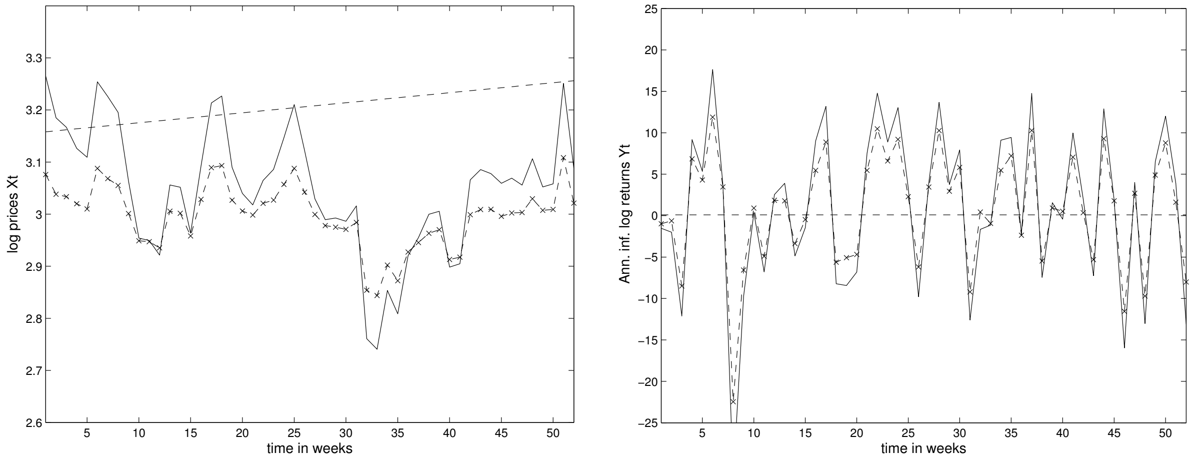


Figure 1. The graphs show simulated sample paths of log prices X_t and annualized infinitesimal log returns Y_t for different values of the overreaction reversal parameter γ. The solid line corresponds to $\gamma = 0.0025$, and the marked dashed line to $\gamma = 0.00125$. The dashed lines show the unconditional mean of the processes. For comparability, the mean reversion and volatility parameters are chosen such that returns' mean reversion parameter and volatility is kept constant, with $\tilde{a} = -1,000$ and $\tilde{\sigma} = 250$. These choices correspond to price mean reversion parameters $a = -2.5$ [$a = -1.25$] and price volatility $\sigma = 0.625$ [$\sigma = 0.3125$], for $\gamma = 0.0025$ [$\gamma = 0.00125$]. The initial trend value is $\mu_0 = 2.8$, and $E = 0.1$ the long-run annualized infinitesimal log return of the stock. The simulation is run on a weekly basis, and the results for year 4 are presented. The two simulations use identical realizations of the randomness in the dynamics.

also document the decreasing difference between infinitesimal and actual log returns for increasing fineness of the simulation time grids.

The simulation is conducted using the joint probability distribution of X_t and Y_t, see Appendix 7.1. Precisely, the distribution of the two-dimensional random variable (X_t, Y_t) is Gaussian, hence the distribution is determined by its first two moments. The moments are reported in Appendix 7.1, formulae (18) and (19)-(21). For practical applications, we expect the overreaction correction parameter γ to be close to zero, according to the intuition that this effect is bound to be limited. To compare processes with different and realistic values of γ, Figure 1 presents simulation results for one year for $\gamma = 0.0025$ (solid line) and $\gamma = 0.00125$ (marked dashed line). The left graph shows the two prices processes, while the right graph shows the corresponding log return processes. For the sake of comparability, identical realizations of the random shocks are used for the two simulations. The right graph of Figure 1 shows the infinitesimal annualized log return process. The log return process with the higher $\gamma = 0.0025$ exhibits, in general, more extreme values than the process corresponding to $\gamma = 0.00125$. Consistent with the results in Daniel, Hirshleifer, and Subrahmanyam (1998), we interpret these more extreme returns as an overreaction effect. After the overreaction effect, we can often see the correction phase, also similar to Daniel, Hirshleifer, and Subrahmanyam (1998): For example, the peaks in week 26 or 28 of the process with higher γ (solid lines) are followed by values of returns that almost coincide with the ones generated with

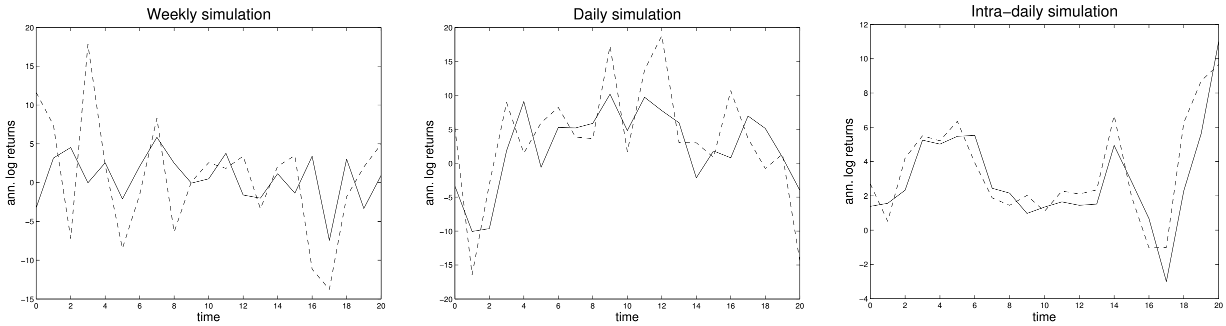


Figure 2. The graphs show the evolution of annualized log returns (solid lines) and annualized infinitesimal log returns Y_t (dashed lines) for different time grids used in the simulation. The left graph simulates weekly data, the middle graph daily data, and the right graph simulates intradaily data, i.e., 20 daily observations. For each time grid, one year of data is simulated and the last 20 observations of the year are presented. The parameters are set to overreaction reversal parameter $\gamma = 0.0025$, mean reversion parameter $a = -2.5$, volatility $\sigma = 0.5$, initial trend value $\mu_0 = 2.8$, and $E = 0.1$ the long-run annualized infinitesimal return of the stock.

the smaller γ (marked dashed lines). The correction phase might also be longer than only one or two weeks, as the simulation shows after week 21. The overreaction peak in week 21 is followed by a correction phase of five weeks until week 26, where the returns almost coincide. The left graph of Figure 1 shows the corresponding price processes. For the price processes, we can also see the overreaction effect documented by Daniel, Hirshleifer, and Subrahmanyam (1998). For example, the price process in week 33 has a down peak, followed by a correction phase until week 36. For both the price and the return process, the graphs document that the impact of γ is not symmetric with respect to the long-run mean of the process as shown by the dashed lines.

Figure 2 presents annualized log returns calculated by using simulated discrete-time price processes (solid lines) and annualized infinitesimal log returns (dashed lines). The discrete time-steps of the simulation were chosen weekly (left graph), daily (middle graph), and intra-daily, i.e., 20 time steps per day (right graph).

Figure 2 confirms that, as the fineness of the simulation grid increases, the discrete-time log returns approach the infinitesimal returns Y_t. Furthermore, it seems that in general the process of infinitesimal log returns exhibits a larger standard deviation than the process of the discrete-time log returns, the intuition being that infinitesimal returns capture only the most recent change in prices, which might be relatively larger than the changes over a discrete-time interval.

3. Estimation and analysis of the firm level overreaction correction parameter

In this section, we first estimate the stock-specific overreaction correction parameter. Next, we analyze the predictability of the stock's overreaction correction parameter using market frictions and other firm specific variables.

3.1. Estimation of the stock specific overreaction correction parameter

We first describe the data set. Next, we present the estimation method and apply it to the data. Finally, we present the descriptive statistics of the estimates.

3.1.1. Data

The sample includes all daily stock data from CRSP in the time period 07/63 - 12/09 with share code 10 or 11. From 1963 to 1973, CRSP contains NYSE and AMEX firms only, whereas NASDAQ firms are included after 1973. As is standard in the literature, we discard all regulated and financial firms[7], i.e., firms whose Standard Industrial Classification code is between 4900 and 4999 or between 6000 and 6999.

To estimate the parameters, weekly data is employed. Higher frequencies, such as daily data, contains more confounding microstructure influences (cf. Hou and Moskowitz, 2005). At higher frequencies, such as monthly data, we expect the overreaction correction effect to be already incorporated. As is standard for constructing weekly data, closing prices and daily returns are taken on each Wednesday. If no closing price is available, the bid-ask midpoint is used (cf. Hou and Moskowitz, 2005). In case of a holiday or missing bid-ask, we consider Thursday or Tuesday instead. Finally, if data are not available between Tuesday and Thursday, that week is discarded for this stock.[8]

We further apply the following filters. We include only firms that are still alive in December 2009. Next, we also discard firms with less than one year of available data. Furthermore, firms with trading gaps of more than four weeks are deleted as well. Finally, in order to exclude abnormal behavior close to default, we do not consider 'penny stocks', i.e., stocks which are traded for less than $5 at some point in time (cf. Pastor and Stambaugh, 2003 and Easley, Kiefer, O'Hara, and Paperman, 1996). For the analysis of the overreaction correction parameter γ, we investigate the impact of different explanatory variables later in the paper. In particular, we also include information uncertainty measures based on I/B/E/S data, as well as probability of informed trading

[7] In section V, we separately examine the evidence regarding financial firms.

[8] Monday and Friday prices are not considered in order to avoid atypical autocorrelation patterns, see e.g. Chordia and Swaminathan (2000).

(PIN) measures. These data are available for a very limited number of firms only, while, for example, firm-level illiquidity measures are available for a large number of firms based on CRSP data. Due to all these constraints, we had to significantly reduce the size of our sample as described above. Our final universe thus consists of 936 firms.

3.1.2. Estimation approach

For each firm, we need to construct the weekly time series $(X_t, Y_t)_{t\geq 0}$. For X_t, we take the log of the observed price weighted with CRSP's cumulative factor to adjust the share price. Y_t is constructed as the annualized daily log return on this date. In order to be consistent with (1), returns are measured excluding cash dividends. The parameters are estimated using a maximum-likelihood approach. The details are provided in Appendix 7.1.

The construction of the processes highlights an interesting aspect of the intuition underlying the assumed dynamics: While the price process X_t contains information about all the past evolution of the stock, the return process Y_t contains only the most recent information at time t. As the model incorporates both processes, we are able to exploit the two sources of information by estimating its parameters.

3.1.3. Estimation results

Table I reports the statistics of the estimated coefficients. Out of the 936 firms in our sample, the maximum-likelihood algorithm converged for 932 firms, i.e., for more than 99.5% of the firms.[9] From now on, we refer to this sample of converged firms as the 'full sample.'

The mean overreaction correction parameter $\gamma * 10^5$ is 187.37. The distribution is approximately symmetric, and 90% of the estimated firms fall in a range between 131.45 and 248.54. While the magnitude of γ is small, we see from the p-values that all overreaction parameters are different from zero even at the 1% level. The mean volatility σ is 0.4614, and the distribution is slightly right-skewed. The volatility parameter is also significant for all firms. The average long-run mean E is 0.0637, and significant at the 5% level for about 60% of the firms. The average mean-reversion parameter a is -1.62, exhibiting a wide range of variation (90% of the firms are between -5.36 and -0.18). It is significant at the 10% level for about 96% of the firms. Finally, the average initial value of the trend process, μ_0, is 2.07, and 90% of its estimates lie between -0.70 and 3.89.

To gain further intuition for the process and the overreaction correction parameter, we investigate the impact of a change in the overreaction correction parameter γ on expected prices and returns in a setting of one overreaction correction phase. The parameters of the base case are chosen to reflect sample means ($10^5\gamma = 190, a = -1.62$), and $\mu_0 = 2, E = 0$ for simplicity. To

[9] The time-series of the four stocks which did not converge mainly suggest that their price processes exhibit jumps, a property not modeled in our framework.

consider a correction phase of an upward price swing, we set $X_0 = 2.2$, corresponding to an excess of ten percent compared to the long-run mean. To initiate the correction phase, we further set $Y_0 = -7.69$, which corresponds to minus one standard deviation. We calculate expected mean prices and returns for time horizons between 1 week and 2 years for values of $10^5\gamma$ between 120 and 250, which roughly corresponds to the range of $10^5\gamma$ in the data (cf. Table I). For different time horizons, Table II presents the percentage change in the expected price (Panel A) and expected returns (Panel B) compared to the base case with $10^5\gamma = 190$.

Table II shows that for all time horizons expected prices and returns are decreasing with an increase in γ. Intuitively, a higher γ corresponds to a stronger overreaction correction, which presses down prices and returns when correcting an upward price swing. Further, for a fixed γ, the impact of a change in γ on expected prices is decreasing in absolute value over the time horizon, corresponding to the intuition that the correction forces have a larger impact at the beginning of the correction phase. Furthermore, for a fixed γ, the time horizon has a positive impact on the percentage difference in expected returns, i.e., for each γ, the expected deviation of returns from the base case is larger for longer time horizons. Intuitively, because the correction forces decline with the time horizon, the time curvature of expected returns is lower for higher γ, because, for a fixed time, a higher correction effect is already inherent in the stock price for higher γ. In summary, the table qualitatively documents that a stronger overreaction correction of a positive price swing results in lower prices, lower returns, and a more convex expected price process. Hence, qualitatively, we conclude that Table II further illustrates the intuition of γ corresponding to an overreaction correction parameter in the spirit of Daniel, Hirshleifer, and Subrahmanyam (1998).

We now turn to the magnitude of the effect of γ on expected log prices and expected log returns. The magnitude of the impact of γ on expected log prices is rather small. For example, Table II shows that a decrease in $10^5\gamma$ from 190 (sample mean) to 160 induces a one-week price change of 0.1%. The magnitudes of changes in expected log returns are larger, for example, a decrease in $10^5\gamma$ from 190 to 160 corresponds to a log return change of 1.05% with a horizon of one week. The last column of Table II presents the mean first difference log price (Panel A) and mean first difference log returns (Panel B) with respect to a change of $10^5\gamma$ by ten. For a one-week horizon, we find an average log price impact of -0.0332% stemming from a change of $10^5\gamma$ of ten, while the average differences for four weeks (six months, one year, two years) are -0.0306% (-0.0165%, -0.0077%, -0.0016%). Regarding the average impact on expected log returns, we find -0.2933% (one week), -0.3869% (four weeks), -0.3981% (six months), -0.4113% (one year), and -0.4378% (two years). When interpreting these quantities, it is important to keep in mind that the reported magnitutes correspond to the impact within one overreaction correction phase. However, in the dynamics, a stock is possibly exposed to many overreaction and correction phases, resulting in presumably larger effects in the time series. Thus, while these quantities offer an intuition in the following analysis, the intuition is limited to one overreaction correction phase only.

3.2. Is the overreaction correction parameter predictable?

In this subsection, we examine whether the overreaction correction parameter can be explained by measures of market frictions at the firm level or by other firm characteristics. As measures of market frictions, we consider firm-level illiquidity, information uncertainty, and informed trading measures. As firm characteristics, we include firms' leverage and stock betas on the market return, on the size factor and on the book to market factor. We then conduct a cross-sectional analysis.

3.2.1. Measures of market frictions and firm characteristics

The considered proxies of (il-)liquidity are average size defined as the average market capitalization (size), average volume (vol), average turnover (to), the average relative bid-ask spread (ba), and the average Amihud (2002) measure (ILLIQ). The monthly measure ILLIQ for stock i in month m is defined as the average ratio of the daily absolute return to daily dollar volume, i.e.

$$ILLIQ_{im} = \frac{1}{D_{im}} \sum_{t=1}^{D_{im}} \frac{|R_{imd}|}{vol_{imd}}, \tag{11}$$

in which D_{im} is the number of trading days for which data is available for stock i in month m, and R_{imd} is the return of stock i in month m on day d.

Information uncertainty measures are constructed as in Zhang (2006): We consider the firm age (age), which is the number of weeks since the firm was first covered by CRSP, analyst coverage (cov), defined as the number of analysts following the firm in the previous year, and forecast dispersion (disp), which is the standard deviation of analyst forecasts in any month scaled by the prior year-end stock price. For each firm, cross-sectional measures are obtained by averaging its time-series.

Measures of informed trading are available for AMEX and NYSE stocks for the years 1983-2004.[10] The probability of informed trading (PIN) is based on the market microstructural model proposed in Easley, O'Hara, and Hvidkjaer (2010), and calculated with the help of order-flow data. It represents the percentage of trades initiated by informed investors. Duarte and Young (2009) found that PIN is not only a proxy of information asymmetry, but also incorporates a proxy of illiquidity unrelated to private information. Hence, they propose an extension of the original model which enables them to decompose the PIN measure into one component they show to be related to illiquidity (PSOS, probability of symmetric order flow shock), and another one found to be related to information asymmetry, but not illiquidity (adjusted PIN, APIN).

We construct measures of leverage using the CRSP-COMPUSTAT merged database. We calculate the book leverage following Baker and Wurgler (2002) and Fama and French (2002). Book

[10]We are grateful to Jefferson Duarte and Lance Young for providing us with their PIN measures calculated in Duarte and Young (2009).

debt is defined as total assets (COMPUSTAT ANNUAL ITEM 6) minus book equity. The latter is defined as total assets less total liabilities (ITEM 181) and preferred stock (ITEM 10) plus deferred taxes (ITEM 35) and convertible debt (ITEM 79). When preferred stock is missing, it is replaced with the redemption value of preferred stock (ITEM 56).

Finally, to estimate firms' betas, the Fama/French factors are taken from the website of Kenneth R. French. More precisely, we estimate the coefficients in a regression that includes the three factors of Fama and French (1996):

$$r_{it}^e = \beta_i^0 + \beta_i^{MKT}\left(MKT - rf\right) + \beta_i^{SMB} SMB + \beta_i^{HML} HML + \epsilon_{it}, \tag{12}$$

in which r_{it}^e denotes stock i's excess return, MKT denotes the excess return on the value - weighted portfolio consisting of all NYSE, NASDAQ and AMEX stocks (from CSRP), rf the risk-free rate, and SMB and HML are payoffs on long-short spreads constructed by sorting stocks according to market capitalization and book-to-market ratios, respectively.

Table III reports descriptive statistics of all explaining variables. In order to exclude outliers, the sample is truncated at the 1% and 99% level for each variable. Next, Table IV reports the correlation between the estimated parameters and the explaining variables. We confirm the liquidity and illiquidity measures to exhibit the expected sign, with the exceptions of the correlations between the bid-ask spread and turnover (positive) and the bid-ask spread and the Amihud (2002) illiquidity measure (negative). The latter may be due to an asynchronous data problem. Further, all correlations within the information uncertainty measures are consistent, and such is also the case for all correlations within the informed trading variables.

3.2.2. Results

We carry out the analysis of the overreaction correction parameter γ scaled by 10^5. We consider a multilinear regression model with a constant and different explaining variables. The explaining variables are the (il-)liquidity measures defined as size, volume, turnover, the Amihud (2002) measure, and the bid-ask spread, the information (un-)certainty measures defined as age, historical volatility σ_{ret}, dispersion in analysts' forecast, and the number of analysts following a stock, and the informed trading measures defined as PIN, adjusted PIN and the probability of symmetric order shock flow PSOS. Further candidates are the stock's estimated Fama-French betas stemming from Fama-French regressions and a stock's leverage. First, to isolate the relation for each explaining variable, we investigate the regressions with one explaining variable (and a constant) at a time. Second, to also capture the impact of different explaining variables simultaneously and to assess their importance in explaining the overreaction parameter, we present the best models according to Bayes' and Akaike Information Criteria.

In all regressions, the estimated constant in the linear regression model is always positive and highly significant (between 158 and 197). We shall omit the discussion of the constant in the following analysis.

Firm-level illiquidity. We consider the explaining variables average size ($size$), average volume (vol), average turnover (to), the average Amihud (2002) measure ($ILLIQ$), and the average relative bid-ask spread (ba). Regression results are presented in Table V. The liquidity measures size, volume and turnover have positive coefficients, while the illiquidity measures Amihud (2002) measure and bid-ask-spread have negative coefficients. This observation intuitively suggests that overreaction corrections are facilitated for liquid stocks, whereas the corrections for illiquid stocks might be hindered by illiquidity constraints[11]. Further, the coefficients of volume and the Amihud (2002) measure are significant on the 1% level, the coefficients of size and bid-ask spread are significant on the 5% level, and the coefficient of turnover is significant on the 10% level. To quantify the impact of the explanatory variables on the overreaction correction parameter γ, consider, for example, the Amihud (2002) illiquidity measure ILLIQ. The coefficient of -23.41 in regression (4) suggests that an increase in one standard deviation of ILLIQ corresponds to a decrease in $10^5\gamma$ of $0.1651 * (-23.41) = -3.8650$. Table II illustrates the impact of a change of ten in $10^5\gamma$ on expected prices and returns in one overreaction correction phase. Using these results, a decrease in $10^5\gamma$ of -3.8650 corresponds to a one week (four weeks, one year) expected price change of 0.0128% (0.0118%, 0.0030%) within one overreaction correction phase, and to one week (four weeks, one year) expected return change of 0.1134% (0.1495%, 0.1590%). Analogous calculations for other explanatory variables yield similar results. Hence, the quantitative impact of the explanatory variables of the expected price and return changes due to a change in γ within one overreaction correction phase is very small, too (less than 1%). Furthermore, explanatory powers are weak: The adjusted R^2 varies between 0.0044% (bid-ask spread), and 1.14% (Amihud, 2002 measure). To conclude, all coefficients show the sign supporting the intuition that overreaction correction is stronger for liquid stocks, but economic impacts and explanatory powers remain low, even for a cross-section.

Information uncertainty. Explaining variables are the firm's age in weeks (age), the stock's return volatility σ_{ret}, the average dispersion of analysts' forecast $disp$, and the coverage cov defined as the average number of analysts following a stock. Table VI presents the regression results. The coefficients of age, return volatility and coverage show the sign consistent with a negative relation between information uncertainty and overreaction correction(positive for age and coverage, negative for return volatility). The coefficients of age and coverage are significant on the 5% level and the coefficient of return volatility is insignificant. The sign of the correlation coefficient of dispersion shows the sign consistent with a positive relation between information uncertainty and overreaction

[11] Avramov, Chordia, and Goyal (2006) show that mean reversal in short-term stock returns is stronger in low liquidity, high turnover stocks. On the contrary, we find that the overreaction correction parameter is weakly positively related with liquidity measures, and turnover seems to be relatively unimportant. Further, Rinne and Suominen (2012) find in a structural model that return reversal is faster when the market is illiquid. Hence, our overreaction correction effect seems to have a distinct origin from the general short-term reversal in stock returns documented in these papers .

(positive sign), and is significant on a 1% level. Strikingly, the explaining power is very weak for all regressions (maximum 0.44%). We conclude that the relation between the overreaction correction effect and information uncertainty effect is ambiguous, and yields almost no explanatory power.

Informed trading. Explaining variables are the measures of informed trading PIN, $APIN$ and $PSOS$. Table VII presents the regression results. None of the coefficients is significant, and all adjusted R^2 are negative. Clearly, there is neither any relation nor any explanatory power using these measures of informed trading. The regressions show that the price corrections that we study are indeed not due to informed traders who adequately exploit their information - in this case the regression coefficients would be positive and significant. Hence, we might interpret these regression results as being consistent with overreaction corrections arising primarily with respect to public information.

While the PIN measures have been established as widely used proxies for adverse selection, the literature also raises the question to which extend these measures capture the presence of informed trading. In particular, Collin-Dufresne and Fos (2012) test whether the traditional PIN measure, among other measures, reveals the presence of informed traders. By using a comprehensive sample of trades by Schedule 13D filers, the authors present evidence that challenges the idea of the traditional PIN measure detecting the presence of informed traders.[12] Importantly, Duarte and Young (2009) decompose PIN into a liquidity-based and an information-asymmetry based component (adjusted PIN). Because the adjusted PIN is corrected for liquidity the question whether this measure is subject to the caveat raised by Collin-Dufresne and Fos (2012) remains open. Regression (2) of Table VII takes into account the Adjusted PIN ($APIN$) and does not suggest a relation between informed trading and the overreaction correction parameter. As a robustness check, we could investigate the predictability of the overreaction correction parameter by using the measures of informed trading as defined by Collin-Dufresne and Fos (2012). Specifically, the authors calculate the following three measures: the probability that a Schedule 13D filer trades at least one share on a given day; the percentage of outstanding shares traded by 13D filers; the probability of trading with a Schedule 13D filer. However, the measures of Collin-Dufresne and Fos (2012) constitute event-driven measures, are defined only at certain periods of time and only for some firms, and exhibit important variation over time. Hence, the informative value of the respective regressions in a cross-sectional analysis would be questionable as well.

Leverage. Explaining variables are average book leverage lev, average book leverage conditional on leverage ≤ 1, lev_1, and average book leverage conditional on leverage being between 0 and 1, lev_{01}. The regression results are shown in Table VIII. The coefficients of lev_1 and lev_{01} are significant at the 10% level, but, again, the explanatory power is very weak. All adjusted R^2 are negative.

[12] Collin-Dufresne and Fos (2012) explain the data as follows: "Rule 13d-1(a) of the 1934 Securities Exchange Act requires investors to file with the SEC within 10 days of acquiring more than 5% of any class of securities of a publicly traded company if they have an interest in influencing the management of the company. [...] Schedule 13D filings reveal the date and price at which all trades by the Schedule 13D filer were executed during the 60 days that precede the filing date."

Stock betas. Explaining variables are the regression coefficients using an alpha and Fama/French's systematic factors β^{MKT}, β^{SML}, and β^{HML}. The firm index is omitted. Table VIII shows the regression results. The market and size betas are significant at a 1% and 5% level, respectively, while the other coefficients are insignificant. The adjusted R^2s are 3.77% and 0.30%, respectively. Thus, a stronger overreaction correction effect is positively related to the stocks' betas on the market excess return and on the size factor. In particular, the coefficient for the market beta indicates that stocks which co-move more strongly with the market -and in light with what we have seen before, with public information on the latter - also tend to exhibit a stronger overreaction correction effects.

Combination of explanatory variables. We now investigate the explanatory power of the overreaction correction parameter when including several explanatory variables. We include a constant, the liquidity measures size, volume, turnover, ILLIQ, and bid-ask spread, the information uncertainty measures firm age, return volatility, dispersion, and coverage, a measure of book leverage, and the estimated alpha as well as the Fama-French betas. We exclude the PIN measures due to their low explanatory power and the small sample size. Table X shows the five best models chosen according to Bayes' Information Criterion (BIC, Panel A, regressions (1)-(5)), and Akaike Information Criterion (AIC, Panel B, regressions (6)-(10)). Panel A of Table X shows that the five best models for our firms' sample according to the BIC all include a highly significant constant (between 185 and 191), a highly significant and negative coefficient on the bid-ask spread, and highly significant and positive coefficient of the market and size betas. Furthermore, all regressions except regression (5) include a highly significant and negative coefficient oo the Amihud (2002) measure. However, as argued in the analysis of the firm-level illiquidity measures, the economic impact of the explanatory variables on implied changes of expected prices and return due to variation in γ is low as well. Further partially included variables are the dispersion (regressions (2) and (5), and β^{HML} (regressions (3) and (5)). Explanatory powers however remain low and range between 4.84% and 6.95%.

These results are mainly confirmed when the best models are chosen according to the AIC (Panel B), which tends to include more variables. The AIC always includes dispersion with a positive and highly significant coefficient. Explanatory powers remain unconvincing, ranging between 6.83% and 7.24%.

Taken jointly, these regression results confirm that the firm specific overreaction correction parameter is negatively related to significant illiquidity measures. The intuition is that liquid stocks overreaction effects are easier to correct. Further, we also observe a positive relation between the overreaction parameter and the stocks' market betas, indicating that stocks that co-move more with the market tend to correct more strongly. While almost all coefficients show the consistent sign, explanatory powers remain weak. We conclude that our overreaction correction parameter is only weakly predictable by standard measures of market frictions at the firm level and by other firm characteristics.

4. Is the overreaction correction factor priced?

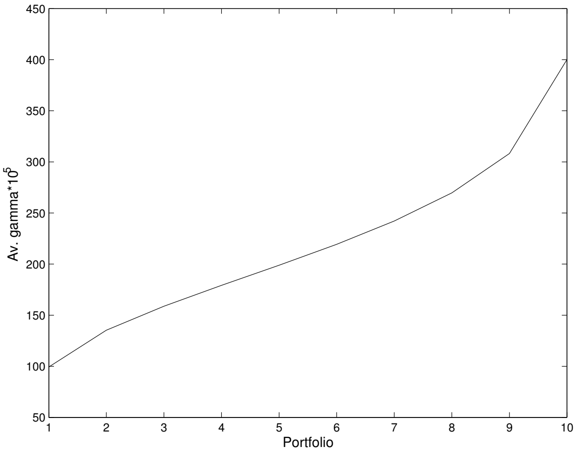
In this section, we investigate whether, at the aggregate level, stocks' overreaction correction, capture a non-diversifiable source of priced risk. Chordia, Roll, and Subrahmanyam (2000), Hasbrouck and Seppi (2001), and Huberman and Halka (2001) document that liquidity is driven by a common factor, and that, hence, there is a systematic premium associated with liquidity risk. Along the same lines, Easley, O'Hara, and Hvidkjaer (2002) document that the probability of informed trading, PIN, is a priced factor, but Duarte and Young (2009) show that it is only the component of PIN that is related to liquidity which is priced. Similarly, overreactions and subsequent stock prices' corrections may be driven by a common factor, which may be related to, for example, a liquidity risk factor, to information-based factors, or to time-varying systematic behavioral biases. Thus, in this section, we first investigate whether the overreaction correction factor is priced at the aggregate level and secondly investigate the relation between the overreaction correction factor and systematic liquidity risk.

We start by constructing the overreaction factor. In each trading year, defined from July to June, we consider all NYSE, AMEX, and NASDAQ stocks from 1963-2009 with share code 10 or 11. Only stocks that have already been traded for more than a year are considered, and we delete penny stocks (stock price of $5 or below during the previous year), as well as stocks that are traded 38 weeks or less (or 200 days or less) in the previous year. We estimate a yearly overreaction reversal parameter for each stock. We then form ten equally -weighted portfolios based on the magnitude of the overreaction parameters in the previous year, in which portfolio P1 denotes the lowest overreaction correction parameter stocks' portfolio, and P10 the highest overreaction correction stocks' portfolio. For each portfolio $p = 1, ..., 10$, we calculate a time series r_t^p of monthly returns in excess of the risk - free rate.

We next investigate whether the overreaction correction factor is priced. As is standard in the literature (see, e.g. Sadka, 2003 or Sadka, 2006), we start with the Fama and French (1996) three-factor model. That is, we adjust the time-series of excess returns for the three Fama-French factors using the time-series regression

$$r_t^p = \alpha_p + \beta_p^{MKT} (MKT_t - rf) + \beta_p^{SMB} SMB_t + \beta_p^{HML} HML_t + \epsilon_t^p. \quad (13)$$

The following Figure 3 show the average scaled overreaction correction parameter $\gamma 10^5$ of each portfolio (left-hand side) and corresponding estimated portfolio alphas (right-hand side). From the left graph, we see that the average overreaction correction over portfolios increases from about 100 (Portfolio 1) to about 400 (Portfolio 10). Next, we investigate the right graph, which displays the alphas calculated with the Fama-French three-factor model. Alphas are quite similar for P5-P10 (between 0.16% and 0.23% monthly premium), and significantly lower for P1 (-0.28% monthly premium), P2 (0.02% monthly premium), P3 (0.08% monthly premium), and P4 (0.15% monthly



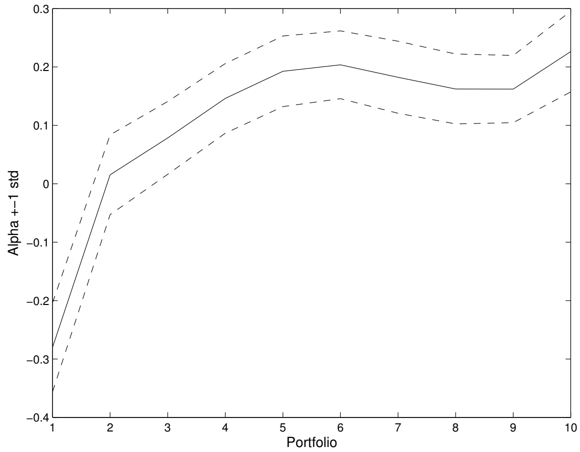


Figure 3. Average $10^5\gamma$ of overreaction portfolios (left) and average portfolio alphas of overreaction portfolios (right). For the right graph, estimated monthly alphas are calculated with the Fama-French three-factor model and drawn with solid lines. Dashed lines indicate one standard deviation

premium). This graph suggests that the premium is indeed increasing in overreaction correction, i.e., portfolios with low overreaction correction earn a lower premium.

Next, we additionally include the momentum factor using the four-factor Carhart (1997) model:

$$r_t^p = \alpha_p + \beta_p^{MKT} MKT_t + \beta_p^{SMB} SMB_t + \beta_p^{HML} HML_t + \beta_p^{MOM} MOM_t + \epsilon_t^p. \tag{14}$$

Portfolio alphas are presented in the left graph of Figure 4. Comparing this graph to the right graph in Figure 3, we can see that the impact of the additional inclusion of the momentum factor is minor. The shape of the graphs is approximately the same, only the level changes slightly. Hence, the comparison of Figs. 3 (right) and 4 (left) suggests that there does not seem to be a systematic relation between the overreaction correction and the momentum factors.

Finally, we also construct a liquidity risk factor based on the Amihud (2002) measure. Each month, stocks are ranked into 6 portfolios according to their annual illiquidity measures at the end of the previous year. For each portfolio p, the monthly return is calculated as

$$r_t^p = \sum_{i \in p} \omega_t^{ip} r_t^i, \tag{15}$$

in which $\omega_t^{ip} r_t^i$ are the weights (either equally-based or value-based). In the following, results are presented for the equally-based weights. Finally, the market-wide liquidity measure in month m is calculated as the average return on the three most illiquid portfolios minus the average return on the three most liquid portfolios. The procedure follows Gibson Brandon and Wang (2011), but we consider 6 portfolios for the sake of comparability to the Fama/French factors. As Gibson Brandon and Wang (2011) remark, the empirical results are quantitatively similar to the ones with value-

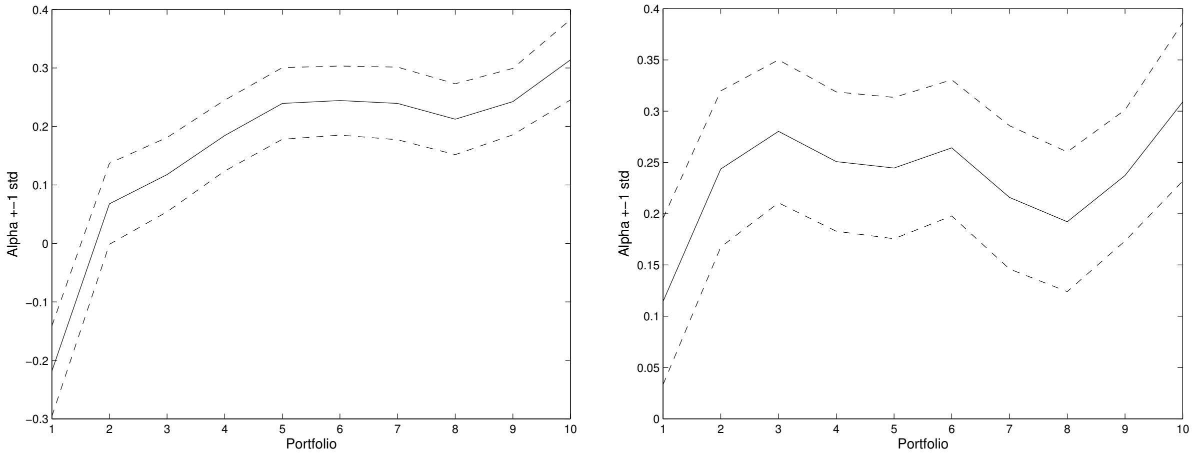


Figure 4. Portfolio alphas of overreaction portfolios estimated according to a 4-factor model (including the momentum factor, left graph) and according to a 5-factor model (including a momentum and a liquidity factor, right graph). Estimated monthly alphas are drawn with solid lines, dashed lines indicate one standard deviation.

based weights. Furthermore, the resulting market-wide liquidity measure is highly correlated with the systematic Pastor-Stambough liquidity measure (Pastor and Stambaugh, 2003). Analogous to Pastor and Stambaugh (2003), we run the regression

$$r_t^p = \alpha_p + \beta_p^{MKT} MKT_t + \beta_p^{SMB} SMB_t + \beta_p^{HML} HML_t + \beta_p^{MOM} MOM_t + \beta^{LIQ} LIQ_t + \epsilon_t^p. \quad (16)$$

The results are shown in the right graph of Figure 4.

We notice a different shape in the graph stemming from the five-factor model (right graph of Figure 4) which accounts for a liquidity risk factor compared to the graph resulting from the three- or four- factor models (right graph of Figure 3 and left graph of Figure 4, respectively). The change in alphas over portfolios due to the additional inclusion of the liquidity factor is positive for low-overreaction portfolios (e.g., the average alpha for portfolio 1 increases from -0.28% to 0.11%), and also positive, but less strong, for high overreaction portfolios (e.g., the average alpha for portfolio 10 increases from 0.23% to 0.31%). This results suggests that part of the premium for holding high-overreaction correction stocks is due to their exposure to systematic liquidity risk. We conclude that while the overreaction parameter on a firm level is positively related with liquidity measures, on an aggregate level, the overreaction factor is positively, but imperfectly, related to systematic liquidity risk.

To formally investigate the intuition suggested by these graphs, we summarize the regression results in Table XI. We focus on the statistics of portfolio 10 minus portfolio 1, ('10-1'), i.e., the high-overreaction correction minus the lowest -overreaction correction portfolio statistics. Interestingly, comparing the results for the three-factor model (Panel B) and the four-factor model (Panel C) yields only very little difference. The coefficients are almost the same, and the explanatory power stays at 30%. The yearly alpha increases very little from 6.12% per year to 6.36% per year, a difference which is not statistically significant. This result shows that the overreaction premium is not explained by the momentum premium. Hence, even though our overreaction correction effect might induce short-term autocorrelation, the effect is not equivalent nor even related to momentum on a systematic level. Next, in Panel D, we additionally include the liquidity risk factor into the regression model(five-factor model). While the market beta stays approximately the same compared to the four-factor model in Panel C, all other coefficients change. In particular, the alpha decreases significantly from 6.36% per year to 2.28% per year. The explanatory power also raises from 30% to 36%. The sign of the liquidity risk beta is positive. Taken jointly, these results lead us to conclude that the overreaction correction factor seems to be priced at the aggregate level, yielding a risk premium slightly higher than 6 % per year. However, about two thirds of the overreaction premium can be attributed to a mere compensation for systematic liquidity risk. It would be interesting to investigate in further research whether the residual overreaction premium of about 2 % per year is related to other behavioral or institutional factors that contribute to arbitrage risk.

5. Further evidence on financial stocks

In this section, we present the main results of a similar analysis conducted with a sample of US financial firms.

5.1. The sample of financial firms

In untabulated results[13], we carry out the analysis for a sample of US financial firms (Standard Industry Classification code 6000-6999). Specifically, we first estimate the overreaction parameter for each financial firm. Next, as in Section 4, we investigate if at the firm-level, the overreaction correction parameter is predictable. Finally, following the procedure in Section 4, we construct an overreaction factor using financial firms and examine if this factor is priced.

Compared to the results for the non-financial sample, the results for the financial sample are fundamentally different. First, we find that in general the overreaction correction parameter of financial firms is significantly lower than for non-financial firms, indicating that the overreaction correction effect seems to be smaller among financial firms. Second, most importantly, we find that the firm-level overreaction parameter is strongly predictable, the most important explaining variables being turnover and the market beta. Adjusted R^2s largely exceed 50%. Third, the alpha based on an overreaction factor built from financial firms is much smaller (3.84% per year), and only marginally significant. Interestingly, the alpha vanishes once a systematic liquidity factor is included. This result suggests that if there is a premium for holding high overreaction correction

[13] These results ,are available from the authors upon request.

financial stocks, this premium is much smaller and fully explained by their exposure to systematic liquidity risk.

6. Conclusion

In this paper, we estimate an overreaction correction parameter governing the dynamics of stock prices. To this end, we propose stochastic dynamics for stock price data that include an overreaction effect as described in Daniel, Hirshleifer, and Subrahmanyam (1998). We then offer two main contributions. First, we estimate this parameter at a firm-level and, in a cross-sectional analysis, show that the overreaction correction parameter is only weakly predictable by traditional measures of market frictions and by firm characteristics. Second, we examine, at the aggregate level, whether the overreaction correction factor is a priced source of risk. For that purpose, we construct an overreaction factor within a portfolio approach sorted by yearly stocks' overreaction correction parameters. We find that buying stocks with the largest overreaction parameters and selling stocks with the lowest overreaction parameter yields a significant yearly alpha of 6.12%. Interestingly, this alpha is almost unaffected when adding a momentum factor, indicating that the overreaction correction factor is not subsumed by the momentum risk factor. However, the alpha decreases to 2.28% per year when a systematic liquidity factor is added. We conclude that about two thirds of the overreaction correction premium originate from stocks' exposure to systematic liquidity risk. This finding is somehow intuitive and suggests that the mere common threat to stocks' prices corrections mechanism originates from unexpected shocks to aggregate stock market liquidity.

One limitation of our approach is the assumption of a constant overreaction parameter. Because we show that there is systematic risk associated with stock prices overreaction corrections, we may conjecture that the overreaction parameter is, in reality, time-varying. Hence, an interesting avenue for future research would be to investigate the properties of a time-varying or stochastically varying overreaction parameters. In particular, would the estimations stemming from a time-varying or stochastic approach enjoy greater predictability than in the static case in which we conducted the analysis? Second, we did not investigate the type of information to which stock prices correct within the framework of our dynamics. Daniel, Hirshleifer, and Subrahmanyam (1998) model overreaction to private signals, and Daniel and Titman (2005) and Lee (2006) show that investors tend to overreact to intangible information. It would be an interesting avenue for future research to test if the overreaction correction effect we investigate is consistent with these views or whether it is a mechanism that is primarily representative of stock prices' overreaction and subsequent adjustment process to public information.Finally, it would be interesting to explore the source(s) that drive the residual overreaction premium -of about 2 % per year- and to determine whether they are primarily rooted in systematic institutional factors or behavioral biases.

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7. Appendix

7.1. Maximum-Likelihood

Using matrix notation, we write the dynamics (1)-(2) as

$$\mathrm{d}\begin{pmatrix} X_t \\ Y_t \end{pmatrix} = A\begin{pmatrix} X_t \\ Y_t \end{pmatrix}\mathrm{d}t + f(t)\,\mathrm{d}t + \begin{pmatrix} 0 \\ \tilde{\sigma} \end{pmatrix}\mathrm{d}W_t, \tag{17}$$

with

$$\begin{aligned} A &:= \begin{pmatrix} 0 & 1 \\ \tilde{a} & -\beta \end{pmatrix} \\ f(s) &:= \begin{pmatrix} 0 \\ -\tilde{a}\left(\mu_0 + Es\right) \end{pmatrix}. \end{aligned}$$

By Theorem 8.2. of Nelson (2001), the conditional random variable $\begin{pmatrix} X_t \\ Y_t \end{pmatrix} | \mathrm{F}_0$ (for fixed t) is Gaussian, and the first moment is given by

$$\mathbb{E}\left[\begin{pmatrix} X_t \\ Y_t \end{pmatrix} | \mathrm{F}_0\right] = e^{tA}\begin{pmatrix} X_0 \\ Y_0 \end{pmatrix} + \int_0^t e^{A(t-s)} f(s)\mathrm{d}s, \tag{18}$$

Here, e^{tA} denotes the matrix exponential of tA, i.e.,

$$e^{tA} = \frac{1}{\gamma_2 - \gamma_1}\begin{pmatrix} \gamma_2 e^{\gamma_1 t} - \gamma_1 e^{\gamma_2 t} & -e^{\gamma_1 t} + e^{\gamma_2 t} \\ \gamma_1\gamma_2 e^{\gamma_1 t} - \gamma_1\gamma_2 e^{\gamma_2 t} & -\gamma_1 e^{\gamma_1 t} + \gamma_2 e^{\gamma_2 t} \end{pmatrix},$$

in which $\gamma_{1,2}$ are the eigenvalues of A, i.e.,

$$\gamma_{1,2} = -\frac{1}{2}\beta \pm \sqrt{\frac{1}{4}\beta^2 + \tilde{a}}.$$

According to Chandrasekhar (1943), page 30, the variance-covariance matrix is determined by [14]

$$
\begin{aligned}
Var\left(X_t\right) &= \frac{\tilde{\sigma}^2}{2\beta\left(-\tilde{a}\right)}\left\{1-e^{-\beta t}\left(2\frac{\beta^2}{\left(\gamma_2-\gamma_1\right)^2}\sinh^2\left(\frac{1}{2}\left(\gamma_2-\gamma_1\right)t\right)\right.\right. && (19)\\
&\quad \left.\left.+\frac{\beta}{\left(\gamma_2-\gamma_1\right)}\sinh\left(\left(\gamma_2-\gamma_1\right)t\right)+1\right)\right\}\\
Var\left(Y_t\right) &= \frac{\tilde{\sigma}^2}{2\beta}\left\{1-e^{-\beta t}\left(2\frac{\beta^2}{\left(\gamma_2-\gamma_1\right)^2}\sinh^2\left(\frac{1}{2}\left(\gamma_2-\gamma_1\right)t\right)\right.\right. && (20)\\
&\quad \left.\left.+\frac{\beta}{\left(\gamma_2-\gamma_1\right)}\sinh\left(\left(\gamma_2-\gamma_1\right)t\right)+1\right)\right\}\\
cov\left(X_t,Y_t\right) &= \frac{2\tilde{\sigma}^2}{\left(\gamma_2-\gamma_1\right)^2}e^{-\beta t}\sinh^2\left(\frac{1}{2}\left(\gamma_2-\gamma_1\right)t\right). && (21)
\end{aligned}
$$

We now show that the random variable $\begin{pmatrix} X_t \\ Y_t \end{pmatrix}|\mathrm{F}_0$ exhibits a Markov property. To this end, we define the transform

$$
\begin{pmatrix} \bar{X}_t \\ \bar{Y}_t \end{pmatrix} := \begin{pmatrix} X_t \\ Y_t \end{pmatrix} - \int_0^t e^{A(t-s)} f\left(s\right)\mathrm{d}s. \tag{22}
$$

An application of Ito's lemma shows that $\begin{pmatrix} \bar{X}_t \\ \bar{Y}_t \end{pmatrix}$ follows the dynamics

$$
\begin{aligned}
\mathrm{d}\bar{X}_t &= \bar{Y}_t\mathrm{d}t && (23)\\
\mathrm{d}\bar{Y}_t &= \tilde{a}\bar{X}_t\mathrm{d}t+\tilde{\sigma}\mathrm{d}W_t-\beta\mathrm{d}\bar{X}_t. && (24)
\end{aligned}
$$

The absence of a time-dependent drift guarantees that $\begin{pmatrix} \bar{X}_t \\ \bar{Y}_t \end{pmatrix}|\mathrm{F}_0$ is Markov (see Karatzas and Shreve (1998), Chapter 5, Theorem 4.20). As $\begin{pmatrix} X_t \\ Y_t \end{pmatrix}|\mathrm{F}_0$ can be written as a transform of $\begin{pmatrix} \bar{X}_t \\ \bar{Y}_t \end{pmatrix}|\mathrm{F}_0$ subject to a deterministic shift, $\begin{pmatrix} X_t \\ Y_t \end{pmatrix}|\mathrm{F}_0$ must exhibit a Markov property as well.[15] Thus, we write the log-likelihood function as

$$
\begin{aligned}
\mathrm{L}\left(\tilde{a},\tilde{\sigma},\beta,E,\mu_0\right) &= \log\left(f\left(X_{t_1},\ldots,X_{t_N},Y_{t_1},\ldots,Y_{t_N}\right)\right) && (25)\\
&= \log\prod_{i=2}^{N}\left(b\left(X_{t_i},Y_{t_i}\left|X_{t_{i-1}},Y_{t_{i-1}}\right.\right)\right) && (26)\\
&= \sum_{i=2}^{N}\log\left(b\left(X_{t_i},Y_{t_i}\left|X_{t_{i-1}},Y_{t_{i-1}}\right.\right)\right). && (27)
\end{aligned}
$$

[14] Chandrasekhar (1943) evaluates matrix exponentials with explicit formulas using the trigonometric functions *sinh* and *cosh*, see, e.g., Bernstein and So (1993). We adapt this exposition in the formulas for the entries of the variance-covariance matrix.

[15] For a formal proof of this argument, see Pearson and Sun (1994).

Here, $b\left(X_{t_i}, Y_{t_i} \,\middle|\, X_{t_{i-1}}, Y_{t_{i-1}}\right)$ is the bivariate normal density with mean as in (18), calculated as

$$\begin{aligned}
\mathbb{E}\left[\begin{pmatrix} X_{t_i} \\ Y_{t_i} \end{pmatrix}; X_{t_{i-1}}, Y_{t_{i-1}}, \mu_{t_{i-1}}\right] &= e^{(t_i - t_{i-1})A} \begin{pmatrix} X_{t_{i-1}} \\ Y_{t_{i-1}} \end{pmatrix} \\
+ \quad \frac{-\tilde{a}}{\gamma_2 - \gamma_1} & \begin{pmatrix} -\left(\frac{\mu_{t_{i-1}}}{\gamma_1} + \frac{E}{\gamma_1^2}\right) e^{\gamma_1 (t_i - t_{i-1})} + \left(\frac{\mu_{t_{i-1}}}{\gamma_2} + \frac{E}{\gamma_2^2}\right) e^{\gamma_2 (t_i - t_{i-1})} \\ -\left(\mu_{t_{i-1}} + \frac{E}{\gamma_1}\right) e^{\gamma_1 (t_i - t_{i-1})} + \left(\mu_{t_{i-1}} + \frac{E}{\gamma_2}\right) e^{\gamma_2 (t_i - t_{i-1})} \end{pmatrix} \\
+ \quad \frac{-\tilde{a}}{\gamma_2 - \gamma_1} & \begin{pmatrix} +\frac{\gamma_2 - \gamma_1}{\gamma_1 \gamma_2} E \left(t_i - t_{i-1}\right) + \frac{\gamma_2 - \gamma_1}{\gamma_1 \gamma_2} \mu_{t_{i-1}} + \frac{\gamma_2^2 - \gamma_1^2}{\gamma_1^2 \gamma_2^2} E \\ +\frac{\gamma_2 - \gamma_1}{\gamma_1 \gamma_2} E \end{pmatrix},
\end{aligned} \tag{28}$$

and the variance-covariance matrix according to (19)-(21).

The parameters $(\tilde{a}, \tilde{\sigma}, \beta, E, \mu_0)$ are then estimated by maximum likelihood.[16] Standard errors are determined by taking the square root of the diagonal elements of the inverse of the Hessian at the estimated point. Next, the estimates of (a, σ, γ) are calculated. Standard errors are determined by the delta method.

[16]Numerical experiments suggest that the parameters are well-identified. For a reasonable range of model parameters, the maximum-likelihood routine applied to simulated data converges to the true parameters for a wide range of starting guesses.

7.2. Tables

Table I
Parameter estimates.

This table reports the descriptive statistics for the results of the maximum likelihood estimation of dynamics (1)-(2). To apply maximum-likelihood estimation, for each firm, the weekly time series (X_t, Y_t) is constructed as the log of the observed price weighted with CRSP's cumulative factor and as the annualized daily log return excluding dividends on this date, respectively. The full sample includes all CRSP firms with share code 10 or 11 between 1963 and 2009, subject to the filters explained in Subsection 3.1.1, resulting in a sample size of 936 firms. For each firm, estimated parameters are the overreaction parameter γ, the volatility σ, the long-run mean E, the mean-reversion parameter a, and the initial value of the fundamental value process, μ_0. For each parameter, the cross-sectional mean is reported as well as 5%, 25%, 50%, 75% and 95% Quantiles. Further, mean p-values are reported, as well as the percentage of firms with a p-value below 0.1, 0.05, and 0.01, respectively. The corresponding standard errors are calculated by the delta method, for details see Appendix 7.1.

Parameter				Quantiles					p-values	
	Mean	5%	25%	Median	75%	95%	mean	≤ 0.1	≤ 0.05	≤ 0.01
$\gamma \cdot 10^5$	187.3670	131.4500	164.8532	186.4428	207.2998	248.5352	0.0000	1.0000	1.0000	1.0000
σ	0.4614	0.2718	0.3526	0.4342	0.5506	0.7361	0.0000	1.0000	1.0000	1.0000
E	0.0637	-0.2282	0.0102	0.0791	0.1269	0.2340	0.1838	0.6448	0.6030	0.5204
a	-1.6186	-5.3583	-1.8096	-0.9298	-0.4934	-0.1839	0.0194	0.9635	0.8970	0.5933
μ_0	2.0673	-0.7046	1.1505	2.3741	3.0945	3.8884	0.0636	0.8605	0.8380	0.7822

Table II

Illustration of the impact of the overreaction correction parameter γ in a setting of one overreaction correction phase.

This table reports the change in the expected log price (Panel A) and expected annualized log returns (Panel B) for different parameter values of the overreaction correction parameter γ and different time horizons compared to the base case with $10^5\gamma = 190$. The considered time horizons are one week, four weeks, six months, one year, and two years, and the range of $10^5\gamma$ is chosen from 120 to 250 with a grid of ten, which roughly corresponds to the range of $10^5\gamma$ in the data (cf. Table I). The base case with $10^5\gamma = 190$ is chosen to reflect the sample mean of 187.37. The mean reversion parameter is set to $a = -1.62$ (the sample mean). For simplicity, $\mu_0 = 2$ and $E = 0$. To investigate the overreaction correction effect, we set $X_0 = 2.2$, corresponding to a 10% excess compared to the long-run mean process, and $Y_0 = -7.69$, corresponding to minus one standard deviation, to initiate the correction phase. The table reports the percentage change in the expected log price (Panel A) and log returns (Panel B) due to the deviation of γ from the sample mean, in which the expectations are calculated according to formula (28). The last column presents the average change in the percentage deviation of the expected log price from the base case (Panel A) or the average change in the percentage deviation of the expected annualized log returns from the base case (Panel B) when $10^5\gamma$ is increased by ten, for $10^5\gamma$ ranging between 120 and 150 with a grid of 10.

Time	Overreaction correction parameter $10^{-5}\gamma$													
	120	130	140	150	160	170	180	190	200	210	220	230	240	250	mean($\Delta\gamma$)
Panel A: Percentage deviation of expected log price. Base case: $10^5\gamma = 190$.															
1 week	0.23	0.20	0.17	0.13	0.10	0.07	0.03	0.00	-0.03	-0.07	-0.10	-0.13	-0.17	-0.20	-0.0332
4 weeks	0.21	0.18	0.15	0.12	0.09	0.06	0.03	0.00	-0.03	-0.06	-0.09	-0.12	-0.15	-0.18	-0.0306
6 months	0.12	0.10	0.08	0.07	0.05	0.03	0.02	0.00	-0.02	-0.03	-0.05	-0.07	-0.08	-0.10	-0.0165
1 year	0.05	0.05	0.04	0.03	0.02	0.02	0.01	0.00	-0.01	-0.02	-0.02	-0.03	-0.04	-0.05	-0.0077
2 year	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	-0.00	-0.00	-0.00	-0.01	-0.01	-0.01	-0.0016
Panel B: Percentage deviation of expected annualized log returns. Base case: $10^5\gamma = 190$.															
1 week	2.58	2.20	1.82	1.44	1.06	0.70	0.34	0.00	-0.32	-0.60	-0.84	-1.04	-1.17	-1.23	-0.2933
4 weeks	2.70	2.32	1.93	1.55	1.16	0.77	0.39	0.00	-0.39	-0.77	-1.16	-1.55	-1.94	-2.33	-0.3869
6 months	2.78	2.38	1.99	1.59	1.19	0.80	0.40	0.00	-0.40	-0.80	-1.20	-1.60	-1.99	-2.39	-0.3981
1 year	2.88	2.47	2.05	1.64	1.23	0.82	0.41	0.00	-0.41	-0.82	-1.24	-1.65	-2.06	-2.47	-0.4113
2 years	3.07	2.63	2.19	1.75	1.31	0.88	0.44	0.00	-0.44	-0.88	-1.31	-1.75	-2.19	-2.63	-0.4378

Table III
Descriptive statistics of the explaining variables.

This table reports the cross-sectional mean and standard deviations (in parenthesis) of the explaining variables the log time-series average market capitalization ($size$), log time-series average volume (vol), log time-series average turnover (to), time-series average Amihud (2002) measure ($ILLIQ$), time-series average relative bid-ask spread (ba), log of the firm age in weeks (age), time-series average daily return volatility σ_{ret}, time-series average dispersion ($disp$), time-series average number of analysts following the stock (cov), (cf. Zhang, 2006), the time-series average probability of informed trading, PIN, see Easley, Kiefer, O'Hara, and Paperman (1996), the time-series average adjusted probability of informed trading, $APIN$, and the time-series average probability of order flow shock, $PSOS$, see Duarte and Young (2009). lev is time-series average book leverage, lev_1 is time-series average book leverage of all observations smaller than 1, and lev_{01} is time-series average book leverage of all observations smaller than 1 and greater than 0. The betas are the estimated coefficients in a regression with the Fama-French factors to explain a stock's returns excess of the risk-free rate: α is the alpha, β^{MKT} is the beta of market return minus the risk free rate, β^{SMB} is the beta on the small minus big factor, and β^{HML} is the beta on the high minus low factor. For each variable, the data is truncated at the 1 and 99% quantiles, resulting in a sample size of 751 firms. Mean and standard deviation are the cross-sectional statistics.

variable	mean	std
$size$	14.0612	(1.2383)
vol	2.2591	(1.4627)
to	1.7910	(0.7580)
$ILLIQ$	0.0732	(0.1651)
ba	0.0349	(0.0108)
age	6.6322	(0.8616)
σ_{ret}	0.0279	(0.0074)
$disp$	0.0031	(0.0029)
cov	1.8728	(0.5949)
PIN	0.1714	(0.0458)
$APIN$	0.1452	(0.0367)
$PSOS$	0.2356	(0.0553)
lev	0.3949	(0.2979)
$lev1$	0.3594	(0.2979)
$lev01$	0.4149	(0.1770)
α	0.4560	(0.8394)
β^{MKT}	1.0058	(0.3821)
β^{SMB}	0.5236	(0.5738)
β^{HML}	0.1433	(0.6179)

Table IV
Correlation of the explaining variables.

This table reports the correlations of the explaining variables. Variables are the log time-series average market capitalization ($size$), log time-series average volume (vol), log time-series average turnover (to), time-series average Amihud (2002) measure ($ILLIQ$), time-series average relative bid-ask spread (ba), log of the firm age in weeks (age), time-series average daily return volatility σ_{ret}, time-series average dispersion ($disp$), time-series average number of analysts following the stock (cov), (cf. Zhang, 2006), the time-series average probability of informed trading, PIN, see Easley, Kiefer, O'Hara, and Paperman (1996), the time-series average adjusted probability of informed trading, $APIN$, and the time-series average probability of order flow shock, $PSOS$, see Duarte and Young (2009). lev is time-series average book leverage. The betas are the estimated coefficients in a regression with the Fama-French factors to explain a stock's returns excess of the risk-free rate: α is the alpha, β^{MKT} is the beta of market return minus the risk free rate, β^{SMB} is the beta on the small minus big factor, and β^{HML} is the beta on the high minus low factor. The data are truncated at the 1 and 99% quantiles for each variable, resulting in a sample size of 764 firms.

	$size$	vol	to	$ILLIQ$	ba	age	σ_{ret}	$disp$	cov	PIN	$APIN$	$PSOS$	lev	α	β^{MKT}	β^{SML}
$size$	1.0000															
vol	0.8914	1.0000														
to	0.1095	0.5190	1.0000													
$ILLIQ$	-0.4240	-0.5146	-0.4310	1.0000												
ba	-0.3184	-0.0676	0.5480	-0.1220	1.0000											
age	0.1698	0.0111	-0.4987	0.2469	-0.6649	1.0000										
σ_{ret}	-0.3029	-0.0508	0.5616	-0.0481	0.9366	-0.6262	1.0000									
$disp$	-0.1332	-0.0711	0.0903	0.0386	0.1763	-0.0752	0.2121	1.0000								
cov	0.7775	0.7644	0.1541	-0.3655	-0.2214	0.2677	-0.2226	-0.0853	1.0000							
PIN	-0.6898	-0.6813	-0.2376	0.5211	0.1700	-0.0470	0.2144	0.0285	-0.6308	1.0000						
$APIN$	-0.7406	-0.7402	-0.2955	0.5475	0.0708	0.0182	0.1321	0.0355	-0.6613	0.9217	1.0000					
$PSOS$	-0.4837	-0.4279	0.0085	0.3986	0.2644	-0.2416	0.33411	0.0040	-0.4451	0.8237	0.6799	1.0000				
lev	0.1310	0.0661	-0.0679	-0.0554	-0.1566	0.0453	-0.4225	-0.1566	0.0866	-0.2387	-0.2435	-0.1819	1.0000			
α	0.0952	0.2962	0.5338	-0.1941	0.4802	-0.4288	0.4927	-0.0494	0.0544	-0.0168	-0.0918	0.1724	-0.0677	1.0000		
β^{MKT}	0.1750	0.2647	0.2403	-0.1379	0.2414	-0.0141	0.3026	0.1670	0.1339	-0.1073	-0.0942	-0.0977	-0.0330	0.1251	1.0000	
β^{SMB}	-0.4078	-0.2310	0.3048	0.0187	0.4873	-0.3924	0.5037	0.0805	-0.3223	0.4257	0.4166	0.4155	-0.0924	0.0804	-0.0153	1.0000
β^{HML}	-0.1096	-0.2071	-0.3317	0.2204	-0.4558	0.3789	-0.4177	0.0104	-0.1353	0.1852	0.2490	0.0852	0.0388	-0.4893	-0.1491	-0.2418

Table V
OLS regression results for the estimated overreaction correction parameter γ.

The dependent variable is the overreaction correction parameter γ scaled by 10^5. Explaining variables are a constant (const), the log time-series average market capitalization (*size*), log time-series average volume (*vol*), log time-series average turnover (*to*), time-series average Amihud (2002) measure ($ILLIQ$), time-series average relative bid-ask spread (*ba*). The sample is truncated at the 1% and 99% percentile for each variable. Standard errors in parentheses. $^{***}: p \leq 0.01, ^{**}: p \leq 0.05, ^{*}: p \leq 0.1$

	(1)	(2)	(3)	(4)	(5)
const	158.30***	183.13***	183.47***	189.76***	196.38***
	(12.29)	(2.01)	(2.84)	(1.20)	(4.6781)
size	2.11**				
	(0.87)				
vol		2.19***			
		(0.74)			
to			2.58*		
			(1.45)		
$ILLIQ$				−23.41***	
				(6.78)	
ba					−231.32**
					(96.03)
Sample size	858	858	858	858	858
F statistic	5.89	8.74	3.14	11.92	5.80
adj. R^2	0.0045	0.0078	0.0013	0.0114	0.0044

Table VI
OLS regression results for the estimated overreaction correction parameter γ.

The dependent variable is the overreaction correction parameter γ scaled by 10^5. Explaining variables are a constant (const),log of the firm age in weeks (*age*), time-series average daily return volatility σ_{ret}, time-series average dispersion (*disp*), and time-series average number of analysts following the stock (*cov*), (cf. Zhang, 2006). The sample is truncated at the 1% and 99% percentile for each variable. Standard errors in parentheses. $^{***}: p \leq 0.01, ^{**}: p \leq 0.05, ^{*}: p \leq 0.1$

	(1)	(2)	(3)	(4)
const	167.72***	191.22***	186.54***	180.60***
	(8.99)	(4.50)	(1.71)	(3.75)
age	3.04**			
	(1.36)			
σ_{ret}		−123.11		
		(152.96)		
disp			385.53***	
			(414.88)	
cov				3.75**
				(1.88)
Sample size	681	681	681	681
F statistic	5.03	0.65	0.86	3.96
adj. R^2	0.0044	-0.0020	-0.0017	0.0029

Table VII
OLS regression results for the estimated overreaction correction parameter γ.

The dependent variable is the overreaction correction parameter γ scaled by 10^5. Explaining variables are a constant (const), the time-series average probability of informed trading, PIN, see Easley, Kiefer, O'Hara, and Paperman (1996), the time-series average adjusted probability of informed trading, $APIN$, and the time-series average probability of order flow shock, $PSOS$, see Duarte and Young (2009). The sample is truncated at the 1% and 99% percentile for each variable. Standard errors in parentheses. $^{***}: p \leq 0.01, ^{**}: p \leq 0.05, ^{*}: p \leq 0.1$

	(1)	(2)	(3)
$const$	188.90*** (5.00)	189.34*** (5.11)	190.48*** (5.49)
PIN	24.92 (28.44)		
$APIN$		26.32 (34.26)	
$PSOS$			11.32 (22.69)
Sample size	421	421	421
F statistic	0.77	0.59	0.25
adj. R^2	-0.0029	-0.0034	-0.0042

Table VIII
OLS regression results for the estimated overreaction correction parameter γ.

The dependent variable is the overreaction correction parameter γ scaled by 10^5. Explaining variables are a constant (const), the time-series average book leverage (lev), the time-series average book leverage of all observations smaller than 1 (lev_1), and the time-series average book leverage of all observations smaller than 1 and greater than 0 (lev_{01}). The sample is truncated at the 1% and 99% percentile for each variable. Standard errors in parentheses. $^{***}: p \leq 0.01, ^{**}: p \leq 0.05, ^{*}: p \leq 0.1$

	(1)	(2)	(3)
$const$	185.24*** (2.08)	184.49*** (2.14)	183.17*** (2.81)
lev	6.00 (4.42)		
lev_1		8.46* (4.95)	
lev_{01}			10.84* (6.29)
Sample size	841	841	841
F statistic	1.84	2.92	2.97
adj. R^2	-0.0001	-0.0013	0.0001

Table IX
OLS regression results for the estimated overreaction correction parameter γ.

The dependent variable is the overreaction correction parameter γ scaled by 10^5. Explaining variables are a constant (const), the Fama-French factor betas, and the corresponding alpha. The betas are the estimated coefficients in a regression with the Fama-French factors to explain a stock's returns excess of the risk-free rate: α is the alpha, β^{MKT} is the beta of market return minus the risk free rate, β^{SMB} is the beta on the small minus big factor, and β^{HML} is the beta on the high minus low factor. The sample is truncated at the 1% and 99% percentile for each variable. Standard errors in parentheses. $^{***}: p \leq 0.01, ^{**}: p \leq 0.05, ^{*}: p \leq 0.1$

	(1)	(2)	(3)	(4)
$const$	187.75***	170.05***	185.00***	186.90***
	(1.24)	(2.91)	(1.44)	(1.12)
α	−1.44			
	(1.23)			
β^{MKT}		17.08***		
		(2.71)		
β^{SMB}			4.17**	
			(1.89)	
β^{HML}				1.25
				(1.76)
Sample size	862	862	862	862
F statistic	1.3653	39.6304	4.8504	0.5072
adj. R^2	-0.0007	0.0418	0.0033	-0.0017

Table X

OLS regression results for the estimated overreaction correction parameter γ.

The dependent variable is the overreaction correction parameter γ scaled by 10^5. Explaining variables are a constant (const.), the log time-series average market capitalization (*size*), log time-series average volume (*vol*), log time-series average turnover (*to*), time-series average Amihud (2002) measure (*ILLIQ*), time-series average relative bid-ask spread (*ba*), log of the firm age in weeks (*age*), time-series average daily return volatility σ_{ret}, time-series average dispersion (*disp*), time-series average number of analysts following the stock (*cov*), (cf. Zhang, 2006), the time-series average probability of informed trading, *PIN*, see Easley, Kiefer, O'Hara, and Paperman (1996), the time-series average adjusted probability of informed trading, *APIN*, and the time-series average probability of order flow shock, *PSOS*, see Duarte and Young (2009). *lev* is time-series average book leverage, lev_1 is time-series average book leverage of all observations smaller than 1, and lev_{01} is time-series average book leverage of all observations smaller than 1 and greater than 0. The betas are the estimated coefficients in a regression with the Fama-French factors to explain a stock's returns excess of the risk-free rate: α is the alpha, β^{MKT} is the beta of market return minus the risk free rate, β^{SMB} is the beta on the small minus big factor, and β^{HML} is the beta on the high minus low factor. Displayed are the five best models according to the Bayes Information Criterion BIC (Panel A, regressions (1)-(5)) and the Akaike Information Criterion BIC (Panel B, regressions (6)-(10)). Standard errors in parentheses. $^{***}: p \leq 0.01, ^{**}: p \leq 0.05, ^{*}: p \leq 0.1$

	Panel A: Bayes' Information Criterion					Panel B: Akaike Information Criterion				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
const	190.38***	190.39***	187.06***	186.10***	187.63***	178.56***	190.39***	187.63***	183.36***	179.91***
	(4.59)	(4.57)	(5.00)	(4.43)	(4.99)	(7.64)	(4.57)	(4.99)	(6.95)	(7.60)
size										
vol						−2.22			−2.43*	
						(1.44)			(1.43)	
to										
ILLIQ	−25.50***	−26.23***	−27.66***		−27.98***	−27.86***	−26.23***	−27.98***	−27.56***	−23.62***
	(7.77)	(7.74)	(7.86)		(7.84)	(8.90)	(7.74)	(7.84)	(8.91)	(8.48)
ba	−574.54***	−628.48***	−506.42***	−511.88***	−567.94***	−497.24***	−628.48***	−567.94***	−573.72***	−513.57***
	(123.97)	(125.54)	(130.41)	(123.36)	(132.94)	(139.13)	(125.54)	(132.94)	(138.86)	(138.86)
σ_{ret}										
disp		698.94**			648.81**	631.04**	698.94**	648.81**	679.82**	655.39**
		(289.33)			(291.42)	(291.42)	(289.33)	(291.42)	(289.87)	(291.29)
cov						6.19**		5.69*	3.04	
						(3.04)		(3.03)	(2.25)	
lev_1										
α										
β^{MKT}	15.08***	14.76***	15.57***	15.76***	15.19***	15.31***	14.76***	15.19***	15.10***	14.55***
	(2.96)	(2.95)	(2.97)	(2.97)	(2.96)	(3.04)	(2.95)	(2.96)	(3.04)	(3.00)
β^{SMB}	9.11***	9.12***	9.38***	8.42***	9.35***	9.37***	9.12***	9.35***	8.89***	10.00***
	(2.17)	(2.17)	(2.18)	(2.18)	(2.17)	(2.26)	(2.17)	(2.17)	(2.24)	(2.22)
β^{HML}			3.32*		2.76	3.11		2.76		3.41*
			(1.99)		(2.00)	(2.07)		(2.00)		(2.06)
Sample size	694	694	694	694	694	694	694	694	694	694
BIC or AIC	4784.3	4785.0	4788.1	4788.5	4789.6	4757.6	4757.8	4757.9	4758.0	4758.4
F statistic	12.66	11.37	10.71	13.11	9.80	7.90	11.37	9.80	8.69	8.67
adj. R^2	0.0617	0.0683	0.0641	0.0484	0.0695	0.0724	0.0683	0.0695	0.0707	0.0706

Table XI
Coefficients of the factor models using portfolios based on the overreaction factor.

The sample consists of all NYSE, AMEX, and NASDAQ stocks between 1963 and 2009 subject to the filtering procedure described in Section 4. For each stock, a yearly overreaction correction parameter is estimated. Next, ten equally-weighted portfolios based on the magnitude of the overreaction parameters in the previous year are formed, in which portfolio P1 denotes the lowest overreaction correction parameter stocks' portfolio, and P10 the highest overreaction correction stocks' portfolio. For each portfolio $p = 1, ..., 10$, we calculate a time series r_t^p of monthly returns in excess of the risk - free rate. Panels A-D report alphas and betas using different factor models to calculate the factor-adjusted returns. In Panel A, a one-factor model is used with only the market return factor excess of the risk-free rate (MKT). Panel B reports results based on the three Fama-French factors, which additionally includes the SMB (small minus big) and HML (high minus low) factors. The four-factor model in Panel C additionally considers the Carhart MOM (momentum) factor, and the five-factor model reported in Panel D also uses a liquidity risk factor based constructed with the Amihud (2002) measure ILLIQ. For each model, the alpha and betas for Portfolios 1 and 10 are reported, as well as for the results obtained from the differences in returns from Portfolio 10 minus Portfolio 1 (10-1). Standard errors in parenthesis. $^{***}: p \leq 0.01, ^{**}: p \leq 0.05, ^{*}: p \leq 0.1$

Portfolio	α	β^{MKT}	β^{SMB}	β^{HML}	β^{MOM}	β^{LIQ}	Adj. R^2
Panel A: one-factor model							
1	0.01	0.90***					0.70
	(0.11)	(0.03)					
10	0.46***	1.21***					0.83
	(0.11)	(0.02)					
$10-1$	0.45***	0.31***					0.29
	(0.09)	(0.02)					
Panel B: three-factor model							
1	−0.28***	0.85***	0.63***	0.37***			0.87
	(−0.08)	(0.02)	(0.02)	(0.03)			
10	0.23***	1.13***	0.63***	0.27***			0.93
	(0.07)	(0.02)	(0.02)	(0.02)			
$10-1$	0.51***	0.28***	0.00	−0.11***			0.30
	(0.09)	(0.02)	(0.03)	(0.03)			
Panel C: four-factor model							
1	−0.22***	0.84***	0.63***	0.35***	−0.06***		0.87
	(−0.08)	(0.02)	(0.02)	(0.03)	(−0.02)		
10	0.31***	1.12***	0.63***	0.24***	−0.09***		0.93
	(0.07)	(0.02)	(0.02)	(0.02)	(−0.02)		
$10-1$	0.53***	0.28***	0.00	−0.12***	−0.03		0.30
	(0.10)	(0.02)	(0.03)	(−0.03)	(−0.02)		
Panel D: five-factor model							
1	0.11	0.86***	0.46***	0.28***	(0.02)	−0.34***	0.89
	(0.08)	(0.02)	(0.03)	(0.03)	(0.02)	(−0.04)	
10	0.31***	1.11***	0.63***	0.24***	−0.09***	0.01	0.93
	(0.08)	(0.02)	(0.03)	(0.03)	(0.04)	(0.02)	
$10-1$	0.19*	0.25***	0.18***	−0.04	−0.11***	0.35***	0.36
	(0.10)	(0.02)	(0.04)	(−0.03)	(−0.02)	(0.05)	